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Enhancing Flexible Ramping in EV-Integrated Power Systems Through Decentralized Optimization

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Abstract. When dealing with large-scale EV groups, existing Electric Vehicle (EV) integrated power systems mostly collect, transmit, and calculate all charging demands and power constraints through a central computing unit, which consumes a lot of computing resources and is difficult to accurately respond to dynamic charging demands and grid load fluctuations. This paper focuses on the problem of system flexible scheduling and combines a decentralized optimization scheduling method to improve the system's scheduling efficiency, reduce charging costs, and achieve load balance and SOC (State of Charge) constraints. First, based on ADMM (Alternating Direction Method of Multipliers), the complex global optimization problem is decomposed into several small local sub-problems, and auxiliary variables are combined with Lagrange multipliers to achieve parallel solution of each sub-problem on multiple nodes. Then, the ADMM algorithm can be optimized through multi-level decomposition, and the clustering algorithm is used to classify and locally optimize EVs according to similarity. Finally, the adaptive step size mechanism is introduced into the iterative algorithm to achieve fast iteration based on gradient. The simulation results show that compared with centralized optimization, the average SOC error decreases by 35.63% and the total charging cost decreases by about 13.39%. The conclusion shows that decentralized optimization helps to improve the computational complexity and accurate response capability in system scheduling, and provides new perspectives and support for large-scale EV access in the future.

Key words. Electric Vehicle, Integrated Power Systems, Flexible Ramping, Decentralized Optimization, Alternating Direction Method of Multipliers

1. Introduction

With the global energy transformation and the focus on environmental protection, EVs are developing rapidly as a means of transportation represented by clean energy [1,2]. At the same time, the integration of a large number of EVs into the existing power system has also brought new challenges to grid management [3,4]. In the large-scale, distributed, and dynamic EV charging scenario, the centralized dispatching method has prominent problems such as low response accuracy and high computational complexity, which seriously restricts the deep integration of EVs and smart grids. As an important means to solve the optimization problems of large-scale complex systems, decentralized optimization has received increasing attention in recent years [5,6]. It can effectively reduce the amount of computation and communication burden by configuring the optimization tasks under local nodes. Based on decentralized optimization, EV charging stations and nodes in the power grid are used as local optimization units, and local scheduling and information interaction are used as means to achieve global coordination and efficient response to EV charging needs. This method is of great significance for reducing communication load and improving the balance and stability of the access process.

Existing research focuses on solving the problem of charging and discharging scheduling costs [7]. Kamboj Vikram Kumar explained how to use the Chaos Zebra Optimization Algorithm to reduce an integrated energy system's (IES) total operational costs when wind and plug-in EVs are included. According on empirical findings, the suggested approach can lower the overall cost of electricity generation by 0.84% [8]. To address the uncertainty of renewable energy and the regional IES of EVs, Wu Gongping developed a robust optimization model with polyhedral uncertainty sets and suggested a multi-objective optimization technique. The case study confirmed that the suggested approach may improve the resilience to uncertainty while attaining system economy and optimal operation after he converted the multi-objective into a single-objective solution [9]. Jia Shiduo developed a hierarchical stochastic optimization scheduling model for electric thermal hydrogen IES taking into account the EV vehicle-grid mechanism to minimize the variance of the load curve. A multi-objective sandcat swarm optimization technique was used to tackle the problem. According to the simulation findings, the suggested approach's operating costs were 16.55% lower than those of the disorderly charging and discharging technique [10]. Li Yang created a two-level optimization dispatch model of community IES with EV charging stations in a multi-stakeholder scenario to manage flexible demand response and the unpredictability of numerous renewable energy sources. The suggested approach effectively balanced the interests of community IES and EV charging stations by coordinating, according to the simulation findings of a genuine community IES in North China [11]. To address the issue of coordinated scheduling, Li Yuanzheng suggested a multi-objective optimization technique based on parameter adaptive differential evolution. The suggested scheduling model showed the link between certain EV integration goals and enhanced wind power absorption and system cost-effectiveness, according to simulation findings based on the upgraded Midwestern power system in the United States [12]. To achieve multi-energy coupling and meet the needs of various types of loads, Zhang Cheng proposed a two-layer optimization configuration method for multi-energy coupling IES low-carbon economic operation under different EV charging modes. He used the CPLEX solver to solve the two-layer model, and through mutual iteration, he was able to determine the best configuration scheme and scheduling outcomes. Lastly, he included simulated examples to show how the suggested approach might greatly lower carbon emissions and raise the system's running costs [13]. Existing research has made certain contributions to improving the economic performance of scheduling, but most of them adopt centralized optimization methods. However, EV charging load has time-varying and uncertain characteristics. Centralized optimization suffers from issues including high connection cost, poor real-time performance, and a lot of computation in real-world applications.

Distributed optimization can achieve efficient parallel computing [14-16]. This provides more possibilities for improving scheduling flexibility and real-time performance. A decentralized fault-tolerant method for EV charging optimization was put out by Aravena Ignacio. The algorithm reformulated the optimum EV charging issue in a fully decentralized way and was based on the alternating direction multiplier approach. Tests demonstrated that the suggested method can resolve the EV charging issue fast enough to include EV charging with the real-time power market, even when there are errors present [17]. Cheng Shan suggested a decentralized optimization and time-of-use electricity price strategy-based EV optimal scheduling technique to increase the computing efficiency of large-scale cluster EV optimum scheduling. The old centralized optimization model was broken down into smaller issues by proposing a decentralized optimization model and its solution using the Lagrangian relaxation approach [18]. Kapoor Aastha proposed a new iterative EV day-ahead optimization scheduling pricing scheme for decentralized models. While achieving the goals of multiple participants, the aggregated load served by the distribution transformers was dispatched, effectively solving the problems of load valley filling and rebound peaks. The results showed that the decentralized model had more critical advantages than the centralized architecture [19]. Boglou Vasileios developed a decentralized energy management system based on a multi-agent system for efficient EV charging. The results showed that the proposed system reduced the peak load and load variance by approximately 17% and 29%, respectively, without changing or delaying EV charging [20]. The current research improves the flexibility and efficiency of the system from the perspective of decentralized optimization, but it still has limitations in accurately responding to dynamic charging demands and grid load fluctuations.

The innovation of this article lies in the distributed optimization algorithm based on ADMM, which decomposes complex global optimization problems into several small-scale local subproblems, allowing them to be solved in parallel on each node, effectively reducing the cost of computing resources and enhancing the responsiveness to power system loads. On this basis, based on multi-level decomposition and K-means clustering methods, personalized charging management is carried out for electric vehicles to ensure that different types of vehicles with different characteristics can obtain the optimal charging solution. An adaptive step size strategy is adopted to accelerate the algorithm's iteration speed while reducing the system's overall power consumption and improving the system's average SOC error, thereby achieving effective load balancing and SOC limit constraints. New ideas and technical support are provided for the integration of large-scale electric vehicles into the power grid to improve their flexibility and robustness.

The organizational structure of this article is as follows: in Chapter 2, the improvement of flexible scheduling capability of EV integrated power system under decentralized optimization is studied; in Chapter 3, a simulation environment is constructed to simulate and analyze its flexible scheduling through case studies; in Chapter 4, the research results, contributions, and conclusions of this article are summarized.

2. Flexible Scheduling Capabilities of EV Integrated Power Systems under Decentralized Optimization

Based on decentralized optimization, this paper reduces the system computing and communication loads by optimizing multiple charging station nodes locally while ensuring the load balance and stability of the power grid. The key is to reasonably allocate the EV charging tasks to each charging station and ensure their accurate and real-time scheduling.

A. Model Assumptions and Parameter Settings

1) Assumptions on EV Charging and Discharging Behavior

It is assumed that the charging and discharging power of each EV changes over time. The charging power $P_{\text{charge}}^{i}(t)$ and discharging power $P_{\text{discharge}}^{i}(t)$ of the i th EV meet the constraints:

$$P_{\text{charge}}^{i}(t) \in \left[0, P_{\max}^{i}\right],\ P_{\text{discharge}}^{i}(t) \in \left[0, P_{\max}^{i}\right],\ \forall t \in \{1, \cdots, T\} \quad (1)$$

Among them, $P_{\max}^{i}$ is the maximum charge and discharge power of the i th vehicle, and T represents the scheduling time period.

2) Battery State and Capacity Constraints

During the charging process of EV, the SOC also changes with time. Assuming that the SOC of each EV at the initial time t_0 is expressed as SOC_0^i, the relationship between the SOC and the charging power change at time t is:

$$SOC_{t+1}^{i} = SOC_{t}^{i} + \frac{P_{\text{charge}}^{i}(t) \cdot \Delta t}{E_{\text{bat}}^{i}} \quad (2)$$

In Formula 2, P_{charge} refers to the charging power of the EV; i represents the EV sequence; t represents the specific time in the scheduling period, and SOC_t^i is the state of charge of the i th EV. Power P (kW), time t (h), SOC (dimensionless percentage or value between 0 and 1). E_{bat}^{i} is the total battery capacity of the i th EV; Δt is the time step, and SOC_t^i is the state of charge of the i th EV. The charging process is constrained:

$$SOC_{\min}^{i} \le SOC_{t}^{i} \le SOC_{\max}^{i},\ \forall t \in \{1, \cdots, T\} \quad (3)$$

Among them, $SOC_{\min}^{i}$ and $SOC_{\max}^{i}$ are the minimum and maximum SOC limits of the i th EVs.

3) EV and Grid Load Balance

When the EV is charging, its required load must match the grid capacity. Assuming that at time t, the load required by the system is $P_{\text{load}}(t)$, and the total charging power of EVs is $P_{\text{EV}}(t)$, then the relationship between the system load and the grid supply is [21,22]:

$$P_{\text{load}}(t) + P_{\text{EV}}(t) = P_{\text{grid}}(t) \quad (4)$$

Among them:

$$P_{\text{EV}}(t) = \sum_{i=1}^{N} P_{\text{charge}}^{i}(t) \quad (5)$$

$P_{\text{grid}}(t)$ is the power supply of the entire power grid. This relationship ensures that the charging behavior of EVs can adapt to the load requirements and capacity of the power grid.

Due to the fact that different models of EVs are equipped with various battery capacities, and as the service life increases, even the same model of EV may experience varying degrees of battery performance degradation. To improve the authenticity of the model, this paper introduces EV individual characteristic parameters to enhance the system's adaptability to EVs.

For the update rule of the charging amount of the i -th EV at time t:

$$C_i(t+1) = C_i(t) + \zeta_i P_{\text{charge}}^{i}(t) \cdot \Delta t \quad (6)$$

Among them, $C_i(t)$ is the actual stored power of the i -th EV at time t, and ζ_i represents the efficiency factor.

The SOC update rule is expressed as:

$$SOC_i(t+1) = SOC_i(t) + \frac{\eta_i P_{\text{charge}}^{i}(t) - \eta_i^{-1} P_{\text{discharge}}^{i}(t)}{E_{\text{bat}}^{i}} \cdot \Delta t \quad (7)$$

The SOC update rule is used to calculate the state charge change of each EV at the next time step.

4) Scheduling Objectives and Constraints

With the goal of minimizing EV charging costs and grid load fluctuations, the system's flexible scheduling capabilities are improved through optimization strategies. The charging cost of an EV depends on its charging power and the real-time electricity price. Assuming that at time t, the electricity price is $P_{\text{price}}(t)$, then the charging cost of the i th car at this time is expressed as $C_{\text{charge}}^{i}(t)$, and there is an objective function:

$$C_{\text{charge}}^{i}(t) = P_{\text{price}}(t) \cdot P_{\text{charge}}^{i}(t) \quad (8)$$

The change of electricity price needs to take the peak-valley difference into account, so the charging behavior should be reasonably adjusted according to the electricity price level. Under the premise of meeting the battery SOC constraint, the charging cost should be minimized, and the system load should be coordinated. Based on this, the global goal is to minimize the sum of the charging costs of all EVs, which is expressed as:

$$\min_{P_{\text{charge}}^{i}(t)} \sum_{i=1}^{N} \sum_{t=1}^{T} C_{\text{charge}}^{i}(t) = \sum_{i=1}^{N} \sum_{t=1}^{T} P_{\text{price}}(t) P_{\text{charge}}^{i}(t) \quad (9)$$

To ensure the dispatch efficiency of EV and system, the battery SOC limit condition is set:

$$SOC_{\min}^{i} \le SOC_{t}^{i} \le SOC_{\max}^{i},\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \quad (10)$$

Charging power limit:

$$P_{\text{charge}}^{i}(t) \le P_{\max}^{i}(t),\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \quad (11)$$

Discharge power limit:

$$P_{\text{discharge}}^{i}(t) \le P_{\max}^{i}(t),\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \quad (12)$$

Load balancing constraints:

$$\sum_{i=1}^{N} P_{\text{charge}}^{i}(t) + P_{\text{grid}}(t) = P_{\text{load}}(t),\ \forall t \in \{1,\cdots,T\} \quad (13)$$

5) EV Dispatch Dynamics and Time Intervals

It is assumed that the dispatch cycle is T duration, and the decision of each time period is adjusted based on the EV charging status, real-time electricity price, and grid load forecast. Under the premise of fully considering the timeliness of EV charging and discharging, the length of each time period is set to one hour, that is, $\Delta t = 1$ hour.

B. Flexible Dispatch Optimization

1) ADMM Dispersion Optimization

The flexible dispatch of EV integrated power systems includes centralized control and decentralized control [23,24]. The centralized control strategy collects data from EVs and the entire power grid in the system, aggregates the data into the Center Controller (CC), and dispatches them uniformly, as shown in Figure 1. CC corresponds to the charging station, and information such as charging/discharging time, user needs, and initial charge state is input into CC. By collecting EV-related data, CC centrally calculates the data of each EV and feeds back the charging status to EV, thereby realizing the regulation of the charging behavior of each EV. This model is based on global optimization and comprehensively considers multiple factors such as load balancing and charging requirements. It has high computational complexity, high communication costs, and is prone to packet loss and network failure. It is difficult to meet the scheduling needs of large-scale dynamically changing systems.

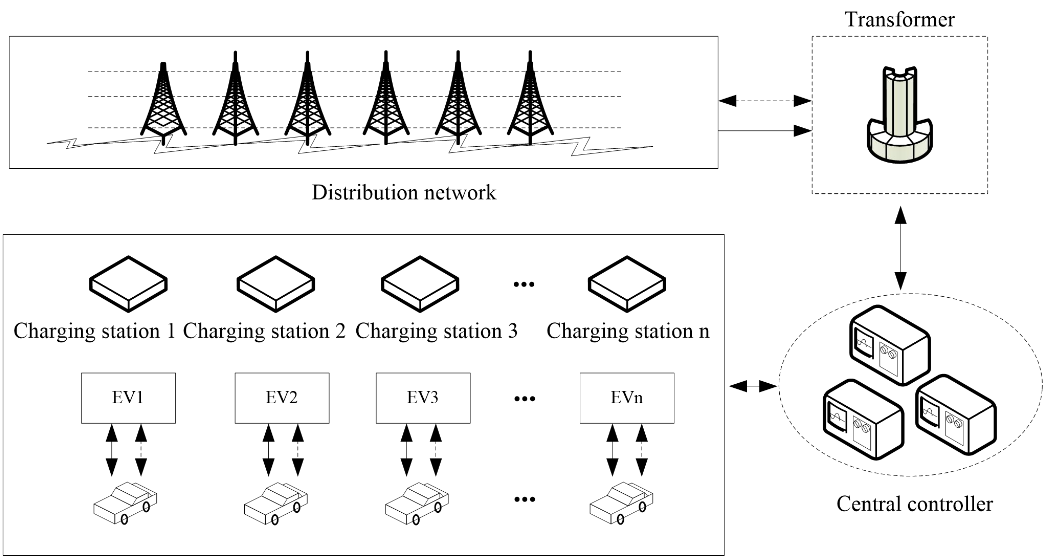


Figure 1. Centralized control strategy

Compared with centralized control, distributed control treats each EV as a separate dispatch unit and makes corresponding dispatch decisions based only on local information [25,26]. Even if one EV fails in the system, other EVs can still operate normally, thus achieving flexible dispatch in a dynamic and changing environment [27-29]. As shown in Figure 2, the core idea of distributed control is to decompose the overall planning problem into several local optimal problems without sharing global information, and each EV is dispatched autonomously according to its own state. It introduces local restrictions and coordination mechanisms to improve the system's adaptability and efficiency without affecting the performance of the entire system.

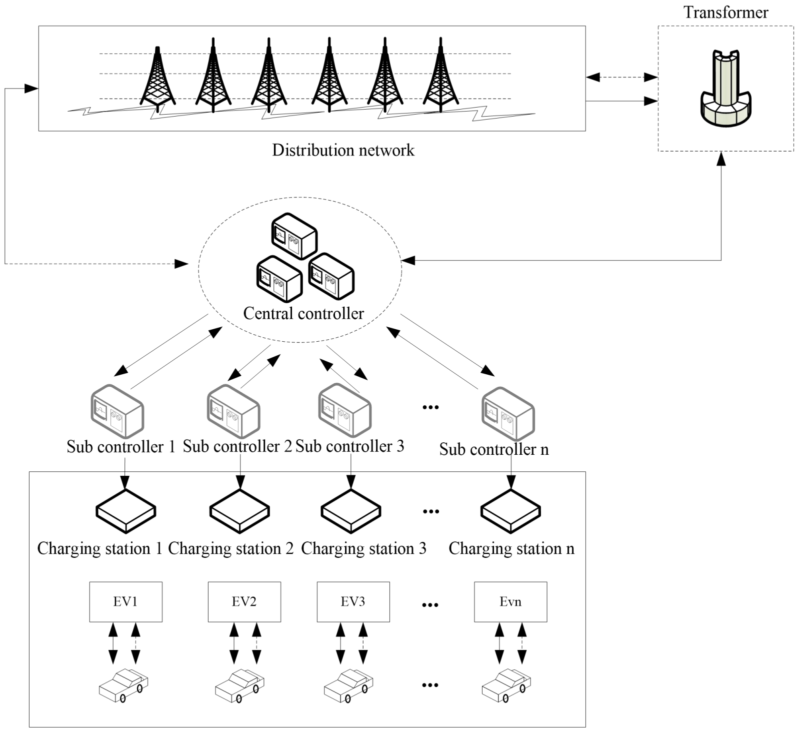


Figure 2. Distributed control strategy

ADMM is an effective algorithm for solving decentralized optimization problems [30-32]. The algorithm can efficiently solve large-scale distributed optimization problems and is suitable for complex systems integrated by large-scale EVs. The algorithm can be expanded smoothly when the number of EVs increases, without significantly increasing the amount of calculation. At the same time, the algorithm has iterative characteristics and can quickly adjust and find new optimization solutions when the system state changes dynamically. For large-scale, nonlinear, or real-time problems, directly solving them using linear programming is time-consuming; Moreover, as the population size increases, the scale of the problem dramatically increases, making it difficult for traditional centralized solving methods to effectively solve this problem. ADMM divides the original problem into several easily manageable sub problems, and based on this, gradually approaches the global optimal solution through continuous updates of global information. Compared with directly solving large-scale linear programming problems, it has significant advantages in greatly reducing computational complexity while ensuring accuracy.

Based on the decentralized optimization of ADMM, this paper decomposes the complex global optimization problem into several small local sub-problems and uses auxiliary variables in combination with Lagrange multipliers to achieve parallel solution of each sub-problem on multiple nodes, thereby optimizing the flexible scheduling capability of the system. Specifically, as shown in Figure 3, in the EV integration scenario, each charging station can make autonomous decisions based on its load conditions and ensure consistency and coordination among various decisions to meet the overall scheduling requirements of the system.

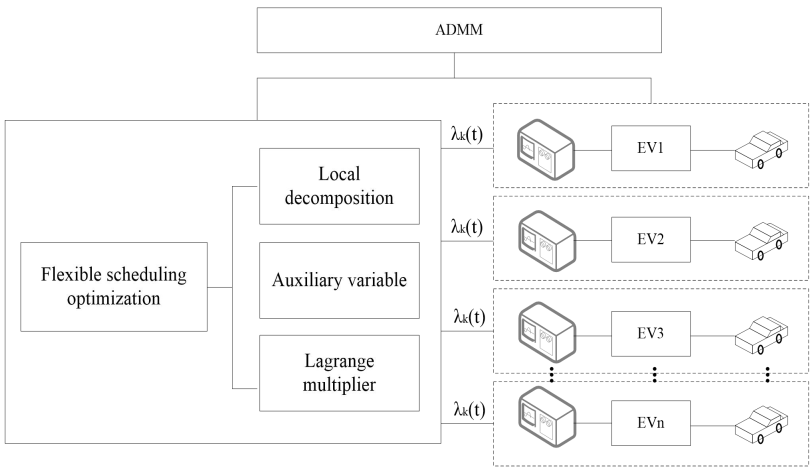


Figure 3. ADMM decentralized optimization

According to the definition, the original problem global objective formula 9 can be rewritten as:

$$\begin{aligned}
&\min \sum_{i=1}^{N} \int_{t_1}^{t_2} C_i\left(P_{\text{charge}}^i(t)\right) \mathrm{d}t \\
&s.t.\ SOC_{\min}^i \le SOC_t^i \le SOC_{\max}^i,\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \\
&P_{\text{charge}}^i(t) \le P_{\max}^i(t),\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \\
&P_{\text{discharge}}^i(t) \le P_{\max}^i(t),\ \forall t \in \{1,\cdots,T\},\ \forall i \in \{1,\cdots,N\} \\
&\sum_{i=1}^{N} P_{\text{charge}}^i(t) + P_{\text{grid}}(t) = P_{\text{load}}(t),\ \forall t \in \{1,\cdots,T\}
\end{aligned} \tag{14}$$

On this basis, the overall optimal problem is transformed into multiple local optimal problems through Lagrange multipliers and alternating direction methods. The global load balance constraint conditions are given:

$$\sum_{i=1}^{N} P_{\text{charge}}^i(t) + P_{\text{grid}}(t) = P_{\text{load}}(t) \tag{15}$$

Under this constraint, Lagrange multipliers $\lambda(t)$ are introduced to relax the problem and divided it into several independent sub-problems.

2) *Multi Level Decomposition*

In EV integration, due to its large scale, if the ADMM algorithm is directly used, the amount of calculation can be too large, and it cannot be optimized in a short time [33,34]. To address this problem, the ADMM algorithm is optimized through multi-level decomposition. First, the clustering algorithm is used to classify EVs according to similarity, and then, local optimization is performed within each EV cluster. Finally, on this basis, global optimization is used to coordinate the charging behavior among clusters, as shown in Figure 4:

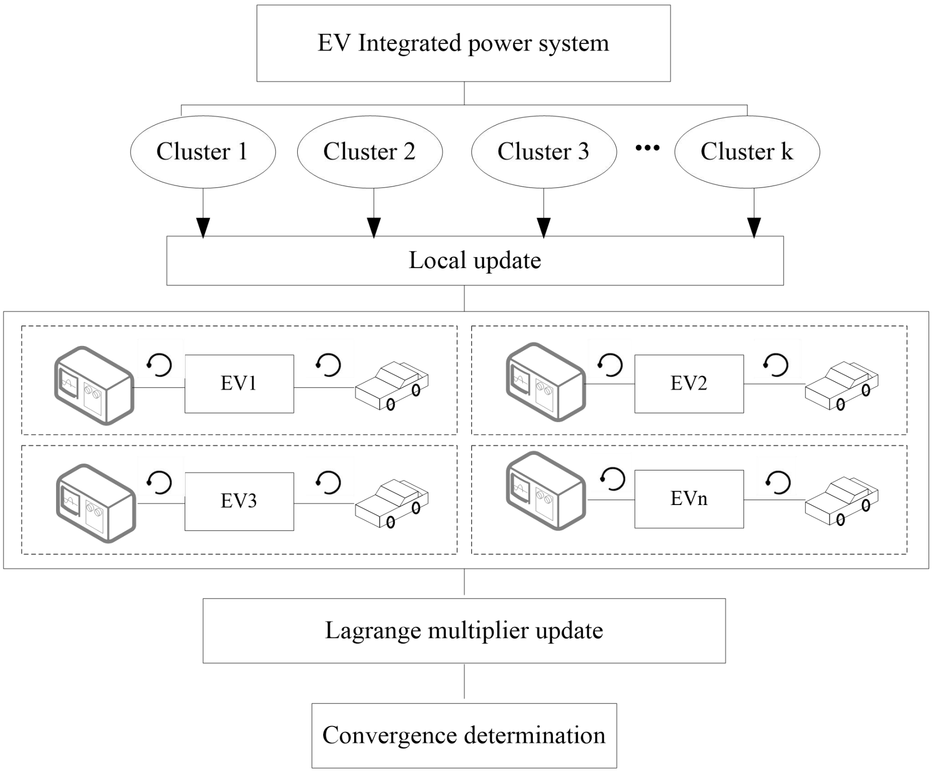


Figure 4. Multi-level decomposition ADMM

In multi-level decomposition ADMM, the algorithm divides the system into several clusters, each of which contains EVs with the same charging requirements. The charging power of EVs in each cluster is optimized separately first, and on this basis, the charging behavior of each node in the cluster is coordinated through the global optimal strategy to ensure the load balance of the entire system and reduce the charging cost.

To achieve efficient hierarchical optimization, EVs are divided into different levels. A cluster model consisting of N_k EVs is established. Its clustering is based on two factors:

(1) The time series characteristics of EV charging demand: EV charging demand has a certain time series change law.

(2) Battery capacity and maximum charging power: These factors have a great impact on the charging amount and endurance of EVs.

The clustering objective is to simplify the scheduling problem and achieve load balancing by grouping EVs with the same charging characteristics. The common clustering methods currently include hierarchical clustering DBSCAN (Density-Based Spatial Clustering of Applications with Noise), Gaussian Mixture Models

(GMM) and the K-means algorithm. Although hierarchical clustering can automatically determine the number of clusters, its computational complexity is large and difficult to meet real-time requirements; the DBSCAN algorithm is easily affected by noise, difficult to adjust parameters, and difficult to process large amounts of data; Gaussian Mixture Model (GMM) can provide soft clustering and is suitable for multimodal distributions, but it cannot distinguish populations well. The K-means algorithm stands out due to its simplicity, high efficiency, and ease of implementation. This method can quickly process massive amounts of data and is very suitable for the dynamic and changing charging environment of EVs. On this basis, the K-means algorithm is used to iteratively optimize the cluster centers, ensuring consistency in the charging requests of electric vehicles within each cluster, in order to reduce charging costs; a global optimization strategy is adopted to collaboratively charge each node to ensure load balance and response efficiency of the entire system.

The K-means clustering method is used to cluster EVs and obtain K th clusters. There are N_k EVs in each cluster. The purpose of cluster analysis is to ensure that multiple EVs in the same cluster have the same charging requirements and operating characteristics. Let the EV cluster be numbered $k = 1, 2, \cdots, K$. In this way, the charging power of the entire system can be expressed as:

$$P_{\text{charge}}^{i}\left(t\right) \; for \; i = 1, 2, \cdots, N_k, \; and \; k = 1, 2, \cdots, K \quad (16)$$

When performing local optimization within cluster k , the charging cost of the EV cluster is minimized while taking into account the SOC, and $P_{\text{charge}}^{i}\left(t\right)$ constraints of each EV. The specific local optimization problem is expressed as:

$$\min_{P_{\text{charge}}^{k}(t)} \sum_{i=1}^{N_k} \int_{t_1}^{t_2} C_i\left(P_{\text{charge}}^{i}(t)\right) \mathrm{d}t + \left(\sum_{i=1}^{N} P_{\text{charge}}^{i}(t) + P_{\text{grid}}(t) - P_{\text{load}}(t)\right) \mathrm{d}t \quad (17)$$

Among them:

$$P_{\text{charge}}^{k}\left(t\right) = \left\{P_{\text{charge}}^{i}\left(t\right), \; i = 1, 2, \cdots, N_k\right\} \quad (18)$$

Then, the Lagrange multipliers $\lambda_k\left(t\right)$ and $P_{\text{charge}}^{i}\left(t\right)$ are iteratively updated using an iterative method to gradually approach the global optimal solution. The multi-level decomposition ADMM optimization process is divided into three stages: local update, Lagrange multiplier update, and convergence judgment.

In the local update, each EV optimizes its own $P_{\text{charge}}^{i}\left(t\right)$ separately to minimize the charging cost and take into account the load balancing and battery SOC constraints. The standard optimization algorithm is used to solve the local optimal problem of each EV. To overcome the disadvantage of the traditional ADMM algorithm that the convergence speed is too fast when solving large non-convex optimization problems. The adaptive step size mechanism can be introduced into the iterative algorithm, and the gradient descent method can be used to achieve fast iteration based on gradient. First, the gradient of the objective function is calculated for $P_{\text{charge}}^{i}\left(t\right)$:

$$\nabla_{P_{\text{charge}}^{i}(t)} \left[C_i\left(P_{\text{charge}}^{i}(t)\right) + \lambda_k(t)\left(\sum_{i=1}^{N} P_{\text{charge}}^{i}(t) + P_{\text{grid}}(t) - P_{\text{load}}(t)\right)\right] \quad (19)$$

For $C_i\left(P_{\text{charge}}^{i}\left(t\right)\right)$, the gradient is:

$$\nabla_{P_{\text{charge}}^{i}(t)} C_i\left(P_{\text{charge}}^{i}\left(t\right)\right) = \frac{\partial C_i}{\partial P_{\text{charge}}^{i}\left(t\right)} \quad (20)$$

In the case of $\lambda_k\left(t\right)$, the gradient is:

$$\nabla_{P_{\text{charge}}^{i}(t)} \left[\lambda_k\left(t\right)\left(\sum_{i=1}^{N} P_{\text{charge}}^{i}\left(t\right) + P_{\text{grid}}\left(t\right) - P_{\text{load}}\left(t\right)\right)\right] = \lambda_k\left(t\right) \quad (21)$$

In this way, the overall gradient is expressed as:

$$\nabla_{P_{\text{charge}}^{i}(t)} \mathcal{L}_k\left(P_{\text{charge}}^{i}\left(t\right)\right) = \frac{\partial C_i}{\partial P_{\text{charge}}^{i}\left(t\right)} + \lambda_k\left(t\right) \quad (22)$$

In the gradient descent method, the objective function is optimized by continuously adjusting $P_{\text{charge}}^{i}\left(t\right)$. Updates are made according to the following rules:

$$P_{\text{charge}}^{i}\left(t\right)^{k+1} = P_{\text{charge}}^{i}\left(t\right)^{k} - \eta \nabla_{P_{\text{charge}}^{i}(t)} \mathcal{L}_k\left(P_{\text{charge}}^{i}\left(t\right)\right) \quad (23)$$

η is the learning rate, which is used to control the update step size. $\mathcal{L}_k\left(P_{\text{charge}}^{i}\left(t\right)\right)$ is the Lagrangian function in the cluster k .

For EV integrated power systems, accurate prediction and control of $P_{\text{charge}}^{i}\left(t\right)$ and SOC are particularly important. Although the ADMM method can achieve near optimal results, in actual operation, there may be significant deviations due to various uncertain factors such as changes in user behavior and power grid fluctuations. Therefore, it is necessary to analyze the deviation between power consumption and SOC.

For the processing of boundaries and restrictions, when performing gradient updates, it is necessary to ensure that $P_{\text{charge}}^{i}\left(t\right)^{k+1}$ meets the physical restrictions, that is:

$$0 \le P_{\text{charge}}^{i}\left(t\right)^{k+1} \le P_{\max}^{i} \quad (24)$$

If the updated $P_{\text{charge}}^{i}\left(t\right)^{k+1}$ exceeds the limit range, it is corrected to the limit value [35]:

$$P_{\text{charge}}^{i}\left(t\right)^{k+1}=\min\left(P_{\max}^{i},\ \max\left(0,\ P_{\text{charge}}^{i}\left(t\right)^{k+1}\right)\right)\quad(25)$$

The updated SOC needs to meet the upper and lower limit constraints. If the SOC is not within the range, it is also corrected to the limit value:

$$SOC_{i}\left(t\right)^{k+1},\ \min\left(SOC_{\max}^{i},\ \max\left(SOC_{\min}^{i},\ SOC_{i}\left(t\right)^{k+1}\right)\right)\quad(26)$$

On this basis, $\lambda_{k}\left(t\right)$ is used to modify the global constraints to ensure that the $P_{\text{charge}}^{i}\left(t\right)^{k+1}$ of each EV can meet the grid load balancing requirements, which is updated according to the formula [36]:

$$\lambda\left(t\right)^{k+1}=\lambda\left(t\right)^{k}+\rho\left(\sum_{i=1}^{N}P_{\text{charge}}^{i}\left(t\right)^{k+1}+P_{\text{grid}}\left(t\right)-P_{\text{load}}\left(t\right)\right)\quad(27)$$

ρ is the step size factor for adjusting the update rate.

The algorithm determines whether it has convergence by judging whether the change of $P_{\text{charge}}^{i}\left(t\right)^{k+1}$ and $\lambda_{k}\left(t\right)$ is smaller than the preset tolerance error ϵ. Specifically [37-39]:

$$\frac{1}{T}\sum_{t=1}^{T}\left|\sum_{i=1}^{N}P_{\text{charge}}^{i}\left(t\right)^{k+1}+P_{\text{grid}}\left(t\right)-P_{\text{load}}\left(t\right)\right|<\epsilon\quad(28)$$

If the condition of formula 28 is met, the algorithm terminates.

3. Example Analysis

A. Simulation Environment and Parameter Setting

To verify the application effect of decentralized optimization in the flexible dispatch of EV integrated power system, this paper simulates its flexible dispatch by constructing a simulation environment. Taking 100 EVs as the object, the charging demand of each EV is comprehensively considered, and the charging behavior of each EV is optimized for 24 hours a day. To simplify the model, it is assumed that the battery capacity of each EV is 30kWh, and the maximum charging power of EV is 6 kW. The initial SOC range of each EV varies in the range of 30%-50%, and charging is carried out in units of 24 hours. At the same time, the upper and lower limits of SOC must be taken into account, and the SOC constraint state of the battery must be guaranteed to be in the range of 30%-80%.

The system load includes EV charging demand and grid load. On this basis, the maximum power supply of the grid is set to 1200kW, and the load fluctuation is realized in the range of 500kW to 1000kW. To simulate the charging demand and load changes of the system, a load curve is generated based on the actual load data. The load fluctuation is affected by the daily period and EV charging behavior.

The specific settings of the simulation parameters are shown in Table 1:

Table 1. Specific settings of simulation parameters

Sequence	Parameter	Specifications
1	Number of EV	100 EV
2	E_{bat}^{i}	30kWh
3	Max $P_{\text{charge}}^{i}\left(t\right)$	6kW
4	SOC initial range	30%-50%
5	SOC restriction	30%-80%
6	Max $P_{\text{grid}}\left(t\right)$	1200kW
7	Load fluctuation range	500kW-1000kW
8	$C_{\text{charge}}^{i}\left(t\right)$ coefficient (yuan per kWh)	Time-sharing strategy
9	Δt	1 hour
10	Total simulation time	24 hours

B. Evaluation Indicators

This paper conducts a comprehensive evaluation from the aspects of load balancing error, SOC error, and total charging cost indicators:

1) Load Balancing Error

The load balancing error is an important indicator used to measure whether the load meets the requirements when the system is running. Specifically, this indicator represents the deviation between the grid load and the

EV integrated system load at each time point, and its calculation formula is:

$$LBT(t) = \left| P_{\text{EV}}(t) + P_{\text{grid}}(t) - P_{\text{load}}(t) \right| \quad (29)$$

As an important indicator to measure the accuracy of system scheduling at each moment, the smaller $LBT(t)$ is, the higher the flexibility of the system is, the more significant its effect on stabilizing load fluctuations in the power grid is, and the more stable the system operation is.

2) *SOC Error*

SOC error is used to measure the difference between the state of charge of each EV battery and the target state of charge. This indicator reflects the accuracy of battery management during charging, that is, whether the battery can be charged accurately according to the established charging strategy. When the SOC error is small, the battery charging behavior can be more reasonable, and the battery loss is less. The calculation formula is:

$$SOC_{\text{error}}(i,t) = \left| SOC_{\text{target}}(i,t) - SOC_{\text{actual}}(i,t) \right| \quad (30)$$

$SOC_{\text{target}}(i,t)$ is the target SOC of the i th EV at time t, and $SOC_{\text{actual}}(i,t)$ is the actual SOC. The smaller the SOC error, the closer the battery charging process is to the expected value.

3) *Total Charging Cost*

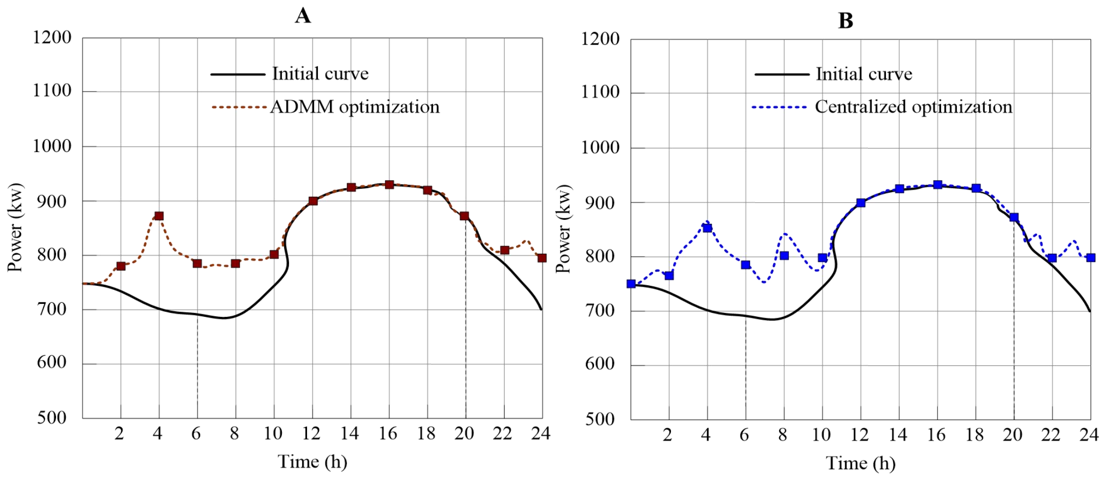
The total charging cost is the total amount of EV charging cost during the scheduling period, and its calculation formula is:

$$C_{\text{total}} = \sum_{i=1}^{N} \int_{t_1}^{t_2} C_i\left(P_{\text{charge}}^{i}(t)\right) dt \quad (31)$$

C. Simulation Results

1) *Load Curve Comparison*

Based on 24 hours of simulation data, the charging behavior of the EV group and the grid load are simulated. On this basis, the ADMM algorithm is compared with the traditional centralized optimization method, and its load curve is analyzed from the change amplitude, fluctuation trend, and peak situation of each period. The results are shown in Figure 5:



A is the ADMM optimization curve

B is the centralized optimization curve

Figure 5. Load curve analysis

As shown in Figure 5, the load curve obtained by using the ADMM algorithm has smaller overall fluctuations and a more gentle load change range compared to the centralized optimization method. In Figure 5A, EVs are mostly charged during the period with the lowest electricity price (24:00-6:00), and they can also generate new load peaks during the valley price period, but they do not exceed the limit due to capacity limitations. In Figure 5B, although EVs under centralized optimization also have a more significant role in filling the load valley, their load curves show large fluctuations, and the load reaches obvious peaks at 4:00, 8:00, etc. Compared with traditional centralized optimization, the ADMM algorithm divides the EV group into several subsystems, each of which optimizes its own energy scheduling, effectively reducing the system load fluctuations caused by centralized optimization. It can more flexibly adapt to the actual needs and charging conditions of EVs, make the load curve smoother, and prevent excessive load peaks in a certain period of time. Through the coordination between the subsystems, the reasonable configuration of charging tasks is achieved, and the load fluctuation of the system is reduced to a certain extent. In contrast, the centralized optimization method is prone to cause large load fluctuations at certain times, increasing the load on the power grid and making it difficult to give full play to the system's flexible scheduling capabilities. Overall, the load curve after ADMM optimization has a smooth transition, reducing load peaks, which is conducive to reducing the overload pressure on the power grid and avoiding overload risks.

2) Comparison of Load Balancing Errors

To further determine the load balancing status, the load balancing errors under the two optimization modes are calculated, and the results are shown in Figure 6:

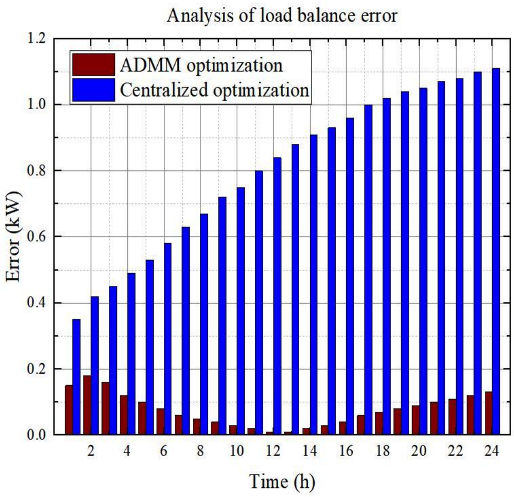


Figure 6. Load balancing error results.

As can be seen from Figure 6, the load balancing error results under ADMM optimization have more significant advantages. In each time period, the error under ADMM optimization is the highest in the 2:00 time period, reaching 0.18kW, and its overall error mean is about 0.078; the error under centralized optimization is the highest in the 24:00 time period, reaching 1.11kW, and its overall error mean is about 0.808. In some periods of time, centralized optimization cannot achieve effective load balancing of the system, causing a certain amount of load on the power grid; at the same time, there are large errors in load balancing. The ADMM algorithm can maintain a small load fluctuation and achieve effective regulation of EV charging power while overcoming the large differences in power demand in a single stage.

3) SOC Error Comparison

SOC error has a direct impact on the charge and discharge management of EV in system integration. This paper compares the SOC errors of the two methods within 24 hours and evaluates the system energy efficiency and stability. The results are shown in Figure 7.

As can be seen from Figure 7, the SOC error of ADMM in each time period is generally lower than that of centralized optimization. From the specific results, its average SOC error reaches 1.03%, which is 35.63% lower than that of centralized optimization. The SOC error changes very little within a 24-hour period and remains at a low level, with good stability and consistency. However, the centralized optimization has large fluctuations in some periods. The lower SOC error means that each EV can be closer to its desired charging state, reducing energy loss caused by overcharging or undercharging, thereby improving the energy utilization of the system. ADMM enables each charging station to make decisions locally, reducing dependence on the central controller, reducing communication delays, reducing the probability of failures, and ensuring that the system can still operate normally when the network topology changes or some nodes fail. It has the ability to quickly adapt to EV charging and discharging behavior, which has a very important impact on reducing the peak load pressure of the power grid and achieving stable system scheduling.

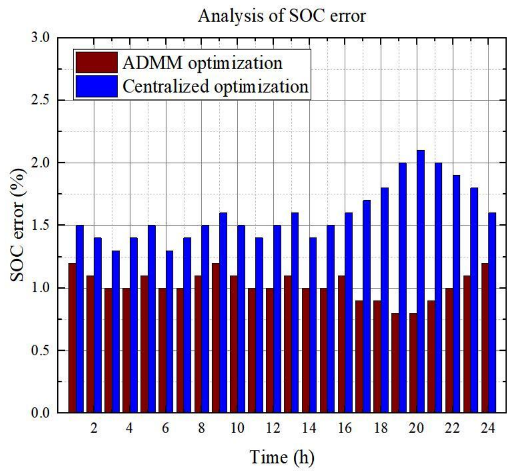


Figure 7. SOC error results.

4) Comparison of Total Charging Costs

By simulating the charging process under the two optimization modes and taking into account the volatility of grid prices, the charging costs of each period are calculated and summed up to calculate the total cost. Taking the total charging cost as the main evaluation indicator, the impact of different optimization modes on the cost is considered. Referring to the common strategies of time-of-use electricity prices and their impact on grid load management, the electricity price parameter settings are shown in Table 2:

Table 2. Electricity price parameter settings

Period of time	Grid price (Yuan per kWh)	Charging station prices (Yuan per kWh)
24:00-06:00	0.358	0.4
06:00-10:00	0.528	1.0
10:00-14:00	0.858	2.0
14:00-18:00	0.528	1.0
18:00-22:00	0.858	2.0
22:00-24:00	0.358	0.4

The final cost comparison results are shown in Figure 8:

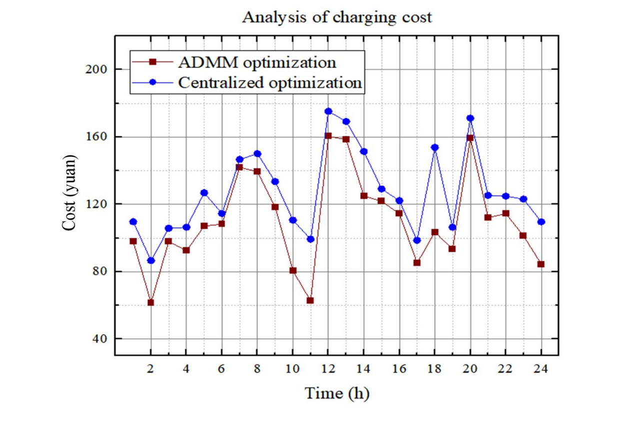


Figure 8. Cost comparison results

As can be seen from Figure 8, there are certain differences in the cost results presented by the two methods in each period. Among them, the total cost of each period under ADMM optimization reaches 2642 yuan, and the total cost result under centralized optimization is 3050.4 yuan. In the comparison of specific results, compared with centralized optimization, the total charging cost of ADMM optimization is reduced by about 13.39%. Although centralized optimization can take into account the overall load balance of the power grid, it lacks flexible scheduling for EV charging demand and electricity price fluctuations. The use of ADMM can achieve refined control of the charging strategy of each EV, thereby reducing the charging cost.

4. Conclusions

This paper uses the ADMM algorithm to study the improvement of the flexible dispatching capability of EV integrated power systems under decentralized optimization, and explores the problems of load balance, SOC constraints, and charging costs faced during EV charging. Through simulation experimental results, this paper verifies the significant advantages of the ADMM method in improving the flexible dispatching capability of EV integrated power systems. Compared with the traditional centralized optimization method, its average SOC error is reduced by 35.63%, and the total charging cost is reduced by about 13.39%. Based on the multi-level ADMM algorithm, this paper combines local and overall optimization, effectively improving the flexibility and responsiveness of system scheduling, and providing effective support for solving problems such as actual communication delay and low computing efficiency. However, this paper also has some shortcomings. Due to the large amount of uncertainty in the EV charging process, this paper has not fully considered the factors affecting EV charging behavior and battery characteristics, and the comprehensive performance of the method needs to be verified in a wider range of application scenarios. Future research can fully consider the impact of complex environmental factors on system scheduling, improve its adaptability in various application scenarios, and promote the comprehensive development of EV integrated power systems.

Consent to Publish

The manuscript has neither been previously published nor is under consideration by any other journal. The authors have all approved the content of the paper.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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