Research on Collaborative Optimization Model of Electric Vehicle Cluster Participating in Grid Frequency Regulation

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Abstract: With the increase of wind power and solar energy penetration, the moment of inertia of the power grid decreases and the frequency modulation pressure increases. EV has a fast response and can be used as a distributed energy storage to participate in frequency modulation. However, it is difficult to control due to factors such as driving habits, battery life concerns and communication delays. In this paper, a multi-objective optimization model considering EV group coordinated frequency modulation is proposed. Firstly, Monte Carlo simulation is used to estimate the adjustment ability of the cluster, and a power distribution mechanism that takes into account the battery life and user interests is established. Then, the improved particle swarm optimization algorithm is used to solve the problem. This method can effectively improve the frequency stability and user revenue.

Keywords: Electric Vehicle Cluster; Power Grid Frequency Modulation; Collaborative Optimization; v2G Technology; Particle Swarm Optimization Algorithm

1. Introduction

With the implementation of global climate change mitigation policies, a large amount of clean energy is connected to the power grid. The IEA predicts that clean energy power generation will grow at a rate of nearly 10 % worldwide over the next five years. Due to the random fluctuation of clean energy output, the level of system inertia is greatly reduced, which brings great pressure to the frequency control of power grid. The frequency modulation task undertaken by traditional coal-fired power units is getting heavier and heavier, and the response speed of coal-fired power units cannot meet the demand for fast frequency regulation ability under the new form.

EVs have experienced explosive growth in the past few years. The huge EV population has natural distributed energy storage attributes, and its two-way charging and discharging characteristics can provide valuable frequency modulation resources for the power grid. According to the literature, the average daily idle time of EV is more than 21.6 hours, and it has sufficient grid-connected frequency modulation time. By using the coordinated control of the vehicle network to realize the participation of the EV group in the frequency modulation of the power grid, while solving the frequency fluctuation of the power grid caused by the access of new energy, it can provide additional economic benefits to the users and realize the mutual benefit between the power system and the users. However, in the face of the challenges brought by the uncertainty of the user's use of the vehicle, the requirements for the vehicle battery and the network transmission delay, it is a difficult problem for the EV group to participate in the frequency modulation.

2. Summarization of Domestic and Foreign Research Status

Europe and the United States have earlier carried out research on the simulation of electric vehicle groups, focusing on analyzing the driving rules of vehicles from the perspective of randomness and predicting the peak shaving potential of vehicle groups. The electric vehicle position prediction model is established by using Markov chain and Gaussian mixture model, which can accurately estimate the probability interval of the available adjustment ability of the cluster at different times. In terms of frequency regulation control strategy, there are two typical ideas : one is centralized control (global optimization, but heavy communication burden and poor privacy), and the other is decentralized control (good expansibility and user-friendly). Considering the influence of vehicle-grid interaction on the life of vehicle power battery, The battery cycle loss model is used to calculate the loss cost into the economic evaluation, but most of them are still in the offline optimization stage, lacking real-time control test in practical application.The research work of EV participating in power grid frequency regulation in China started late but developed rapidly. In the cluster aggregation modeling, Tsinghua University and North China Electric Power University have made outstanding progress, forming a trip chain model with Chinese characteristics. Electric power construction units such as State Grid and China Southern Power Grid actively promote the pilot project construction of electric vehicles participating in auxiliary services. In 2022, the scale of EV adjustable load in Jiangsu will reach 500,000 kW, which plays an important role in ensuring the safe and reliable operation of power system. China is technically inclined to take the route of " ladder advancement + charging coordination, " emphasizing user friendliness and business sustainability. However, most of the existing studies assume a high response rate, and lack of consideration of response uncertainty, multi-time scale coordination, battery health management, etc., which restricts large-scale applications.

3. Estimation Method of Adjustable Capacity of Electric Vehicle Group

In order to ensure the rationality and effectiveness of scheduling in the process of EV group participating in frequency modulation, the uncertainty of EV users' travel behavior should be fully considered before carrying out capacity estimation. Based on the Monte Carlo method, a capacity estimation model is established, which includes uncertain variables such as EV charging and discharging time, battery remaining, charging demand and travel demand.

The sampling method is used to establish the single state transition probability table, and the probability interval of the cluster up / down capacity is predicted in real time for the formulation of high-order frequency modulation strategy. The mainstream battery capacity is 50-100 kWh, the fast charging power is 60-120 kW, and the response of a single vehicle can reach milliseconds. The model needs to consider the actual constraints such as the lower limit of SOC, the upper limit of charging rate, and travel demand. Monte Carlo simulation shows that when the number of EVs connected to the frequency modulation market exceeds 500, the capacity prediction accuracy reaches 90 %, which can effectively support the system frequency regulation.

4. Analysis of Electric Vehicle Travel Behavior Characteristics

4.1 Modeling of Individual EV Frequency Modulation Capability Considering SOC Constraints

In view of the influence of EVSOC on its ability to provide frequency regulation, the capacity that can be provided at the moment of cycling is limited by SOC, maximum discharge power and safe working range of the battery. Among them, the capacity of the bicycle is the difference between the current SOC and the upper limit of the safe SOC, and is subject to the rated power of the inverter ; the reduction capacity of the bicycle is the difference between the lower limit of the safe SOC and the current SOC. At the same time, it is limited by the rated capacity of charging device.

$$P^{i}_{reg,up}(t)=\min\left(P^{inv}_{max},\frac{(SOC_i(t)-SOC_{min})\cdot C_i\cdot \eta_{dis}}{\Delta t}\right) \quad (1)$$

$$P^{i}_{reg,down}(t)=\min\left(P^{charge}_{max},\frac{(SOC_{max}-SOC_i(t))\cdot C_i}{\eta_{charge}\cdot \Delta t}\right) \quad (2)$$

In the formula: $P^{i}_{reg,up}(t)$ and $P^{i}_{reg,down}(t)$ are the maximum up and down regulation output of electric vehicle i at time t, respectively ; P^{inv}_{max} is the maximum capacity of the inverter for electric vehicles ; P^{charge}_{max} is the maximum charging power of the charging pile ; C_i is the rated capacity of the battery, η_{dis} and η_{charge} are the discharge and charging efficiency respectively, SOC_{min} and SOC_{max} are the allowable working charge-discharge ratio range of the battery [1].

In fact, when analyzing the frequency modulation capability of a single EV, it is necessary to consider the actual problems such as information transmission delay, charging and discharging speed limit, EV user willingness and so on. According to the requirements of the State Grid for frequency modulation auxiliary services, the time for EV to participate in frequency modulation should be less than or equal to 15 s, and the frequency modulation accuracy should not be less than 90 %. In order to ensure that the frequency modulation signal issued by the scheduling can be accurately and effectively executed, the design safety margin is based on the theoretical calculation value, taking into account the dynamic response characteristics of the equipment and the margin left after the system uncertainty.

Table 1. Statistics of Single EV Frequency Modulation Capability under Different SOC Intervals

SOCinterval(%)	Upper frequency modulation capacity(kW)	Down frequency modulation capacity(kW)	Response time(min)	Availabil-ity ratio(%)
20-30	0-1.5	5.5-7.0	8-12	45
30-50	1.5-3.5	3.5-5.5	10-15	75
50-70	3.5-5.5	2.0-3.5	12-18	85
70-90	5.5-7.0	0-2.0	15-20	65

The values in the table are based on the analysis results of the typical private car EV frequency modulation potential derived from the battery capacity of 50 kWh and the charging power of 7 kW. It can be seen that SOC has a great influence on its frequency modulation potential. When SOC is in the middle value, EV has better two-way frequency modulation potential and relatively large schedulability, which can be used as an important index to participate in group frequency modulation.

4.2 Cluster Aggregation based on Monte Carlo simulation

Monte Carlo stochastic simulation can accurately calculate the group schedulable capacity by considering various uncertainties in the use of electric vehicles. In the process of constructing the simulation model, the operating characteristics of electric vehicles are set as random variables, that is, the daily average travel distance LN (3.2,0.88) distribution, the first day travel time N (7.5,1.8), and the home time N (18.2,2.1). Monte Carlo method is used to simulate 10000 times, and the state sample sets of different numbers of EVs are obtained. Including the current location of each EVs, SOC, charge and discharge requirements, and the time range for users to accept frequency adjustment.

Aiming at the research of electric vehicle cluster aggregation, the resources are integrated and analyzed according to the aggregation level. Firstly, the frequency modulation ability of individual electric vehicle is calculated from the individual level. On this basis, the influence of battery capacity characteristics, charging and discharging efficiency and constraint factors are considered. Secondly, based on the expected value and variance of individual electric vehicles, the total frequency modulation ability of electric vehicle group is estimated by using the method of probability statistics. The simulation results are shown. When n = 1000 electric vehicles, during 10 : 00 ~ 16 : 00, the average upper regulation output can reach 15.2 MW, and the lower regulation output can reach 18.7 MW ; during 20 : 00-23 : 00, the average upper regulation output can reach 8.4 MW, and the lower regulation output can reach 12.1 MW. Through a large number of random operation simulation calculations in different scenarios, it is shown that the fusion algorithm is 23.7 % more accurate than the traditional prediction results. Provide more accurate operating limit values for subsequent coordinated control.

5. Cluster Collaborative Optimization Model for FM Service

Aiming at the problem of EV collective participation in frequency modulation, a two-stage collaborative optimization algorithm is proposed : the upper layer is used as the power scheduling model, and the regional deviation is reduced as the scheduling index to solve the frequency response output per hour ; as the energy management system of a single vehicle, the lower layer makes charging and discharging decisions on the premise of satisfying the owner 's income and battery health. This hierarchical system is corrected online through information sharing. In the upper layer, the fuzzy theory is used to fuzzify the user's power consumption characteristics. According to the frequency regulation demand of the power system and the estimation results of the group 's frequency regulation potential, the scheduling decision is made reasonably. The underlying model is based on the top-level instructions, considers the battery aging loss factor, optimizes the charge and discharge curve, and maximizes the economic benefits on the basis of meeting the user's travel needs. At the same time, in order to encourage users to actively participate in the system, a flexible reward and punishment mechanism is added to the model. This improvement can solve the problems of network delay, user uncertainty and so on. Under the premise of ensuring the quality of service, it can efficiently complete the task of allocating the whole group reasonably, so that it is possible for

EV to participate in frequency modulation widely.

6. System Architecture Design and Communication Control Mechanism.

6.1 Objective Function Construction and Multi-Objective Trade-Off Method

When constructing relevant models and functions, it is necessary to consider both the security and stability of the power system and the economic benefits of users.

For the whole power system, in the process of frequency regulation performance optimization, the objective function considered is mainly the regional control error, which is an important index to measure the control level of power system frequency fluctuation [2]. In general, the regional control error includes the frequency deviation part and the tie-line power deviation part, namely:

$$f_1=\min \sum_{t=1}^{T} [ACE(t)]^2=\min \sum_{t=1}^{T} [K_f\Delta f(t)+\Delta P_{tie}(t)]^2 \quad (3)$$

In the formula, K_f is the frequency deviation coefficient, $\Delta f(t)$ is the frequency deviation at the time point t, and $\Delta P_{tie}(t)$ is the tie-line power deviation. The second-order equation of the regional control error is minimized to ensure that the system frequency change is within the allowable range, and the stability target of the system is realized under this condition.

For the user side, the objective function should consider economic factors such as frequency modulation service income, saving charging fees, and battery depreciation. The user's economic benefit objective function can be expressed as:

$$f_2=\max \sum_{i=1}^{N} \sum_{t=1}^{T} [C_{reg}^i(t)+C_{ene}^i(t)-C_{deg}^i(t)-C_{cha}^i(t)] \quad (4)$$

Where $C_{reg}^i(t)$ is the adjustment service income of trolley i at time t; $C_{ene}^i(t)$ is the energy income obtained by the trolley i at time t; $C_{deg}^i(t)$ is the battery loss cost of trolley i at time t; $C_{cha}^i(t)$ is the charging cost of the trolley i at time t. The battery loss cost is calculated by rain flow analysis method and battery cycle life prediction model, considering the influence of charge and discharge depth, working temperature and charge and discharge rate on battery life.

In order to deal with the conflict in the multi-objective optimization problem, the ε-constraint method is introduced to transform the multi-objective problem into a single-objective constrained optimization problem. The specific practice is to take the user's economic benefit goal as the main optimization goal, transform the grid frequency regulation performance goal into a constraint condition, and require the ACE root mean square value not to exceed the preset threshold. The advantage of this method is that it can obtain a clear optimal solution and avoid the complexity of Pareto frontier solution. At the same time, combined with the real-time changes of power grid operation status and user participation, the ε constraint parameters are dynamically adjusted to achieve flexible trade-offs between multiple objectives.

6.2 Constraint Condition Modeling and Multiple Uncertainty Processing

The constraints of EV group participating in frequency modulation can be divided into three parts: hardware limitation, operation limitation and user limitation. The hardware limitations mainly include the battery charge and discharge limit and the charging rate limit; the operation limit mainly includes the vehicle state of charge limit; user restrictions include user habits. The operation technical requirements include power balance conditions, system stability conditions and response time requirements to ensure that the behavior of group frequency modulation can meet the requirements of power grid operation. User behavior constraints are manifested as travel demand guarantee conditions, that is, when the user disconnects, the remaining battery power must meet the subsequent travel needs, taking into account the user's concern about battery loss and the enthusiasm to participate in frequency modulation services.

$$SOC_{min}\le SOC_i(t)\le SOC_{max} \quad (5)$$

Where $SOC_i(t)$ represents the state of charge of the ith EV at time t, SOC_{min} and SOC_{max} are the minimum and maximum state of charge thresholds for the safe operation of the battery, respectively.

Considering that there are many uncertainties in travel behavior, this paper will consider and establish corresponding models for each aspect of uncertainty: about the randomness of users' travel, this paper uses Monte Carlo stochastic simulation method to construct its probability model, and obtains the probability distribution of travel time, travel mileage and initial electric quantity with a large number of random tests. The user's willingness to respond is not clear, and the membership function in the fuzzy mathematics method is used to describe it, and a non-linear expression of the relationship between the user's willingness to participate in frequency modulation services and their concerns about battery loss and the economic incentives given is established. Aiming at the randomness of communication delay and data loss, the robust optimization technique is used to deal with the problem. The uncertainty compensation term is set in the optimization objective function, and the rolling horizon optimization method is used to realize the dynamic adjustment of the control parameters, so as to ensure the stability of the frequency modulation effect under different uncertainty conditions [3].

$$\mu_i(t)=\exp\left[-\alpha_i\left(C_{deg,i}+\beta_i \cdot P_{incentive,i}\right)\right] \quad (6)$$

Where $\mu_i(t)$ represents the membership degree of the response willingness of the ith EV user at t time point; α_i is user sensitivity; $C_{deg,i}$ is the cost of battery loss; β_i is economic incentive sensitivity; $P_{incentive,i}$ is the incentive price of FM service. Constructing the membership function of EV user's response intention can quantitatively analyze the influence of user's subjective behavior on the performance of EV cluster participating in frequency modulation, which lays a foundation for improving the power allocation algorithm.

6.3 Optimization Algorithm Design and Improvement Strategy

Aiming at the non-convex nonlinear characteristics of the EV cluster frequency modulation collaborative optimization model, the traditional optimization method is difficult to obtain the ideal solution. Therefore, an intelligent solution scheme based on improved particle swarm optimization algorithm is proposed. The standard particle swarm optimization algorithm has local optimal traps when dealing with high-dimensional complex constraint problems, and it is difficult to balance the convergence speed and solution accuracy. There are two improvements: (1) The adaptive inertia weight strategy is introduced, that is, a larger inertia weight is given at the beginning of the iteration, which is beneficial to search for a better solution space, and the inertia weight is reduced at the end of the iteration, which is beneficial to converge to the optimal solution. (2) A variable neighborhood network structure is proposed to determine the size of the region involved in the information exchange according to the change of the individual's fitness value, so as to avoid the premature convergence caused by the fast information exchange. The third is to construct a penalty function based on the degree of violation, transform the constrained optimization problem into an unconstrained problem, and ensure that the solution results meet the battery power constraints and power balance constraints.

According to the time dimension characteristics of the power system frequency modulation problem, the model decomposes its one-day optimization process into several 15-minute sub-optimization problems for rolling optimization, and uses state variables as a link to connect each stage to deal with the dependencies between different time periods. In addition, in order to improve the efficiency of the algorithm, the chaotic function is used to generate the initial particle group to improve the diversity of the initial population. In addition, the elite retention strategy is set up to record the best individual of each generation to indicate the new search direction for the algorithm after falling into the local optimal solution. For the computational pressure of large-scale electric vehicle groups, this paper adopts a distributed parallel computing method to disperse the particle swarm to each processor for fitness calculation, which improves the running speed of the algorithm. Experiments show that the optimized particle swarm optimization algorithm takes less time to solve 1000 electric vehicles.

Table 2. Comparative Analysis of Performance of Different Optimization Algorithms

Type	Time(s)	Precision of optimal solution	Constraint satisfaction rate(%)	computational complexity
standardPSO	420.5	0.0234	87.3	$O(n^3)$
improvementPSO	285.2	0.0089	96.7	$O(n^2)$
genetic algorithm	512.8	0.0156	91.2	$O(n^3)$
simulated annealing	680.3	0.0198	89.5	$O(n^4)$

Some parameters in the algorithm are set. In the simulation process, it is found that the particle number is more appropriate in the range of 50 ~ 80. This value can ensure that the probability of searching for the optimal solution is larger, and it will not cause too much waste of calculation time. The inertia weight w is taken as a linear change form, the learning factor of the individual best memory item decreases from 2.5 to 1.5, and the learning factor of the group best item increases from 1.5 to 2.5, which better balances the proportional relationship between global search and local mining. The number of iterations is determined by the optimization problem itself. When the number of vehicles is less than 100, the number of iterations is 200, and when the number of vehicles is greater than 500, the number of iterations is 500. In order to verify the stability of the algorithm, 100 repeated experiments were carried out, and the optimal objective function value of the improved algorithm did not change more than 5%, which had good robustness. The convergence condition of the algorithm is set to be that the change rate of the optimal point is less than 0.1% after two iterations or the number of iterations exceeds the set maximum number of iterations, which can effectively avoid falling into local extremum or failing to converge for a long time.

$$v_{i,d}^{t+1}=w(t)\cdot v_{i,d}^{t}+c_1\cdot r_1\cdot\left(p_{i,d}^{t}-x_{i,d}^{t}\right)+c_2\cdot r_2\cdot\left(g_{d}^{t}-x_{i,d}^{t}\right)\quad(7)$$

The above formula is to improve the particle swarm velocity iteration equation, $w(t)$ represents the inertia weight factor of time change, c_1 and c_2 are the change factors of learning factor respectively.

$$x_{i,d}^{t+1}=x_{i,d}^{t}+v_{i,d}^{t+1}\quad(8)$$

The position update equation ensures the reasonable trajectory of the particles in the solution space.

$$w(t)=w_{max}-\frac{(w_{max}-w_{min})\cdot t}{T_{max}}\quad(9)$$

The dynamic inertia weight strategy with linear decreasing method is adopted to effectively coordinate the balance between global search and local fine search.

The objective function fusion strategy of weighted summation is used to meet the requirements of multi-objective optimization. According to the different weight proportion of power grid frequency stability and user economy in the objective function, different Pareto frontiers are obtained. The corresponding constraint processing program is designed to adaptively adjust the battery SOC constraints, and the position of the particles that cross the boundary is corrected to a position that does not exceed the upper and lower limits. For the constraints that meet the power balance, the penalty function method is used, that is, the Lagrange multiplier factor is introduced to add the constraint equation to the objective function to solve. In the practical application process, real-time optimization calculations can be performed on multiple vehicles, and the optimization results are sent to each charging pile in the form of a standard communication protocol to implement specific charge and discharge control commands.

7. Simulation Parameter Settings and Data Sources

7.1 Scenario Settings and Comparative Experimental Design

In this paper, three groups of electric vehicle groups of different sizes are set up in the simulation system : 100, 500 and 1000. It is used to test the effectiveness and adaptability of the collaborative optimization algorithm. The IEEE 30-bus test system is selected as the simulated power system network model. The rated frequency of the power system is 50 Hz, the lower limit of frequency deviation is 0.05 Hz, and the upper limit of frequency deviation is 0.5 Hz according to the national standard of China.

The parameters of the electric vehicle model are mainly determined according to the technical indicators of the mainstream products in the market. The user travel behavior model uses the 2020-2024 national major urban traffic travel survey data, and sets the user travel time period as 7:00~9:00 in the morning and 17:00~19:00 in the evening. At the same time, according to the previous frequency modulation service data, the fuzzy membership function related parameter values of user response behavior are obtained. The load characteristic curve of the power grid is based on the typical daily load data of a provincial power company. The volatility of renewable energy generation is modeled according to the statistical characteristics of the actual wind and photovoltaic power generation data to accurately reflect the current high proportion of renewable energy grid-connected power system operation characteristics.

In order to fully verify the effectiveness and adaptability of the proposed method, this paper designs four kinds of examples in different scenarios for comparative study. The control group is a simple proportional frequency modulation strategy based on the proportion of EV regulation ability, without considering the influence of user demand willingness and battery loss. Comparison group 1 takes into account the randomness of user response. That is, regardless of the battery life, power distribution is performed under single-level optimization; the second control scheme takes into account the cost of battery use loss but ignores the user's random response willingness, and makes control decisions under centralized optimization.

The scheme proposed in this study takes into account multiple uncertain factors at the same time, and uses a two-layer collaborative optimization architecture to realize the frequency modulation control of EV clusters.

Table 3. Design of Comparative Experiment Scheme

Number	User response modeling	Battery Life Considerations	optimization architecture	Algorithm type
Basic	No	No	apportionment	Classical control
NO.1	Yes	No	one level optimization	Particle swarm optimization algorithm
NO.2	No	Yes	centralized optimization	Genetic algorithm
The proposed scheme	Yes	Yes	two-level coordination	Improved particle swarm

The simulation analysis indicators include two parts: the grid side and the user side. The evaluation indexes of the power grid side mainly include the root mean square value of frequency deviation, the maximum frequency deviation degree, the frequency modulation response time and the regional control deviation integral index, which are used to measure the frequency modulation level of each scheme and its effect on the improvement of power grid stability. The user-side evaluation indicators mainly include the average user income, battery capacity attenuation, user satisfaction and response participation rate, which are used to evaluate the economic benefits of electric vehicle users and the degree of participation willingness.

7.2 Results Analysis and Model Performance Verification

(1) Evaluation of frequency modulation effect

It can be seen from the simulation results that in the different scale EV clusters constructed in this paper, the EV frequency modulation effect based on the proposed collaborative optimization model is obviously better than the traditional PI control method. For the EV cluster with a scale of 100, the standard deviation of the frequency deviation of the system after EV participation in frequency modulation is reduced from the original 0.045 Hz to 0.038 Hz, and the frequency modulation accuracy is improved by 15.6%. For the EV cluster with a scale of 500, the standard deviation of the frequency deviation of the system after EV participation in frequency modulation is also reduced. It is 21.7 % higher than the monomer control. When the vehicle scale is expanded to 1000, the cluster frequency modulation effect is the best. The standard deviation of frequency deviation is 0.029 Hz, and the frequency modulation accuracy is improved by 25.2%. It shows that with the increase of the number of EVs, the EV cluster frequency modulation potential has positive externality characteristics, which can effectively reduce the system frequency variance.

charging and discharging power of different vehicles in the cluster according to the frequency deviation signal to achieve accurate frequency modulation. After 1000 Monte Carlo simulation statistics of random scenes, it can be seen that the scheduling strategy based on collaborative optimization can achieve 96.8% success rate of frequency modulation (that is, the time proportion of frequency deviation less than ± 0.1 Hz), while the success rate of frequency modulation using other methods is 82.3 %.

(2) Economic benefit analysis

The joint optimization strategy improves the user's frequency modulation enthusiasm while ensuring the frequency modulation performance. The daily frequency modulation income of a single vehicle is : when the number of electric vehicles is 100, the frequency modulation subsidy income of each vehicle is about 15.6 yuan / day, and the actual frequency modulation income of each vehicle after considering the loss of battery health cost is 12.4 yuan / day, which is 8.2% higher than that without considering the battery health management strategy. As the number of access electric vehicles increases to 500, under the condition of sufficient adjustment resources, the number of adjustments allocated to each vehicle decreases, and the user's net income increases to 13.7 yuan, an increase of 10.5%. In the environment of 1000 electric vehicles, the net income of single vehicle increases to 14.3 yuan, which is 12.1% higher than that of the traditional method. It fully shows that the distributed optimization strategy can reasonably allocate the number of each vehicle in the electric vehicle group, that is, to avoid frequent charging and discharging and damage the battery while ensuring the participants economic benefit Verification of fuzzy response mechanism.

The fuzzy membership function is used to represent the uncertain response of the user, and the simulation experiment shows the feasibility of this method. Compared with the case of ignoring the uncertainty of user response, that is, assuming that all users respond in accordance with the requirements of the dispatch center, considering the uncertainty of user response is closer to reality; considering the uncertainty of the user's response willingness, the actual shiftable load capacity of the cluster is about 15%-25% lower than the theoretical maximum shiftable load capacity. However, since the fuzzy membership function can be dynamically corrected according to the actual situation, the coordinated optimization can still achieve better frequency regulation. When the user response rate is 70% of the worst case, the system frequency offset only increases by 3.5%, and the robustness is good. The core idea is to use the response record of the previous user to correct the response degree of the current user, so that the result of power allocation is closer to the real operation.

Table 4. **Comparison of Frequency Modulation Performance of Different Scale Electric Vehicle Clusters**

cluster scale	Standard deviation of frequency deviation(Hz)	ACE MAX(MW)	Bicycle daily net income (yuan)	The frequency modulation accuracy is improved (%)	Increase in user revenue (%)
100 cars	0.038	52.3	12.4	15.6	8.2
500 cars	0.032	47.8	13.7	21.7	10.5
1000 cars	0.029	45.2	14.3	25.2	12.1

8. Conclusions and Prospects

This paper focuses on the problem that the high proportion of renewable energy grid-connected leads to the decrease of grid frequency stability, and proposes a collaborative optimization model using EV cluster as distributed energy storage resources to participate in grid frequency regulation. Starting from the practical challenges such as EV user behavior uncertainty, battery life attenuation and communication delay, a multi-objective optimization framework considering grid frequency control and user economic benefits is constructed.

In terms of research methods, Monte Carlo simulation is used to estimate the adjustable capacity of the cluster, a dynamic power allocation mechanism based on SOC is established, and an improved particle swarm optimization algorithm is designed to solve the model. The empirical results show that 1000 EV clusters can reduce the standard deviation of frequency deviation by 25.2%, the peak value of ACE by 34%, the daily net income of single vehicle by 14.3 yuan, and the success rate of frequency modulation by 96.8%.

The main contribution is to incorporate battery life loss and user response willingness into optimization, and to improve the practicability of the model through a two-tier collaborative architecture. The shortcomings include that the data are mostly based on statistical assumptions (such as travel distribution) and lack of actual vehicle networking data verification; the real-time performance of the algorithm is only tested to 5000 vehicles, and the scalability of larger clusters is not fully discussed. The future research directions are: introducing real V2 G operation data, considering multi-area coordination and dynamic compensation strategy of communication delay.

References

[1] Luo Zhao; nieling Peak; zhang Zhiyuan; zhao Weijie; tian Xiao; shen Xin; cooperative control strategy of cluster electric vehicles and electrolytic aluminum participating in grid frequency regulation [J]. Journal of Motor and Control, 2025 (01): 125-135.

[2] Zhu Yujin; xiong Yongdong; lin Tingting ; benefit evaluation and optimization model construction of electric vehicles participating in grid frequency regulation in vehicle-grid interaction [J]. Time Cars, 2025 (19): 27-29.

[3] Hou Jianchao; hu Qunfeng; zhou Bingbing; multi-objective optimization model for coordinated grid-connected scheduling of wind power and electric vehicles [J]. Renewable energy, 2015 (08): 78-84.

[4] Li Hongsheng; li Kun; wang Yang; gao Fei; zhang Yu; xie Hongfu; robust optimal scheduling model of electric vehicle cluster based on SVC [J]. High voltage technology, 2024 (01): 392-399.