A Secure Intra-Regional-Inter-Regional Peer-to-Peer Electricity Trading System for Electric Vehicles

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***Abstract*—Peer-to-peer (P2P) trading is becoming a prominent topic and demonstrating the development trend of integration with other theories in order to achieve an efficient allocation of electricity resources in the electric vehicle (EV) market. In this article, we present a novel Secure iNtra-regional-Inter-regional P2P Electricity Trading System (SNIPPETS) for EVs. A trading information prediction model is constructed based on Ensemble Learning, upon which an intra-regional-inter-regional trading mechanism is proposed to find the optimal electricity allocation strategy, including the price and volume of electricity traded between EVs, in order to maximize the regional overall social welfare. In the intra-regional-inter-regional trading mechanism, multi-objective optimization is performed within each region to coordinately maximize the benefits of different types of EVs, followed by an investigation of pricing competition among neighboring regions based on a supermodular game. Furthermore, blockchain is introduced to support transaction payments and improve data security and privacy. Finally, the proposed SNIPPETS is validated through case studies. Compared to the traditional energy trading system and representative existing trading systems, SNIPPETS can effectively improve the regional overall social welfare and has higher computational efficiency.**

***Index Terms*—Multi-objective optimization, peer-to-peer electricity trading, supermodular game.**

I. Introduction

IN RECENT years, the continual deployment of distributed energy resources has introduced new opportunities as well as challenges to the electrical market, particularly the transaction pattern of the market. Peer-to-peer (P2P) energy trading, a new transaction pattern, has been proposed in this context to better coordinate distributed energy. Instead of the traditional hierarchical grid structure, P2P electricity trading platforms offer a flat network architecture that encourages distributed node interaction while also providing competition in a transparent market [1]. Several studies have shown that P2P electricity trading not only allows participants to earn significant revenues from it [2], but also facilitates the power grid to reduce peak demand [3] and improve reliability [4].

On account of these advantages, increasing attention has been paid to the investigation of P2P electricity trading. To mention a few, [5] suggested a P2P electricity trading strategy based on the maximum and minimum electricity to guarantee the profitability of both consumers by considering the actual electricity market structure of South Korea. [6] investigated the internal mechanism of a community P2P electricity trading system and designed a three-layer framework to implement the system in practice. [7] established P2P electricity trading, combining flexible resources and various on-site generation to provide significant economic benefits to individual customers and industrial sites. [8] reported a localized electricity market architecture for P2P electricity trading among residential prosumers with smart meters, renewable energy resources, and home energy management systems. Specific to the field of electric vehicles (EVs), P2P electricity trading allows EVs to participate in electricity transactions and thereby increase the energy efficiency of the distribution network by actively trading and sharing electricity. Since [9] introduced P2P electricity trading to the EV area, a lot of breakthroughs in related research have been made, the majority of which are focused on optimizing the benefits of trade participants. To name a few, [10] designed an EV bidding agent that can realize benefits for EVs and leveling effect of the power demand through the day. [11] presented a system based on the quality of service to match single-consumers to multiple-providers and multiple-consumers to multiple-providers based on the needs of various EVs, resulting in resilient and reliable transactions. For inter-regional P2P electricity trading, [12] introduced the superconductive magnetic energy storage technology, which improves the success rate of user matching.

Overall, according to the trading process and the mode of information interaction between participants, P2P electricity markets can be divided into decentralized markets and coordinated markets [13]. In a decentralized market, the trading process and the information interaction are carried out in a decentralized manner, thus better protecting data security and privacy [2]. However, due to the lack of centralized control [14], decentralized markets are relatively inefficient, and social welfare cannot be maximized [13]. In a coordinated market, peers within a P2P network communicate and trade through a centralized coordinator, and the benefits of the entire P2P trading network are allocated among the buyers and sellers according to rules

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predetermined by the coordinator [13]. Although coordinated markets compromise on the degree of decentralization, their key advantage is the ability to maximize social welfare [15]. Meanwhile, one of the latest developments in P2P electricity trading with EVs is the introduction of blockchain [16]. It can improve the energy efficiency of electricity trading and enhance the security and privacy of transaction data, thus compensating to some extent for the weaknesses of coordinated markets.

Despite the fact that numerous advances have been achieved in the area of P2P electricity trading with EVs, there are still some research gaps. First, electricity consumption prediction is needed to obtain a range of future P2P electricity trading volumes, but few of the existing studies have considered the impact of occupants' electricity use behavior on their electricity consumption. Besides, previous research on P2P trading has a number of unaddressed issues that make it challenging to improve the overall social welfare of all trading participants. For example, there is a potential benefit conflict between electricity buyers and sellers, where buyers and sellers have opposing preferences for trading prices, but existing studies often do not address this issue head-on and do not suggest ways to reconcile the conflict directly. As another example, existing studies mostly consider P2P trading only within local regions, without taking into account potential competition among neighboring regions. Motivated by the above discussions, we propose a Secure iNtra-regional-Inter-regional P2P Electricity Trading System (SNIPPETS) in a coordinated market in this study, where an intra-regional-inter-regional transaction mechanism is developed to enhance regional overall social welfare including the benefits of all EVs and all aggregators (AGs, aka coordinators). Ethereum is also deployed to compensate for data security and privacy. Case studies are carried out to verify the effectiveness and superiority of the proposed SNIPPETS. The main contributions of this paper are summarized as follows:

1) We propose a coordinated P2P market that is more practicable in the near future, consisting of different market participants: electricity buyers, electricity sellers, and a regional coordinator. Furthermore, a two-stage intra-regional-inter-regional trading mechanism is designed for the proposed market.
2) We develop an EV electricity consumption prediction model based on Ensemble Learning, which learns from historical data about external conditions (e.g., battery type, driving status, etc.) as well as users' energy use behavior (e.g., more wasteful or more frugal) to predict EVs' future electricity consumption. Tests on real data demonstrate the high accuracy of the established prediction model, which facilitates subsequent P2P electricity trading.
3) We propose a coordination method based on a multi-objective optimization problem (MOP) to optimize the allocation of electricity within each geographical region in SNIPPETS, which addresses the benefit conflicts between electricity buyers and sellers.
4) We propose a supermodular game to model the price competition across geographically neighboring regions and to reach a Nash equilibrium. Simulation results indicate that our model has a significant impact on improving the overall social welfare of the market.

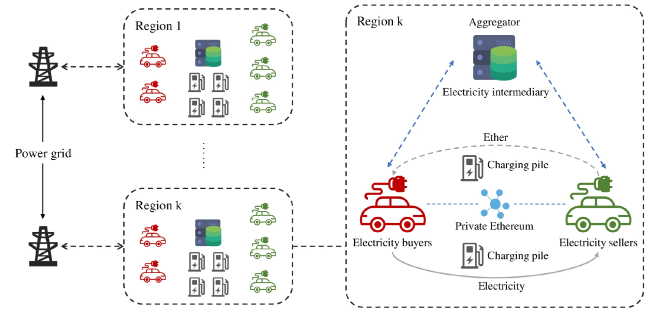


Fig. 1. P2P electricity trading system architecture.

The rest of this paper is organized as follows. Section II introduces the system architecture of SNIPPETS. Section III explains the procedures and detailed trading rules of P2P electricity trading in SNIPPETS. Section IV proposes the related algorithms and Section V shows the simulation results, respectively. Section VI concludes the paper.

II. System Architecture of SNIPPETS

In this section, a novel decentralized P2P electricity trading system, i.e., SNIPPETS, is proposed and the specific system architecture is shown in Fig. 1.

It is observed from Fig. 1 that the whole trading area can be geographically divided into k ($k \in \mathcal{K} = \{1, 2, \ldots, K\}$) regions, where each region contains one AG, several EVs and charging piles. This paper assumes the electricity trading takes place in the slot-ahead market and considers a time-slotted system, where time is denoted as $t \in \mathcal{T} = \{1, 2, \ldots, T\}$ and the duration of each time slot is 60 minutes. Before the starting of a time slot t, each EV determines the electricity amount range to trade in t and send this transaction information to the local AG, then the information will be spread to all neighboring intermediaries through the communication network. With the participation of both the local AG and neighboring AGs, the electricity buyers and sellers reach an agreement and complete the transaction through an intra-regional-inter-regional transaction mechanism. After that, the transaction data would be updated on Ethereum. On the one hand, Ethereum has properties, such as decentralization and tamper-proofness, which enables electricity trading to be executed in decentralized, transparent, and secure market environments and can improve the security of transactions. On the other hand, compared to other cryptocurrencies, Ethereum has a smart contract function, where it is easier to define transaction rules, and the transaction payments and information storage are executed through these pre-defined rules.

The P2P electricity trading model of SNIPPETS includes the following entities:

1) EVs: EVs play different roles in SNIPPETS, e.g., electricity buyers (charging EVs), electricity sellers (discharging EVs), and other EVs without charging or discharging needs that are not considered in our research. Each EV chooses its role and

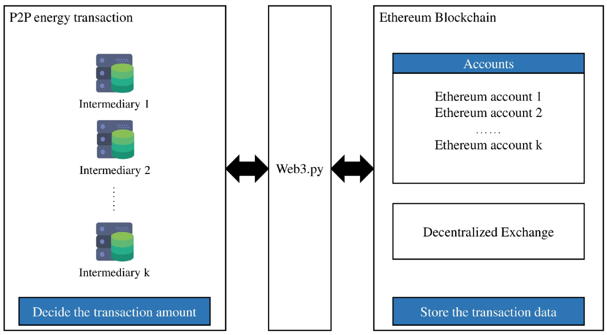


Fig. 2. Information flow between P2P electricity transactions and Ethereum.

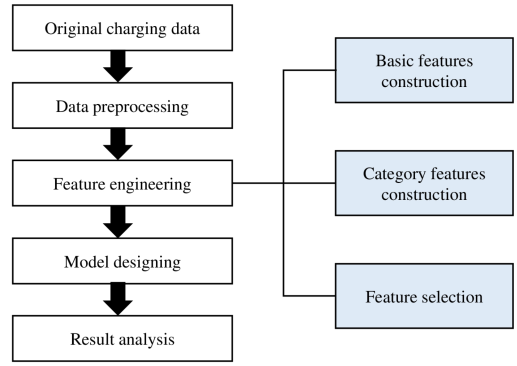


Fig. 3. Technical framework of the EV consumption prediction model.

determines the electricity trading range based on the current state of charge (SOC) and the electricity consumption prediction.

2) AGs (Electricity Intermediary): AGs act as electricity intermediaries in SNIPPETS. They provide EVs with access to the electricity market and wireless communication services [17]. After receiving the transaction information from local and neighboring EVs, the AG would organize transactions among EVs based on all collected information.

3) Charging Piles: each charging pile in SNIPPETS has a built-in smart meter for calculating and recording transactions in real time. EVs could go to charging piles to charge or discharge, then electricity buyers pay sellers for the electricity through intermediaries according to the records in smart meters of charging piles.

4) Ethereum: Ethereum supports the proposed energy trading mechanism as a payment instrument and distributed database in SNIPPETS, where each EV and each AG has an Ethereum account for the payment process. Under the organization of AGs, once the P2P energy trading details (including the traders, volume, price, etc.) are determined, buyers and sellers will complete the payment and receipt via the regional AGs and Ethereum. Then, the detailed transaction and payment information will be recorded on Ethereum. During this process, an API named web3.py will be used to realize the information interactions between the trading mechanism and Ethereum, as shown in Fig. 2.

III. P2P Electricity Trading System

In this section, the main elements of the proposed SNIPPETS such as the EV consumption prediction model, the intra-regional-inter-regional transaction mechanism, and the private Ethereum are presented, where the details of P2P electricity trading rules and procedures of SNIPPETS are elaborated.

A. Determination of Electricity Trading Amount Range

This subsection shows how to determine the EV electricity trading amount range. An electricity consumption model is firstly designed to predict the electricity consumption during the next time slot and then combined with consideration of the current SOC of EVs to determine the range of electricity trading amount.

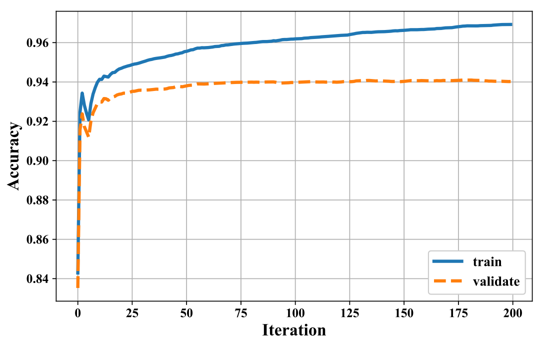
1) Electricity Consumption Prediction Model: The existing methods to predict EV electricity consumption can be divided into two categories, i.e., indirect methods and direct methods. Indirect methods predict the electricity demand through intermediate variables, such as daily agendas consisting of a sequence of episodes [9], while direct methods predict the electricity demand by establishing a mapping between the available data set and the electricity consumption [18]. In real-world scenarios, the direct methods may be more efficient than the indirect methods, thus this paper focuses on predicting the EV electricity demand in a direct manner. In particular, a new prediction model based on the LightGBM algorithm is proposed, which uses the operating data of 87 pure EVs in Beijing from October to December 2019 [19] to predict the EVs' electricity consumption during the next time slot, then take it as an input for subsequent P2P electricity trading research. Table I presents the original data classified into three categories, i.e., time, vehicle information, and charging information.

As shown in Fig. 3, the prediction model is built with four steps, i.e., data preprocessing, feature engineering, model designing, and result analysis. Firstly, we perform data preprocessing by removing and filtering abnormal data. Then, we carry out the feature engineering to generate the feature set, where the basic information (daq_time, soc, etc.) in Table I is adopted as basic features. Afterward, category features such as mileage features, electricity consumption features, temporal features, and electricity consumption behavioural features are derived through data attribute integration and segmentation. In particular, the electricity consumption behavioral feature is to compare a user's electricity consumption per unit distance per unit time, with the average of ones of all other users under similar conditions. This feature reflects the "level of wastefulness" of the user's electricity use behavior.

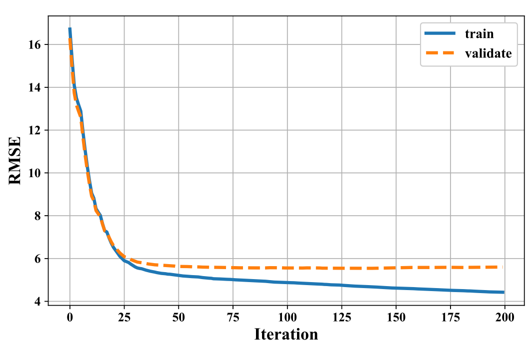
Then, features related to electricity consumption prediction are selected according to the feature importance, and the feature set is generalized hereto. After the feature engineering stage, the LightGBM algorithm is utilized to predict EV electricity consumption during a time slot. Finally. the indexes of Accuracy and Root Mean Squared Error (RMSE) are introduced to judge the predictive effect of the established model. Fig. 4 shows the training process and the effectiveness of the proposed model, where for the training set and the validation set respectively, the

TABLE I
DATA CLASSIFICATION AND DESCRIPTION

Classification	Data field name	Date type	Description
Time information	daq_time	int	Data acquisition time
	pdate	string	Data acquisition date
Vehicle information	vid	string	Unique EV ID
	power_type	string	Type of vehicle power
	battery_type	string	Type of vehicle battery
	power_amount	float	Total EV battery capacity
Charging information	d_status	float	EV driving status
	c_stat	float	EV charging status
	soc	float	State of charge of EV
	lng	float	Longitude
	lat	float	Latitude



(a)



(b)

Fig. 4. Training process with LightGBM algorithm. (a) Accuracy during training. (b) RMSE during training.

accuracy can be greater than 95% and the RMSE scores can be less than 6.

In actual applications, based on the EV's basic information (battery type, capacity, etc.) and vehicle real-time information obtained by sensors (soc, latitude, longitude, etc.), EVs only need to input the expected mileage in the next time slot as mileage features, then the estimated electricity consumption can be given by the model as is illustrated in Fig. 5.

2) EV Classification: After predicting the EV electricity consumption of the next time slot and considering each EV's current

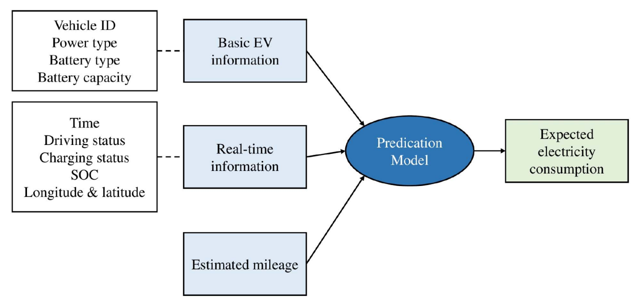


Fig. 5. Data flow of the EV electricity consumption prediction model.

SOC, two different groups of EVs are found in our research, i.e., Electricity Buyers (EBs) and Electricity Sellers (ESs). In view of the uncertainty of electricity trading demand in actual trading scenarios, we determine the amount range of trading electricity in what follows by discussing the minimum and maximum trading electricity amount of these two groups, respectively.

- **EBs** are expected to be unable to meet their electricity demand in the next time slot with the remaining electricity, i.e., the EBs need to be charged in the next time slot and will participate in P2P electricity transactions as buyers. We denote each EB as EB_i with $i \in \mathcal{I} = \{1, 2, \ldots, I\}$, the corresponding minimum electricity demand value $d_{i,\min}$ and maximum electricity demand value $d_{i,\max}$ of EB_i are described as

$$d_{i,\min} = \min\left[c_i^{EB} - STO_i^t, d_{i,\max}\right], \forall i \in \mathcal{I}, \tag{1}$$

$$d_{i,\max} = STO_i^0 - STO_i^t, \forall i \in \mathcal{I}, \tag{2}$$

where c_i^{EB} is the predicted electricity consumption of EB_i given by the prediction model, STO_i^t is the current battery state of EB_i at time t and STO_i^0 denotes the battery capacity of EB_i. Therefore, the expected electricity trading range of EB_i is $(d_{i,\min}, d_{i,\max})$.

- **ESs** are expected to have surplus electricity in the next time slot, i.e., they do not need any intermediate charging during the next time slot and have the willingness to sell the surplus electricity to get additional income. Similarly, we denote each ES as ES_j with $j \in \mathcal{J} = \{1, 2, \ldots, J\}$, the corresponding minimum

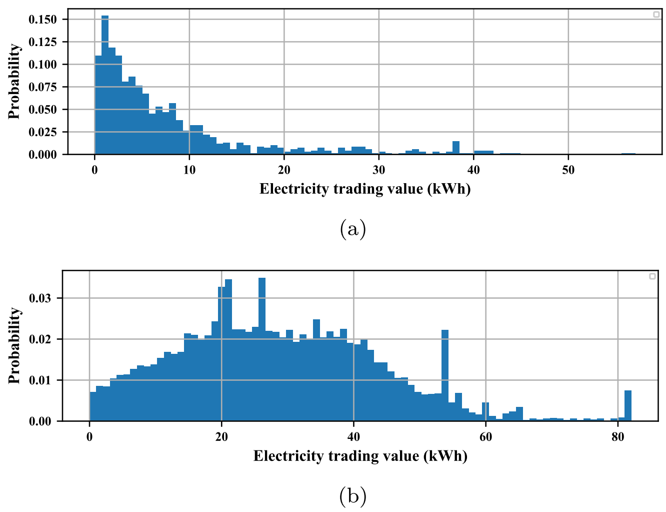


Fig. 6. Electricity trading demand distribution of EVs. (a) Histogram of electricity trading demand of EBs. (b) Histogram of electricity trading demand of ESs.

and maximum electricity supply value of ES_j are described as

$$s_{j,\min} = 0, \forall j \in \mathcal{J}, \tag{3}$$

$$s_{j,\max} = STO_j^t - c_j^{ES}, \forall j \in \mathcal{J}, \tag{4}$$

where c_j^{ES} is the predicted electricity consumption of ES_j given by the prediction model, STO_j^t is the current battery state of ES_j at time t and STO_j^0 denotes the battery capacity of ES_j. Therefore, the expected electricity trading range of ES_j is $(s_{j,\min}, s_{j,\max})$.

We present the aforementioned operating data of 87 pure EVs [19] in Fig. 6, which shows the electricity trading demand distribution of EBs and ESs respectively during a time slot. To be more specific, we feed the data [19] into the electric consumption prediction model to obtain the predicted electricity consumption of EVs. Then the EVs are divided into energy buyers and sellers according to the methodology in Section III-A2, and their energy trading demands, i.e. the $d_{i,\min}$ of buyers and the $s_{j,\max}$ of sellers, are determined respectively and finally used to create Fig. 6.

It can be observed that most EBs require a small amount of electricity less than 10 kWh, while most ESs have more than 20 kWh of electricity storage to trade. This suggests that the existing electricity utilization efficiency of EVs can be greatly improved and the P2P trading may be helpful to facilitate the utilization of idle electricity.

B. Intra-Regional Electricity Allocation Optimization

This subsection aims to optimize the trading electricity allocation of EBs and ESs within the region such that the benefits of EBs and ESs can be maximized. As presented in Section II, the whole trading area is divided into several regions with one AG acting as an electricity intermediary in each region, and the intermediary in the region k is denoted as AG_k with $k \in \mathcal{K}$. AG_k could communicate with every local EV to establish a real-time electricity trading market and promote electricity trading [20]. In region k, we denote each EB as EB_i^k with $i \in \mathcal{I}$ and each ES as ES_j^k with $j \in \mathcal{J}$. In transactions, any EB/ES could trade electricity with multiple ESs/EBs simultaneously. The trading electricity amount d_i^k denotes the overall electricity actually purchased by EB_i^k and the trading electricity amount s_j^k denotes the overall electricity actually sold by EB_i^k, and the corresponding expressions are

$$d_i^k = \sum_{l=1}^{J} d_{i,l}^k = \rho \sum_{l=1}^{I} s_{l,i}^k, \tag{5}$$

$$s_j^k = \sum_{l=1}^{I} s_{j,l}^k = \frac{1}{\rho} \sum_{l=1}^{J} d_{l,j}^k, \tag{6}$$

where $d_{i,j}^k$ is the electricity amount bought by EB_i^k from ES_j^k, $s_{j,i}^k$ is the electricity amount sold by ES_j^k to EB_i^k, and ρ indicates the average electricity transmission efficiency.

Denote ω_i as the charging willingness constant of EB_i^k, then the utility function of EB_i^k is described as

$$U(EB_i^k) = \frac{\omega_i}{STO_i^t} \ln(d_i^k - d_{i,\min}^k + 1). \tag{7}$$

The corresponding cost function of EB_i^k is

$$C(EB_i^k) = C_1(EB_i^k) + C_2(EB_i^k), \tag{8}$$

where

$$C_1(EB_i^k) = q d_i^k \tag{9}$$

represents the commission with a rate q required to be paid to the intermediary by EB_i^k for the maintenance of AGs and

$$C_2(EB_i^k) = l_1 {d_i^k}^2 + l_2 d_i^k \tag{10}$$

represents the transmission loss during transaction of EB_i^k with $l_1 > 0, l_2 > 0$ are constants indicating cost factors.

Similarly, denote ω_j as the charging willingness constant of ES_j^k, then the utility function of ES_j^k is described as

$$U(ES_j^k) = \omega_j STO_j^t \ln(s_j^k - s_{j,\min}^k + 1). \tag{11}$$

The corresponding cost function of ES_j^k is

$$C(ES_j^k) = C_1(ES_j^k) + C_2(ES_j^k) \tag{12}$$

with

$$C_1(ES_j^k) = q s_j^k \tag{13}$$

represents the commission to be paid to the intermediary by ES_j^k and

$$C_2(ES_j^k) = l_1 {s_j^k}^2 + l_2 s_j^k \tag{14}$$

represents the transmission loss during the transaction of ES_j^k.

Now, the optimization problem to maximize the overall benefit of both EB_i^k and ES_j^k can be expressed as

$$\begin{aligned}\max_{d_{i,j}^k, s_{j,i}^k} F(d_{i,j}^k, s_{j,i}^k) = &\left(\sum_{i\in\mathcal{I}}[U(EB_i^k) - C(EB_i^k)],\right.\\ &\left.\sum_{j\in\mathcal{J}}[U(ES_j^k) - C(ES_j^k)]\right)^T\\ \text{s.t.}\quad & d_{i,\min}^k \le d_i^k \le d_{i,\max}^k\\ & s_{j,\min}^k \le s_j^k \le s_{j,\max}^k\\ & d_i^k = \sum_{l=1}^{J} d_{i,l}^k = \rho \sum_{l=1}^{I} s_{l,i}^k\\ & s_j^k = \sum_{l=1}^{I} s_{j,l}^k = \frac{1}{\rho}\sum_{l=1}^{J} d_{l,j}^k\\ & i\in\mathcal{I}, j\in\mathcal{J}. \end{aligned} \tag{15}$$

Once the local intermediary receives the electricity trading range information from local EBs and ESs, it will share the information with neighboring intermediaries through the communication network. By utilizing the collected electricity trading information of local and neighboring EVs, the optimization problem (15) will be organized by the intermediaries in the local region and every neighboring region. The optimization problem needs to weigh the benefits of both EBs and ESs, therefore, we regard it as a MOP that contains multiple objective functions. The purpose of the MOP is to find the optimal electricity allocation strategy that balances all optimization objectives well, that is, find the Pareto set that contains all Pareto optimality allocations and does not exist any so-called Pareto improvement [21].

To maximize the overall benefit of both EBs and ESs and find optimal electricity allocation solutions (Pareto set), each intermediary needs to solve the MOP (15) within the region. A variant of methods can be utilized to find the Pareto set of the MOP, such as the Non-dominated Sorting Genetic Algorithm (NSGA-II), the Multiple Objective Particle Swarm Optimization (MOPSO), etc. Considering the Multi-objective Evolutionary Algorithm Based on Decomposition(MOEA/D) [22] possesses lower time and space complexity, thus we introduce it to solve the MOP in this paper and the detailed process is described in Algorithm 1 of Section IV-A.

C. Inter-Regional Price Competition Game

This subsection takes into account the price competition among neighboring regions to determine the electricity price of each region, where the competition mechanism and corresponding characteristics are analyzed based on the Supermodular game theory.

1) Preliminaries of Supermodular Game: Supposing that all the intermediaries of neighboring regions participate in the electricity price competition and that each intermediary has its individual benefit to maximize selfishly, this can be described as a non-cooperative game.

Supermodular game is one of the most important non-cooperative game theories and it provides a general and brief method for analyzing games with complementary strategies [23]. Specifically, when one player takes a higher action in the supermodular game, the best response of the others is to increase the strategies as well, which is applicable to our inter-regional competition situation. Herein, we adopt the supermodular game theory to describe the inter-regional price competition such that the electricity price of each region can be determined. In the following, two definitions related to the supermodular game are presented:

Definition 1: F is a function from the lattice $\mathcal{S}$ to the real number set $\mathbb{R}$, i.e. $F : \mathcal{S} \longrightarrow \mathbb{R}$. In the case of function $F(\mathbf{x})$ is twice differentiable, $F(\mathbf{x})$ is supermodular if the following inequality holds [24]:

$$\frac{\partial^2 F(\mathbf{x})}{\partial x_i \partial x_j} \ge 0, \forall \mathbf{x}\in\mathcal{S}, j\ne i. \tag{16}$$

Definition 2: A game is a supermodular game, if 1) The set of strategies S_i of player i is a compact subset of $\mathbb{R}$ and 2) F is supermodular.

2) Formulation of Supermodular Game: We formulate the inter-regional price competition mechanism in SNIPPETS as a static non-cooperative game based on supermodular game theory. The game takes place in the local region and all neighboring regions, where each intermediary acts as a game participant and determines its regional pricing strategy. During the game, intermediaries do not cooperate with each other, i.e., they set the strategies independently and selfishly by considering other players' strategies of the last round so as to maximize individual benefits. Specifically, we formulate the competition and interaction among regions as follows:

Players: Intermediaries from a local region and its neighboring regions.

Strategy: The player's strategy is to adjust the regional electricity trading price within the region. In other words, the strategy of AG_k is to set the electricity price p_k, where $p_k \in (0, mp_0)$ limits the price in a reasonable range, p_0 indicates the real-time power grid electricity price and $m\in\mathbb{R}_+$ is a constant. We use $\mathbf{p}_{-k} = (p_1, \ldots, p_{k-1}, p_{k+1}, \ldots, p_K)$ to denote the electricity price vectors of AG_k's all neighboring intermediaries and each component p_l of $\mathbf{p}_{-k}$ satisfies $p_l \in (0, mp_0)(1\le l\le K, l\ne k)$ as well.

Benefit: The regional benefit $\pi_k(p_k, \mathbf{p}_{-k})$ of AG_k is related to the monetary income obtained by AG_k.

In this case, $\pi_k(p_k, \mathbf{p}_{-k})$ is expressed as

$$\pi_k(p_k, \mathbf{p}_{-k}) = p_k g_k(p_k, \mathbf{p}_{-k}), \tag{17}$$

where $g_k(p_k, \mathbf{p}_{-k})$ is the total regional electricity trading demands of EBs in response to the electricity prices and is given by

$$g_k(p_k, \mathbf{p}_{-k}) = d^k_{\min} + (d^k_{\max} - d^k_{\min}) f\left(-\alpha_k p_k + \left(\sum_{l=1, l\neq k}^{K} \beta_{k,l} p_l\right) + \theta_k\right). \tag{18}$$

The function $f(.)$ in above equation is defined as

$$f(x) = \frac{x + m\alpha_k p_0 - \theta_k}{m p_0 (\alpha_k + \sum_{l=1,l\neq k}^{K} \beta_{k,l})}, \tag{19}$$

where $\alpha_k > 0$ is the demand response coefficient for the price of AG_k, $\beta_{k,l} > 0$ is the demand response coefficient for the cross-price of AG_k with its neighbors, and θ_k indicates the market share of AG_k.

As each intermediary wants to maximize the individual benefit by setting its electricity price, AG_k must solve the following maximization problems to determine p_k:

$$\begin{aligned} \max_{p_k \in \mathbb{R}_+} \quad & \pi_k(p_k, \mathbf{p}_{-k}) \\ \text{s.t.} \quad & k \in \mathcal{K} \end{aligned} \tag{20}$$

and the solution p_k^* of (20) can be written as

$$p_k^* = \underset{p_k \in \mathbb{R}_+}{\operatorname{argmax}}\ \pi_k(p_k, \mathbf{p}_{-k}). \tag{21}$$

3) Supermodularity and Convergence of the Game: This subsection verifies the price competition game among regional intermediaries is a supermodular game and shows the convergence of the game based on its supermodularity.

According to the definitions of the supermodular game in Section III-C1, the sufficient condition for the benefit function of the intermediary having the supermodularity is

$$\frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l} \geq 0. \tag{22}$$

To check (22), take the derivative of (17), we get

$$\frac{\partial \pi_k(p_k, \mathbf{p}_{-k})}{\partial p_k} = g_k(p_k, \mathbf{p}_{-k}) + p_k \frac{\partial g_k(p_k, \mathbf{p}_{-k})}{\partial p_k}, \tag{23}$$

$$\frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l} = \frac{\partial g_k(p_k, \mathbf{p}_{-k})}{\partial p_l} + p_k \frac{\partial^2 g_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l}, \tag{24}$$

where

$$\frac{\partial g_k(p_k, \mathbf{p}_{-k})}{\partial p_l} = \frac{d^k_{i,\max} - d^k_{i,\min}}{m p_0 (\alpha_k + \sum_{l=1,l\neq k}^{K} \beta_{k,l})} \beta_{k,l} \geq 0, \tag{25}$$

$$p_i \frac{\partial^2 g_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l} = 0. \tag{26}$$

Therefore, it is obvious that (22) holds, i.e., the inter-regional price competition game is a supermodular game indeed.

Then, we analyze the convergence of the game. It is well-known that there must be a Nash equilibrium for the supermodular game and according to [25], the condition for the existence of the unique Nash equilibrium is

$$-\frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial^2 p_k} \geq \sum_{k\neq l} \frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l}. \tag{27}$$

Recalling (24), (25) and (26), we obtain

$$\sum_{k\neq l} \frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial p_k \partial p_l} = \frac{d^k_{i,\max} - d^k_{i,\min}}{m p_0 (\alpha_k + \sum_{l=1,l\neq k}^{K} \beta_{k,l})} \sum_{l=1,l\neq k}^{K} \beta_{k,l}. \tag{28}$$

On the other hand, the following equations can be derived from (23), i.e.,

$$-\frac{\partial^2 \pi_k(p_k, \mathbf{p}_{-k})}{\partial^2 p_k} = 2\alpha_k \frac{d^k_{i,\max} - d^k_{i,\min}}{m p_0 (\alpha_k + \sum_{l=1,l\neq k}^{K} \beta_{k,l})}. \tag{29}$$

Substituting (28) and (29) into (27), we know that the supermodular game of this paper has a unique Nash equilibrium if and only if

$$2\alpha_k \geq \sum_{l=1,l\neq k}^{K} \beta_{k,l}. \tag{30}$$

Based on the study in [24], the Nash equilibrium can be obtained with the best response algorithms, therefore, we adopt the idea of the best response algorithm to realize the supermodular game process and finally obtain the Nash equilibrium, i.e., each intermediary determines its regional electricity price and corresponding benefits. (More details of the algorithm can be found in Algorithm 2 of Section IV-A.)

After the regional electricity price determination process of each intermediary through Algorithm 2, the final bid-winning intermediary and its region will be chosen according to the following optimization problem:

$$\begin{aligned} \min_{k} \quad & \left[\sum_i (\delta_1 p_k d_i^k + \delta_2 (a r_{i,k}^2 + b r_{i,k}))\right] \\ \text{s.t.} \quad & d_i^k = g_k(p_k, \mathbf{p}_{-k}), k \in \mathcal{K}, \end{aligned} \tag{31}$$

where $r_{i,k}$ denote the geographical distance between EB_i and region k, $a > 0$ and $b > 0$ are constants indicating the distance influence, $\delta_1 > 0$ and $\delta_2 > 0$ are the the influence coefficients on decision making, δ_1 represents the payment influence and δ_2 represents the geographical distance influence.

Once the trading region and its electricity price are determined, the total regional electricity trading demand is then determined by (18), with which we can select the optimal electricity allocation scheme from the Pareto set generated in Section III-B. Finally, the payment amount that EB_i^k will pay the chosen intermediary is

$$pay(EB_i^k) = p_k d_i^k + q d_i^k \tag{32}$$

and the payment amount that ES_j^k will gain from the intermediary is

$$pay(ES_j^k) = p_k s_j^k - q s_j^k \tag{33}$$

Assuming that the transaction takes place in the region k^*, the overall social welfare SW_k^* of the region k^*, which contains

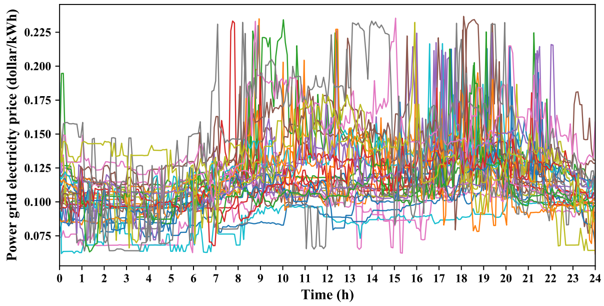


Fig. 7. Power grid electricity price over 24 h for multiple days.

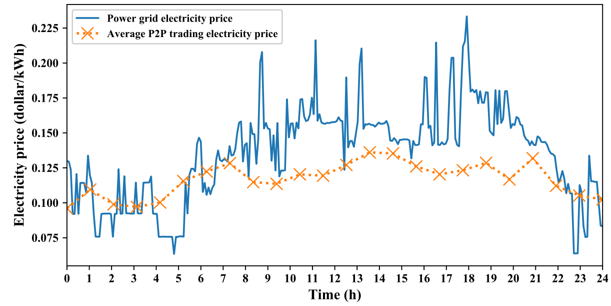


Fig. 8. Power grid electricity price and average P2P trading electricity price over one day.

the benefit of all trading participants (including EBs, ESs, and the intermediary), can be calculated as

$$SW_k^* = \pi_k(p_k^*, \mathbf{p}_{-k}^*) + \sum_{i \in I}[U(EB_i^{k^*}) - C(EB_i^{k^*})] + \sum_{j \in J}[U(ES_j^{k^*}) - C(ES_j^{k^*})]. \quad (34)$$

IV. Algorithms

A. Electricity Allocation Optimization Algorithm

In order to solve the intra-regional MOP in Section III-B and find the Pareto Set, we design an electricity allocation optimization algorithm based on the MOEA/D algorithm [22]. The idea of the algorithm is to transform the MOP into a series of single-objective optimization sub-problems (SOPs), and then use the adjacent SOPs' information to optimize each SOP simultaneously by evolutionary algorithms. Considering each solution on the Pareto front corresponds to the optimal solution of every SOP, as a consequence, a set of Pareto optimal solutions can be finally obtained by solving the MOP. We use the Tchebycheff approach as the decomposition strategy, which is presented as follows:

$$\min\ g^{te}(x \mid \lambda^*, z^*) = \max_{1 \leqslant m \leq M} \{\lambda_m |f_m(x) - z_m^*|\}$$
$$\text{s.t. } x \in \Omega, \quad (35)$$

where $f_i(x)$ is the objective function, g^{te} is the new objective function obtained by using Tchebycheff decomposition strategy, $z^* = \{z_1^*, \ldots, z_M^*\}$ is the reference point with $z_m^* = \max\{f_m(x) \mid x \in \Omega\}$ for $\forall m = 1, \ldots, M$. For each Pareto optimal solution x^*, there always exists a weight vector λ^* such that the solution of (35) is a Pareto optimal solution corresponding to the optimal solution of the original MOP. The details of the algorithm can be found in Algorithm 1.

B. Electricity Price Competition Game Algorithm

In order to solve the inter-regional competition problem in Section III-C formulated by the supermodular game, we adopt the idea of the best response algorithm to realize the game process and obtain the Nash equilibrium, which means the

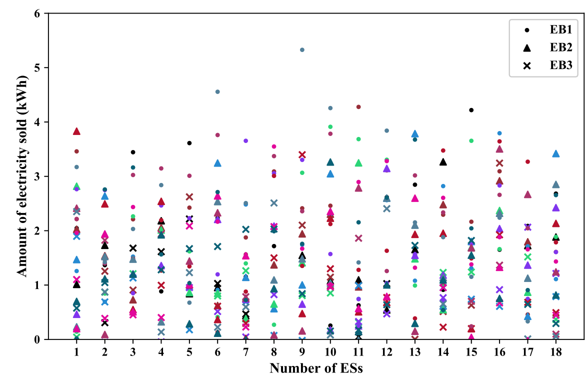


Fig. 9. Solution set of the optimal electricity allocation schemes in region 2.

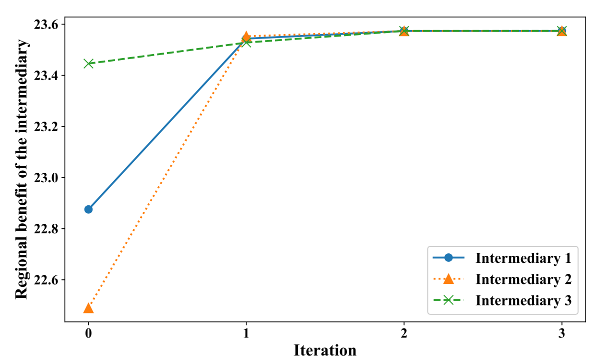


Fig. 10. Convergence evolution of regional benefit of intermediaries.

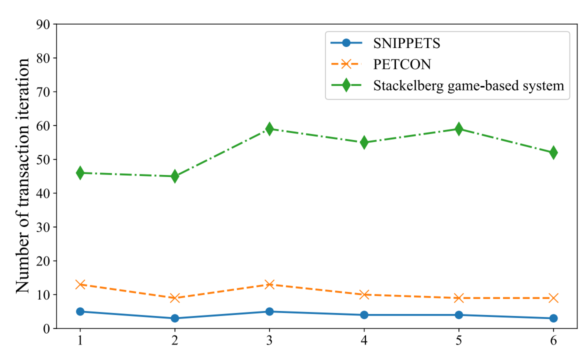


Fig. 11. Iterations comparison of SNIPPETS and PETCON.

Algorithm 1: Electricity Allocation Optimization Algorithm.

Input: The stopping criterion r; The MOP $F(x) = F(d^k_{i,j}, s^k_{j,i})$; The number of SOPs considered in MOEA/D N; A uniform spread of N weight vectors $\{\lambda_1, \ldots, \lambda_N\}$; The number of the weight vectors in the neighborhood of each weight vector T; Convergence threshold ε;
Output: External population(EP), which is used to store Pareto optimal solutions;
1: Initialization: EP $\leftarrow \emptyset$; set $B(n) \leftarrow \{n_1, \ldots, n_T\}$,where $\lambda_{n_1}, \ldots, \lambda_{n_T}$ are the T closest weight vectors to λ_n; $FV_n \leftarrow F(x_n)$; $z = \{z_1, \ldots, z_m\}$; $M = 2$; $T = 5$; $N = 1000$; $\varepsilon = 0.001$;
2: **for** $n = 1, 2, \ldots, N$ **do**
3: randomly select k, l from $B(n)$;
4: generate a new solution y from x_k and x_l by using genetic operators;
5: **if** y invalidates any constraints**then**
6: repair y to produce y';
7: **end if**
8: **for** $m = 1, \ldots, M$ **do**
9: **if** $z_m < f_m(y')$ **then**
10: $z_m \leftarrow f_m(y')$;
11: **end if**
12: **if** $g^{te}(y' \mid \lambda_m, z) \leq g^{te}(x_m \mid \lambda_m, z)$ **then**
13: $x_m \leftarrow y'$;
14: $FV_m \leftarrow F(y')$;
15: **end if**
16: **if** no vectors in EP dominate $F(y')$**then**
17: add $F(y')$ to EP;
18: **else**
19: remove all the vectors dominated by $F(y')$ from EP;
20: **end if**
21: **if** $r < \varepsilon$ **then**
22: go to final;
23: **else**
24: go to line 3;
25: **end if**
26: **end for**
27: **end for**
28: **final**;
29: **return** EP;

benefits of each intermediary converge and each regional electricity price is determined. Noting that in the initialization of the designed algorithm, the condition (30) ensuring the unique Nash equilibrium should be satisfied. After the initialization, every intermediary set the strategy in each iteration according to other players' strategies adopted in the previous iteration to maximize its benefit as demonstrated in (21). The details of the algorithm can be found in Algorithm 2.

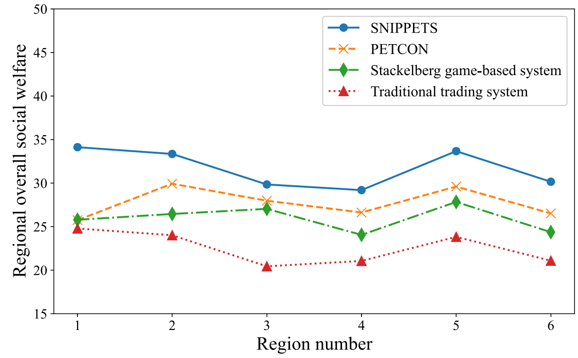


Fig. 12. Comparison of regional overall social welfare between SNIPPETS and traditional trading system.

TABLE II
COMPARISON OF SOLUTION TIMES FOR DIFFERENT SYSTEMS

System	Solution time(s)
SNIPPETS	72.48
PETCON [27]	143.92
Stackelberg game-based trading system [28]	177.64

Algorithm 2: Electricity Price Competition Game Algorithm.

Input: The number of EVs I, J; The number of intermediaries K; The price-demand factor $\boldsymbol{\alpha} = \{\alpha_k \mid k \in \mathcal{K}\}$, $\boldsymbol{\beta} = \{\beta_{k,l} \mid k, l \in \mathcal{K}, k \neq l\}$, $\boldsymbol{\theta} = \{\theta_k \mid k \in \mathcal{K}\}$; Bid price of each intermediary $\mathbf{p} = \{p_k \mid p_k \in (0, mp_0), k \in \mathcal{K}\}$; Bid price of each intermediary from the previous iteration $\mathbf{p^{old}} = \{p^{old}_k \mid p^{old}_k \in (0, mp_0), k \in \mathcal{K}\}$; Benefit of each intermediary $\boldsymbol{\pi} = \{\pi_k \mid k \in \mathcal{K}\}$; Charge rate q; Demand range of EBs $\mathbf{d_{min}}, \mathbf{d_{max}}$; Supply range of ESs $\mathbf{s_{min}}, \mathbf{s_{max}}$; Convergence threshold ϵ; Maximum iterations I_{max}
Output: The bid price vector of intermediaries $\mathbf{p}$; The benefit vector of intermediaries $\boldsymbol{\pi}$;
1: Initialization: $sum = 1$; $\boldsymbol{\pi} = 0$; $\epsilon = 0.001$; randomly assign values to $\mathbf{p}$ and $\mathbf{p^{old}}$ respectively;
2: **for** $i = 1 : I_{max}$ **do**
3: **for**episode $k = 0 : K$**do**
4: $p_k \leftarrow$ argmax $\pi_k(p_k, \mathbf{p}^{old}_{-k})$,
5: $\pi_k \leftarrow$ max $\pi_k(p_k, \mathbf{p}^{old}_{-k})$
6: $sum \leftarrow \mid \mathbf{p} - \mathbf{p^{old}} \mid$
7: **if** $sum < \epsilon$ **then**
8: go to final;
9: **end if**
10: **end for**
11: $\mathbf{p^{old}} \leftarrow \mathbf{p}$;
12: **end for**
13: **final**;
14: **return** $\mathbf{p}, \boldsymbol{\pi}$;

TABLE III
TRANSACTION DETAILS OF REGION k IN SNIPPETS

Transaction payers	Transaction recipients	Amount(ETH)	Transaction ID
EB 1	Intermediary k	4.75	0xfe5a637c67c0b9e4facfaf3d42b5afde16e9196c67aae1b64d69f5438dbe73f2
EB 2	Intermediary k	2.32	0x2663924cbcee7fb2ca5ef5b0d69ce9e281fb44a03921236b8cc9129599967289
EB 3	Intermediary k	1.04	0x31b739811af54cb81ec1ca34a56d5b257988eef5643c8049601ee1c35a64e54a
Intermediary k	ES 1	0.89	0x2a337130b3cf0bf177df2d1e113ac0906b08ef78961d4262c881c8ee68c9febf
Intermediary k	ES 2	1.48	0x1791b9c45465a7f1ab61b1a200bd03db52bf9dbff42ce208274964663df25fa0
Intermediary k	ES 3	0.81	0x02432ae47c1724060b849447e6274f4f994ee1f7807c231aaf346a287ace483d
Intermediary k	ES 4	1.48	0xe39559f0becf790d3416d1500be19c4cf258d1abfae5c1c0a814e481fd332452
Intermediary k	ES 5	1.61	0x359c8ebf3412d61d89034d21255c4dbfa8ad573022d4c66638406e71e57b3e28
Intermediary k	ES 6	1.08	0x5987c43ee3443f755232ab258f5e98709da436fb2c37a64da224fb32611e9dd1

V. CASE STUDY

In this section, we evaluate the effectiveness of the proposed SNIPPETS on a real dataset in an urban area of Beijing [19]. The latitude of the observed area is from 36.129 to 42.595 and the longitude is from 115.885 to 118.543. We randomly take the data on 06 December 2019 as an example. The cost factors l_1 is taken as 0.01 and l_2 is taken as 0.015 in (10) and (14), respectively. The average electricity transmission efficiency coefficient ρ is taken as 0.9 while the convergence thresholds ε and ϵ are taken as 0.001.

To show the general trend of daily electricity prices, we use a real electricity price dataset [26] to stack grid electricity price movement graphs for one month in Fig. 7, where each line represents the price of electricity for one day (0:00 to 24:00), in order to show the general trend in electricity prices over a 24-hour period, including peak and trough periods. It demonstrates that the power grid electricity price is relatively high between 7:00 to 22:00, which is exactly the time when P2P transactions are most likely to occur. The power grid electricity price and hourly average transaction electricity prices of SNIPPETS over one day are depicted in Fig. 8. According to Fig. 8, the transaction price is lower when trading in our proposed P2P trading system compared to trading directly with the grid between 7:00 to 22:00. However, the price difference is not much at night since the power grid price falls and most EVs are inactive at night, which is in accordance with practical situations. Fig. 8 mainly demonstrates two advantages of our proposed trading system: 1) the proposed P2P trading mechanism can reduce costs in terms of electricity trading price, and 2) the proposed P2P energy trading can bring a leveling effect to reduce fluctuations in load, therefore reducing the cost of power plants [10].

To reveal more details about the transactions, we randomly selected the data at 19:00-20:00 on 06 December 2019, where transactions take place in six regions totally during this time slot. Taking region 2 as an example, after the intra-regional optimization mechanism, i.e. Algorithm 2, a set of solutions for the optimal electricity allocation in the region is generated, as shown in Fig. 9, where each point represents the amount of electricity sold by an ES to an EB.

Since region 2 and its two neighboring regions are involved in one game, thus we take them as an example. Fig. 10 shows the convergence evolution of the benefits of the intermediaries in regions 1-3 achieved by Algorithm 2, where all the regional benefits converge after only several iterations.

In order to demonstrate the superiority and effectiveness of the proposed trading system, we next compare it with some other trading systems.In addition to the proposed SNIPPETS, the systems involved in the comparison include

1) PETCON: PETCON is proposed by [27] for the EV P2P energy trading scenario. PETCON uses an iterative double auction mechanism to determine energy trading schemes among EVs.

2) Stackelberg Game-Based Trading System: the trading system proposed by [28] is used for P2P energy trading, where the Stackelberg game approach is used to model the interaction between energy buyers and sellers.

3) Traditional Trading System: in a traditional electricity trading scenario, once EBs have predicted the future electricity consumption and determined their trading demands, they purchase electricity directly from the power grid at the real-time grid tariff. Since there are no more intermediaries in the traditional energy trading system, the social welfare function differs slightly from (34), where the benefits of intermediaries are no longer considered, i.e. the overall social welfare is

$$SW_k = \sum_{i \in I} [U(EB_i^k) - C(EB_i^k)] + \sum_{j \in J} [U(ES_j^k) - C(ES_j^k)]. \tag{36}$$

Comparing SNIPPETS with the trading systems described above, we present the comparison results in several aspects.

Fig. 11 shows the transaction iteration number comparison of SNIPPETS, PETCON [27], and Stackelberg game-based trading system [28] for all the regions, where it is observed the proposed SNIPPETS requires fewer iterations to reach the Nash equilibrium.

Table II shows the solution time required for these P2P trading systems. It can be seen that the proposed SNIPPETS takes the shortest time compared to PETCON [27] and the Stackelberg game-based trading system [28], which indicates that SNIPPETS has the best algorithmic computing performance.

Further, we show the comparison results of regional overall social welfare, which is composed of the benefit of EBs, ESs, and the regional intermediary as defined in (34). In particular, we compare the regional overall social welfare of the proposed SNIPPETS, PETCON [27], Stackelberg game-based trading system [28], and the traditional trading system. The comparison results are presented in Fig. 12. It can be seen that SNIPPETS has the highest regional overall social welfare compared to other trading systems, indicating that the proposed SNIPPETS can be effective in improving the overall social welfare of the regions.

Finally, we demonstrate how the coordinated P2P energy trading market could be implemented on blockchain as a digital platform. Indeed, blockchain offers an achievable way to construct a secure and privacy-preserving trading environment due to its inherent technical characteristics, such as traceability, immutability, transparency, and automation [29]. Therefore, Ethereum, a decentralized blockchain with smart contract functionality [30], is used to execute the payment process. In the transaction, we create one account with 10000 ETH for each EV and one account with 10000 ETH for each AG. When the transaction details are determined under the coordination of the intermediary, each EB pays for the electricity with an additional commission charge to the intermediary, and the intermediary transfers the payment to ESs after deducting the commission charge for ESs. The payment information for each participant is then written to their accounts. Taking Region k for example, its detailed transaction information is shown in Table III to represent the deployment of Ethereum, where each transaction that occurs on Ethereum corresponds to a unique ID and shows that the transaction process has been completed on Ethereum.

VI. Conclusion

In this paper, we proposed a novel P2P electricity trading system with EVs named SNIPPETS. The system addressed benefit conflicts between electricity traders, as well as price competition among neighboring regions, thereby improving overall social welfare.

SNIPPET is made up of the following components. To begin, a LightGBM-based prediction model was constructed, which used category information and driving data of EVs to classify them into different categories and predict their electricity trading volume. Then, an intra-regional-inter-regional transaction mechanism was proposed for SNIPPETS to maximize social welfare throughout the transaction, where the MOEA/D algorithm was developed to solve the MOP for coordinating benefits of all EBs and ESs within each neighboring region by adjusting the trading volume, and the supermodular game theory was adopted to model the price competition among neighboring regions using the trading price as the main variable. Furthermore, Ethereum was deployed to execute the payment process and record the transaction data.

The effectiveness of SNIPPETS was verified through simulation experiments. The results show that 1) the proposed energy consumption prediction model has good predictive effectiveness. 2) SNIPPETS requires fewer iterations and shorter solution time compared to other trading systems. 3) SNIPPETS can achieve the highest overall social welfare when compared to other trading systems.

A limitation of our study is that the Ethereum module of SNIPPETS only supports transaction payments and data storage, and lacks the protection of transaction information during the trading process. Future research needs to focus on better integration of blockchain into energy trading systems to achieve more comprehensive protection of trading data.

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