Blockchain-Based Trustworthy Energy Dispatching Approach for High Renewable Energy Penetrated Power Systems

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***Abstract*—Renewable energy sources (RES) and low-carbon technology users play a vital role in modern power systems. However, RES generation is easily affected by the environment. Meanwhile, the load, such as electric vehicles (EVs) and prosumers, accounts for most low-carbon technology users. Their power is usually superimposed on peak loads without dispatching, which also exacerbates the instability of the power system. Current optimal dispatching mechanisms mainly rely on centralized organizations, while their dispatching process is not open and transparent. In this article, we propose a blockchain-based trustworthy dispatching approach for the distribution network in high renewable energy penetrated power systems. We first develop an optimal dispatching model considering EVs' charging behavior and the prosumers' economic benefits. With the model, prosumers can be dispatched to balance power and consume renewable energy, reducing the impact of disorderly charging on the grid and the abandonment of RES generation. An orderly charging iteration optimization (OCIO) algorithm is proposed to implement orderly EV charging while considering the charging cost and the period. We also propose a modified particle swarm optimization (mPSO) algorithm to publish dispatching tasks based on real-time power balance. Furthermore, blockchain is applied as an open and transparent ledger to record each entity's power generation and consumption information, ensuring that the dispatching process is trustworthy. Finally, the effectiveness of the dispatching approach is verified in the modified IEEE 33-bus test system and Ethereum-based smart contracts.**

***Index Terms*—Blockchain, electric vehicle (EV), optimal dispatching, prosumer, renewable energy power generation.**

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I. Introduction

CLEAN energy and low-carbon technology users play a crucial role in modern power systems. Recently, there has been a rise in clean energy power generated using renewable energy sources (RES), accounting for an increasing proportion of the power system. For example, about 25% of electricity generated in the U.K. comes from RES [1], forming high renewable energy penetrated power system. Simultaneously, the number of low-carbon technology users, such as electric vehicles (EVs) and prosumers [2], is also gradually increasing [3]. These trends have effectively reduced fossil fuel consumption and greenhouse gas emissions. However, they have also offered new challenges to the construction and design of distribution power networks [4].

It is known that the stability of RES generation is affected by the environment [5]. Consequently, high penetration of RES in the power system may affect the reliability and security of the distribution network. At the same time, the behavior of low-carbon technology users in the grid is cyclical. When the grid power reaches its peak, the electricity consumption of EVs also reaches its peak. This power superposition phenomenon aggravates the instability of the grid [6]–[8]. The resulting fluctuations in the frequency may bring some security hazards to the operation of the power equipment and severely cause the loss of users' life and property. Therefore, the power balance of high renewable energy penetrated power systems is essential for its wide-scale use.

Under the circumstances, the distribution network dispatching approaches based on intelligent algorithms and advanced information management systems have emerged [9]–[14]. They establish some models to analyze the power situation under different scenarios, so as to enhance the robustness of the power system and improve the flexibility of the distribution network. However, there are some problems that need to be addressed to deploy them in practice. First, the scenarios considered by these approaches are relatively simple. In the complex energy dispatching of the distribution network, a single dispatch for EVs or prosumers alone cannot accurately describe the power changes. In addition, the power trading of low-carbon technology users has the characteristics of high-frequency and distribution. But most of the approaches rely on a trusted third party to collect information and implement dispatch, which face risks, such as single point of failure

TABLE I
DESIGN OF A VARIETY POWER BALANCE DISPATCHING FOR DISTRIBUTION NETWORKS

Reference	[21] [22]	[18]	[23] [24]	[19] [20]	[25] [26] [27]	Our scheme
Measures	Optimal model	P2P trading	Vehicle to grid	EV dispatching	Game theory	Optimal dispatching
Information management	N	N	Blockchain	Blockchain	Blockchain	Blockchain
Scenario	MG/CHP	MG+batteries	EVs	MG+EVs	MG+prosumers	MG+EV+prosumers

and performance bottlenecks. Even worse, their dispatch is not open and transparent, and does not consider individual electricity costs. While the low-carbon technology users, such as EVs and prosumers, have their own electricity consumption plans, which may lead to conflicts between the dispatching and consumption. Some rational low-carbon technology users may choose when and where to charge and discharge, and may be distrustful and reluctant to comply with the dispatch.

With the increasing intelligence of power systems, technologies, such as AI, cloud computing, and blockchain have been widely used in many aspects of power systems [15]–[17]. Among them, the blockchain technology has the characteristics of decentralization and tamper resistance, which can realize open and transparent information sharing, and make the energy dispatching trustworthy. Researchers have used blockchain to establish decentralized power trading markets and realize open and transparent management of electricity information [18]–[20]. These blockchain-based approaches can directly connect RES producers and consumers, greatly reducing power trading costs, and simplifying the complex multilevel structure of the existing power system. However, the scenarios that these approaches focus on are still simple. They did not consider the interests of the users participating in the dispatching, but assumed that users would resolutely obey the dispatching plan. It is difficult to effectively ensure the stability of the grid in a high penetration renewable energy system.

Motivated by the above challenges, we propose a blockchain-based trustworthy dispatching approach to fully mobilize low-carbon technology users and protect the stability of the distribution network in a high renewable energy penetrated power system. In our approach, the distribution system operator (DSO) regularly collects and publishes distribution network load information on the blockchain. EVs and prosumers also publish their charging load and remaining storage capacity. Based on this data, we design a two-phase algorithm for dispatching EVs and prosumers that fully consider their benefits, instead of just dispatching one of them roughly like other solutions. An orderly charging iteration optimization (OCIO) algorithm is used to dispatch EVs for orderly charging at a low cost. A modified particle swarm optimization (mPSO) algorithm is designed to determine the optimal trading task for prosumers. The above algorithms are also recorded on the blockchain, and the dispatched user can verify whether the dispatch result is trustworthy based on the blockchain data. The main contributions of this article are threefold.

1) We develop an optimal dispatch model for a high renewable energy penetrated power system. This model intends to protect the interests of low-carbon technology users, effectively dispatch them to improve the grid's stability and reduce the abandoned RES generation.
2) We construct a blockchain-based power dispatching framework. In the proposed framework, we store the power information in the high renewable energy penetrated power system and dispatch algorithms on the blockchain, enabling low-carbon technology users to trust and follow power dispatching.
3) We propose a two-phase optimal dispatching algorithm. By designing and improving OCIO and particle swarm optimization algorithms, the two-phase algorithm realizes optimal dispatch considering individual electricity costs of low-carbon technology users, such as EVs and prosumers.

The remainder of this article is organized as follows. The literature review is in Section II. The system framework is described in Section III. Section IV formulates the optimization dispatching of EVs and prosumers. The detailed process of the application in Section V. Finally, evaluation results are presented in Section VI, and the conclusions are drawn in Section VII.

II. RELATED WORK

In this section, we summarize some traditional power dispatching approaches, and provide some background about the blockchain technology. The comparison of some approaches is summarized in Table I.

A. Traditional Dispatching Approaches

There exist many related works to cope with the dispatching under the complex distribution network model. Nosair and Bouffard [21] used the dynamic envelopes to reflect the uncertainty and variability of the distribution network resources, and proposed an optimal plan of the stability with the envelope. In addition, given that the EV swap stations have the function of backup energy and energy transfer, literature [23] and [28] used EVs to improve the stability of the distribution network. Mueller *et al.* [22] proposed a scheme that can use the thermal energy storage system in the cogeneration device to balance renewable energy fluctuations in the grid. The system can store excess energy and release it to balance the residual load. Dallinger *et al.* [24] thought that the grid connection of EVs brings greater stability to the microgrid (MG) containing RES, and use the agent-based simulation model PowerACE to analyze the improvement of RES power generation fluctuation brought by the grid connection of EVs. Guo *et al.* [29] gave a dispatching algorithm suitable for multiregional power systems based on multilinear programming theory. The algorithm enhances the robustness of the multiregion interconnected power system, and also improves the stability of the distribution network. However, most of the above approaches only focus on dispatching a certain type of users in a high renewable energy penetrated power system, their optimized scenario is simple, and does not consider the individual electricity cost of low-carbon technology users. Meanwhile, these schemes also rely on trusted third parties. The frequent power trading may bring challenges to the existing centralized management construction in terms of information security and transaction transparency.

B. Blockchain and Relevant Approaches

1) Blockchain: The blockchain technology is a hybrid technology composed of the P2P network, cryptography, consensus mechanism, distributed ledger, and smart contract, which has the characteristics of anti-tampering, traceability, and decentralization. Its core idea is to establish trust between nodes without the trusted third-party [30]–[32].

The data a node sends to the blockchain is packaged into a block. Each block stores the hash value of the previous block, which links all blocks together. When the data in the block is tampered with, it will cause blockchain changes of the hash index of all subsequent blocks, which can prevent malicious nodes from tampering with the blockchain data. The smart contract is an event-driven code that runs on the blockchain, and is automatically executed after being triggered by events. Profited from Turing's complete smart contract language, smart contracts can implement more complex functions.

The state update and the consistency of the blockchain are guaranteed by the consensus mechanism. Among them, the consortium blockchain is responsible for generating new blocks by some nodes with higher capabilities and reputation. It adopts the consensus mechanism, such as PoS and PBFT to research consensus, having good performance, and suiting for a distributed environment with entities, such as DSO and RES.

2) Blockchain-Based Approaches: Recently, blockchain-based energy dispatching and multiuser power energy trading have become popular research topics. The European transmission system operator and clean energy supplier cooperation projects Piclo [33] and sonnenCommunity [34] have applied blockchain to energy supply. The blockchain technology can also integrate the flexible capacity of electric energy transactions of low-carbon technology users into the grid to maintain the balance of power supply and demand. Luth *et al.* [18] proposed a blockchain-based power trading framework for the battery electricity market, which not only improves the economy of prosumers' battery but also provides stability to the local distribution network. Zhang *et al.* [19] proposed SMERCOIN, a real-time charging system for EVs based on blockchain cryptocurrency. The system arranges the charging of EVs based on the green energy usage history of EV users. And in the form of cryptocurrency, the users in the system are charged and motivated. Fu *et al.* [20] provided a blockchain-based charging information management system for EVs, and formulate smart contracts based on a bio-objective mixed-integer programming model (BOMILP) to balance the income of various energy companies. Jiang *et al.* [25] gave a blockchain-based power trading pricing system. Their scheme uses game theory to determine the trading price of prosumers, and uses blockchain to ensure the fairness of the pricing process. To solve the power trading problem caused by the fluctuation of renewable energy power, Cui *et al.* [26] designed an energy sharing model based on the sample weighted average approximation and random game. The model introduces the blockchain network as an information management system to ensure the security of transaction information. Similarly, in order to deal with the power fluctuations of RES, Siano *et al.* [27] established a prosumer dispatching model of distribution network based on the blockchain. These approaches use the blockchain technology to build some open and transparent decentralized platforms. But they fail to consider the power consumption characteristics of low-carbon technology users, and the dispatching effect needs to be further improved.

TABLE II
NOTATIONS

Notation	Description
t	unit time interval in the dispatching plan
$\mathcal{N}$	set of EVs
$\mathcal{K}$	set of prosumers
$T_{(\cdot)}$	time period set of $(\cdot)$
$B_{(\cdot)}$	battery capacity of $(\cdot)$
$x_{i,t}$	EV charging Boolean variable at t
$P^{ch}_{(\cdot),t}$	charging power of $(\cdot)$ at t
$P^{dch}_{(\cdot),t}$	discharging power of $(\cdot)$ at t
D_i	driving distance between charging locations
$SOC_{(\cdot),t}$	state-of-charge of $(\cdot)$ at t
ΔSOC_i	lowest SOC of a typical day single trip
DT	time set of EVs orderly charging plan
C_i	charging cost of EV
P^{pg}	purchasing power from the superior grid
P^{RES}_t	power of RES generation at time t
P^{reg}	power of prosumers participating in dispatching tasks
f_{op}	distribution network operating cost
f_{pro}	dispatching expenditures of prosumers
p	penalty for abandoned RES generation
f	total economic cost of the distribution network
$\varphi^{(\cdot)}$	corresponding electricity purchase price of $(\cdot)$
$\eta^{\mathrm{ch}}_{(\cdot)}$	charging efficiency of $(\cdot)$
C_{loss}	cost of network loss
C_{us}	cost of using prosumers' energy storage
P^{flu}_t	power fluctuation at time t
ε	power fluctuation criterion
X_j	initial random dispatching task for prosumers
V_j	initial velocity of the algorithm
$X_{\mathbf{g}best_i}$	best dispatching task for prosumer j

III. System Framework

In this section, we introduce the mathematical model of each entity in the distribution network. In order to explain our model, we define an operation cycle T, which is composed of multiple time periods t. Each t is the minimum period during which operation variables remain unchanged. The main notations and their definitions are summarized in Table II.

A. Renewable Energy Source

RES uses wind or solar radiation to generate electricity, and it can estimate its own power generation based on weather forecasts. Wind and solar radiation, as the energy conversion sources of wind turbine (WT) power generation and PV, are time-varying resources with the change of environment, which cause the uncertainty of RES. This article will not redundantly describe the above RES generation data. We use actual data as the power data in the system, and arrange the load according to the forecast data of the RES.

We use m to denote the RES power generation node. The power generation of RES is shown as follows:

$$P_t^{\text{RES}} = \sum_{m \in PV} P_{m,t} + \sum_{m \in WT} P_{m,t}. \tag{1}$$

As an entity that works for a long time and has good computing and communication capabilities, RES can be responsible for saving complete blockchain and generating new blocks.

B. Electric Vehicle

The EV can be regarded as the mobile controllable load in our system. Adjusting the charging period of EVs can reduce the peak-to-valley difference in the distribution network. On the premise of not changing the travel habits of the EV, charging costs can also be reduced. Let $i \in \mathcal{N}$ denote the EV index. $\mathcal{N}$ is the set of all EVs, and the number of its elements is N. The charging model of EVs is as follows:

$$\text{SOC}_{i,t} = \text{SOC}_{i,t-1} + (B_i)^{-1} \eta_i^{\text{ch}} P_{i,t}^{\text{ch}} t \tag{2}$$

$$P_{i,\min}^{\text{ch}} \leq P_{i,t}^{\text{ch}} \leq P_{i,\max}^{\text{ch}} \tag{3}$$

$$0 < \text{SOC}_{i,\min} \leq \text{SOC}_{i,t} \leq \text{SOC}_{i,\max} < 1 \tag{4}$$

where $\text{SOC}_{i,t}$ is the state-of-charge (SOC) of the i, B_i is the battery capacity of EV_i, $P_{i,t}^{\text{ch}}$ is the charging power, and η_i^{ch} is the charging efficiency of EV_i's battery. Therefore, (2) defines the SOC discretization calculation formula of EV, (3) defines the constraints of charging power, and (4) defines the constraint of SOC.

The charging status of EV is closely related to the personal driving behavior. Therefore, we research the driving behavior of EV to arrive at the travel model for a typical working day.

As shown in Fig. 1, travel on a working day is generally a two-point travel mode between office and home. The allowable charging period T_{allow} is composed of the parking period T_{here} at the current parking location and the parking period T_{next} at the next parking location. Fig. 1 also shows the comparison of the EV charging effect. Compared with disorderly charging, orderly charging avoids the peak load in the user's allowed charging period. It can reduce the peak-to-valley difference of the power system and reduce the charging cost of EVs. The detailed algorithm process is shown in Algorithm 1 in the next section.

To calculate the EV orderly charging plan, the SOC change of EV driving should also be defined. We assume the distance D_i between office and home meets the Gaussian distribution. Due to the occurrence of traffic jams, the trip time of EV is often longer than the driving time, departure time, and arrival time can not reflect the driving time. According to [35], we assume the travel distance D_i and driving time t_{driv} meets $t_{\text{driv}} = d_1 D_i + d_2$. Therefore, the change in SOC during the travel for a typical working day is defined as follows:

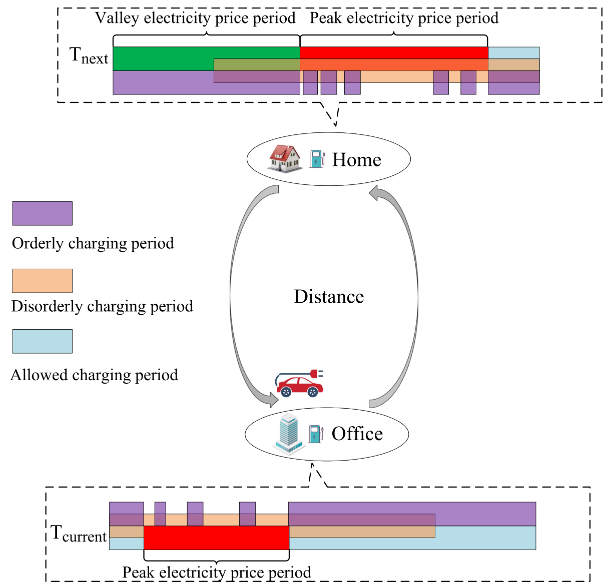

Fig. 1. Typical daily behavior of EVs.

$$\Delta\text{SOC}_i = \text{SOC}_{i,\text{depar}} - \text{SOC}_{i,\text{arri}} = B_i^{-1} P_{i,\text{driv}} t_{\text{driv}} \tag{5}$$

where $\text{SOC}_{i,\text{depar}}$ and $\text{SOC}_{i,\text{arri}}$ are the SOC of departure and arrival time, respectively, D_i is the distance traveled, and $P_{i,\text{driv}}$ is the driving power.

EVs are also join to the blockchain. Since EVs need to move between multiple regions, they can join the blockchain as light nodes without keeping the complete data.

C. Prosumer

Prosumers are entities that have the ability to generate and use electricity. Except for buying electricity as a consumer, it also can build rooftop PV generation systems, home energy storage to sell. Our recherche scope is based on its grid-connected roof-top PV power and saleable energy storage capacity. So we regard its consumption as a normal load.

The prosumer node $j \in \mathcal{K} = \{1 \cdots K\}$ in the distribution network become producers when they generate electricity in the system. While meeting their demands, the prosumers' rooftop PV will also connect to the grid. After meeting its demand, the surplus electricity is stored in the household energy storage and can participate in dispatching tasks.

The household energy storage constraints of prosumers are as follows:

$$0 \leq P_{j,t}^{\text{ch}} \leq P_{j,\text{Max}}^{\text{ch}} \tag{6}$$

$$0 \leq P_{j,t}^{\text{dch}} \leq P_{j,\text{Max}}^{\text{dch}} \tag{7}$$

$$\text{SOC}_{j,t} = \text{SOC}_{j,t-1} + B_{j,t}^{-1} \left(P_{j,t}^{\text{ch}} \eta_j^{\text{ch}} - P_{j,t}^{\text{dch}} \eta_j^{\text{dch}} \right) t \tag{8}$$

$$0 < \text{SOC}_{j,\min} \leq \text{SOC}_{i,t} \leq \text{SOC}_{j,\max} < 1 \tag{9}$$

where $P_{j,t}^{\text{ch}}$ and $P_{j,t}^{\text{dch}}$ are the charging and discharging power of prosumers' energy storage at time t, respectively, $\text{SOC}_{j,t}$ is the state of charge of prosumers' energy storage at time t, B_j

is the capacity of prosumers' energy storage, and η^{ch} and η^{dch} are the charging and discharging efficiency of energy storage.

D. Other Entities

DSO is a crucial part of the distribution network and is responsible for dispatching the power balance of the distribution network in the region. DSO guarantees the power balance in the distribution network by dispatching RES and low-carbon technology users. DSO collects power data and publishes the best dispatching task to ensure the maximum benefit of the entire system under the constraints of the distribution network. It provides a cost-effective supply system for both power suppliers and users.

Also, there are many other loads besides EVs and prosumers, but they are not the focus of this article. In this article, we simply express it as comprehensive load data. DSO collects the real-time load uploaded by each entity and calculates the predicted load. However, there is a deviation between the predicted value and the real-time value, which has caused an imbalance in the power system. When the deviation between power generation and consumption is too large, DSO will publish dispatching tasks to ensure system stability.

IV. Distribution Network Design Goals

In this section, we propose a two-phase algorithm considering the behavior of EVs and the economic benefits of prosumers. It can save charging costs and reduce the impact on the distribution network by arranging the orderly charging of EVs, and dispatch prosumers to participate in the power consumption balance.

A. Phase I: Orderly Charging Plan for EVs Based on the OCIO Algorithm

The objective function at this phase is the charging cost of EVs. On the premise of ensuring the charging demand of EVs, we need to reduce the impact of disorderly charging on the distribution network, and arrange the most economical charging plan within the allowable charging period.

The calculation equation for the minimum charging cost of EVs at t is as follows:

$$\begin{aligned} \min \ & \sum_{i \in \mathcal{N}} C_{i,t}\left(x_{i,t}^{\mathrm{ch}}, P_{i,t}^{\mathrm{ch}}, \varphi^{\mathrm{ch}}, t\right) \\ \text{s.t.} \ & (2)-(4). \end{aligned} \tag{10}$$

The objective function of charging cost C_i at time period t is defined as

$$C_{i,t} = \varphi^{\mathrm{ch}} \cdot x_{i,t}^{\mathrm{ch}} \cdot P_{i,t}^{\mathrm{ch}} \cdot t \tag{11}$$

$$x_{i,t}^{\mathrm{ch}} = \begin{cases} 0/1, & t \in T_{\mathrm{allow}} \\ 0, & t \notin T_{\mathrm{allow}}. \end{cases} \tag{12}$$

φ^{ch} is the charging price of EVs, $x_{i,t}^{\mathrm{ch}}$ is a boolean variable representing the charging state of EV, and $x_{i,t}^{\mathrm{ch}} = 1$ indicates the EV is in a charging state.

The dispatch of EVs should meet the charging demand of users and conduct optimal dispatching according to the power fluctuations. In addition, the orderly charging of EVs should also meet the following constraints:

Algorithm 1: OCIO

Input: The length of time periods tp, EV number N, all electricity price φ_t^{ch}, EVs' charing power $P_{i,t}^{ch}$, maxium SOC SOC_{max}, current SOC $SOC_{i,t}$, and minimum SOC for trip ΔSOC_i $(i \in \mathcal{N},\ t \in T)$

Output: An orderly charging plan DT

```
Sort φ_t^ch from small to large and add corresponding time period t in Φ;
forall the i = 1; i ≤ N; i++ do
    if SOC_{i,t} < ΔSOC_i then
        k = 0;
        while k < length(Φ) && SOC_{i,t} < ΔSOC_i && Φ[k] ∈ T_here do
            if (ΔSOC_i − SOC_{i,t})/P_{i,k}^ch ≤ tp then
                SOC_{i,t} ← ΔSOC_i;
            else
                SOC_{i,t} ← SOC_{i,t} + tp ∗ P_{i,k}^ch;
            Add Φ[k] into DT;
            k++;
    if SOC_{i,t} < SOC_max then
        k = 0;
        while t < length(Φ) && SOC_{i,t} < SOC_max && Φ[k] ∉ DT && Φ[k] ∈ T_allow do
            if (SOC_max − SOC_{i,t})/P_{i,k}^ch ≤ tp then
                SOC_{i,t} ← SOC_max;
            else
                SOC_{i,t} ← SOC_{i,t} + tp ∗ P_{i,k}^ch;
            Add Φ[k] into DT;
            k++;
return DT;
```

$$\mathrm{SOC}_{i,\mathrm{depar}} > \Delta \mathrm{SOC}_i \tag{13}$$

$$DT \subset T_{\mathrm{allow}}. \tag{14}$$

$\mathrm{SOC}_{i,\mathrm{depar}}$ is the state of charge of the EV_i at the time of departure. $\Delta\mathrm{SOC}_i$ is calculated by (5), which measures the minimum SOC requirement of EV_i for a one-way trip. Finally, DT denotes an orderly charging plan, which is a set of charging time periods.

On this basis, we propose the OCIO algorithm to realize the orderly charging of EVs with a low cost. Considering the regular daily behavior of EVs, the algorithm gives priority to meeting the needs of $\mathrm{SOC}_{i,depar}$, and then arranges EVs to fill their SOC during the period of lower electricity price. Among them, arranging the lowest cost charging plan for an EV with a fixed SOC constitutes a knapsack problem. The specific algorithm is shown in Algorithm 1.

B. Phase II: Power Balance Dispatching Task for Prosumers Based on the mPSO Algorithm

The objective function f at this phase is the cost of the system, which is determined by the operating cost f_{op}, the dispatching expenditures of prosumers f_{pro} and the penalty p.

First, the operating cost f_{op} is composed of the network loss and the cost of purchasing power from the superior grid.

Let $P_{i,t}^{pg}$ denote the purchasing power from the superior grid, φ^{pg} denotes the purchase price, and C_{loss} denote the cost of network loss. f_{op} is defined as follows:

$$f_{op,t} = \varphi^{pg} P_t^{pg} + C_{\text{loss},t}. \tag{15}$$

In order to measure the stability of the distribution network, then we define the power fluctuation of the distribution network as follows:

$$\left|P_t^{\text{flu}}\right| = \left|\left(P_t^{\text{RES}} + \sum_{j\in\mathcal{K}} P_{j,t}^{rt}\right) - \left(P_t^L + \sum_{i\in\mathcal{N}} P_{i,t}^{\text{ch}}\right)\right| \le \varepsilon \tag{16}$$

where ε is the threshold of fluctuation, P_t^L is the load in the distribution network, P_t^{RES} is the RES generation, and P_t^{flu} is the power fluctuation. When $|P_t^{\text{flu}}| > \varepsilon$, it is considered the power fluctuates greatly, and DSO will publish the dispatching task to prosumers. When $P_t^{\text{flu}} > 0$, dispatching tasks published to prosumers are energy-consuming tasks. Otherwise, it is the task of supplying power to the system.

Second, the dispatching expenditures of prosumers is defined by the roof-top grid-connected PV power, the levelized cost of using storage [36] and the dispatching task reward.

The objective function definition formula is as follows:

$$f_{\text{pro},t} = \alpha \sum_{j\in\mathcal{K}} C_{us}\left(\left|P_{j,t}^{\text{reg}}\right|\right) + \sum_{j\in\mathcal{K}} \left|P_{j,t}^{\text{reg}}\right| \varphi_{j,t}^{\text{reg}} + \varphi^{rt} \sum_{j\in\mathcal{K}} P_{j,t}^{rt} \tag{17}$$

where $P_{j,t}^{rt}$ is the grid-connected roof-top PV power of the prosumer, φ^{rt} is the price of grid-connected roof-top PV power, α is the dispatching coefficient, φ^{reg} is the dispatching task reward, and its value should be greater than the real-time price and less than the purchase price from the superior grid to be reasonable.

Among them, C_{us} is the cost of using prosumers' energy storage. It is defined as follows:

$$C_{us} = \frac{C_{\text{inv}} + \sum_t^{T_{ESl}} \frac{CES_t}{(1+r)^t}}{\sum_t^{T_{ESl}} \frac{P_{j,t}^{\text{reg}}}{(1+r)^t}}. \tag{18}$$

In this equation, C_{inv} is the initial investment cost. CES_t is the prosumers' energy storage cost at t over the energy storage life T_{ESl}. Its sum defines the annual cost. $|P_{j,t}^{\text{reg}}|$ is the energy storage power of the prosumer participating in dispatching task at t, including $P_{j,t}^{\text{reg},dch}$ and $P_{j,t}^{\text{reg},ch}$. Both the CES_t and $P_{j,t}^{\text{reg}}$ are discounted with the interest rate r.

Third, p is defined as the penalty for abandoned RES energy generation. Let β and γ are the penalty coefficient of abandoned PV power generation and abandoned WT power generation, respectively. $P_{m,t,\max}$ is the maximum power of RES node m at time t, $P_{m,t}$ is the actual power at t. At time t, p is defined as follows:

$$p_t = \beta \sum_{m\in PV} \left(P_{m,t}^{\max} - P_{m,t}\right) + \gamma \sum_{m\in WT} \left(P_{m,t}^{\max} - P_{m,t}\right). \tag{19}$$

In addition, the distribution network should satisfy the active power balance constraint

$$P_t^{\text{RES}} + \sum_{j\in\mathcal{K}} P_{j,t}^{rt} + \sum_{j\in\rho} P_{j,t}^{\text{reg},dch} = P_t^L + \sum_{i\in\mathcal{N}} P_{i,t}^{\text{ch}} + \sum_{j\in\sigma} P_{j,t}^{\text{reg,ch}}. \tag{20}$$

$\rho \in \mathcal{K}$ is the set of prosumers who participate in the dispatching task to supply power. $\sigma \in \mathcal{K}$ is the set of prosumers who consume energy.

In summary, after two phases of dispatching for EVs and prosumers, the optimal cost function of the distribution network is as follows:

$$\begin{aligned} \min\ & f_t = f_{op,t} + \sum_{j\in\mathcal{K}} f_{\text{pro},t} + \sum_{m\in\text{RES}} p_t \\ \text{s.t.}\ & (6){-}(9),\ (20). \end{aligned} \tag{21}$$

Notice that the dispatching task reward for prosumers is much lower than the cost of purchasing electricity from the grid. It is also lower than the penalty of abandoned RES generation for achieving the same power balance effect. Therefore, the higher the value of f_{pro}, the better. This design can reduce the operation cost of distribution network and improve the economic benefit of prosumers. Meanwhile, we also consider the relationship between prosumers in the dispatching. The relationship between prosumers is similar to the cooperation and competition between particle swarms that the PSO algorithm relies on. So we propose a modified PSO algorithm to generate dispatching tasks for prosumers.

In the mPSO algorithm, we set the initial position $X_j = \{P_{1,\text{ini}}^{\text{reg}}, \ldots, P_{K,\text{ini}}^{\text{reg}}, \varphi_{\text{ini}}^{\text{reg}}\}^{\text{T}}$ as an initial dispatching task. The global optimal location $X_{\mathbf{g}\text{best}_j}$ can be obtained through the PSO algorithm, which is the best dispatching task for the prosumer. However, the traditional PSO algorithm limits the search range of particles due to the convergence of particles. Therefore, we introduce a new velocity V_j update equation to improve its performance

$$\begin{aligned} V_j^{k+1} = (1-\lambda)\Big\{ & V_j^k + c_1 \cdot \text{rand}_1 \cdot \left[X_j^k - X_{\mathbf{p}\text{best}_j}\right] \\ & + c_2 \cdot \text{rand}_2 \cdot \left[X_j^k - X_{\mathbf{g}\text{best}_j}\right]\Big\} + \lambda \cdot V_j^{k-1} \end{aligned} \tag{22}$$

$$X_j^{k+1} = X_j^k + V_j^{k+1}. \tag{23}$$

Let V_j^k denotes the velocity of j at iteration k. c_1 and c_2 are weight factors. rand_1 and rand_2 are random numbers between [0, 1]. $\lambda \in [0, 1]$ is the smoothing factor. The larger the value of λ, the better the smoothing performance of mPSO. X_j^k is the dispatching task of j at iteration k. The mPSO algorithm can smooth the trajectory of particles and then eliminate the stagnation of local optimization due to the nonconvergence and the oscillation at the later stage of the iteration. Through the mPSO algorithm, we can obtain the best dispatching task $X_{\mathbf{g}\text{best}_j}$ for prosumers. The detail of the mPSO algorithm is shown in Algorithm 2.

The algorithm first generates a set of random numbers within the range that meets the power constraints and the power price constraints to initialize. It records the position of each particle as a partial optimal solution $X_{\mathbf{p}\text{best}_j}$, and calculates the fitness function F of each particle to determine the optimal location $X_{\mathbf{g}\text{best}_j}$. $F = \sum_{j\in\mathcal{K}}(|P_{j,t}^{\text{reg}}|, \varphi^{\text{reg}})$ is the fitness function of mPSO which is used to measure the expenditure of dispatching task for prosumers.

The mPSO is different from the other method of modifying the weight coefficient of the speed update equation. It changes the original particle velocity update equation from a first-order difference equation to a second-order difference equation. This

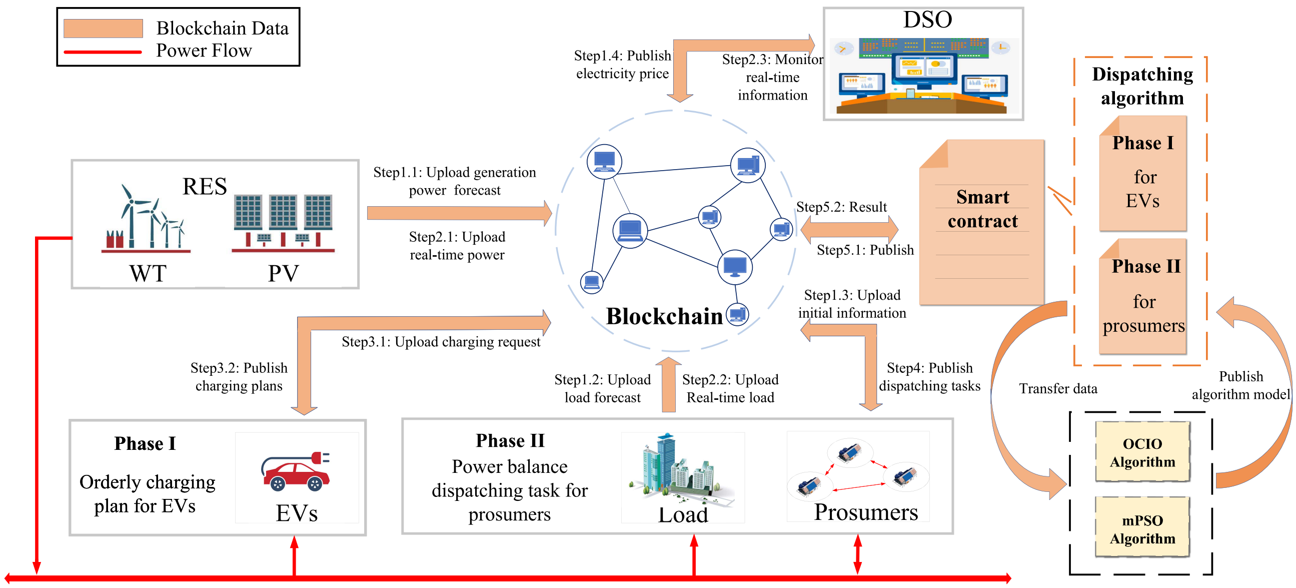

Fig. 2. Blockchain-based trustworthy energy dispatching approach.

Algorithm 2: Optimal Economic Dispatch mPSO

Input: Particle swarm scale: K; Boundary conditions for each particle: Eq.(6) (7); The number of iterations: I

Output: The best dispatching task $X_{\mathbf{g}best_j}$

Initialize the velocity V_j and the dispatching task X_j;
$X_{\mathbf{p}best_j} \leftarrow X_j$;
for $j = 1$ *to* K **do**
  if $X_{\mathbf{p}best_j} < \min X_{\mathbf{p}best_j}$ **then**
    $\min X_{\mathbf{p}best_j} \leftarrow X_{\mathbf{p}best_j}$;
while *The number of iterations is not met* I **do**
  for $j = 1$ *to* K **do**
    Update V_j and X_j, calculate fitness F;
    if $F < F(X_{\mathbf{p}best_j})$ **then**
      $X_{\mathbf{p}best_j} \leftarrow X_j$;
    if $F < F(X_{\mathbf{g}best_j})$ **then**
      $X_{\mathbf{g}best_j} \leftarrow X_j$;
    Update the task and velocity by Equation (22) and (23);
return $X_{\mathbf{g}best_j}$

improvement makes the operation of the algorithm simpler and faster, eliminates the oscillation in the late iteration and the stagnation of local optimum due to nonconvergence.

Then, the algorithm is iterated according to (22) and (23). In each iteration step k, the position X_j^k and velocity V_j^k must be calculated, and the partial optimum solution $X_{\mathbf{p}\text{best}_j}$ and the best optimal solution $X_{\mathbf{g}\text{best}_j}$ of the must be determined. Note that when the price is updated, the power of prosumers who participate in the adjustment will change due to demand response [37].

Finally, when the number of iterations reaches the I, the algorithm ends. Get the dispatching task $X_{\mathbf{g}\text{best}_j}$ and bring it back to (21) to get the minimum system cost f_t.

V. Implementation

The workflow of the approach is shown in Fig. 2. In order to process blockchain data reasonably and obtain good performance, the dispatching approach is deployed on the consortium blockchain, and entities with good reputations and capabilities, such as DSO and RES are used as authority nodes to maintain the blockchain. Loads and low-carbon technology users, such as EV and prosumer also join the blockchain network as light nodes. For EVs, because they are charged when the electricity price is low, the orderly charging completed by participating in the dispatching can save their charging costs without affecting their travel needs. For prosumers, they can participate in the dispatching tasks of the excess power from rooftop photovoltaic power generation, which can save energy storage costs and obtain photovoltaic grid benefits. In addition, they can also use their energy storage to participate in dispatching tasks to obtain economic benefits. So they are motivated to participate in dispatching.

The scheme is deployed in an area, such as a town of 2000 households. The peak-to-valley electricity price of the grid is disclosed on the blockchain. In each cycle, each entity uploads its charging and discharging requirements through the blockchain. Then, DSO uses the OCIO algorithm to generate dispatching results of EVs based on the on-chain data, and publishes results on the blockchain. Further, DSO uses the mPSO algorithm to generate and publish the dispatching results of the prosumer on the blockchain. The dispatching algorithms and their inputs and outputs are published. Based on this immutable on-chain data, the dispatched entity can verify that the dispatching process is fair and in their interest, and is willing to remain in the system to perform dispatching tasks. The detailed workflow is demonstrated as follows.

Step 1 (Upload Forecast Information): At the beginning of an operating cycle, RES nodes upload power generation forecast information to the blockchain, and the loads also upload their forecast information. The DSO publishes the peak-to-valley electricity price information φ to each node through the blockchain. Although the forecast information may be different from the real situation, these entities can provide as accurate forecasts as possible because it is in their own interest to do so. Finally, the above on-chain data is stored immutably as a basis for dispatching.

Step 2 (Monitor Real-Time Information): Then the system collects real-time power generation P_t^{RES} and electricity consumption information P_t^L at regular intervals. Specifically, an operating cycle is divided into multiple fixed-length time periods. Before entering a time period, RES uploads P_t^{RES} in the previous time period to the blockchain. Meanwhile, prosumers need to upload their real-time power information $P_{j,t}^{rt}$ and $P_{j,t}^{\mathrm{reg}}$ so that the DSO can publish dispatching tasks for them. This information also include the saleable energy storage capacity and the cost of using energy storage C_{us}. In addition, any EV that needs to be charged can upload its charging demand on the blockchain at any time. The charging demand includes EV charging time t, allowable charging period T_{allow}, SOC, and other information.

Step 3 (Arrange for Orderly Charging of EVs): At the beginning of a time period, DSO generates EVs dispatching results based on the on-chain data and the OCIO algorithm (see Algorithm 1). According to the OCIO algorithm, within the EV's charging time, the EV is arranged to be charged at the time when the load and the charging cost $C_{i,t}$ are low. Then, DSO uploads the dispatching results of EVs to the blockchain.

Step 4 (Publish the Dispatching Task of Prosumers): After generating and publishing the dispatching result of EVs, DSO decides whether the power is balanced according to (15), and thus decides whether to generate a dispatching task for prosumers. Specifically, if $P^{\mathrm{flu}} > 0$, DSO will use the mPSO algorithm to generate a consumption task, the task will be published on the blockchain. Similarly, when $P^{\mathrm{flu}} < 0$, DSO will generate and publish a supply task to dispatch prosumers to supply power to improve grid stability.

Step 5 (Result and Feedback): Eventually, EVs are charged according to the dispatching task, and pay the charging fee to complete the transaction and upload the execution result. Similarly, after prosumers complete the dispatching task, they get task rewards and update their remaining capacity.

If EVs or prosumers have doubts about the dispatching task, they can obtain all the data used to generate this dispatching task from the blockchain. In order to avoid being affected by the randomness of the mPSO algorithm, they also request the setting of the algorithm from the DSO. Subsequently, they repeated the calculation locally to verify the correctness of the dispatching task.

VI. Evaluation

A. Experiment Environment

We evaluate the effectiveness and performance of our scheme with an Intel Core CPU i7-9750H @ 2.6 GHz, 16 GB RAM. We set an operating cycle $T = 24$ h, and a fixed-length dispatching time period t is 15 min. In our distribution network, the time-of-use electricity price based on RES generation forecast and load forecast is shown in Table III. The RES generation is based on wind and PV generation, and its forecast and real-time information is based on actual conditions. We modify IEEE 33-bus test feeder and place wind generation, solar panels, and prosumer nodes in the network. In addition to the experiment to test the delay of the OCIO algorithm and mPSO algorithm, the number of EV in the other experiments is 100, and the number of prosumers is 50. We assume EV's travel is a typical day behavior. Then, we use the Monte Carlo method to simulate the load of EVs, in which the driving distance follows the Gaussian distribution, and the one-way driving time follows the normal distribution. In order to test the scalability, we also gradually increased the number of users in the system to more than 1000, which is equivalent to the number of households in towns. The mPSO algorithm has 100 iterations to obtain the optimal solution. Based on Ethereum, we build a consortium blockchain with a PoA consensus mechanism to implement the on-chain part, and test the performance with Truffle.

TABLE III
Time-of-Use Pricing in Our Distribution Network

Load condition	Period	Price ($)
Peak	0 - 8 A.M.	0.129
Normal	8 A.M. - 5 P.M. and 9 P.M. - 0	0.103
Valley	5 P.M. -9 P.M.	0.054

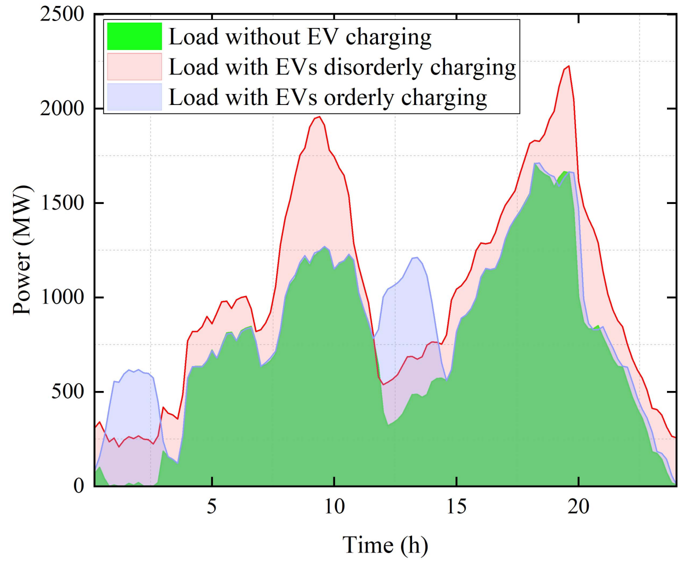

Fig. 3. Distribution network load curve.

B. Experiment Results

1) Effectiveness: We first test the impact of different EV dispatching methods on the power of the distribution network within an operating cycle. As shown in Fig. 3, the 8–11 A.M. is the daytime peak power consumption of Load, and the 6–8 P.M. is the evening peak power consumption. Without using our scheme, EVs in the system are charged immediately

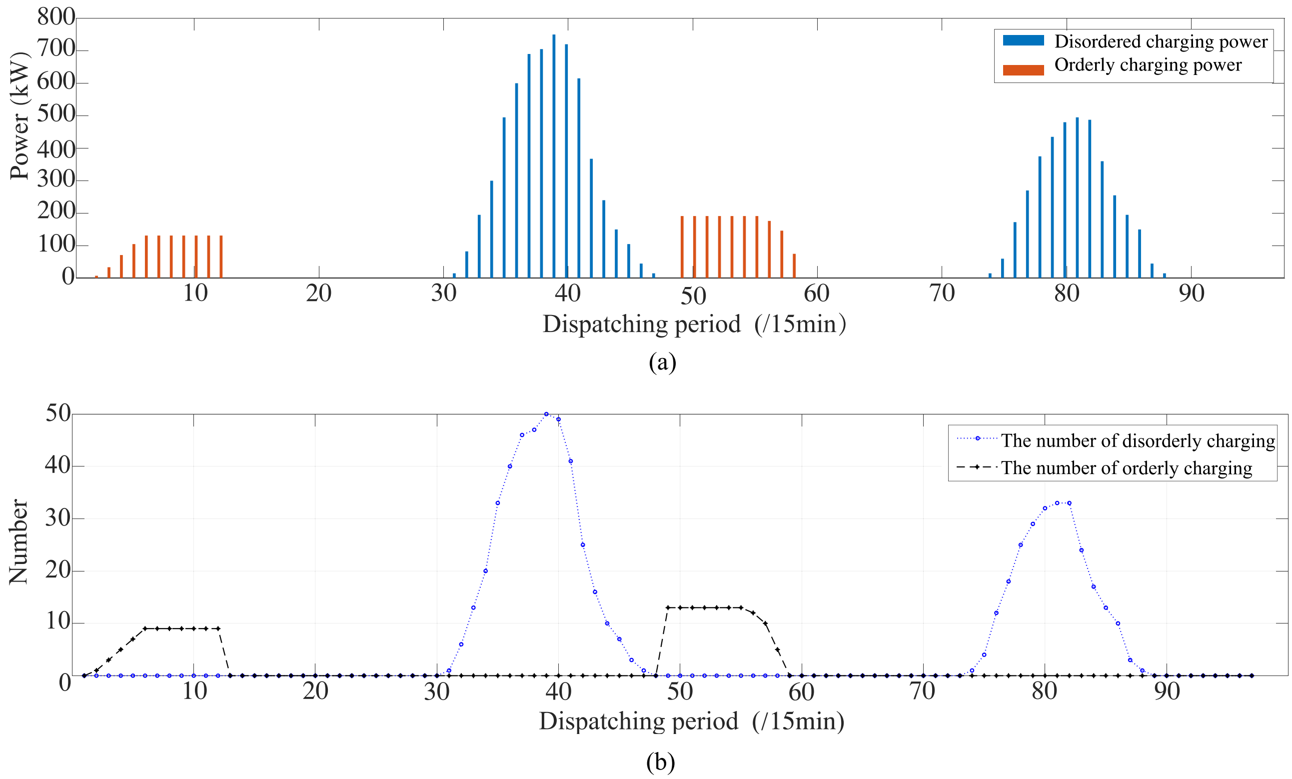

Fig. 4. Dispatching effect of EVs orderly charging. (a) EV charging behavior. (b) Delay of blockchain node operation.

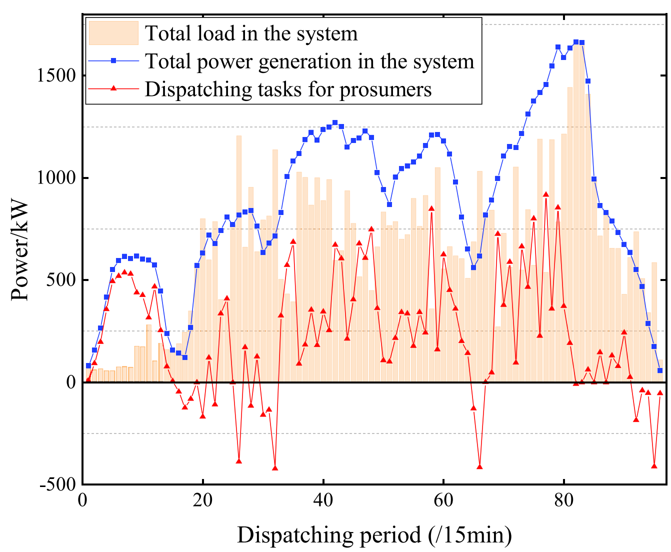

Fig. 5. Power balance effect of the distribution network.

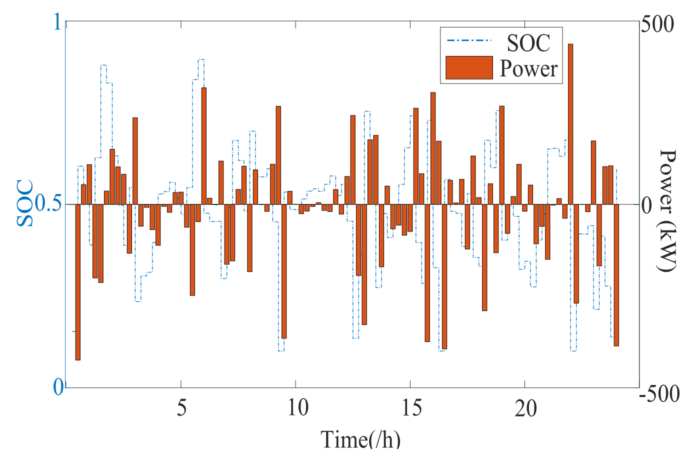

Fig. 6. 24 h change in energy storage of prosumers.

after reaching the destination, and their disorderly charging will impact the grid in the morning and evening peaks. Through the deployment of our scheme, the orderly charging of EVs reduces the peak-valley difference and improves the stability of the grid.

We further show in detail the number of EVs to be charged and their power in each dispatching period, and compare them with the situation during disorderly charging. As shown in Fig. 4(a), we use the Monte Carlo method to simulate the disordered charging of EVs. In this scenario, the EV is charged immediately after reaching the destination, forming a charging peak. At the same time, this peak coincides with the peak load, which exacerbates the peak-to-valley difference in the total load of the system. In Fig. 4(b), after implementing our OCIO algorithm, during the morning load peak, the maximum charging EV number in the unit period is reduced from 50 to 15, and their charging time is postponed to the valley of load. Similarly, at night load peaks, the maximum charging EV number in the unit period is reduced from 35 to 10. Obviously, the use of our scheme can effectively avoid the power superposition.

Figs. 5 and 6 show the dispatching effects of prosumers in an operating cycle. The histogram in Fig. 5 shows the

TABLE IV
EV CHARGING COSTS AND PROSUMER BENEFITS

Entity	with our scheme ($)	without our scheme ($)
Prosumers	71.906	-
EVs	252.77	321.536

total load in each time period, including the power consumption of EVs and other users. The blue curve is the total power generation in the system, including the RES generation and the prosumers' rooftop PV grid-connected power. The red curve is the power generation and consumption when prosumers participate in dispatching tasks. It can be seen that when the load is higher than the power generation, prosumers will generate power. Otherwise, they use electricity to help consume renewable energy. Obviously, the power generation or consumption of prosumers is close to the total power generation of the system when superimposed on the total load As shown in Fig. 6, the energy storage of prosumers changes according to the dispatching task. The blue line reflects the SOC change of energy storage, and the orange histogram reflects the output of energy storage. The energy storage of prosumers provides the energy provided by the power shortage of the grid, and provides the consumption capacity for the power surplus. These dispatching tasks effectively dispatch prosumers, and encourage them to complete the dispatch tasks to obtain the maximum benefit. The benefits that our scheme brings to prosumers and EVs in Table IV.

2) Performance: Fig. 7 shows the time required for the OCIO algorithm and mPSO algorithm to generate dispatching results. When there are 700 EVs and 350 prosumers in the system that need to be dispatched, it takes about 650 and 700 ms to generate the dispatching results, which is negligible for a time period. In addition, we evaluate the improvement effect of the mPSO algorithm. When the number of iterations is 100 times, we compare our algorithm with the standard PSO algorithm, and the experimental result is shown in Fig. 8. The mPSO algorithm requires fewer iterations to generate the optimal value. Therefore, our algorithm has a good improvement effect and requires less calculation.

Finally, we evaluate the performance of on-chain operations by testing gas consumption and delay on the Truffle testing framework. It should be noted that this delay is only for performing on-chain operations, and the delay for the transaction to be confirmed can be ignored in our consortium blockchain-based scheme. In the Ethereum platform, performing on-chain operations requires a certain amount of gas, which can reflect the calculation and storage overhead of the operation. For reference, storing a 256-bit integer on the blockchain requires 20 000 units of gas.

As shown in Fig. 9, all on-chain operations consumed less than 120 000 units of gas. According to the current gas price of Ethereum and the price of Ether, the operation that consumes the most gas requires about 0.00032 Ether, which is about U.S. $0.797 USD. All entities in the system can accept this overhead. Besides, the delay is no more than 50 ms when the real-time information is uploaded and no more than 55 ms when the forecast information is uploaded. This delay can be ignored in one dispatching period and can meet the delay requirements of the distribution network.

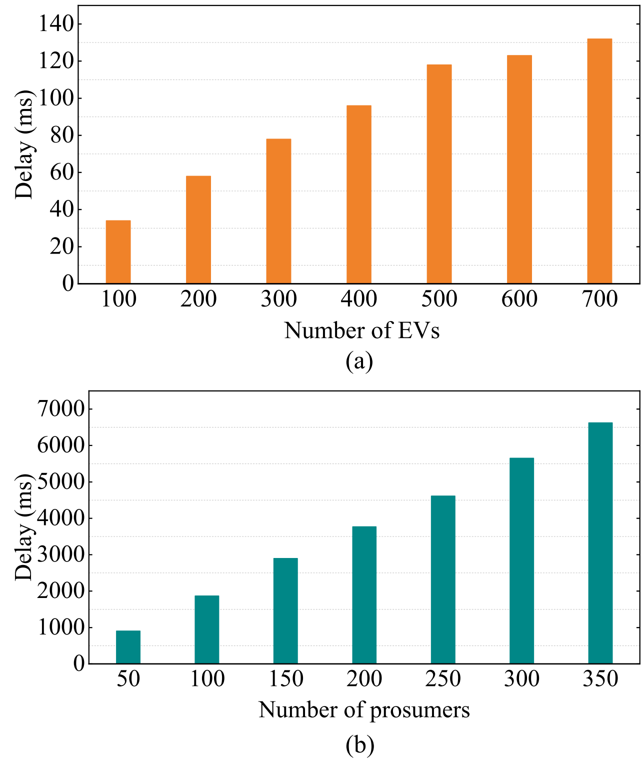

Fig. 7. Delay of the OCIO algorithm and mPSO algorithm. (a) Delay of the OCIO algorithm. (b) Delay of the mPSO algorithm.

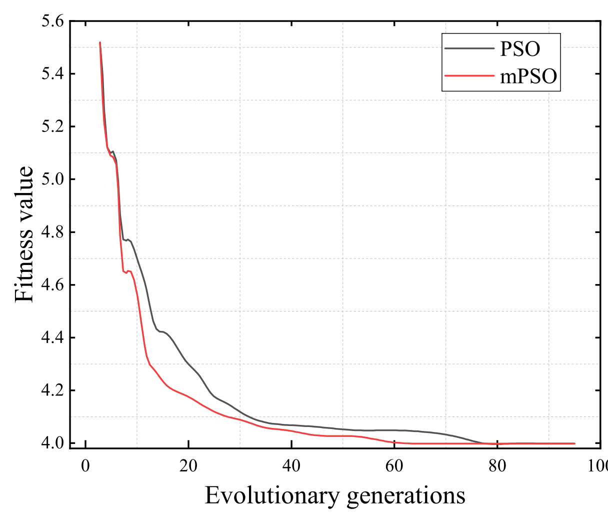

Fig. 8. mPSO iteration situation.

VII. CONCLUSION

In this article, we proposed a blockchain-based trustworthy dispatching approach for high renewable energy penetrated power systems. The proposed approach can help in protecting the interests of low-carbon technology users. The grid's

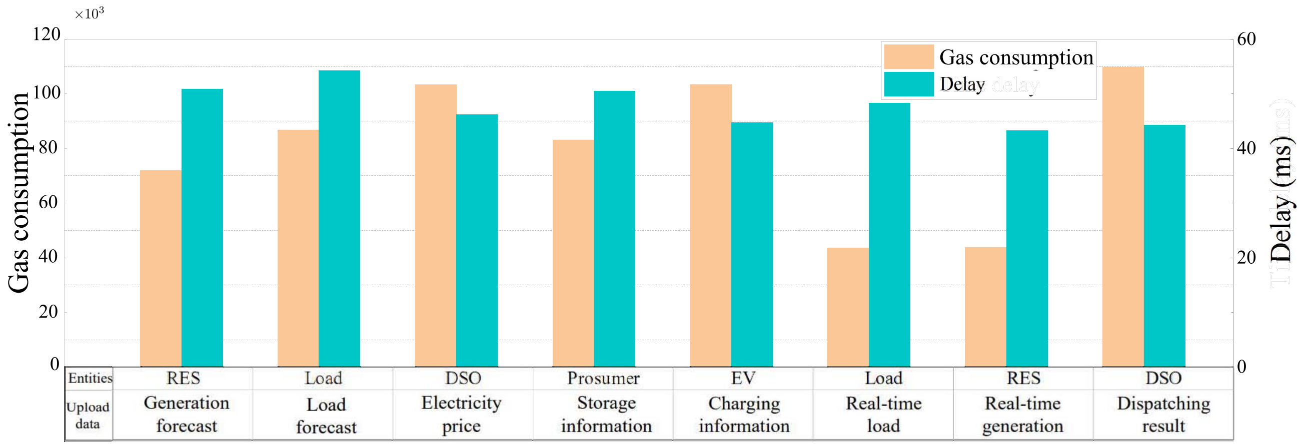

Fig. 9. Performance of on-chain operations.

stability can be improved by effectively dispatching them, and the abandoned RES generation can be reduced. The effectiveness of the dispatching approach has also been verified in the modified IEEE 33-bus test system and Ethereum-based smart contracts. The disadvantage of the current related schemes is that the application scenarios are not complex enough and cannot be well adapted to practice. For future work, we plan to design a scheme that adapts to more complex scenarios. We intend to account for electrical loads, consider heating and cooling loads, and use the characteristics of EVs to ensure the flexibility of the distribution network. We also intend to expand the research on smart contracts and the distributed algorithms and use more efficient algorithms to complete dispatching and verifications on the blockchain.

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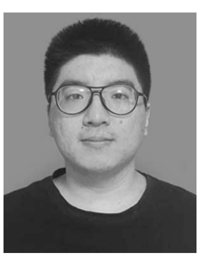

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