

Coordinating EV Charging via Blockchain

Jian Ping, Zheng Yan, Sijie Chen, Liangzhong Yao, and Minhui Qian

Abstract—The increasing electric vehicle (EV) penetration in a distribution network triggers the need for EV charging coordination. This paper firstly proposes a hierarchical EV charging coordination model and an algorithm based on Lagrangian relaxation. A barrier to the implementation of the coordination algorithm is that there usually does not exist a reliable coordinator of charging stations. This paper shows that an unreliable coordinator may collude with some charging stations and behave dishonestly by disobeying the coordination algorithm. Thus, the collusion coalition can gain more profits while lowering the profits of others and the total social welfare. To provide reliable coordination of charging stations, a novel blockchain-based coordination platform via Ethereum is established, including a coordination structure and a smart contract. A mathematical analysis is given to show that the proposed platform can mitigate the collusion behaviors in the coordination. Simulation results show the consequence of collusion and how blockchain can prevent the collusion.

Index Terms—Electric vehicle (EV) charging coordination, collusion, blockchain, smart contract.

I. INTRODUCTION

THE increasing electric vehicle (EV) penetration brings overload risks to distribution system facilities, necessitating EV charging coordination [1]. Due to the huge number of EVs, a hierarchical approach is usually appropriate for charging coordination because it protects user privacy and ensures satisfactory convergence. In existing studies on hierarchical charging coordination, a common assumption is that there exists an honest and reliable coordinator so that the coordination process is fair [2]. However, this assumption may not hold in practice. In a distribution network, there is not always a mature and reliable coordinator of charging stations. A utility company may potentially be a reliable coordinator, but it may bring the utility an extra burden to manage all charging stations in its territory, and charging

power allocation is beyond its duty. A third-party coordinator, on the other hand, may not behave fairly and honestly.

With the absence of an honest coordinator, the problem of how to provide reliable coordination for EV charging stations is addressed in this paper.

Hierarchical EV charging coordination methods have been extensively studied. The optimal charging schedule is derived through iterations between a central coordinator and local controllers. In [3], a central controller forecasts the load curve of conventional loads, and local controllers optimize local charging schedules while omitting system security constraints. Reference [2] considers the maximum total available power of all charging stations, and uses the alternating direction method of multipliers (ADMM) to solve the coordination problem. Reference [4] formulates an EV charging coordination problem as an extended day-ahead security-constrained unit commitment problem and proposes a partial decomposition method based on Lagrangian relaxation. Reference [5] minimizes the total energy losses of a distribution network considering the charging of EVs based on ADMM. These studies rely on a three-layer structure, including a central coordinator, a local aggregator, and EVs. In [6], [7], signals are directly transmitted between a central coordinator and individual EVs, which performs better on privacy protection. The approaches in the above studies protect EVs' privacy and ensure satisfactory convergence. However, these studies assume that the central coordinator is mature and reliable, i.e., it would not collude with local controllers and disobey the coordination algorithm. The case where a mature and reliable central coordinator is absent is rarely concerned in these studies.

Recently, the blockchain, a novel cryptography technology deemed as capable of ensuring trust and transparency, is gaining increasing attention [8]. Since an energy technology company, LO3 Energy, establishes a blockchain-based peer-to-peer (P2P) energy market in a Brooklyn microgrid [9], energy blockchain applications have been preliminarily studied, especially in P2P energy trading. In [10], blockchain is utilized as a trusted and secure settlement tool of electricity trading among prosumers. Reference [11] implements P2P energy trading on blockchain. Reference [12] proposes a credit-based payment scheme to accelerate P2P energy trading on blockchain. Reference [13] proposes an energy loss allocation mechanism in blockchain-based P2P energy trading in a microgrid. Reference [14] performs security and privacy analysis of the blockchain-based P2P energy trading. These studies give demonstrations about how to ensure fair and transparent P2P energy trading in a decentralized manner via blockchain.

Manuscript received: June 13, 2019; accepted: October 10, 2019. Date of CrossCheck: October 10, 2019. Date of online publication: April 23, 2020.

This work was jointly supported by National Key Research and Development Program of China (No. 2016YFB0900100), National Natural Science Foundation of China (No. U1866206), and Young Elite Scientists Sponsorship Program.

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DOI: 10.35833/MPCE.2019.000393



In the area of blockchain-based EV charging coordination, multiple electricity trading mechanisms of EVs on blockchain are implemented. Reference [15] utilizes blockchain as a P2P electricity trading platform for EVs within the same charging station. Reference [16] introduces an Iceberg order execution algorithm to schedule EV charging and develops a transaction scheme. Reference [17] presents a consensus mechanism of energy blockchain and a transaction scheme that captures EVs' individual energy preferences. In general, existing studies utilize blockchain as an electricity trading platform for individual EVs. Few studies focus on the potential of utilizing blockchain as a coordinator of charging stations in a hierarchical coordination algorithm.

This paper makes the following contributions.

1) This paper proposes an EV charging coordination model and a hierarchical EV charging coordination algorithm. Then it shows that in a hierarchical EV charging coordination approach, a coordinator may behave dishonestly by disobeying the proposed coordination algorithm and colluding with some charging stations. The collusion coalition (consisting of the dishonest coordinator and the charging stations which collude with the coordinator) can gain illegal profits while lowering the profits of others and the total social welfare. Both theoretical analysis and simulation are given to demonstrate the motivation and the harmfulness of the collusion.

2) This paper uses the blockchain to provide reliable coordination for EV charging stations. The proposed coordination algorithm is implemented on Ethereum blockchain by proposing a coordination structure and deploying a smart contract. The blockchain-based EV charging coordination platform is robust against single-point failures and potential collusion behaviors. A mathematical analysis is conducted to show that the blockchain-based platform can mitigate the collusion so long as the proportion of total computational power of malicious charging stations is less than 50%.

3) This paper tests the performance of the platform by deploying it on an Ethereum private chain. The simulation results show that the platform can ensure satisfactory convergence and coordination reliability. We state the general merits of blockchain in EV coordination and quantify the value of blockchain via mathematical analysis and simulation.

The rest of the paper is organized as follows. Section II presents the EV charging coordination model. Section III gives the coordination algorithm and analyzes potential collusion behaviors. Section IV presents how to utilize blockchain to mitigate the collusion. Section V demonstrates the merits of the blockchain-based EV charging coordination platform via the simulation. Section VI concludes the paper.

II. MODEL OF EV CHARGING COORDINATION

A. Modeling Features and Assumptions

1) Security risks exist when plenty of EVs are charged at the same time, i.e., the transformer at the transformation and distribution (T-D) station might be overloaded [1]. To protect the transformer at the T-D station, the permissible total charging load of charging stations in each period is pre-

mined at the beginning of the period according to the historical conventional load curve and capacities of facilities.

$$P_t^{ch,max} = P^{cap} - P_t^{CL} \quad t \in [1, T] \quad (1)$$

where $P_t^{ch,max}$ is the permissible total charging load in period t ; P^{cap} is the capacity of the transformer at the T-D station; P_t^{CL} is the forecasting of the conventional load in period t ; and T is the number of periods in a day.

2) EVs only arrive and leave at the beginning or the end of each period. If an EV parks in a charging station at the beginning of period t , its charging process starts from period t . And EV charging power is constant during a period.

3) A charging station is an agent of on-site EVs, which always seeks the optimal charging power of on-site EVs. The revenue of a charging station is determined by the electricity consumption of on-site EVs. A charging station only has the real-time states of charge (SOCs), battery constraints and the departure time of parked EVs. The information of the real-time electricity price and the amount of EVs in the future are unpredictable by a charging station. In this paper, a charging station always makes "here-and-now" decisions at the beginning of each period. It determines the charging power in this period based on the status of parked EVs including EVs that arrived in past periods and EVs that arrived at the beginning of the current period.

B. Objective Function

The objective of the EV charging coordination problem is to maximize the total social welfare of EVs in the current period.

$$\max \sum_{i \in \Omega^{CS}} \sum_{j \in \Omega_{i,t}^{EV}} (U_{j,t} - C_{j,t}) \quad (2)$$

where Ω^{CS} is the set of charging stations; $\Omega_{i,t}^{EV}$ is the set of EVs at the charging station i in period t ; and $U_{j,t}$ and $C_{j,t}$ are the utility and the cost of EV j in period t , respectively.

The charging cost of EV j in period t is given as:

$$C_{j,t} = \pi_t P_{j,t} \Delta t \quad (3)$$

where π_t is the basic real-time charging price in period t ; Δt is the duration of a period; and $P_{j,t}$ is the charging power of EV j in period t .

In order to model EV's utility, concave and non-decreasing functions such as quadratic functions [18] - [21] have been extensively accepted. Inspired by the above studies, an EV's utility is indicated by a quadratic function.

$$U_{j,t} = \alpha_j \left[1 - \left(1 - q_{j,t} / q_j^{\max} \right)^2 \right] / \tau_{j,t} \quad (4)$$

where α_j is the coefficient for charging willingness of EV j ; $q_{j,t}$ is the SOC of EV j at the end of period t ; q_j^{\max} is the desired SOC of EV j at departure; and $\tau_{j,t}$ is the number of periods from period t to the departure time of EV j .

According to (4), the utility of an EV is associated with its current SOC, desired SOC, and departure time. The function has the following properties:

1) When being charged, the utility of an EV increases where as the marginal utility $dU_{j,t}/dq_{j,t} = 2\alpha_j(1/q_j^{\max} - q_{j,t}/(q_j^{\max})^2)/\tau_{j,t}$ decreases.

2) For two EVs with the same percentage of SOC, the EV

which will shortly depart and has higher charging utility.

These two properties mimic the EV's preference in reality that an EV which has lower SOC and departs earlier is more willing to be charged. Note that the proposed mechanism also applies other utility function forms.

C. Constraints

1) Facility Constraint

From the perspective of a distribution network, the total charging power cannot exceed the permissible total charging load to protect the transformer at the T-D station.

$$\sum_{i \in \Omega^{CS}} \sum_{j \in \Omega_{i,t}^{EV}} P_{j,t} \leq P_t^{ch, \max} \quad (5)$$

From the perspective of a charging station, the total charging power of on-site EVs can not exceed the maximum charging power of the charging station, as shown in (6).

$$\sum_{j \in \Omega_{i,t}^{EV}} P_{j,t} \leq P_i^{CS, \max} \quad i \in \Omega^{CS} \quad (6)$$

where $P_i^{CS, \max}$ is the maximum total charging power of charging station i .

2) EV Constraints

An EV has the following constraints as for its battery.

$$0 \leq P_{j,t} \leq P_j^{EV, \max} \quad j \in \Omega_{i,t}^{EV}, i \in \Omega^{CS} \quad (7)$$

$$0 \leq q_{j,t} \leq q_j^{\max} \quad j \in \Omega_{i,t}^{EV}, i \in \Omega^{CS} \quad (8)$$

$$q_{j,t} = q_{j,t-1} + \eta_j P_{j,t} / E_j^{\max} \quad j \in \Omega_{i,t}^{EV}, i \in \Omega^{CS} \quad (9)$$

where $P_j^{EV, \max}$ is the maximum charging power of EV j ; and η_j is the charging efficiency of EV j .

Constraint (7) represents the charging power limit of an EV. Constraint (8) shows the lower and upper limit of SOC of an EV, respectively. Constraint (9) indicates the change of SOC during the charging process. $q_{j,0}$ is the SOC of EV j at the beginning of the first period in a day. The optimization problem is to maximize an objective function (2) with constraints (3)-(9).

III. EV CHARGING COORDINATION ALGORITHM AND POTENTIAL COLLUSION RISK

A. Decomposition and Coordination

A hierarchical coordination algorithm is given in this subsection.

In the optimization problem indicated by (2) - (9), constraint (5) is the coupling constraint. By relaxing constraint (5) with Lagrangian relaxation method [22], the Lagrangian function for the original problem is defined as follows.

$$L_t(P_i, \mu_t) = \sum_{i \in \Omega^{CS}} \sum_{j \in \Omega_{i,t}^{EV}} (U_{j,t} - C_{j,t}) - \mu_t \left(\sum_{i \in \Omega^{CS}} \sum_{j \in \Omega_{i,t}^{EV}} P_{j,t} - P_t^{ch, \max} \right) = \sum_{i \in \Omega^{CS}} L_{i,t}(p_i, \mu_t) + K_t(\mu_t) \quad (10)$$

$$L_{i,t}(p_i, \mu_t) = \sum_{j \in \Omega_{i,t}^{EV}} (U_{j,t} - C_{j,t}) - \mu_t \sum_{j \in \Omega_{i,t}^{EV}} P_{j,t} \quad (11)$$

$$K_t(\mu_t) = \mu_t P_t^{ch, \max} \quad (12)$$

where P_i is the set of $P_{j,t}$ for all EVs in all charging stations;

p_i is the set of $P_{j,t}$ for all EVs in charging station i ; and μ_t is the Lagrangian multiplier of constraint (5) in period t , which also indicates the congestion price in period t .

Maximizing (11) with constraints (6)-(9) is an independent sub-problem for each charging station. The sub-problem also indicates maximizing the total welfare of EVs parked at the charging station while considering the congestion price. By decomposing the original problem into the independent sub-problems, each charging station can efficiently optimize its charging demand with a given congestion price μ_t . And the value of μ_t is updated according to the feedback of charging stations. According to the duality theorem [22], the global optimal charging schedule can be derived in such a hierarchical way because the original optimization problem is convex.

Based on the proposed coordination model, an EV charging coordination algorithm is proposed as follows.

Step 1: initialization. The coordinator sets the permissible total charging load $P_t^{ch, \max}$ and the current round of iteration $v=0$, and initializes the Lagrangian multiplier $\mu_t^{(0)}=0$.

Step 2: solving sub-problems. According to the given multiplier, each charging station optimizes its charging schedule by solving sub-problems indicated by (6)-(9), (11). It then submits its total power demand $\sum_{j \in \Omega_{i,t}^{EV}} P_{j,t}$ to the coordinator.

Step 3: multiplier update. The coordinator collects the power demand from all charging stations. It can update the multiplier using multiple methods such as the sub-gradient method, the cutting plane method, and the trust region method. In this work, the sub-gradient method is applied for updating the multiplier ((13)-(15)), because it is simple to implement and has small computation burden [22].

$$\Delta P_t = \sum_{i \in \Omega^{CS}} \sum_{j \in \Omega_{i,t}^{EV}} P_{j,t} - P_t^{ch, \max} \quad (13)$$

$$\Delta \mu_t = \begin{cases} 0 & \mu_t^{(0)}=0 \text{ and constraint (5) is met} \\ \Delta P & \text{otherwise} \end{cases} \quad (14)$$

$$\mu_t^{(v+1)} = \mu_t^{(v)} + \Delta \mu_t / (a + bv) \quad (15)$$

where ΔP_t is the amount of facility overload; $\Delta \mu_t$ is the difference of μ_t ; a, b are scalar parameters in the sub-gradient method [22]; and $\mu_t^{(v)}$ is the Lagrangian multiplier at iteration v in period t .

Step 4: convergence check. If $|\mu_t^{(v+1)} - \mu_t^{(v)}| \leq \varepsilon$ (ε is a small positive number), the charging demand is deemed as converging to the optimum. The coordinator stops updating μ_t . Otherwise, the coordinator sets $v=v+1$, and returns to *Step 2*.

In practice, if an EV arrives just after the coordination process in a period, there are two possible situations. ① If constraint (5) is not binding, i.e., $\mu_t=0$, the EV is allowed to be charged immediately. ② If constraint (5) is binding, i.e., $\mu_t \neq 0$, the EV has to wait for the coordination process in the next period.

The pros and cons of the proposed algorithm are as follows.

1) Limited information exposure. Only little information of EVs is submitted to the coordinator. The privacy of individuals such as $q_{j,v}$, q_j^{\max} and $\tau_{j,v}$ can be protected in the algo-

rithm.

2) Low computational burden. In period t , the coordinator needs to optimize $\sum_{i \in \Omega^{CS}} N_{i,t}^{EV}$ in the primary problem while it only needs to optimize one variable (the Lagrangian multiplier) in the coordination algorithm, where $N_{i,t}^{EV}$ is the number of EVs at charging station i in period t . Compared to the centralized optimization, in the proposed algorithm, the coordination model is decomposed and solved in a hierarchical way, which significantly reduces the computational burden for the coordinator.

3) Satisfactory convergence. The proposed hierarchical algorithm has satisfactory convergence, as shown in Section V-B.

4) Vulnerability to single-point failures. The coordinator in the proposed algorithm is vulnerable to single-point failures [23]. A cyber-attack on the coordinator will result in the failure of coordination.

5) Vulnerability to dishonest coordinator behaviors. This will be detailed in Section III-B.

B. Potential Collusion with a Dishonest Coordinator

In the proposed algorithm, a basic assumption is that the coordinator is honest, i.e., the coordinator updates and broadcasts multipliers correctly according to the proposed algorithm. However, to gain profits, the coordinator might behave dishonestly and be in the collusion with a part of charging stations. Here is a demonstration to show how collusion may affect the social welfare and individual profits.

In iteration v , the coordinator calculates the multiplier by (13), (14), and (16) but broadcasts the multiplier dishonestly in iteration $v+1$, as shown in (17) and (18).

$$\bar{\mu}_t^{(v+1)} = \bar{\mu}_t^{(v)} + \Delta \bar{\mu}_t / (a + bv) \quad (16)$$

$$\bar{\mu}_{i,t}^{(v+1)} = \begin{cases} \omega \bar{\mu}_t^{(v+1)} & i \notin \Omega^{col} \\ \bar{\mu}_t^{(v+1)} & i \in \Omega^{col} \end{cases} \quad (17)$$

$$\omega > 1 \quad (18)$$

where Ω^{col} is the set of charging stations in the collusion coalition; ω is a parameter which represents the degree of congestion price distortion; and $\bar{\mu}_{i,t}^{(v+1)}$ is the multiplier which actually sent to charging station i at iteration $v+1$ in period t . In the rest of this paper, variables influenced by a dishonest coordinator will have an overline.

According to (17) and (18), the coordinator sends different multipliers to charging stations depending on whether they are affiliated with the collusion coalition. Charging stations affiliated with the collusion coalition receive the true congestion price, whereas charging stations unaffiliated with the collusion coalition receive a higher congestion price.

Theorem 1 The total social welfare derived by a dishonest coordinator is different from the optimal total social welfare when constraint (5) is binding, i.e., $\bar{\mu}_t, \mu_t \neq 0$.

Proof For a charging station far from the collusion coalition, the Karush-Kuhn-Tucker (KKT) condition of its sub-problem should be met.

$$\frac{\partial L_{i,t}}{\partial \bar{P}_{j,t}} = \frac{\partial (U_{j,t} - C_{j,t})}{\partial \bar{P}_{j,t}} - \bar{\mu}_{i,t} = 0 \quad j \in \Omega^{EV}, i \notin \Omega^{col} \quad (19)$$

Combined with $\bar{\mu}_t < \bar{\mu}_{i,t}$, this implies that $\bar{P}_{j,t}$ cannot meet the KKT condition for the original problem.

$$\frac{\partial L_{i,t}}{\partial \bar{P}_{j,t}} = \frac{\partial (U_{j,t} - C_{j,t})}{\partial \bar{P}_{j,t}} - \bar{\mu}_t > \frac{\partial L_{i,t}}{\partial \bar{P}_{j,t}} = 0 \quad j \in \Omega^{EV}, i \notin \Omega^{col} \quad (20)$$

The charging power of EV j derived by a dishonest coordinator $\bar{P}_{j,t}$ is different from its charging power in the optimal solution $P_{j,t}^*$. The iteration influenced by the collusion converges to a non-optimal solution. The collusion decreases the efficiency of welfare allocation.

Theorem 2 Influenced by the collusion, EVs (whose interests are represented by charging stations) in/not in the collusion coalition gain more/less welfare.

Proof Assume that EV j is parked at charging station i . If there is not a collusion coalition, the welfare of EV j is given as:

$$W_{j,t}^* = \alpha_j \{1 - [1 - (q_{j,t-1} + \eta_j P_{j,t}^* / E_j^{\max}) / q_j^{\max}]^2\} / \tau_{j,t} - \pi_t P_{j,t}^* \Delta t - \mu_t P_{j,t}^* \quad (21)$$

If there is a collusion coalition, and charging station i is not in the collusion coalition, the welfare of EV j is given as:

$$\bar{W}_{j,t} = \alpha_j \{1 - [1 - (q_{j,t-1} + \eta_j \bar{P}_{j,t} / E_j^{\max}) / q_j^{\max}]^2\} / \tau_{j,t} - \pi_t \bar{P}_{j,t} \Delta t - \bar{\mu}_{i,t} \bar{P}_{j,t} \quad (22)$$

By putting $\partial L_{i,t} / \partial P_{j,t}^* = 0$ and $\partial L_{i,t} / \partial \bar{P}_{j,t} = 0$ into (21) and (22), respectively, (23)-(26) can be obtained.

$$W_{j,t}^* = c_{j,1} (P_{j,t}^*)^2 + c_{j,2} \quad (23)$$

$$\bar{W}_{j,t} = c_{j,1} \bar{P}_{j,t}^2 + c_{j,2} \quad (24)$$

$$c_{j,1} = \frac{\alpha_j}{\tau_{j,t}} \left(\frac{\eta_j}{E_j^{\max} q_j^{\max}} \right)^2 > 0 \quad (25)$$

$$c_{j,2} = \frac{\alpha_j}{\tau_{j,t}} \left[\frac{2q_{j,t-1}}{q_j^{\max}} - \left(\frac{q_{j,t-1}}{q_j^{\max}} \right)^2 \right] \quad (26)$$

The values of $W_{j,t}^*$ and $\bar{W}_{j,t}$ are determined by $P_{j,t}^*$ and $\bar{P}_{j,t}$, respectively. According to the second derivative of the Lagrangian function given by (27) and a natural corollary of (20) as shown in (28), $P_{j,t}^* > \bar{P}_{j,t}$ can be obtained. Hence, $W_{j,t}^* > \bar{W}_{j,t}$. For charging stations which are not affiliated with the collusion coalition, the welfare of on-site EVs is decreased.

$$\frac{\partial^2 L_{i,t}}{\partial P_{j,t}^2} = -\frac{2\alpha_j}{\tau_{j,t}} \left(\frac{\eta_j}{E_j^{\max} q_j^{\max}} \right)^2 < 0 \quad (27)$$

$$\frac{\partial L_{i,t}}{\partial \bar{P}_{j,t}} > 0 = \frac{\partial L_{i,t}}{\partial P_{j,t}^*} \quad (28)$$

Similarly, it can be proved that when constraint (5) is binding, EVs parked in charging stations which are in the collusion coalition can gain more profits. For EVs parked in charging stations which are affiliated with the collusion coalition, a part of their profits would be given to the coordinator as its income. Such profits can motivate charging stations and the coordinator to form a collusion coalition. The rule of income distribution in the collusion coalition is out of the scope of this paper.

The influence of the collusion is visualized in Fig. 1. For

simplicity, only two charging stations are considered. Station 1 colludes with the coordinator whereas Station 2 does not. The blue areas in quadrant I and quadrant II represent the increase and decrease of the total welfare of EVs parked in Station 1 and Station 2, respectively. The green area and the red dashed area represent the social welfare with/without the influence of the collusion.

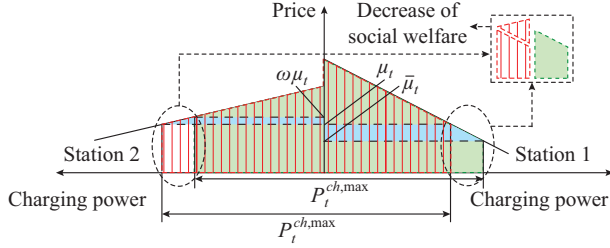


Fig. 1. Schematic diagram to illustrate influence of collusion.

The difference between the green and red dashed areas is the decrease of the social welfare due to the collusion, as shown in the sub-figure.

In summary, in a peak-load period, i.e., constraint (5) is binding, the collusion coalition can gain illegal profits with the proposed strategy while the social welfare is decreased. The charging coordination algorithm is vulnerable to dishonest coordinator behaviors.

IV. PROPOSED COORDINATION METHOD VIA BLOCKCHAIN

To overcome the drawbacks of the algorithm presented in Section III-A, the blockchain is introduced to the EV charging coordination problem. According to [24], Ethereum is the most widely used platform for energy blockchain development. In this section, the coordination method is implemented on Ethereum by building a coordination structure and deploying a smart contract. Notably, other blockchain platforms can also be utilized to coordinate EV charging.

A. Overview of Key Concepts of Ethereum

1) Smart contract. A smart contract is a program implementation of an algorithm via a set of functions. After being deployed on Ethereum, the functions can never be tampered with. When a participant calls a function in a smart contract (known as sending a transaction), it needs to spend a commission fee which is similar to the fee in a stock market. The amount of the required commission fee depends on the computational complexity of the function [25].

2) Miner. On Ethereum, participants can choose whether to be a miner at its own will. A miner, firstly, collects the transaction broadcast by all participants, and updates the system state by executing the smart contract. Secondly, a miner needs to solve a difficult proof-of-work (PoW) problem [26]. Then, a miner can broadcast its block to others. The rest of miners would verify the execution of the smart contract and the PoW in this block. A miner who firstly broadcasts a new valid block becomes the actual creator of the new block, and can receive the commission fees paid by participants who broadcast transactions as a reward. The new valid block would be added to the chain. Non-miner participants would

only check the PoW and accept blocks as long as the PoW is valid. If there is more than one chain whose blocks are valid, non-miners would always trust the longest chain in the network, which is known as the longest chain rule [25].

B. Structure of EV Charging Coordination Platform

The structure of the proposed EV charging coordination platform is illustrated in Fig. 2. The platform is established on a decentralized P2P network consisting of all charging stations. In this network, each charging station has two identities: a sub-problem solver and a miner.

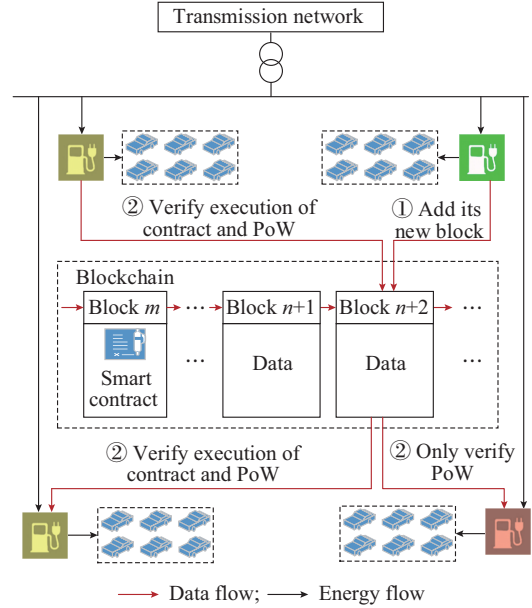


Fig. 2. Structure of EV charging coordination platform on Ethereum (in Block $n+2$, the green station is the first successful miner, the yellow stations represent other miners, and the red station represents non-miner stations).

1) As a sub-problem solver, a charging station optimizes its charging demand off-chain, i.e., optimizes its charging demand locally based on the multiplier $\mu_i^{(0)}$ recorded in the smart contract, and broadcasts its power demand by calling the corresponding function in the smart contract.

2) A charging station can choose whether to be a miner at its own will. As a miner, firstly, a charging station performs the duty of the coordinator. That is, it collects the power demand broadcast by others, and updates variables (including multipliers, charging demands, and some auxiliary variables) recorded on the smart contract. Secondly, a charging station needs to solve a PoW problem. A charging station who firstly broadcasts a new valid block becomes the actual coordinator in this block.

On the platform, the authority of the coordinator is distributed to all miners, enabling fully decentralized coordination. The platform can function as long as there are some charging stations that are willing to be miners. Hence, the mechanism can withstand single-point failures. If some miners manipulate the multiplier, other honest miners would check and reject the result, making the mechanism robust against malicious coordination behaviors.

C. Smart Contract Design

On Ethereum, smart contracts are programmed by a Turing-complete language, Solidity [27]. However, directly translating the proposed algorithm into Solidity language may encounter difficulties.

1) On Ethereum, only if someone calls the contract, miners would execute the corresponding function. The “coordinator” on Ethereum can neither update multipliers nor check the convergence if nobody calls corresponding functions.

2) A transaction ordering attack may happen when appointing a particular charging station or always requiring the last submitter in each iteration to update multipliers and check the convergence [28]. That is, malicious miners interfere with the normal iteration process by changing the order of received transactions. Thus, the multiplier updating process should be asynchronous. Once a station submits its demand, the coordinator would update the multiplier by (13)-(15). Such an asynchronous algorithm also converges to the optimum [6].

The details of primary functions in the smart contract are stated below. And Algorithm I demonstrates the coordination process on the proposed EV coordination platform.

Algorithm I: EV charging coordination process on the proposed platform

Init:

Initialize $P_t^{ch, \max}$

Register $(k_i^{per}, k_i^{add}, C^{dep})$

Verify k_i^{per} and C^{dep}

Add k_i^{add} to L^{CS}

While (True):

Reset:

Reset ΔP_i and $\mu_i^{(0)}$

Record the present time as t^{submit}

Repeat:

Submit and update $(k_i^{add}, \sum_{j \in \Omega_{k,t}^{EV}} P_{j,t})$

Reject this submission if k_i^{add} is illegal

Update ΔP_i and $\mu_i^{(v+1)}$

Record the present time as t^{submit}

Until: no one has called Submit function from t^{submit} to $t^{submit} + \tau^{wait}$

1) Init. The Init function initializes the permissible total charging load $P_t^{ch, \max}$ in all periods. The value of $P_t^{ch, \max}$ is pre-determined according to the historical conventional load curve and capacities of facilities. After being initialized, $P_t^{ch, \max}$ cannot be modified by charging stations.

2) Register. To take part in the EV charging coordination platform, a charging station needs to get its permission code k_i^{per} off-chain. Then the station can call the Register function. The inputs of the Register function include the station's ID k_i^{id} , permission code k_i^{per} , and virtual address on Ethereum k_i^{add} . Meanwhile, to prevent malicious submission from the station, the station must pay a fixed deposit C^{dep} to the contract. After k_i^{per} and C^{dep} are verified, station i is appended to a coordinated station list L^{CS} .

3) Reset. Before the beginning of each period, the Reset

function is called, resetting ΔP_i and $\mu_i^{(0)}$.

4) Submit. By continuously monitoring the smart contract, a charging station can view the current period and the latest multiplier. When a new period begins or $\mu_i^{(0)}$ is updated, a charging station solves its sub-problem based on $\mu_i^{(0)}$. If the increase of welfare by updating its power demand is larger than the commission fee of calling the Submit function, the station calls this function to submit its new demand $\sum_{j \in \Omega_{k,t}^{EV}} P_{j,t}$.

The Submit function records $\sum_{j \in \Omega_{k,t}^{EV}} P_{j,t}$ and updates ΔP_i and $\mu_i^{(v+1)}$ by (13)-(15) after verifying the inputs. In the contract, when there is no new submission at a fixed time τ^{wait} , the latest multiplier is regarded as the optimal congestion price. After that, the smart contract will reject new submissions for the current period.

D. Collusion Mitigation

The EV charging coordination platform implemented on Ethereum can mitigate the collusion mentioned in Section III-B.

Malicious charging stations in the collusion coalition must act as miners. These malicious miners execute the smart contract incorrectly, and broadcast blocks with incorrect Lagrangian multipliers. Meanwhile, honest miners broadcast blocks with correct Lagrangian multipliers. According to the longest chain rule, miners in the collusion coalition must keep the chain they generated being the longest one. Assuming that all charging stations have identical computational power, the probability of keeping a malicious chain longer than a valid chain during all the iteration periods can be calculated by (29). With the increase of the number of blocks, the collusion can be prevented when the proportion of malicious charging stations is less than 50%.

$$P^M = \frac{[g/(g+h)]^N}{[g/(g+h)]^N + [h/(g+h)]^N} = \frac{1}{1+(h/g)^N} \quad (29)$$

where P^M is the probability that the malicious chain is the longest; g and h are the numbers of charging stations in/not in the collusion coalition, respectively; and N is the number of blocks.

Moreover, if malicious miners insist on optimizing their charging demand with the congestion price recorded on the malicious chain, they would be penalized during the settlement. This is because they will be charged according to the correct congestion price recorded on the longest chain, which is higher than the congestion price recorded on the malicious chain.

V. SIMULATION RESULTS

A. Simulation Parameters

The simulation is performed on a distribution network with 780 houses [2]. The number of periods in a day is set to be $T=96$. The permissible total charging load curve is determined by the capacity of the transformer at the root of the network and a base load curve provided by Fig. 2 in [2]. The data of the base load curve are shown in Fig. 3. The ba-

sic electricity price is set to be 0.641 CNY/kWh, which is the electricity price for non-residential customers below 1 kV in Shanghai, China. To simulate a scenario with high penetration of EVs, it is assumed that there are 390 EVs in this network, and those EVs are equally distributed in 10 charging stations. For simplicity, the 390 EVs have the same parameters: $E_i^{\max} = 20$ kWh, $P_i^{EV, \max} = 3.2$ kW, and $\eta_j = 0.95$. The coefficient α_i is subject to the normal distribution $N(5000, 500^2)$, which mimics the EVs' preferences in reality. The arrival time and departure time of EVs are set according to the statistical estimates of [29], which are widely used in EV coordination studies [4], [30], [31]. Parameters in the multiplier updating procedure are problem-dependent [22]. These parameters are set to be $a = 1500$, $b = 100$. The parameters can be consistent in days because the driven pattern of EVs is similar every day in statistical meaning.

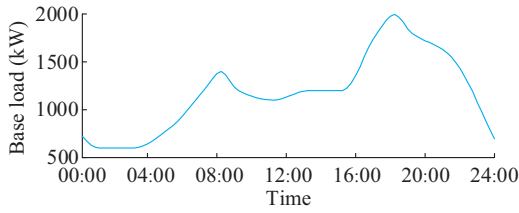


Fig. 3. Base load curve in distribution network.

An Ethereum private chain is created on which the smart contract coordination for EV charging is deployed. All charging stations are miners on the Ethereum private chain.

B. Coordination Results

Figure 4 demonstrates the total charging load curves with/without EV charging coordination. Without EV charging coordination, the transformer at the T-D station might be overloaded at peak hours. With EV charging coordination, the proposed algorithm avoids the overload by incentivizing stations to lower charging demand during peak hours. The proposed algorithm is effective in mitigating facility overload with high penetration of EVs.

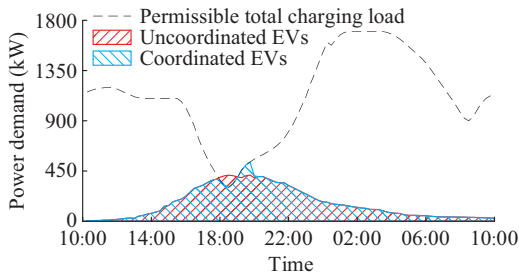


Fig. 4. Total charging load curve with/without EV charging coordination.

Figure 5 illustrates the iteration processes of the congestion prices in some peak-load periods. The multiplier at the convergence is set as the base value in each period. As shown in Fig. 5, in each period, 10 charging stations update the multiplier for no more than 105 times in total. A charging station only needs to solve a small-scale sub-problem for about 10 times. The algorithm converges to the global optimum rapidly.

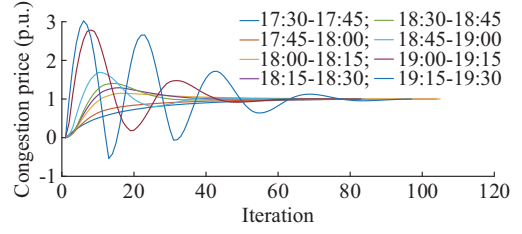


Fig. 5. Iteration process of congestion prices in peak-load periods.

C. Impact of Possible Collusion and Mitigation via Blockchain

To illustrate the impact of the collusion on the welfare of charging stations, the collusion mentioned in Section III-B is simulated. Charging stations A-C are malicious stations, whereas charging stations D-J are not in the collusion coalition. Figure 6 demonstrates the total welfare of EVs in each charging station in a peak-load period (18:00-18:15) with/without the collusion. Welfare allocation with different ω is illustrated in Fig. 6, where $\omega = 1.0$ represents that there is no collusion. Stations A-C donate the collusion coalitions, while D-J denote the honest stations. Table I shows the total social welfare in 18:00-18:15 with different ω .

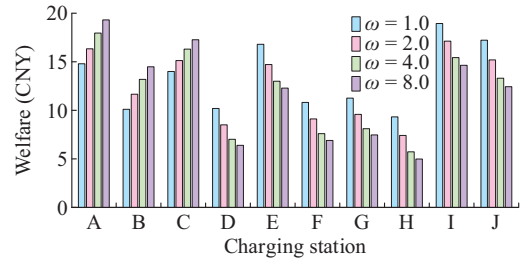


Fig. 6. Total welfare of EVs in each charging station in 18:00-18:15 with/without collusion.

TABLE I
TOTAL SOCIAL WELFARE WITH DIFFERENT ω

ω	Total social welfare (CNY)
1.0	178.82
2.0	178.06
4.0	176.44
8.0	174.96

According to Fig. 6 and Table I, in a scenario without the blockchain, when the collusion occurs, EVs park in charging stations which are in the collusion coalition can gain higher profits, whereas the total social welfare deviates from the optimum and the profits of others decrease. The consequence of the collusion is more serious for a larger value of ω .

Then, an analysis is given to show how the blockchain can mitigate the above-mentioned collusion. In congestion periods, the numbers of blocks when the multipliers converge are shown in Table II. The multiplier in 17:30-17:45 converges after only 28 blocks, which is the fewest among all peak-load periods. According to (29), 17:30-17:45 is the most vulnerable time period against the attacks. To test whether blockchain can prevent the collusion, the mining ac-

tivities during 17:30-17:45 with different proportions of malicious miners are simulated. Each proportion level has 10 times simulations. Figure 7 shows the average number of blocks mined by honest and malicious miners in 10 simulations.

TABLE II
NUMBERS OF BLOCKS IN CONGESTION PERIODS WHEN MULTIPLIERS
CONVERGE

Time	Number of blocks	Time	Number of blocks
17:30-17:45	28	18:30-18:45	39
17:45-18:00	50	18:45-19:00	57
18:00-18:15	45	19:00-19:15	57
18:15-18:30	52	19:15-19:30	54

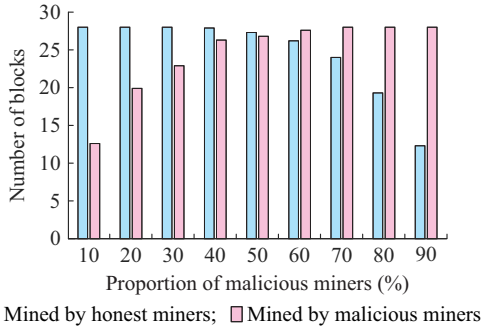


Fig. 7. Mining results in 17:30-17:45 with different proportion of malicious miners.

As demonstrated in Fig. 7, if less than 50% of miners are malicious, honest miners can always be the first to generate 28 blocks. If exactly 50% of miners are malicious, the winner of the mining competition is uncertain. If more than 50% of miners are malicious, the malicious miner coalition would be the leader in the mining process. Given the longest chain rule [25], such results substantiate that the blockchain can prevent the collusion as long as more than 50% of miners in the network are honest.

D. Computational Cost of Blockchain

The computational time in each period is shown in Fig. 8. In non-congestion periods, the computational time is negligible. In congestion periods, the computation takes no more than 3.02 min, which is acceptable for real-time operation. There is room for optimizing our smart contract and input/output data formats, so a shorter computational time could be expected in practice.

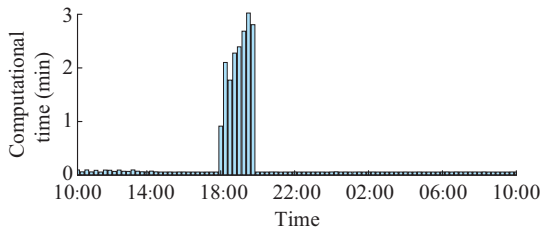


Fig. 8. Computational time in all periods.

The main operation cost of the blockchain-based platform is the electricity consumed by miners who execute the smart contracts and solve the PoW problems. Given that the simu-

lation for each period is run on a personal computer with rated power of 0.4 kW for less than 3.02 min, the estimated operation cost in one period is less than $0.4 \text{ kW} \times 3.02 \text{ min} \times 0.641 \text{ CNY/kWh} = 0.0129 \text{ CNY}$. The operation cost of the platform is negligible compared with the total social welfare (around 0.01%).

From the perspectives of charging stations, the total commission fee they pay should cover the cost of miners. Table III shows the total commission fee and total charging cost of charging stations in congestion periods. According to Table III, the commission fee represents a low portion in the charging cost, which is even lower than the stock market (about 0.03% commission fee in China). The simulation results substantiate that the platform can coordinate EV charging with a low operation cost.

TABLE III
COMPARISON OF TOTAL COMMISSION FEE AND TOTAL CHARGING COST IN
CONGESTION PERIODS

Time	Commission fee (CNY)	Charging cost (CNY)	Commission fee/charging cost (%)
17:30-17:45	0.00391	59.31	0.007
17:45-18:00	0.00898	52.06	0.017
18:00-18:15	0.00757	48.47	0.016
18:15-18:30	0.00973	53.72	0.018
18:30-18:45	0.01023	61.78	0.017
18:45-19:00	0.01148	73.08	0.016
19:00-19:15	0.01292	84.50	0.016
19:15-19:30	0.01199	85.09	0.014

VI. CONCLUSION

This paper proposes a reliable EV charging coordination method via the blockchain. The proposed EV charging coordination algorithm can coordinate all charging stations in a hierarchical way. And the implementation via blockchain can be robust against single-point failures and potential collusion behaviors in the coordination process. Simulation results show that: ① without collusion behaviors, the proposed coordination algorithm converges to the global optimum rapidly; ② a collusion coalition could gain profits while reduce the social welfare; ③ the proposed blockchain-based platform can mitigate the collusion behaviors as long as the proportion of colluded charging stations is less than 50%; ④ the computational cost of the platform can meet the requirement of real-time EV charging coordination.

Future work can focus on optimizing the EV charging coordination smart contract, or the scalability of blockchain-based EV coordination platform.

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