Peer-to-Peer Energy Sharing in Distribution Networks With Multiple Sharing Regions

Liudong Chen, *Student Member, IEEE*, Nian Liu, *Member, IEEE*, and Jianhui Wang, *Senior Member, IEEE*

***Abstract*—Peer-to-peer energy sharing in the distribution networks (DN) is an emerging issue with the large-scale development of photovoltaic (PV) prosumers. The DN can be classified into energy-shared regions (ESR) to enable the zonal energy trading. A Stackelberg-game-based energy-sharing framework is recommended for DN with multi-ESR, where the energy-sharing provider (ESP) works as a leader with dynamic pricing for multi-ESR, whereas PV prosumers serve as followers with the demand response's (DR) ability to choose an ESR to link and modify their flexible loads. A profit maximization model, along with multi-ESR pricing and a network usage fee, is designed for the ESP operation in this article. This involves a utility model with DR strategies, including ESR selection and load adjustment, which is proposed for the prosumers. Moreover, the presence and uniqueness of the Stackelberg equilibrium are being provided. Finally, through the use of a real system, the simulation results show that the ESP profit and prosumers can be increased whereas the impact of PV uncertainty and variability on the utility grid is reduced.**

***Index Terms*—Demand response (DR), distribution network (DN), dynamic pricing, optimization, peer-to-peer (P2P), prosumers, Stackelberg game.**

Nomenclature

N	Number of energy-sharing regions (ESRs) in the DN.
M	Number of prosumers in the DN.
B	Number of buyers in the DN.
S	Number of sellers in the DN.
H	Number of time slots of the energy-sharing operation.
i	Index for prosumers.
n	Index for ESR.
h	Index for time slot.
$g_{s,h}$	Selling prices of utility grid.
$g_{b,h}$	Buying prices of utility grid.
$p_{sn,h}$	Dynamic internal selling prices of ESR n.
$p_{bn,h}$	Dynamic internal buying prices of ESR n.
λ_{med}	Transmission–distribution prices in medium voltage level.
λ_{high}	Transmission–distribution prices in high voltage level.
$\Delta\lambda$	Network usage fee.
$x_{i,h}$	Energy consumption of prosumers i.
$x_{i\text{min},h}$	Lower bounds of energy consumption.
$x_{i\text{max},h}$	Upper bounds of energy consumption.
$l_{ni,h}$	ESR selection variable of prosumer i (access to ESR n).
$E_{i,h}$	Energy production by the photovoltaic (PV) panel of prosumer i.
$E_{si,h}$	Selling energy of prosumer i.
$E_{bi,h}$	Buying energy of prosumer i.
$E_{sn,h}$	Total amount of energy selling in ESR n.
$E_{bn,h}$	Total amount of energy buying in ESR n.
$E_{b,h}$	Total buying energy in the DN with N ESRs.
$E_{s,h}$	Total selling energy in the DN with N ESRs.
$E_{\text{loss},h}$	Entire network losses in time slot h.
$E_{g,h}$	Amount of energy that the utility grid sends to the DN in time slot h.
$E_{\max,h}$	Maximal energy limit of the 10 kV transformer power line.
pl_i	Transmission capacity corresponding to the power line of prosumer i.
$k_{i,h}$	Preference parameter of prosumer i.
$\gamma E_{i,h}$	Subsidy of PV energy from the government.
$R(p_{bn,h}, p_{sn,h})$	Profit function of the ESP.
$V_{i,h}(x_{i,h}, l_{ni,h})$	Utility function of PV prosumers.
$Vn_{i,h}(x_{i,h}(n))$	Utility of prosumers i in ESR n.
$x_{i,h}(n)$	Consumption of prosumer i in ESR n.

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(Corresponding author: Nian Liu.)

Liudong Chen and Nian Liu are with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing 102206, China (e-mail: liudong@ncepu.edu.cn; nianliu@ncepu.edu.cn).

Jianhui Wang is with the Department of Electrical and Computer Engineering, Southern Methodist University, Dallas, TX 75205 USA (e-mail: jianhui@smu.edu).

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I. Introduction

Distributed energy resources (DERs) are widely used to reduce greenhouse gas emissions and increase grid resilience. Also, consumers with DERs can provide electricity to the utility system whenever necessary. This creates an entity with the competence of both production and consumption called prosumer [1]. With the emergence of prosumers, demand response (DR) has gradually become a popular research topic for the solution to the energy management problem (e.g., peak energy consumption) [2]. Among all forms of DERs, photovoltaics (PVs) are currently being diffusely installed with a promising impact [3], [4]. Regarding the energy balance requirement, the large-scale connection of PV systems and energy usage of prosumers will have a significant effect on the operation of the electric power system. The transactive energy emerges as an effective market-based control to resolve this challenge and enables the energy transactions among the distributed entities [5], [6]. Accordingly, peer-to-peer (P2P) energy sharing is receiving extensive research interest [7].

In general, P2P energy-sharing research can be grouped into the following connected network levels: 1) microgrid (MG) and 2) distributed network (DN). The first category is focused on energy sharing among the prosumers inside the MG. The operational goal is to increase the profit of the prosumers [1], [8]. The bilateral contracts [9] and economic dispatch [10] are proposed to facilitate P2P energy trading. In [3] and [6], a concept of P2P platform agent is suggested to control the energy trading among the PV prosumers with their heterogeneous preferences. A multiagent system uses P2P energy sharing as a solution to address the complexity of the transactions [11], increase network efficiency and energy security [10], and schedule the DER unit commitment [12]. A canonical coalition game with social cooperation among the prosumers is used to promote sustainable participation in P2P trading [13]. In addition, P2P energy sharing can also be used in the efficient energy management of smart energy buildings via distributed optimization [14].

With the large-scale connection of PVs, it can have a significant impact on P2P energy sharing brought by their volatile generation output [15], extending the MG-level energy sharing to the DN level, such as with community MGs [16]. This has become an essential topic [17], [20]. Some researchers provide game theoretical approaches for P2P energy sharing in DN [17]–[19]. For instance, an overview of the potential of game theory approaches for energy management in a P2P network is discussed in [18]. In reference to [19], it proposes a game theory model, including a Stackelberg game, an evolutionary game, and a noncooperative game for real-time P2P energy sharing in a community MG. In addition to the game theory, blockchain technology and software-defined networks (SDNs) have also been applied to P2P energy sharing. Blockchain can be used to build a new market structure for big industrial energy users, which consists of contracts, day-ahead optimization, adjustment, and real-time balancing with the goal of minimizing the electricity cost [21]. Blockchain can also be combined with deep learning technology to incorporate a new P2P energy trading system to achieve high throughput [22]. SDNs can be used to enhance the flexibility and effectiveness of the energy internet to facilitate large-scale P2P energy delivery [23]. Several other applications in a P2P energy-sharing framework in DN are evaluated (e.g., electric vehicles [24]).

Currently, to facilitate energy trading among the DERs, the different DN usage charges are analyzed to promote the use of renewable energy in the local DN. In [25], the network charges for the costs of using common infrastructure and services are considered in an exogenous way, such as via electrical distance. The P2P transaction is also charged with the extra cost associated with the physical energy exchanged, such as losses [26]. To guarantee economic efficiency and fairness, a graph-based loss allocation framework that harmonizes the physical attributes and financial transactions has been presented [27]. In practice, U.K. has already set policies of common distribution charging methodology and extra high voltage distribution charging methodology, which includes the distribution network operators to get their revenue from customers through distribution use of system charges [28]. In this article, the focus is placed on China's policies [29]. To accelerate the development of DER and determine the problems of the market, public service, and management system, P2P energy sharing is based on power exchange to set up the regional distributed generation trading platform. The transaction is between the DERs that is less than 20 MW (in 35 kV network) and the nearby users in the DN. The utility grid organizes the market-oriented transaction and charges the network usage fees. Generally, there are two forms of network usage fees: 1) free network usage, where the energy flow between the prosumers is at the same voltage level as a distribution line; and 2) network usage fee charged by the amount of the traded energy, where the utility grid charges for P2P trading as the energy flow crosses the different voltage levels of distribution lines. With this, the DN can be divided into energy-sharing regions (ESRs) with the different network usage fees. Also, the large industrial and commercial prosumers usually have more than one access point into the DN. This means the prosumers can select the access point, and thus, reduces network usage fees and increases their utilities.

In this article, the work presented in [30] is extended, involving the DN, multiple ESRs, and the selective access points of prosumers that are patterned in the energy-sharing framework. The main contributions include the following.

1) An energy-sharing framework with multiple ESRs and selective access points of prosumers is created, where an energy-sharing provider (ESP) is employed to provide a dynamic pricing scheme for ESRs while the prosumers have the DR capacity to join a connected ESR.
2) An optimal profit maximization model is suggested for the ESP operation, enabling the ESP to set the different internal prices of ESRs and network usage charges.
3) A utility model for ESR selection and load adjustment is proposed for the prosumers, which allows them to adjust their flexible load and autonomously participate in a particular ESR to optimize their utilities.

II. Framework

A. Topology of the System

The entities in the energy-sharing system are PV prosumers equipped with a user energy management system (UEMS), an ESP, and the utility grid. With the competence of production and consumption of PV prosumers, they act either as a seller or buyer based on their profits. The system adopts the dual-radial connection mode that is typical in China, in which prosumers are supplied with at least two feeders and possess the switches to

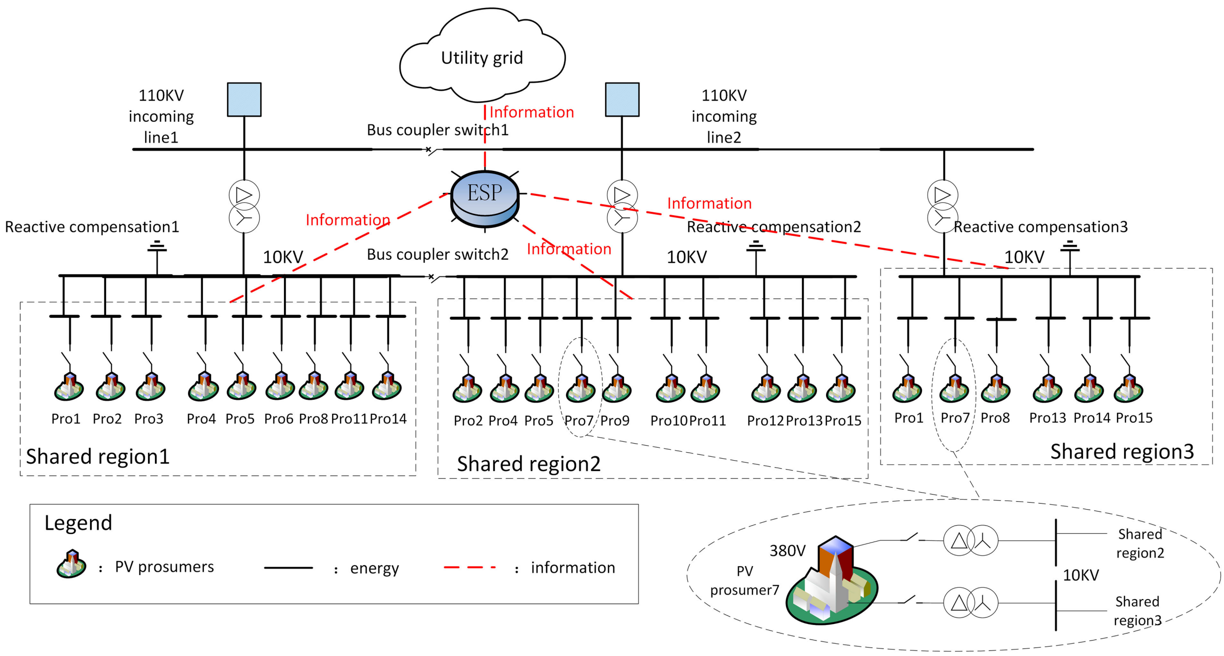

Fig. 1. Topology of the distribution networks.

access different ESRs [31]. According to the network usage fee cited in [29] and multipoint access of prosumers, the topology of the energy-sharing system with multi-ESR partitioned by transformers is shown in Fig. 1. The DN is grouped into N ESRs according to the range covered by the transformers. Moreover, taking PV prosumer 7 as an example, it links to ESR2 or ESR3 with the different switches.

B. Energy-Sharing Mode

Based on the energy trading policy in DN, energy sharing can be grouped into two types.

1) *Inside an ESR*. In general, energy is initially shared by the P2P mode inside one ESR when PV prosumers' self-product energy is a surplus or deficit and the energy-sharing process is not crossing the different voltage levels so there is free network usage fee.
2) *Interdifferent ESRs*. When selling or buying energy in one ESR, this cannot be balanced. The unbalanced energy will be trading interdifferent ESRs by crossing voltage levels to strike a balance with the ESP coordination. For example, the energy-sharing process crosses 10 kV and 110 kV networks with the different transmission–distribution prices λ_{med} and λ_{high}, respectively. This will be charged for the network usage fee $\Delta\lambda = \lambda_{\text{med}} - \lambda_{\text{high}}$ per kWh.

According to the regulation of the DER market transactions, DERs and prosumers can directly trade energy so that the P2P energy-sharing method proposed in this article can be realized [29]. The policy also points out that a market-based sharing platform for DERs and prosumers will be established to organize P2P energy sharing. In the current energy market of China, energy retailers can replace the role of ESPs suggested in this article to organize the P2P energy sharing. In addition, some emerging new business entities can also adopt such P2P energy-sharing business models, such as grid-connected MGs operators.

C. ESP and Prosumer Strategy

ESP is an intermediary agent that coordinates the sharing activities among PV prosumers and utility grid with the function to create the internal dynamic prices of ESRs. In this article's framework, the ESP profit is impacted by the energy-sharing modes. There is a free network usage fee when energy sharing occurred inside an ESR, whereas the energy sharing in the inter-different ESRs will be charged for a network usage fee. Therefore, ESP should have the rationale to maximize the operating profit by using a multiregional pricing strategy that provides the different internal prices of ESRs. Through differentiated energy sharing prices, the renewable energy consumption features are affected. The ESP is set to pay the network usage fee, as it is the organizer of energy sharing and can get profit from the trading.

In the mechanism of multi-ESR pricing, PV prosumers can use DR strategies of ESR selection and load adjustment to maximize their profits, which include the two strategies. First, there is the flexible load management. The different load demands can change the unbalanced energy inside an ESR that may cause different profits. Second there is the ESR selection. The switches of PV prosumers are high-speed switching devices, which allow PV prosumers to choose an alternative access point autonomously to participate in the different ESRs, which is affected by the internal prices set by ESP to trade with other prosumers in energy sharing. Thus, each prosumer has two variables, such as self-consumption energy (i.e., load demand) and ESR selections.

III. System Model

A. ESP Profit Model

The internal prices of multi-ESR determined by ESP are expressed as

$$P_s = \begin{bmatrix} p_{s1,1} & \cdots & p_{s1,h} & \cdots & p_{s1,H} \\ \vdots & & \vdots & & \vdots \\ p_{sn,1} & \cdots & p_{sn,h} & \cdots & p_{sn,H} \\ \vdots & & \vdots & & \vdots \\ p_{sN,1} & \cdots & p_{sN,h} & \cdots & p_{sN,H} \end{bmatrix}$$

$$P_b = \begin{bmatrix} p_{b1,1} & \cdots & p_{b1,h} & \cdots & p_{b1,H} \\ \vdots & & \vdots & & \vdots \\ p_{bn,1} & \cdots & p_{bn,h} & \cdots & p_{bn,H} \\ \vdots & & \vdots & & \vdots \\ p_{bN,1} & \cdots & p_{bN,h} & \cdots & p_{bN,H} \end{bmatrix}. \quad (1)$$

Let $g_{b,h}$ and $g_{s,h}$ denote the buying and selling prices of the utility grid, respectively; the constraint of the internal prices is set as [8], [30]

$$g_{s,h} < p_{sn,h} < p_{bn,h} < g_{b,h}. \quad (2)$$

The values of $g_{s,h}$ and $g_{b,h}$ are determined by the feed-in tariff of PV energy of some countries. Generally, the selling prices are lower than the buying prices to encourage local consumption of PV energy. According to the business model of ESP, the profit comes from the difference between the internal prices and the utility grid prices and is affected by the network losses. The internal buying prices should be greater than the internal selling prices.

With multi-ESR pricing strategy and different network usage fees, the profit function of the ESP is formed by a three-part series: trade with prosumers, trade with the utility grid, and network usage fee

$$R\left(p_{bn,h}, p_{sn,h}\right) = \begin{cases} \sum_{n=1}^{N} p_{bn,h}E_{bn,h} - \sum_{n=1}^{N} p_{sn,h}E_{sn,h} + g_{b,h}\left(E_{s,h} - E_{b,h}\right) \\ \qquad - \left(\lambda_{\text{med}} - \lambda_{\text{high}}\right) E_{s,h} \;\; E_{b,h} > E_{s,h} \\ \sum_{n=1}^{N} p_{bn,h}E_{bn,h} - \sum_{n=1}^{N} p_{sn,h}E_{sn,h} + g_{s,h}\left(E_{s,h} - E_{b,h}\right) \\ \qquad - \left(\lambda_{\text{med}} - \lambda_{\text{high}}\right) E_{b,h} \;\; E_{b,h} \le E_{s,h} \end{cases}. \quad (3)$$

$E_{b,h}$ and $E_{s,h}$ can be expressed as follows:

$$E_{s,h} = \sum_{n=1}^{N} E_{sn,h}, \quad E_{b,h} = \sum_{n=1}^{N} E_{bn,h}. \quad (4)$$

The total amount of energy buying and selling in ESR n at time slot h can be further described as

$$E_{sn,h} = \sum_{i \in S} l_{ni,h}E_{si,h}, \quad E_{bn,h} = \sum_{i \in B} l_{ni,h}E_{bi,h}. \quad (5)$$

When $l_{ni,h} = 1$, it means prosumer i selects to participate in ESR n at time slot h. According to the open-loop principle for the operation of DN, the prosumer i is only permitted to participate in one ESR at each time slot, which is denoted as $\boldsymbol{l}_{-ni,h} = 0$, where $\boldsymbol{l}_{-ni,h} = [l_{1i,h}, \ldots l_{(n-1)i,h}, \; l_{(n\,+\,1)i,h}, \ldots l_{Ni,h}]$ $\text{n} \in [1, 2, \ldots N]$.

When $E_{b,h} > E_{s,h}$, the network usage fee in (3) is $(\lambda_{\text{med}} - \lambda_{\text{high}})E_{s,h}$ and the energy $(E_{s,h} - E_{b,h})$ trade with the utility grid with the price $g_{b,h}$, whereas when $E_{b,h} \le E_{s,h}$, the network usage fee in (3) is $(\lambda_{\text{med}} - \lambda_{\text{high}})E_{b,h}$, and the energy $(E_{s,h} - E_{b,h})$ trade with the utility grid with the price $g_{s,h}$. Taking $E_{b,h} > E_{s,h}$ for analysis, the buying and selling energies from prosumers are balanced in one ESR, and then the surplus selling energy from the different ESRs initially be traded with other ESRs with surplus buying energy. This should be exchanged across 10 kV and 110 kV power lines and need to pay the network usage fee. Then, the rest of buying energy will be traded with the utility grid to attain the energy balance in the DN.

There will be some constraints in DN, such as AC power balanced, power line capacity (i.e., congestion) and voltage deviation [32], [33], which keep the normal operation of the DN. The voltage is assumed to be regulated by the utility grid to meet the operational requirements. The constraints of energy balance should always be satisfied in the energy-sharing mechanism. The power line capacity, the 10-kV transformer and power feeder, is generally checked by the distributed services operator (DSO), and the interaction between the ESP and DSO is expressed as follows.

1) The ESP and prosumers determine the P2P energy-sharing mechanism, i.e., their strategies.
2) The information obtained by the ESP and prosumer will send to the DSO to check whether the power flow exceeds the power line transmission capacity and results in congestion. If there is overload in the power line, the power line transmission capacity will be a constraint added to the next optimization process to obtain the new energy-sharing schedule.

The constraints of energy balance and power line capacity can be expressed as follows:

$$|E_{s,h} - E_{b,h}| + E_{\text{loss},h} = E_{g,h} \quad (6)$$

$$|E_{sn,h} - E_{bn,h}| \le E_{\max,h} \quad \text{n} \in [1, 2, \ldots N] \quad (7)$$

$$|E_{si,h}| \le pl_i \; |E_{bi,h}| \le pl_i \;\; i \in [1, 2, \ldots M] \quad (8)$$

where $E_{\text{loss},h}$ can be acquired from the smart meters of prosumers.

B. Utility Model of Prosumer

As large industrial users, PV prosumers can adjust the energy consumptions and ESR selection variables (i.e., turn ON/OFF the switches) that affect the buying and selling energy in an ESR. In the energy-sharing framework, the two variables are used by the internal prices set by ESP.

In the DN, there are M prosumers divided by $M_B = |B|$ buying prosumers and $M_S = |S|$ selling prosumers. The energy consumption of each prosumer can be decided by itself

$$E_{si,h} = E_{i,h} - x_{i,h}\, E_{bi,h} = x_{i,h} - E_{i,h}. \tag{9}$$

The utility function of PV prosumers can be defined as follows:

$$V_{i,h}\left(x_{i,h}, l_{1i,h}, \cdots, l_{ni,h}\right) = \begin{cases} k_{i,h}\ln(1+x_{i,h}) + \sum\limits_{n=1}^{N} l_{ni,h}p_{sn,h}\left(E_{i,h} - x_{i,h}\right) \\ \quad + \gamma E_{i,h} \;\; E_{i,h} - x_{i,h} > 0 \\ k_{i,h}\ln(1+x_{i,h}) + \sum\limits_{n=1}^{N} l_{ni,h}p_{bn,h}\left(E_{i,h} - x_{i,h}\right) \\ \quad + \gamma E_{i,h} \;\; E_{i,h} - x_{i,h} \le 0 \end{cases} \tag{10}$$

where the utility function is divided into three parts. The first part $k_{i,h}\ln(1 + x_{i,h})$ means the utility by using energy $x_{i,h}$. It is noted that $k_{i.h}$ is a preference parameter of prosumer i in time slot h and changes with the behavioral characteristics of the prosumer. $\ln(\cdot)$ has been widely used in economics for modeling the preference ordering of users and decision making. Also, recently, it has been shown to fit for designing the utility of energy consumers [34]. The second part $l_{ni,h}p_{sn,h}(E_{i,h} - x_{i,h})$ or $l_{ni,h}p_{bn,h}(E_{i,h} - x_{i,h})$ represents the profit or cost of energy sharing. The prosumers may opt to link the different ESRs by ESR selection variables $l_{ni,h}$ to maximize utilities. The third part $\gamma E_{i,h}$ is the subsidy of PV energy from the government.

Based on the open-loop operation requirement of DN, each prosumer can only trade with only one ESR in a time slot. Moreover, the loads (i.e., consumption) can generally be classified as fixed or flexible loads [35]. Thus, the energy consumption should have upper and lower bounds. Therefore, there are three constraints for the utility model

$$\sum_{n=1}^{N} l_{ni,h} = 1, \quad l_{ni,h} = \{0, 1\} \tag{11}$$

$$x_{i\min,h} < x_{i,h} < x_{i\max,h}. \tag{12}$$

For the two variables, $x_{i,h}$ is a general variable, whereas $l_{ni,h}$ is an integer variable (only 0/1). Thus, the utility function is a nonlinear mixed integer programming problem, which is complicated to resolve. For simplicity, (10) can be further changed into a splitting function. Consider $E_{i,h} - x_{i,h} \le 0$ for analysis

$$\begin{cases} V1_i^h\left(x_i^h(1)\right) = k_i^h \ln(1 + x_i^h(1)) \\ \qquad\qquad + p_{b1}^h\left(E_i^h - x_i^h(1)\right) \qquad l_{1i} = 1 \\ \vdots \\ Vn_i^h\left(x_i^h(n)\right) = k_i^h \ln(1 + x_i^h(n)) \\ \qquad\qquad + p_{bn}^h\left(E_i^h - x_i^h(n)\right) \qquad l_{ni} = 1 \\ \vdots \\ VN_i^h\left(x_i^h(N)\right) = k_i^h \ln(1 + x_i^h(N)) \\ \qquad\qquad + p_{bN}^h\left(E_i^h - x_i^h(N)\right) \qquad l_{Ni} = 1 \end{cases}. \tag{13}$$

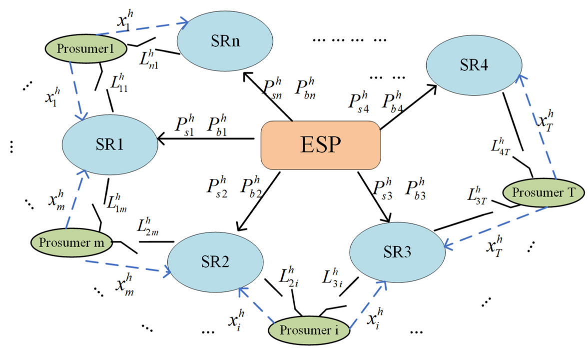

Fig. 2. Schematic diagram of the interaction of ESP and prosumers.

It is easy to prove that the utility function is convex while the maximum value can be taken from the extremum

$$x_{i,h} = \frac{k_{i,h}}{\sum_{n=1}^{N} l_{ni,h} \cdot p_{bn,h}} - 1. \tag{14}$$

Equation (14) also has a splitting form

$$\begin{cases} x_{i,h}(1) = k_{i,h}/p_{b1,h} - 1 \quad l_{1i,h} = 1 \\ \vdots \\ x_{i,h}(n) = k_{i,h}/p_{bn,h} - 1 \quad l_{ni,h} = 1 \\ \vdots \\ x_{i,h}(N) = k_{i,h}/p_{bN,h} - 1 \; l_{Ni,h} = 1 \end{cases}. \tag{15}$$

Thus, based on the internal prices $p_{sn,h}$ and $p_{bn,h}$ set by ESP, the prosumers can calculate the participating optimal consumption in each ESR. Finally, the prosumers compare the results of energy consumption and identify the most profitable scenario.

IV. Stackelberg Game Model and Algorithm

A. Stackelberg Game Model

The Stackelberg game is a theory used to provide solutions for the asymmetric competition among multiagents. The participants are grouped as leaders and followers, where time differences exist between them in making decisions. First, leaders make strategies, whereas followers interact to maximize their benefits [36], [37]. There is only one optimal solution called Stackelberg equilibrium (SE), which leads both players to maximize the profit.

In the energy-sharing framework, ESP acts as the leader with multi-ESR pricing strategy, which sets dynamic internal prices in the different ESRs considering the energy consumption and balance inside an SE. The PV prosumers act as the followers, who can do DR based on the internal prices set by ESP. The DR strategies may include ESR selection and load adjustment. The interaction between ESP and prosumers is shown in Fig. 2.

The game between ESP and prosumers is defined by the strategic form as follows:

$$K = \begin{Bmatrix} (M \cup \text{ESP}), \{\boldsymbol{X}_h\}, \{\boldsymbol{L}_h\}, \{\boldsymbol{P}_{s,h}\}, \\ \{\boldsymbol{P}_{b,h}\}, \{\boldsymbol{V}_h\}, \{R_h\} \end{Bmatrix} \tag{16}$$

where $\boldsymbol{X}_h$ and $\boldsymbol{L}_h$ are the optimal energy consumptions and the optimal ESR selection variables provided by all prosumers based on the internal prices set by ESP, respectively; $\boldsymbol{P}_{s,h}$ and $\boldsymbol{P}_{b,h}$ are the internal selling and buying prices of each ESR set by ESP based on prosumer's inclined (e.g., consumption, role, ESR selection, and PV generation), respectively; $\boldsymbol{V}_h$ is the profit function of prosumers, which depends on their consumption, ESR selection, and subsidies; R_h is the profit function of ESP, which is based on the shared energy, the unbalanced energy traded with the utility grid, and the network usage fee between ESR.

In game K, the ESP and prosumers are set to get the maximum profit. For this purpose, one feasible solution is SE where the leader attains its optimal prices with the followers' best responses.

Definition 1: There has a unique SE in the given Stackelberg game K such as $(\boldsymbol{X}'_{i,h}, l'_{ni,h}, p'_{sn,h}, p'_{bn,h})$, if and only if it satisfies the following set of inequalities:

$$\begin{aligned} &V_{i,h}\left(\boldsymbol{X}'_{i,h}, l'_{ni,h}, p'_{sn,h}, p'_{bn,h}\right) \\ &\quad \geq V_{i,h}\left(x_{i,h}, \boldsymbol{X}'_{-i,h}, l_{ni,h}, p'_{sn,h}, p'_{bn,h}\right) \\ &\quad \forall i \in M, \forall x_{i,h} \in \boldsymbol{X}_{i,h}, \forall l_{ni,h} \in \boldsymbol{L}_{i,h} \end{aligned} \tag{17}$$

$$\begin{aligned} &R_h\left(\boldsymbol{X}'_{i,h}, l'_{ni,h}, p'_{sn,h}, p'_{bn,h}\right) \geq R_h\left(\boldsymbol{X}'_{i,h}, l'_{ni,h}, p_{sn,h}, p_{bn,h}\right) \\ &\quad \forall p_{bn,h} \in \boldsymbol{P}_{bn,h}, \forall p_{sn,h} \in \boldsymbol{P}_{sn,h} \end{aligned} \tag{18}$$

where $\boldsymbol{X}'_{-i,h} = [x'_{1,h}, x'_{2,h}, \cdots, x'_{i-1,h}, x'_{i+1,h}, \cdots, x'_{M,h}]$.

When all participants (such as ESP and prosumer) reach SE equilibrium, they can attain the maximum profits. ESP cannot increase profit by solely modifying its pricing. Similarly, the prosumers cannot increase the profit by simply reselecting the ESR or adjusting the energy consumption.

Theorem 1: The unique SE always exists in the proposed Stackelberg game *K* between the ESP and prosumers.

Proof: Compared with the Stackelberg game presented in [30], the ESR selection variables are added into the utility function (10) of prosumers and multi-ESR into profit function (3) of ESP. It is given in (10), (13), and (15), where the utility function of the prosumers is strictly concave with respect to $x_{i,h}, l_{ni,h}, \forall i \notin M$, and $n \in N$.

To show the uniqueness of SE in-game *K*, the uniqueness of the optimized prices $p'_{bn,h}$ and $p'_{sn,h}$ should be proven. By substituting (9) and (15) into (5) with each $l_{ni,h}$, the following can be obtained:

$$\begin{aligned} E_{bn,h} &= \frac{\sum_{i\in B} l_{ni,h}\cdot k_{i,h}}{p_{bn,h}} - \sum_{i\in B} l_{ni,h} - \sum_{i\in B} l_{ni,h}\cdot E_{i,h} \\ E_{sn,h} &= \sum_{i\in S} l_{ni,h}\cdot E_{i,h} - \frac{\sum_{i\in S} l_{ni,h}\cdot k_{i,h}}{p_{sn,h}} + \sum_{i\in S} l_{ni,h}. \end{aligned} \tag{19}$$

When $E_{b,h} > E_{s,h}$, the objective function of ESP can be achieved by substituting (19) into (3) as follows:

$$\begin{aligned} &\max R\ (p_{bn,h},\ p_{sn,h}) \\ &= \sum_{n\in N} p_{bn,h}\left(\frac{\sum_{i\in B} l_{ni,h}\cdot k_{i,h}}{p_{bn,h}} - \sum_{i\in B} l_{ni,h} - \sum_{i\in B} l_{ni,h}\cdot E_{i,h}\right) \\ &- \sum_{n\in N} p_{sn,h}\left(\sum_{i\in S} l_{ni,h}\cdot E_{i,h} - \frac{\sum_{i\in S} l_{ni,h}\cdot k_{i,h}}{p_{sn,h}} + \sum_{i\in S} l_{ni,h}\right) \\ &+ g_{b,h}\left(\sum_{n\in N}\left(\sum_{i\in S} l_{ni,h}\cdot E_{i,h} - \frac{\sum_{i\in S} l_{ni,h}\cdot k_{i,h}}{p_{sn,h}} + \sum_{i\in S} l_{ni,h}\right)\right. \\ &\left. - \sum_{n\in N}\left(\frac{\sum_{i\in B} l_{ni,h}\cdot k_{i,h}}{p_{bn,h}} - \sum_{i\in B} l_{ni,h} - \sum_{i\in B} l_{ni,h}\cdot E_{i,h}\right)\right) \\ &- \Delta\lambda \sum_{n\in N}\left(\sum_{i\in S} l_{ni,h}\cdot E_{i,h} - \frac{\sum_{i\in S} l_{ni,h}\cdot k_{i,h}}{p_{sn,h}} + \sum_{i\in S} l_{ni,h}\right). \end{aligned} \tag{20}$$

Because $E_{b,h} \leq E_{s,h}$ is similar to $E_{b,h} > E_{s,h}$, their differences are that the utility $g_{b,h}$ changes to $g_{s,h}$ and the network usage fee changes to

$$\Delta\lambda \sum_{n\in N}\left(\frac{\sum_{i\in B} l_{ni,h}\cdot k_{i,h}}{p_{bn,h}} - \sum_{i\in B} l_{ni,h} - \sum_{i\in B} l_{ni,h}\cdot E_{i,h}\right). \tag{21}$$

Consequently, the feasible region Ω is divided into Ω_1 and Ω_2 according to $E_{b,h}$ and $E_{s,h}$, and $(p_{(bn1,h)}, p_{(sn1,h)}) \in \Omega_1$, $(p_{(bn2,h)}, p_{(sn2,h)}) \in \Omega_2$ is defined. It is shown that

$$\Omega_1 \cup \Omega_2 = \Omega, \quad \Omega_1 \cap \Omega_2 = \emptyset. \tag{22}$$

With the different ESR *n,* just the sum in *R* and different sums of the terms do not change the convexity, the $N = 2$ is set to analyze the Hessian matrix when $E_{b,h} > E_{s,h}$ The Hessian matrix *H* of *R* with respect to $p_{(sn,h)}$ and $p_{(bn,h)}$ is as follows:

$$H = \text{diag}\left\{\begin{array}{c} -\left(1+20g_{b,h}\right)\sum_{i\in B} l_{1i,h}\cdot k_{i,h}/10p^3_{b1,h}, \\ -2g_{b,h}\sum_{i\in S} l_{1i,h}\cdot k_{i,h}/p^3_{s1,h} \\ -\left(1+20g_{b,h}\right)\sum_{i\in B} l_{2i,h}\cdot k_{i,h}/10p^3_{b2,h}, \\ -2g_{b,h}\sum_{i\in S} l_{2i,h}\cdot k_{i,h}/p^3_{s2,h} \end{array}\right\}. \tag{23}$$

When $E_{b,h} \leq E_{s,h}$, the situation is similar. Considering that $k_{i,h} > 0, p_{bn,h} > 0, p_{sn,h} > 0, g_{b,h} > 0, g_{s,h} > 0, \quad \forall i \in M, \forall h \in H, \forall n \in N$, H is the negative definite and *R* is strictly concave with respect to $p_{sn,h}$ and $p_{bn,h}$. Therefore, the optimal internal prices $(p'_{sn1,h}, p'_{bn1,h})$ and $(p'_{sn2,h}, p'_{bn2,h})$ are existent and unique in Ω_1 and Ω_2. The optimal prices in Ω are given as follows:

$$\begin{aligned} &\left(p_{bn,h}{}', p'_{sn,h}\right) \\ &= \arg \max_{\left(p_{bn,h}, p_{sn,h}\right)} \left(R\left(p_{bn1,h}{}', p_{sn1,h}{}'\right), R\left(p_{bn2,h}{}', p_{sn2,h}{}'\right)\right). \end{aligned} \tag{24}$$

Then, the ESP can provide the optimal internal prices $(p'_{sn,h}, p'_{bn,h})$ to maximize its profits. Thus, there exists a unique SE and Theorem 1 is proved.

B. Solution Process of the Game

By establishing $\partial^2 Vn_{i,h}/\partial(x_{i,h}(n))^2 < 0$ when $\forall i \in M$, it is noted that the utility function $Vn_{i,h}$ of the prosumers is strictly

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Algorithm 1.

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1. Input the initial date and set the parameters, γ, $\lambda_{\text{med}} - \lambda_{\text{high}}$, $g_{b,h}$ and $g_{s,h}$, $g_{b,h}$ and $g_{s,h}$, will be set as the initial prices, respectively.
2. ***For*** each time $h \in H$
3. Each prosumer calculates the value of $k_{i,h}$ by Eq. (15) and selects the role of the seller or buyer, then submits the initial data $k_{i,h}$, $l_{ni,h}$, and their role.
4. Optimize $p_{sn,h}$ and $p_{bn,h}$ by solving the nonlinear constrained programming by interior point method.
   Max R_h
   s.t.
   $g_{s,h} < p_{sn,h} < p_{bn,h} < g_{b,h}$
   $E_{b,h} > E_{s,h}$, buyer > 0
   $E_{b,h} \leq E_{s,h}$, seller > 0
   The objective function R_h can be calculated based on (20).
5. If seller $= 0$ and buyer $= 0$, set $p_{sn,h}$ and $p_{bn,h}$ equal to $g_{b,h}$ and $g_{s,h}$, respectively.
6. Send ESP prices to each prosumer
7. Each prosumer calculates the value of $x'_{i,h}$, chooses the best $l'_{ni,h}$, and estimates their profits.
8. ***End for***

---

convex at $x_{i,h}\,\forall i \in M$. That is, in one ESR, the consumption $x_{i,h}$ of prosumers will be uniquely based on the internal prices set by ESP. So, Stackelberg game K achieves SE when both consumption $x_{i,h}$ and internal prices $p_{sn,h}$ and $p_{bn,h}$ are optimal solutions. Because of the formulas and constraints of the ESP and prosumers' profit are cited earlier, Stackelberg game K can be solved by a centralized algorithm to achieve the maximum profit. The implementation is seen in Algorithm 1.

To implement the function of coordinating the P2P energy sharing and setting the dynamic internal prices, a server should be deployed in the ESP. On the prosumer side, the UEMS with smart meters should be used to execute their strategies. In addition, the interaction between the prosumer and ESP is realized via an advanced metering infrastructure system [38].

V. Case Study

A. Basic Data

An industrial park of the DN in Guangdong Province, China, is used as the study case. This involves 15 PV prosumers while the DN is grouped into three ESRs (e.g., $N = 3$) by 110 kV/10 kV transformers, as shown in Fig. 3. The load information shown in Fig. 3 is the netload of each prosumer at time slot 7 (i.e., the first time slot), and all the possible ESR selections are also expressed. Each prosumer will access a certain ESR determined by an initial ESR selection strategy. Moreover, each prosumer can be part of the different ESRs based on the connections. However, this only enables to connect one ESR in the one-time slot because of an open-loop operation requirement. The ESR selection variables only can be set as 0 or 1. The data of energy consumption, PV generation, and netload per hour are collected from the smart meters installed in the prosumer side (see Fig. 4). Based on the netload, prosumers act as sellers or buyers in an ESR, using the internal prices set by ESP to trade with other prosumers. The PV subsidies, $\gamma = 0.378$, where the price of utility grid adopts feed-in tariff of distributed PV energy in most Chinese areas, $g_{s,h}$ and $g_{b,h}$ are set as 0.4 and 1.0 CNY/kWh, respectively.

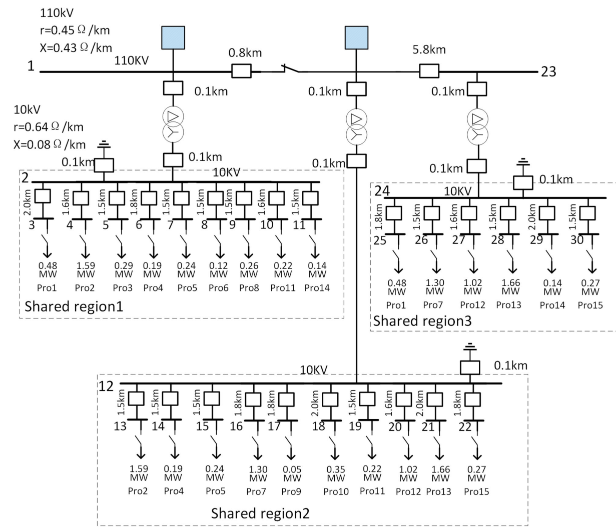

Fig. 3. Topology of the case study.

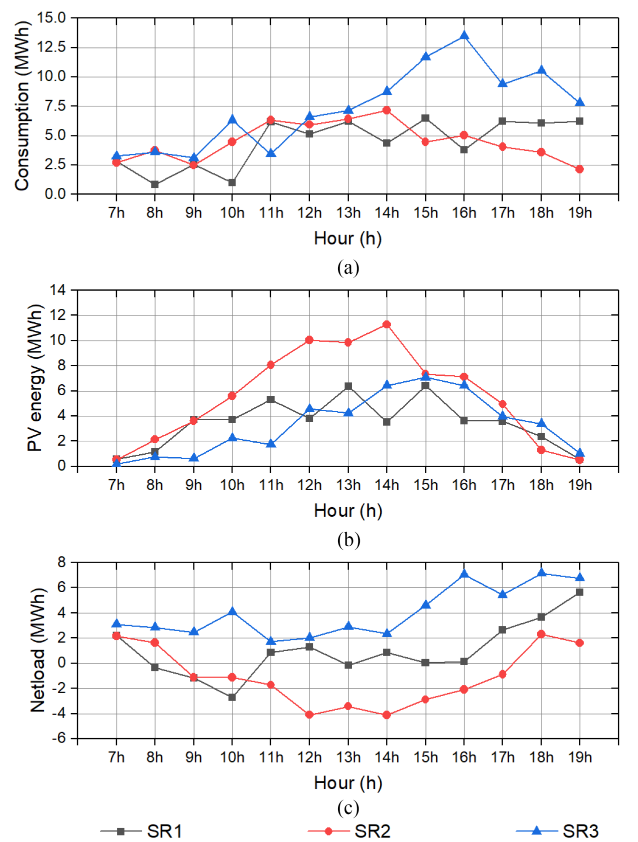

Fig. 4. Consumption, PV generation, and netload of PV prosumers in each ESR. (a) Original consumption. (b) Original PV energy. (c) Original netload.

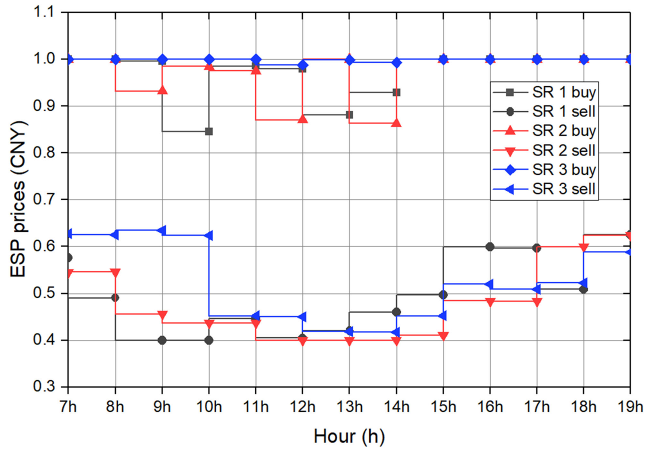

Fig. 5. Internal prices set by ESP.

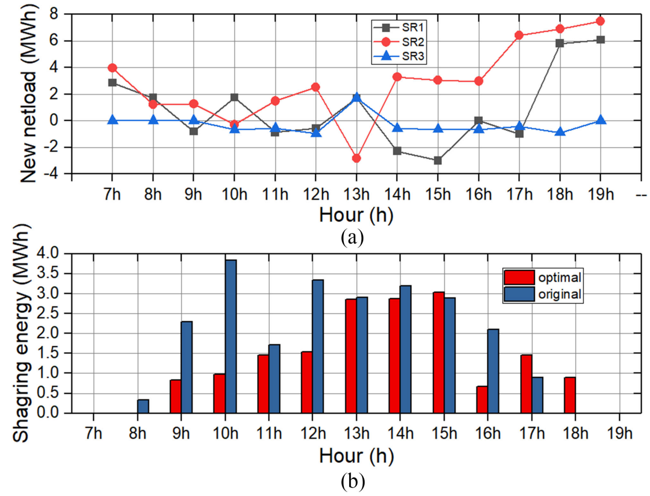

Fig. 6. Optimized netload and its standard deviation compared with the original. (a) New netload. (b) Sharing energy.

The transmission–distribution prices are set as $\lambda_{\text{med}} = 0.45$ and $\lambda_{\text{high}} = 0.40$ CNY/kWh [29].

B. Analysis of the Results

1) Results of Internal Prices: Fig. 5 shows the internal prices of the different ESRs set by ESP. Based on the results, it can be seen that the internal prices of the different ESRs are tightly correlated with the original netloads of ESRs, as shown in Fig. 4(c). Considering the different profiles of the three ESRs netloads, the results of pricing can be analyzed into two aspects.

a) Internal prices of ESR1 and ESR2: In time slots 7 and 15–19, the internal buying prices are nearly similar to the utility grid, whereas the internal selling prices are higher than the utility grid. The reason is that the PV energy in these time slots is insufficient. Thus, ESP stimulates the prosumers to sell more energy by increasing the internal selling prices.

In time slots 10–14, the internal selling prices are approximately equal to that of the utility grid, whereas the internal buying prices are lower than the utility grid. The results show that the ESP turns down the internal buying prices and then motivates the prosumers to increase the consumption of PV energy.

b) Internal prices of ESR3: The results of the internal buying prices in ESR3 are different from the ESR1 and ESR2. In Fig. 5, the internal buying prices in ESR3 are equal or near the price of the utility grid, mostly in every time slot. This is mainly brought by the original netload of ESR3, which is all positive and the PV energy is a scarce resource. In contrast, the internal selling prices are higher than the price of the utility grid, especially in the time slots with insufficient PV energy.

2) Results of Prosumer Actions: After the results of the internal prices of the different ESRs, the prosumers are being incentivized to change a participated ESR and the energy consumptions. Fig. 6(a) shows the optimal netloads of the three ESRs, whereas Fig. 6(b) shows the sharing energy of the ESRs. Aside from the results presented in Fig. 6(a), the number of participating prosumers in the three ESRs is listed in Table I.

TABLE I
SUMMARY OF ESR SELECTION VARIABLES IN EACH ESR

	ESR 1		ESR 2		ESR 3	
	Opti-mal	Ori-ginal	Opti mal	Ori-ginal	Opti-mal	Ori-ginal
7h	9	6	6	5	0	4
8h	8	4	7	6	0	5
9h	5	6	10	5	0	4
10h	6	4	8	7	1	4
11h	9	5	5	7	1	3
12h	7	3	6	7	2	5
13h	9	4	2	7	4	4
14h	9	3	5	7	1	5
15h	8	4	6	5	1	6
16h	9	3	5	6	1	6
17h	7	4	7	6	1	5
18h	4	4	10	4	1	7
19h	5	5	10	4	0	6

In Fig. 6(a) and Table I, it is noted that ESR selection variables and netloads are different from the original in all the time slots. For instance, in time slots 7–10, the buyer has the main function, since the PV energy is scarce and the selection in ESR3 has turned to ESR1 and ESR2 with the reduced buying prices. This leads to the new netload in Fig. 6(a) focused on ESR1 and ESR2. However, in time slots 13–15, the netloads fluctuate to zero, as the PV energy is sufficient in these time slots, where the current selling and buying prosumers in each ESR work together to increase the profit of ESP by boosting the sharing energy inside the ESR. In this case, the ESR selections in the three ESRs are in desperation. Furthermore, in time slots 18–19, the energy refocuses on ESR1 and ESR2 to minimize the dispersion of energy for the convenience of ESP to selling the energy.

Fig. 6(b) shows that the total sharing energy within ESRs is reduced from 23.5 to 16.56 MW in all the time slots. Thus, it is shown that the optimal results increase the sharing energy inside an ESR for a higher ESP profit and minimize the sharing energy in the inter ESRs for a reduced network usage fee, as compared with the original setting.

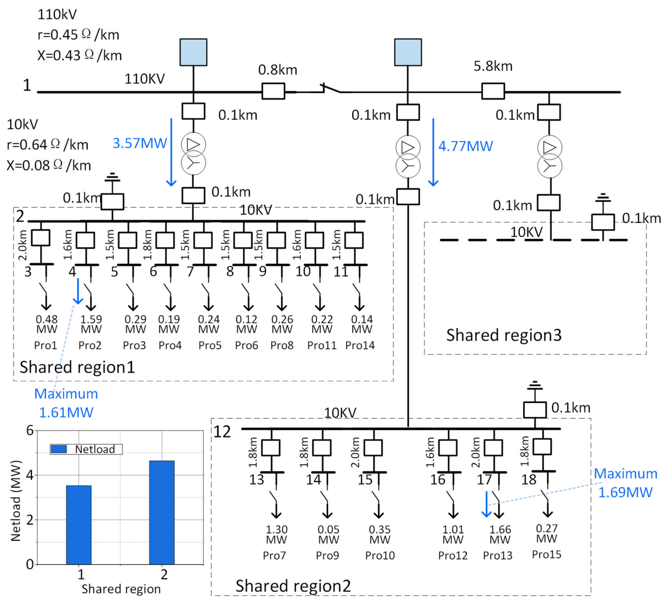

Fig. 7. Load distribution and main power flow in time slot 7.

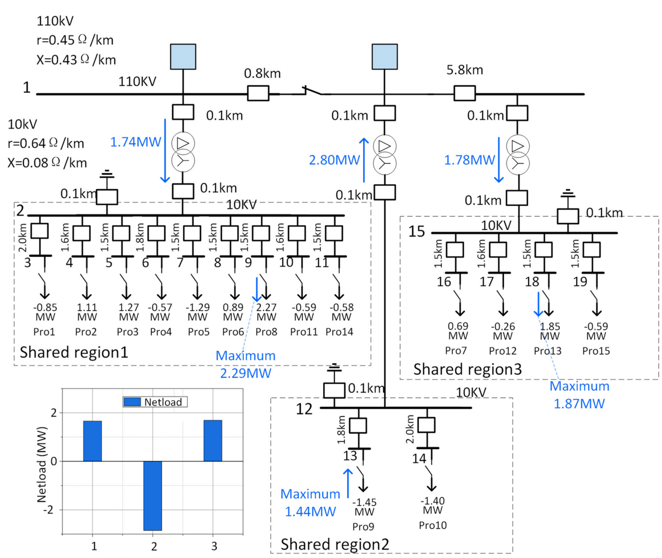

Fig. 8. Load distribution and mainly power flow in time slot 13.

3) Results of Power Flow in the DN:

After the Stackelberg game K, the prosumers and ESP will obtain their optimal strategies. Because the load distribution and ESR selection of prosumers are different from the initial distribution and selection, the power flow of the system will change. In addition, the netload within each ESR will also be different. Therefore, the power line capacity should be checked following the steps listed in Section III. The *Matpower* toolbox in MATLAB was used to calculate the power flow of the system, and the results are presented in Figs. 7 and 8.

Fig. 7 illustrates the load distribution and main power flow of the optimal strategies of the prosumer in time slot 7, which is the same time slot as that presented in Fig. 3. It is clear that the ESR selection of the prosumer has changed, and due to the low PV production, the load information of the prosumer is the same as before. However, with the different ESR selections, the netloads in each ESR are different from the original netload, resulting in the change of the power flow of the DN. In addition, the power flow on each power line is satisfied the constraints of power line capacity, and network losses of the entire system are 0.204 MW.

Fig. 8 illustrates the main power flow and load distribution of the optimal strategies of the prosumer in time slot 13, which is one of the time slots with the most PV production. Combined with Fig. 7, it can be seen that with the increase in PV production, the role of prosumers changes to the seller role from the buyer role (i.e., a negative netload appears). Under the influence of dynamic internal prices, prosumers also adjust the load distribution and ESR selection, so that the load distribution in each ESR changes, resulting in the new power flow. Additionally, the network loss of the system is 0.167 MW (except for the power losses in the 110 kV power line), which is lower than the network loss with less PV production.

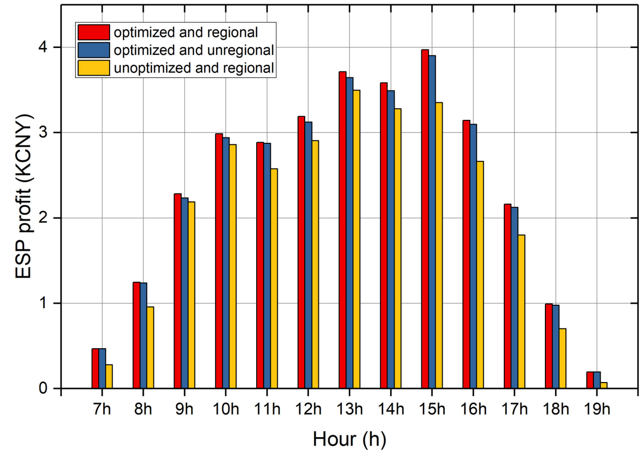

Fig. 9. Profit of ESP.

C. Comparing With the Method Without Multi-ESR Pricing Strategy

To show the advantage of multi-ESR pricing strategy, the results with the method presented in [30] are compared. The three scenarios include 1) optimized and regional, 2) optimized and unregional [30], and 3) unoptimized and regional.

Fig. 9 shows the hourly profit of ESP in the three scenarios. The profit of ESP in the optimal and regional scenarios is higher compared with others all the time, especially in time slots 12–16. At this time, they have the most PV energy. Also, it is noted that the ESP profit basically comes from PV energy. Moreover, the difference in the profits between regional and unregional is also based on the network usage fee. Without a multiregional pricing strategy, all prosumers will select different ESRs at random, which increases the unbalanced energy in each 10 kV side, indicating a higher network usage fee. Also, the unoptimized

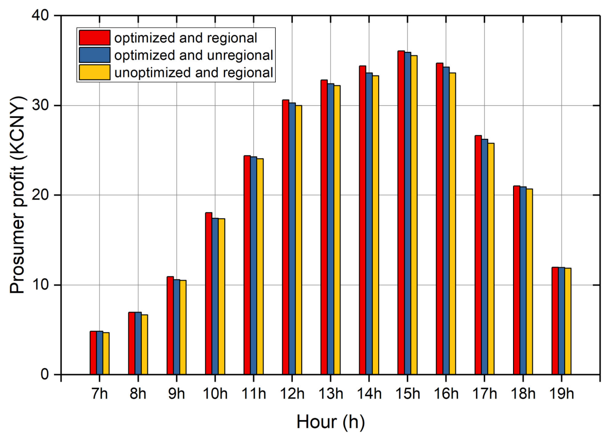

Fig. 10. Profit of the PV prosumers.

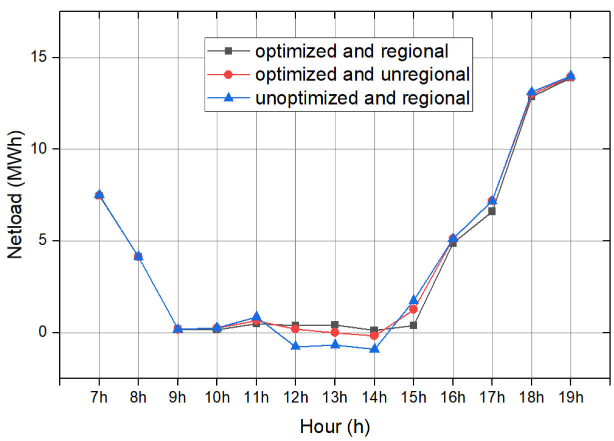

Fig. 11. Aggregated netload profile of all the prosumers.

profit of the ESP is lower than the optimized in all available times.

Fig. 10 shows the hourly profits of PV prosumers in the three scenarios. The optimized and regional profits are higher in time slots 9–17, highlighting that the multi-ESR pricing strategy has a more profitable strategy than other scenarios. This is the reason prosumers can operate more flexible with the DR strategies of ESR selection and load adjustment. However, in time slots 7-8 and 18-19, PV energy is reduced and the regional profit is equal to the unregional profit. Such phenomenon shows that the advantage of multi-ESR pricing strategy decreases when PV energy is low, but there are many time slots that PV energy is high within the day.

By combining Fig. 9 and 10, it can be concluded that the multi-ESR pricing strategy and DR strategies of ESR selection and load adjustment can increase the profits of PV prosumers and ESP. This can be done by setting the different internal prices and considering the ESR selection variables of the prosumers.

Fig. 11 shows the aggregated netload profiles of all the prosumers. The netload profile that uses the optimized and regional methods has the lowest impact on the utility grid in time slots 11–15 when there is more PV energy.

D. Analysis of the Practical Realization

For Stackelberg game K, a centralized algorithm is designed to resolve it. Initially, the prosumers provide the original energy consumption, PV energy generation, ESR selection, and participating role (buyer or seller) to the ESP. Then, the ESP can set the internal prices $p_{sn,h}$ and $p_{bn,h}$ and return it to the prosumers. The prosumers create their new strategies based on the internal prices to optimize their profits. Ultimately, both the prosumers' and ESP's profits are maximized at SE. In this process, only a few kB of information needs to be exchanged between the prosumers and ESP, which can almost instantaneously be completed by the existing advanced equipment and sensors of the distribution network. Furthermore, a computer with Intel Core i5-8250 CPU 1.60 GHz, 16 G memory, and MATLAB 2018a is used as the testing environment for the algorithm. For the proposed model with multi-ESR, the calculation time is 1.104 s and that for the model without ESR partition is 0.728 s. Both calculation times are measured in seconds, and the computation complexity will not increase with the number of the prosumers since the computation complexity is O (1).

VI. Conclusion

In this article, a P2P energy-sharing framework was proposed based on Stackelberg game with multiregional pricing strategy in the ESP and DR strategies of ESR selection and load adjustment in the prosumers. Based on the framework, a profit model of ESP was created considering the differentiation dynamic internal prices. Also, a utility model of the prosumers was designed, including the ESR selection and flexible load. For the ESP and prosumers, the framework can increase energy-sharing flexibility by formulating the multi-ESR pricing strategy of ESP and the DR strategies of the prosumers. As for the DN, the framework can reduce the negative impact of PV energy on the utility grid. Moreover, the rationale and possible responses of the different PV prosumers were considered in this article. Through the realistic data from a demonstration project, it can be concluded that the ESP and prosumers can increase profits compared with utility grid prices and unregional scenarios. Also, the energy sent into the utility grid was mildly benefiting the stability of a utility grid. Thus, for the real DN in Guangzhou Province, China, it highlights the potential benefits of the P2P energy-sharing framework in the practical operation. Future work will include an investigation of the dynamic ESR partitioning method to better adapt it to the DN and of a day-ahead business model with time-coupled flexible load to better fit complex application.

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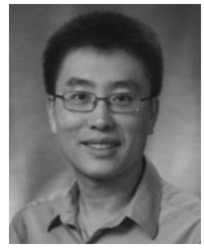
Liudong Chen (Student Member, IEEE) is currently working toward the master's degree in electrical engineering with the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China.

His current research interests include distribution system optimization, smart grids, and edge computing.

Nian Liu (Member, IEEE) received the B.S. and M.S. degrees in electric engineering from Xiangtan University, Hunan, China, in 2003 and 2006, respectively, and the Ph.D. degree in electrical engineering from North China Electric Power University, Beijing, China, in 2009.

He is currently a Professor with the School of Electrical and Electronic Engineering, North China Electric Power University. He is also a Member of the State Key Laboratory of Alternate Electrical Power System With Renewable Energy Sources and a Member of the Standardization Committee of Power Supply and Consumption in Power Industry of China. He was a Visiting Research Fellow with the Royal Melbourne Institute of Technology (RMIT) University, Melbourne, VIC , Australia, from 2015 to 2016. He has authored or coauthored more than 160 journal and conference publications and has been granted for more than 10 patents of China. His current major research interests include multienergy system integration, microgrids, cyber-physical energy system, and renewable energy integration.

Dr. Liu is an Editor of the IEEE TRANSACTIONS ON SMART GRID, IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, IEEE POWER ENGINEERING LETTERS, and *Journal of Modern Power Systems and Clean Energy*.



Jianhui Wang (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from Illinois Institute of Technology, Chicago, IL, USA, in 2007

He is currently an Associate Professor with the Department of Electrical and Computer Engineering, Southern Methodist University, Dallas, TX, USA. He has authored or coauthored more than 300 journal and conference publications, which have been cited for more than 20 000 times by his peers with an H-index of 69. He has been invited to give tutorials and keynote speeches at major conferences including IEEE Innovative Smart Grid Technologies (IEEE ISGT), IEEE Smart Energy Grid Engineering (IEEE SEGE), IEEE High Performance and Smart Computing (IEEE HPSC), Inven Global Esports Conference (IGEC-XI).

Dr. Wang is the past Editor-in-Chief of the IEEE TRANSACTIONS ON SMART GRID and an IEEE PES Distinguished Lecturer. He is also a Guest Editor of a Proceedings of the IEEE special issue on power grid resilience. He was the recipient of the IEEE PES Power System Operation Committee Prize Paper Award in 2015 and the 2018 Premium Award for Best Paper in IET Cyber-Physical Systems: Theory & Applications. He is a 2018 and 2019 Clarivate Analytics highly cited researcher for production of multiple highly cited papers that rank in the top 1% by citations for field and year in Web of Science.