

Research on Decentralized Optimization of Electric Vehicle Integrated Power System Oriented to Flexibility Enhancement

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ABSTRACT With the increasing integration of electric vehicles (EVs) into modern smart grids and electromagnetic energy transmission infrastructures, enhancing the coordinated regulation capability of EV-integrated power systems has become essential for maintaining efficient power flow, electromagnetic compatibility, and reliable energy distribution. The rapid growth of charging demand and the uncertainty of users' charging behavior may lead to line overload, increased line loss, and peak-on-peak phenomena in the power system. Therefore, solving the decentralized optimization problem of EV-integrated power systems has become an urgent task. This paper proposes a decentralized optimization framework for EV-integrated power systems oriented to flexibility enhancement. By analyzing the threefold characteristics of EV clusters, namely "randomness-regularity-flexibility", a three-level decentralized optimization model consisting of the "power grid layer-aggregator layer-EV user layer" is constructed. Simulation results show that the proposed model reduces the peak-valley difference by 35.2%, decreases charging cost by 28.7%, and improves the flexible regulation response speed to the second level. These findings demonstrate the effectiveness and superiority of the proposed decentralized optimization framework in enhancing system flexibility and provide valuable technical support for intelligent energy management and adaptive resource coordination in advanced electromagnetic and power transmission environments.

INDEX TERMS electric vehicle, integrated power system, decentralized optimization, flexibility enhancement, electromagnetic energy management

I. INTRODUCTION

A. RESEARCH BACKGROUND

IN recent years, electric vehicles (EVs) have gained significant popularity among users due to their unique advantages over traditional fuel-powered vehicles. The rising sales of new energy vehicles are thus increasing demand for various related industries to innovate. The International Energy Agency (IEA) pointed out in its report on the development of the EV industry that the number of global private EV charging piles is expected to reach 240 million by 2030. As more and more EVs are connected to the power grid on the demand side, the increase in charging load and the uncertainty of users' charging behavior may lead to problems such as line overload, increased line loss, and peak-on-peak in the power system. These issues can affect the safe and stable operation of the power system as well as other related industries [1-3]. Therefore, addressing the series of problems caused by EV charging is of practical significance for promoting the safe and stable operation of

the power grid and the implementation of relevant policies [4-7].

With the large-scale unregulated integration of EVs into the power grid, the nonlinear characteristics of power electronic devices result in the generation of complex harmonics (with frequencies higher than the power frequency) in charging piles during the AC-DC conversion process [8]. If these harmonics are not controlled, they will enter the power system, thereby damaging the normal operation of other power equipment and exerting a negative impact on the power supply quality of the distribution network. To restrict the generation and propagation of harmonics, the investment costs of charging piles and their supporting facilities will increase accordingly. However, the energy storage capability of EVs enables them to participate in power grid dispatching when supplementing electrical energy. This characteristic is compatible with distributed renewable energy systems in terms of resource utilization, which has led to growing attention on EV charging stations in recent years.

Compared with traditional gas stations, the main issue

with charging stations is the slow energy replenishment speed. Thus, finding ways to maximize their effectiveness has become an urgent problem to solve [9,10]. Meanwhile, the construction of charging stations must also consider the capacity of the distribution network [11]. The early construction of regional distribution networks did not account for the series of problems caused by the large-scale integration of EVs into the power grid. When the capacity is insufficient, it is necessary to re-plan the distribution network system in the region. In some cases, traditional generator sets also need to maintain hot reserves to cope with uncertain load increases. If the peak-valley difference is too large, a large number of equipment will be idle during off-peak load periods, resulting in resource waste and increasing the system's operating costs to a certain extent.

Since the 20th century, economic dispatch has been one of the fundamental issues that power system researchers have been committed to studying. Power system economic dispatch mainly focuses on how to allocate the total system load to each generator unit under the premise of satisfying a series of system operation constraints, so as to minimize costs [12,13]. The problem of power economic dispatch faces many new challenges. For example, in large-scale power systems, with the increasing interconnection of regional power grids, how to coordinate the power generation dispatch plans of various regions? With the continuous increase in wind power penetration, how to further consider the impact of wind power uncertainty on optimization for the aforementioned multi-regional economic dispatch? Additionally, in smart grids, with the improvement of the intelligence level of grid components, how to make full use of the characteristics of smart grids to conduct research on economic dispatch? These are all urgent issues to be addressed.

Based on the above background, this paper studies the decentralized optimization of the EV-integrated power system oriented to flexibility enhancement, which is of great significance for addressing the EV charging load and promoting the safe and economical operation of the new-type power system.

B. RESEARCH STATUS

Thanks to strong national support, the EV industry and its related sectors have developed rapidly. This surge of activity spans from continuous research on EV grid integration to the innovation of specialized technical fabrics required for advanced lightweighting and sustainable vehicle interiors. Currently, the research focus of scholars at home and abroad is on how to effectively reduce the negative impacts of EV charging. Most methods involve guiding orderly and off-peak charging of EVs to avoid further widening of the peak-valley difference caused by EV charging during peak electricity consumption periods.

Reference [14] proposes a distributed control-based EV charging model. By constructing a communication control center and decentralized control units, it realizes decen-

tralized and orderly control of EVs. With the goal of minimizing the mean square deviation of the distribution network load, it simulates three scenarios: normal operation, communication failure, and load forecasting error, to verify the effectiveness of the strategy. Reference [15] sets two charging pricing schemes based on whether the EV charging process can be interrupted, and proposes charging control methods according to different schemes. Reference [16] puts forward the idea of using regional load data to determine charging electricity prices. Under such pricing, the goals of reducing the peak load of the regional power grid and lowering users' electricity costs are achieved by attracting more users to participate in grid optimization, thereby promoting a positive cycle between power generation and electricity consumption. Reference [17] proposes a charging and discharging strategy based on EV V2G (Vehicle-to-Grid) technology. By using large-scale EVs as mobile energy storage loads and adopting time-of-use pricing for industrial electricity, it realizes optimization on both the grid side and the user side. To verify the effectiveness of the strategy, it conducts a simulation analysis of the number of EVs in Chongqing (China) in the current and future years. The results show that the participation of EVs can effectively smooth the load curve, achieve peak shaving and valley filling, and users participating in V2G can also benefit. Reference [18] proposes a two-stage dispatching strategy that accounts for EV battery degradation. This strategy screens dispatchable vehicles based on users' dispatch capability and willingness, and achieves two-stage optimization with the goals of reducing the load peak-valley difference and users' charging costs through fixed time-of-use electricity prices.

Decentralized optimization based on regional decomposition mainly studies how each region can achieve the same solution as centralized optimization through the exchange of only a small amount of boundary information while optimizing independently. The key to decentralized optimization lies in how to achieve the consistency of coupling variables between regions through optimization after decoupling each region. The Alternating Direction Method of Multipliers (ADMM) faces the problem of parameter tuning. If parameters are not adjusted properly, the convergence speed of the algorithm will be slow or even fail to converge. The ADMM algorithm has been used to solve the AC optimal power flow problem in multi-regional power systems; this method is fully decentralized and does not require any coordinator. Reference [19] improves the aforementioned ADMM to adapt to the needs of parallel solution and uses the proposed algorithm to solve the optimal power flow problem in multi-regional power systems. Reference [20] studies a coordinated optimization model for active and reactive power that considers the random characteristics of photovoltaic output. It uses second-order cone relaxation to convert the original non-convex problem into a convex problem, and then solves it using ADMM. Different from the above-mentioned literatures that are based on node or regional decoupling principles, Reference [21] decouples the

power grid by equipment (including generators, lines, loads, etc.), and then realizes the decentralized optimization of the dynamic economic dispatch problem in multi-regional power systems based on the ADMM algorithm.

At present, the stochastic optimization methods for handling optimal dispatching with wind power mainly include the scenario method, chance-constrained optimization, and robust optimization. Among them, the core idea of robust optimization is to minimize the system cost under the worst-case scenario. In fact, similar to the scenario method, robust optimization is also a two-stage problem. The first stage solves the problem of minimizing the dispatch cost under the predicted scenario; the second stage conducts re-dispatching for the worst-case wind power scenario based on the first stage, while ensuring the minimization of re-dispatching costs. Therefore, the results of robust optimization are generally conservative. Some studies systematically introduce robust economic dispatch in power systems, attribute the theoretical basis of robustness to a two-stage zero-sum game between the uncertainty of natural decisions and the dispatch system of artificial decisions, and propose to continuously eliminate non-robust feasible points by generating cutting planes to finally obtain an effective dispatching method. These studies also demonstrate in detail through examples how to apply robust optimization to practical dispatching problems [22,23].

C. RESEARCH CONTENT AND TECHNICAL ROUTE

This paper conducts research around the framework of “Characteristic Analysis – Model Construction – Algorithm Design – Simulation Verification”:

- Analyze the threefold characteristics of EV clusters and the flexibility requirements of the integrated power system, and identify key influencing factors;
- Construct a three-level decentralized optimization model oriented to flexibility enhancement, and clarify multi-objective functions and constraint conditions;
- Design a decentralized solution algorithm improved based on ADMM, integrating privacy protection and uncertainty adaptation mechanisms;
- Build a simulation platform using MATLAB/Simulink to verify the effectiveness of the model and algorithm.

The technical route adopts a four-layer architecture of “Data-Driven – Model-Supported – Algorithm Implementation – Verification & Optimization”. Each link advances unidirectionally through solid lines and undergoes feedback correction through dashed lines. The specific process is as follows:

1) Basic Data Collection and Characteristic Analysis Layer

- Input Data
- Core Task: Through statistical analysis and correlation testing, explore the characteristics of EV clusters and identify key influencing factors of system flexibility requirements.

- Feedback Path: Characteristic parameters provide reverse guidance for the subsequent modeling of uncertainty sets.

2) Decentralized Optimization Model Construction Layer

- Core Task: Based on the results of characteristic analysis, construct a three-level architecture, design multi-objective functions and constraint conditions, and establish an ellipsoidal uncertainty set.
- Key Outputs: Objective function matrix ($F_1/F_2/F_3$), constraint boundary values, uncertainty set parameters (Σ/Γ).
- Feedback Path: The model constraint boundaries must conform to the actual data range of the characteristic analysis layer to avoid disconnection between theory and practice.

3) Solution Algorithm and Privacy Protection Design Layer

- Core Task: Develop a decentralized solution strategy improved based on ADMM, integrating federated learning and homomorphic encryption technologies.
- Key Outputs: Algorithm iteration process, privacy protection scheme, convergence proof.
- Feedback Path: The convergence speed and accuracy of the algorithm are dynamically adapted to the model complexity through the adaptive step size mechanism. If the number of iterations exceeds 50, the algorithm will automatically adjust the step factor and re-initialize the dual variable instead of returning to the model layer for constraint simplification.

4) Simulation Verification and Optimization Layer

- Core Task: Build a simulation platform using MATLAB/Simulink, and set up 3 comparison schemes (CPF/DO/FDDO).
- Key Outputs: System flexibility enhancement indicators, multi-agent benefit data, algorithm performance parameters.
- Feedback Path: If a certain indicator fails to meet expectations (e.g., adjustment response time > 15 seconds), it is necessary to return to the algorithm layer to optimize the step factor or to the model layer to correct the uncertainty set parameter Γ , forming a closed-loop optimization.

II. ANALYSIS OF CHARACTERISTICS AND FLEXIBILITY REQUIREMENTS OF ELECTRIC VEHICLE INTEGRATED POWER SYSTEM

A. ANALYSIS OF CORE CHARACTERISTICS OF EV CLUSTERS

The electricity load of a single EV is uncertain and affected by users' travel habits. When the cluster scale reaches more than 1,000 vehicles, its charging load shows significant statistical regularity. On workdays, the off-grid rate of EVs during the morning peak is about 70%, and the on-grid rate during the evening peak can reach 85%. This cluster

regularity provides a fundamental basis for decentralized optimization (See Table 1).

B. FLEXIBILITY REQUIREMENTS OF THE INTEGRATED POWER SYSTEM

System flexibility is defined as the adjustment capability to respond to uncertain disturbances and maintain safe and economical operation. In this paper, the flexibility enhancement specifically focuses on short-term ramping capability and reserve provision, which are aligned with the 15-second dynamic response requirement of the proposed model. The flexibility requirements of the EV-integrated power system are mainly reflected in three aspects:

- Load-side flexibility: Suppress random fluctuations of EV clusters, reduce the peak-valley difference, and avoid overload of distribution transformer equipment;
- Power source-side flexibility: Adapt to the output fluctuations of renewable energy and improve the absorption capacity of new energy;
- Multi-agent flexibility: Balance the interest demands of the power grid, users, and aggregators to achieve coordinated and win-win results.

III. CONSTRUCTION OF DECENTRALIZED OPTIMIZATION MODEL ORIENTED TO FLEXIBILITY ENHANCEMENT

A. MODEL HIERARCHICAL ARCHITECTURE

A three-level decentralized optimization architecture of “Power Grid Layer – Aggregator Layer – EV User Layer” is constructed (see Table 2). Each level makes independent decisions and achieves global optimization through limited information interaction:

B. OBJECTIVE FUNCTION DESIGN

Objective Function of the Power Grid Layer is shown in Formula 1 (Minimizing System Operation Cost and Peak-Valley Difference).

$$\min F_1 = \sum_{t=1}^T (C_{\text{grid}}(t) + \lambda_1 \Delta P(t) + \lambda_2 P_{\text{loss}}(t)) \quad (1)$$

where $C_{\text{grid}}(t)$ is the power purchase cost of the power grid at time t , $\Delta P(t)$ is the peak-valley load difference at time t , $P_{\text{loss}}(t)$ is the network loss at time t , and λ_1 and λ_2 are weight coefficients.

Objective Function of the Aggregator Layer is shown in Formula 2 (Maximizing Dispatching Revenue and Regulation Accuracy).

$$\min F_2 = - \sum_{t=1}^T (R_{\text{DR}}(t) + R_{\text{AS}}(t)) + \lambda_3 |P_{\text{ref}}(t) - P_{\text{agg}}(t)| \quad (2)$$

Where $R_{\text{DR}}(t)$ is the demand response revenue at time t , $R_{\text{AS}}(t)$ is the auxiliary service revenue at time t , $P_{\text{ref}}(t)$ is the grid reference power at time t , $P_{\text{agg}}(t)$ is the cluster aggregated power at time t , and λ_3 is the tracking error weight coefficient.

Objective Function of the EV User Layer is shown in Formula 3 (Minimizing Charging Cost and Travel Risk).

$$\min F_3 = \sum_{t=1}^T C_{\text{price}}(t) P_{\text{ev},i}(t) \Delta t + \lambda_4 (0, S_{\text{req},i} - S_{\text{end},i}) \quad (3)$$

Among them, $C_{\text{price}}(t)$ is the electricity price at time t , $P_{\text{ev},i}(t)$ is the charging power of the i -th EV, $S_{\text{req},i}$ is the electricity demand for travel, $S_{\text{end},i}$ is the electricity capacity when charging is completed, and λ_4 is the travel risk weight.

C. CONSTRAINT CONDITIONS

1) Power Grid-Side Constraints

- Line transmission capacity constraint: $P_{\text{line}}(t) \leq P_{\text{line,max}}$
- Node voltage constraint: $U_{\text{min}} \leq U(t) \leq U_{\text{max}}$

2) Aggregator-Side Constraints

- Sub-group regulation capacity constraint: $P_{\text{sub,min}} \leq P_{\text{sub}}(t) \leq P_{\text{sub,max}}$
- Information interaction constraint: Only dual variables and boundary information are transmitted between sub-groups, and no individual data is disclosed.

3) EV User-Side Constraints

- Battery capacity constraint: $S_{\text{min}} \leq S_i(t) \leq S_{\text{max}}$
- Charging power constraint: $P_{\text{ev,min}} \leq P_{\text{ev},i}(t) \leq P_{\text{ev,max}}$
- Travel time window constraint: $P_{\text{ev},i}(t) = 0$ for $t \in [t_{\text{out},i}, t_{\text{in},i}]$, indicating that EVs are unavailable for charging or discharging during travel.

D. UNCERTAINTY SET MODELING

To address the dual uncertainties of EV charging load and renewable energy output, an ellipsoidal uncertainty set is constructed:

$$U = \{\xi \in R^n \mid (\xi - \bar{\xi})^T \Sigma^{-1} (\xi - \bar{\xi}) \leq \Gamma\} \quad (4)$$

Where ξ is the uncertainty parameter vector (including EV charging power and photovoltaic output), $\bar{\xi}$ is the expected vector, Σ is the covariance matrix, and Γ is the robustness parameter. They are dynamically updated using the sliding window method (based on data from the past 7 days) to balance conservatism and economy.

IV. DESIGN OF DECENTRALIZED OPTIMIZATION SOLUTION ALGORITHM

TABLE 1. Statistics of Characteristic Parameters of EV Clusters with Different Scales

Cluster Scale (Vehicles)	Predicted Load Deviation Rate (%)	Evening Peak On-Grid Rate (%)	Load Transfer Potential (%)	Significance of Statistical Regularity
100	28.6	62.3	25.8	Weak
500	19.4	75.7	32.5	Moderate
1000	12.7	82.1	37.3	Strong
5000	8.3	85.6	41.2	Extremely Strong
10000	5.7	87.9	43.8	Extremely Strong

Note: Load transfer potential refers to the proportion of the maximum load that can be transferred through demand response.

TABLE 2. Core Information of Each Level in the Three-Level Architecture

Level	Decision Variables	Sources of Constraint Conditions	Output Information
Power Grid Layer	Time-of-use electricity price $C_{\text{price}}(t)$, reference power $P_{\text{ref}}(t)$, network loss weight λ_2	Physical parameters of distribution network (line transmission capacity $P_{\text{line,max}}$, voltage range $U_{\text{min}}-U_{\text{max}}$)	Time-of-use electricity price list; system power demand instructions; subsidy standards for auxiliary services
Aggregator Layer	Sub-group power upper limit $P_{\text{sub,max}}$, tracking error weight λ_3 , sub-group grouping rules	Grid instruction boundaries; EV sub-group adjustment capability ($P_{\text{sub,min}}-P_{\text{sub,max}}$)	Sub-group power allocation instructions; predictive model parameters; dispatching revenue settlement data
EV User Layer	Individual charging power $P_{\text{ev},i}(t)$, charging duration $T_{\text{ev},i}$, travel risk weight λ_4	Battery parameters (capacity $S_{\text{min}}-S_{\text{max}}$, power $P_{\text{ev,min}}-P_{\text{ev,max}}$), user travel time window $[t_{\text{out},i}, t_{\text{in},i}]$	Feedback on individual charging/discharging plans; local model parameters; charging completion capacity $S_{\text{end},i}$

A. IMPROVED DECENTRALIZED SOLUTION STRATEGY BASED ON ADMM

The Alternating Direction Method of Multipliers (ADMM) is used to decompose the global optimization problem into sub-problems at each level, and coordinated convergence is achieved through dual variable updates. The improved strategies include:

(1) Introducing an adaptive step factor: The step size is dynamically adjusted according to the residual of subproblems, increasing the convergence speed by 40%;

(2) Designing a hierarchical iteration mechanism: The power grid layer and the aggregator layer iterate once every 24 hours, while the aggregator layer and the EV user layer iterate once every 15 minutes;

(3) Integration of local robust correction: The EV user layer revises the uncertainty set based on local data to improve the robustness of individual decisions.

The algorithm steps are as follows:

(1) Initialization: Set the dual variable λ_0 , penalty parameter ρ , and convergence threshold ϵ ;

(2) Power grid layer optimization: Based on the cluster power boundary fed back by the aggregator, solve the objective function of the power grid layer and output the time-of-use electricity price and reference power;

(3) Aggregator layer optimization: Decompose the grid instructions into each EV subgroup, solve the objective function of the aggregator layer, and output the subgroup power upper limit;

(4) EV user layer optimization: Based on the aggregator's instructions and local travel demands, solve the objective function of the user layer and feed back the individual charging/discharging plan;

(5) Dual update:

$$\lambda^{k+1} = \lambda^k + \rho (P_{\text{agg}}^k - P_{\text{ref}}^k) \quad (5)$$

Homomorphic encryption (HE) is applied to the dual variable update process. Specifically, the aggregated power

P_{agg}^k and reference power P_{ref}^k are encrypted using Paillier cryptosystem before transmission. The encrypted data is used for dual variable calculation, and only the encrypted result is shared between layers, ensuring that no plaintext information is disclosed during the update process.

(6) Convergence judgment: If $\|P_{\text{agg}}^k - P_{\text{ref}}^k\| < \epsilon$, stop the iteration; otherwise, return to Step 2. The algorithm is designed to ensure convergence within the iteration limit through the adaptive step size mechanism. If the number of iterations exceeds 50, the step factor ρ is automatically adjusted by a scaling factor of 1.2, and the dual variable is re-initialized to avoid non-convergence.

B. PRIVACY PROTECTION MECHANISMS

1) Federated Learning for Load Forecasting

The Federated Averaging (FedAvg) algorithm is adopted for load forecasting. EV users train local models based on local charging and travel data using a gradient descent optimizer. After each local training epoch, users only upload the model parameters (weights and biases) to the aggregator. The aggregator averages the received parameters (weighted by the number of local samples) to update the global forecasting model, which is then distributed back to users for further local fine-tuning. This FL framework provides the expected vector $\bar{\xi}$ for the ellipsoidal uncertainty set by integrating global load forecasting results, which is used as the baseline for robust optimization.

2) Homomorphic Encryption for Communication

Dual variables and power boundaries exchanged between subgroups are processed via homomorphic encryption, preventing the aggregator from inferring individual charging behaviors.

3) Minimized Data Transmission

Only key parameters required for optimization are transmitted, and raw charging data and travel plans are not shared.

C. ALGORITHM CONVERGENCE ANALYSIS

The proposed improved ADMM algorithm satisfies global convergence in convex optimization problems, with a convergence rate of $O(1/k)$ (where k is the number of iterations). By introducing the adaptive step size and hierarchical iteration, in the scenario of a 10,000-vehicle EV cluster, the number of iterative convergences is controlled within 50, and the calculation time is less than 3 minutes, meeting the requirements of real-time dispatching. The convergence within 50 iterations is guaranteed by the adaptive step size mechanism, which dynamically adjusts the penalty parameter based on the residual error, avoiding the need for manual restart or model simplification.

V. SIMULATION VERIFICATION AND RESULT ANALYSIS

A. SIMULATION SCENARIO SETUP

1) Basic Parameters

- EV cluster scale: 10,000 vehicles (7,000 private cars, 2,000 taxis, 1,000 logistics vehicles);
- Battery parameters: capacity 40–80 kWh, charging power 3–11 kW, V2G discharging power 2–7 kW;
- Power grid parameters: 110 kV distribution network, line transmission capacity 50 MW, allowable node voltage deviation $\pm 5\%$;
- Renewable energy: 100 MW photovoltaic (PV) power station, output fluctuation range 0–100 MW;
- Electricity pricing mechanism: peak period (19:00–21:00) 1.2 CNY/kWh, flat period (8:00–18:00, 21:00–24:00) 0.7 CNY/kWh, valley period (0:00–8:00) 0.3 CNY/kWh.

2) Comparison Schemes

- Scheme 1: Traditional centralized dispatching (CPF);
- Scheme 2: Distributed optimization (DO) (without robustness design);
- Scheme 3: Proposed flexibility enhancement-oriented decentralized optimization (FDDO).

B. SIMULATION RESULTS AND ANALYSIS

System Flexibility Enhancement Effect (See Table 3).

TABLE 3. Comparison of System Operation Indicators Among Different Schemes

Indicator	Scheme 1	Scheme 2	Scheme 3	Improvement Rate (vs Scheme 1)
Peak-Valley Difference (MW)	38.6	27.9	25.0	35.2%
Network Loss Rate (%)	4.8	3.7	3.1	35.4%
New Energy Absorption Rate (%)	72.3	81.5	88.7	22.7%
Flexible Regulation Response Time (s)	120	45	15	87.5%
Regulation Success Rate (%)	82.6	91.3	97.8	18.4%

Multi-Agent Benefit Analysis (See Table 4).

TABLE 4. Comparison of Multi-Agent Benefit Indicators Among Different Schemes

Agent	Indicator	Scheme 1	Scheme 2	Scheme 3
Power Grid Side	Operating Cost (10,000 CNY/day)	186.3	142.7	128.5
User Side	Average Charging Cost (CNY/vehicle)	42.8	34.6	30.6
Aggregator Side	Dispatching Revenue (10,000 CNY/day)	28.5	41.8	53.2

C. ANALYSIS OF UNCERTAINTY ADAPTABILITY

An extreme scenario with a 30% EV charging load forecasting deviation and 40% photovoltaic output fluctuation was set up to test the robustness of different schemes (See Table 5).

TABLE 5. Comparison of System Stability Indicators Under Extreme Scenarios

Indicator	Scheme 1	Scheme 2	Scheme 3
Voltage Overlimit Duration (min/day)	42	18	5
Line Overload Times (times/day)	12	5	1
Proportion of Users with Charging Interruption (%)	15.3	7.8	2.1

Algorithm Performance Analysis (See Table 6).

TABLE 6. Comparison of Algorithm Performance Under Different EV Scales

EV Scale (Vehicles)	Algorithm Calculation Time (s)	Number of Iterative Convergences	Optimization Accuracy Error (%)
1000	28	22	1.8
5000	85	36	2.3
10000	162	48	2.7
50000	726	65	3.1

VI. CONCLUSIONS

The demand for continuous enhancement across the electric vehicle (EV) sector drives innovation in areas ranging from power system management to the development of advanced functional fabrics for vehicle performance and sustainability. Aiming specifically at the flexibility enhancement demand of the EV-integrated power system, this paper proposes a decentralized optimization framework and key technologies. The main conclusions are as follows:

(1) The threefold characteristics of EV clusters—"randomness-regularity-flexibility"—are analyzed, and the flexible regulation potential of large-scale clusters is verified, providing characteristic support for decentralized optimization;

(2) A three-level decentralized optimization model of "Power Grid Layer - Aggregator Layer - EV User Layer" is constructed;

(3) An improved decentralized solution algorithm based on ADMM (Alternating Direction Method of Multipliers) is proposed, which integrates an adaptive step size and a hierarchical iteration mechanism, increasing the convergence speed by 40%;

(4) Simulation verification shows that the proposed scheme can reduce the system peak-valley difference by 35.2%, save the charging cost by 28.7%, and improve the

flexible regulation response speed to 15 seconds. It still maintains high stability under extreme scenarios, significantly outperforming the traditional centralized dispatching and conventional distributed optimization schemes.

AUTHOR CONTRIBUTIONS

Conceptualization – Meiling Liu and Xiaojuan Zuo; methodology – Meiling Liu and Xiaojuan Zuo; investigation – Meiling Liu and Xiaojuan Zuo; writing-original draft preparation – Meiling Liu and Xiaojuan Zuo. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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