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# Optimal Scheduling Strategy and Benefit Allocation of Multiple Virtual Power Plants based on General Nash Bargaining Theory

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## Abstract

The benefits of small-scale renewable energy resources are restricted by a feed-in-tariff strategy that works with distribution grids only. Virtual Power Plant (VPP) aggregates diverse distributed energy resources on the demand side for efficient control, which can improve their revenue and encourage the growth of renewable energy. Based on the general Nash bargaining theory, this paper proposes a multi-VPP energy-sharing mechanism. This approach enables VPPs to increase their revenue by engaging in peer-to-peer energy transactions. First, a general Nash bargaining-based model is proposed for multi-VPPs energy sharing considering peer-to-peer energy transactions. The model is then decomposed into two subproblems: minimizing the total cost of the VPP energy-sharing alliance, and the cost allocation of peer-to-peer energy transactions. Considering the privacy protection of VPPs, the first subproblem is solved by a distributed algorithm based on the alternating direction multiplier method. In the second subproblem, due to the introduction of a bargaining factor that is positively related to each VPP's contribution to energy sharing alliance, the cost allocation better reflects their contribution. The numerical test demonstrates the proposed energy-sharing mechanism, with little computational complexity, delivers a cost distribution result that is comparable to the classical Shapley value while promoting the development of renewable energy resources.

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*Keywords:* distributed energy resources; game theory; General Nash bargaining; peer-to-peer energy trading; virtual power plant

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## Nomenclature

### Abbreviations

<i>ADMM</i>	Alternating direction multiplier method
<i>AG</i>	Active generator
<i>DER</i>	Distributed energy resources
<i>ES</i>	Energy storage
<i>GNB</i>	General Nash bargaining
<i>GT</i>	Gas turbine
<i>KKT</i>	Karush–Kuhn–Tucker
<i>MG</i>	Microgrid
<i>P2P</i>	Peer-to-peer
<i>RE</i>	Renewable energy
<i>SoC</i>	State of Charge
<i>SV</i>	Shapley Value

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**Sets and Indexes**

$I$	Set of VPP $i$ within the energy-sharing alliance
$M$	Set of GT $m$ managed by each prosumer
$N$	Total number of EVs managed by VPP $i$
$T$	Set of time periods index $t$
$\Phi$	Constraints set for FL
$\Theta$	Constraints set for EV
$\Xi$	Constraints set for AG
$\Psi$	Constraints set for GT

**Parameters**

$\Delta t$	Time interval
$\lambda^b$	Vector of the time-of-use price of the retailer
$\lambda^s$	Vector of the feed-in tariff of retailer
$N_c$	The total number of EVs arrived at a charging station
$E_n^r$	The rated energy capacity of EV $n$
$\tilde{l}_{i,t}^{fl}$	Original load curve of FL
$p_n^r$	Rated charging power of EV $n$
$t_n^d$	Charging period of EV $n$
$\tilde{p}_{i,t}^{re}$	Forecasted RE power of VPP $i$
$a_g/b_g/c_g$	Cost factors of GT $g$
$c_{i,g}^{gt,su}, c_{i,g}^{gt,sd}$	Start-up/ shutdown cost of GT $g$
$\Delta_{i,g}^{gt}$	Maximum ramping rate of GT $g$
$p_{i,g}^{gt,max}$	The maximum power output of GT $g$
$p_{i,g}^{gt,min}$	The minimum power output of GT $g$
$p_{i,t}^{bl}$	Fixed load demand of VPP $i$
$r_i^{DR}$	The adjustable capacity ratio of FL
$\eta_i^c, \eta_i^d$	Charge/discharge efficiency of ES in AG
$\xi$	Convergence factor for price mechanisms
$r_k, s_k$	Convergence factors for fast-ADMM algorithm
$\tau$	Dual update step length
$c^{dis}$	Transmission cost per kWh of P2P transaction
$d^{i,j}$	Electrical distance for P2P transactions
$\gamma_t^{i,j}$	Transmission cost between VPP $i$ and VPP $j$
$\alpha_i$	Contribution factor of VPP $i$

**Variables**

$\lambda_t^{i,j}$	P2P trading price between VPP $i$ and VPP $j$
$p_{i,t}^{fl}$	Flexible load of VPP $i$
$L_{i,t}^u, L_{i,t}^d$	Load decrease or load increase of FL in VPP $i$
$u_{i,t}^u, u_{i,t}^d$	State variables corresponding to FL in VPP $i$
$p_{i,t}^{ev}$	EV charging power of VPP $i$
$u_{n,l}^{ev}$	State variables related to charging of EV $n$
$p_{i,t}^{re}$	RE power output in VPP $i$
$p_{i,t}^{ag}$	AG power output in VPP $i$
$p_{i,t}^{s,d}, p_{i,t}^{s,c}$	ES charging/discharging power in AG
$E_{i,t}^s$	State of charge of ES in AG
$p_{i,t}^{s,c}, p_{i,t}^{s,d}$	Charge/discharge power of ES in AG
$E_{i,g,t}^{gt}, p_{i,g,t}^{gt}$	Energy/power of GT $g$ in VPP $i$
$u_{i,g,t}^{gt}$	On/off state of GT $g$ in VPP $i$

$e_t^{i,j}$	P2P trading power between VPP $i$ and VPP $j$
$\varepsilon_t^{i,j}$	Coupled auxiliary variable for P2P transaction
Other notations are defined in the text.	

## 1. Introduction

### 1.1. Motivation and Background

Extreme weather induced by global climate change, as well as the energy crisis driven by geopolitics, have accelerated the growth of renewable energy (RE). However, the integration of large-scale RE into the power grid and the electrification of the final energy consumption will alter the pattern of power sources in response to variations in load demand. At the same time, the on-site access to enormous distributed energy resources (DERs) will challenge the instantaneous balance of the power system. Thus, besides the power plants on the supply side, it is critical and urgent to awaken demand-side DERs to improve the power system flexibility. However, as scattered small-scale RE units proliferate in the demand side of the power system, government subsidies for them are dwindling. Therefore, to be profitable and competitive, these DERs must transit from uncontrolled to controlled mode and participate in market transactions. To meet the necessary market access criteria, those DERs must first be regulated through aggregation<sup>[1]</sup>. Compared with microgrids or load aggregators, virtual power plant (VPP) aggregates small-scale DERs located across the distribution network for optimal control and engagement in market trading<sup>[2]</sup>.

Firstly, some papers have studied the internal optimal scheduling and trading with retailers of VPP in recent years. Most of them focused on smart grid control, the structure of VPP, types of RE and their intermittent impact on the grid, and their economic policies<sup>[3]</sup>. For example, in [4], an optimal VPP energy management strategy that takes into account the optimal power flow in the distribution network is proposed. However, current VPP business models that leverage the time-of-use price or feed-in-tariff as an incentive also put a cap on their profitability and zeal. Since this model only permits the VPPs to transact with a distribution network or retailer that is far more powerful than they are at unfavorable prices. As a result, an energy-sharing platform that allows VPPs to directly trade electrical energy with one another is required<sup>[5]</sup>. In [6], peer-to-peer (P2P) based VPPs are proposed for risk-averse energy trading of small-scale generations and consumers. While authors in [7] evaluated the feasibility of VPP participating in the Energy Internet under layered typical application scenarios. Considering the uncertainty of uncontrollable sources, an optimal bidding strategy of renewable-based VPP is developed in the day-ahead market in [8]. As in [9], combining VPPs and P2P energy trading will enable the achievement of energy matching, uncertainty reduction, and preference satisfaction for individual DERs on a larger scale.

By enabling direct trading amongst DERs, P2P trading aims to disrupt the grid's conventionally centralized structure. It helps prosumers by generating income, lowering electricity prices, and lessening their reliance on the grid<sup>[10]</sup>. Such as in [11], an inter-VPP P2P electricity trading scheme is proposed based on the blockchain platform, while authors in [12] developed the framework of a decentralized transaction for active prosumers in P2P markets. According to the energy-sharing mechanism for P2P electricity transactions, each participant strategically adapts the strategy to maximize their profits. The equilibrium is achieved when no participant could change unilaterally their strategy to increase their payoff. Thus, given the dynamic and antagonistic nature of power trading, studying P2P electricity trading based on game theory will provide theoretical and technical support for the decision-making process of VPPs with independent stakeholders<sup>[13]</sup>.

### 1.2. Relevant Literature

As a tool for analyzing strategies in competitive situations, game theory has two primary branches: non-cooperative games and cooperative games. The energy-sharing system based on the former takes into account the participants' conflicts of interest. The platform-led auction model is one of them. As the initial decision-making party, the platform takes the initiative, and the participants are the price takers. Typically, the model is built as a two-stage Stackelberg game problem, which is then solved by converting it to a mixed integer linear programming problem based on the Karush-Kuhn-Tucker (KKT) optimal condition. For example, the authors in paper [14] presented a cooperative Stackelberg game in which the power system plays as the leader and sets the price during peak demand, while prosumers act as followers and respond to that price. A shared energy storage auction system is proposed in the paper [15], where the interaction between auctioneers and bidders is modeled as a Stackelberg game. Even though this

mechanism can maximize societal welfare, it needs a centralized supervisor to coordinate. Also, participants' enthusiasm is suppressed as price takers.

The participant-led auction model is another energy-sharing technique based on non-cooperative games. In this mode, a third-party platform is either not required or is just used as additional assistance. For instance, the paper [16] first abstracts a set of prosumers considering the physical constraints of the network as a virtual microgrid. The energy exchange process between prosumers is then modeled as a Stackelberg game. Authors in [17] further develop an energy-sharing allocation method based on the fast alternating direction multiplier method (ADMM) in the case of equal status of prosumers to minimize the total system cost. While a centralized organizer is not required in this mechanism, the market role of the participant, i.e., seller or buyer, must be decided in advance, such as in [18]. As a result, the flexibility of the participants could be limited.

Therefore, it makes more sense for the energy-sharing market to endogenously define market roles, transaction power, and trading prices for the participants. This is the advantage of the energy-sharing mechanism based on cooperative games. Firstly, a redistribution agreement, such as the Shapley value method<sup>[19]</sup>, nucleolus method, and heuristic method, must be signed by alliance members. They then consider the potential benefit enhancement when making decisions. The cooperative game-based Nash bargaining (NB) strategy has been extensively applied to energy sharing. It has been proven that it can overcome the non-coalition optimality in non-cooperative games<sup>[20]</sup>. In [21], for example, the individual microgrid is encouraged to actively trade energy and realize fair benefit sharing by the application of an incentive mechanism based on NB. The authors in [22] presented an energy trading model based on the NB game between an energy manager and numerous EVs. The proposed algorithm is proven to be able to find optimal global solutions efficiently and accurately. In [23], an optimal operation of multi-agent electricity-heat-hydrogen sharing in integrated energy system is developed based on NB. To calculate the energy-sharing costs of prosumers in energy cooperation, an NB-based benefits-sharing model is provided in [24]. However, the participants in the aforementioned research using NB will receive an equal “benefits increment” concerning the breakdown point of the negotiation, which is unjust to those who contributed differently. Recently, there are a few energy-sharing research relating to improved NB techniques to address the issue. The direct P2P electricity transactions between prosumers were conceptualized as a general Nash bargaining (GNB) problem in [25]. Authors in [26] also proved the monotonicity of GNB. While in [27], to balance the profits of multiple players, a profit allocation model considering the real contribution of each player is proposed based on the Nash-Harsanyi bargaining game theory. It can be seen that the theory similar to GNB includes a bargaining power parameter that is positively related to the energy-sharing contribution of participants. This coefficient, as an important “asymmetric” index, can help to fairly distribute benefits.

The solution to the energy-sharing model is the last but certainly not the least. One typical method is to convert a two-stage model to a single-layer issue with KKT optimization conditions, which is then solved by commercial solvers, such as in [25]. Nevertheless, given the communication pressures imposed by enormous energy-sharing entities and the potential for privacy leakage, decentralized solutions are becoming increasingly popular. The ADMM, for example, combines the decomposability of the dual ascent approach with the robustness of the augmented Lagrangian method to solve convex optimization problems<sup>[28]</sup>, such as in [17, 21].

### 1.3. Construction of references

Following the research works presented above, this work focuses on the energy-sharing mechanism of multiple VPPs. The contribution is to compensate for the current works' failure to consider the independence of P2P electricity transaction participants, and the benefit distribution of the energy-sharing alliance does not take into account the promotion of RE. To be specific, the contributions are summarized as follows:

- First of all, a multi-VPP energy-sharing model is proposed based on GNB theory to ensure the fairness of electricity transactions amongst VPPs of various stakeholders. The optimization model also considers the cost of network transmission to encourage the consumption of RE nearby.
- Second, the original optimization problem is divided into two manageable sub-problems by utilizing analogous transformation to solve the non-convex GNB-based energy-sharing model.
- Considering the privacy protection of VPPs with different stakeholders in practical applications, a distributed method based on the fast-ADMM is developed. In addition, a fully decentralized solution of the fast-ADMM algorithm is achieved by solving the analytical solution based on the KKT optimal condition.

- A profit distribution technique is proposed by establishing a contribution factor that considers the contribution of each VPP, especially that of the RE generation. The method is proven to be effective in promoting RE revenue and can deliver benefit distribution results that are close to the classic Shapley value (SV).

The rest of the paper is structured as follows: In Section 2, cost-benefit models for various DERs are developed. A GNB-based optimization model with P2P transactions is developed in Section 3. A distributed model based on the fast-ADMM is offered in Section 4, as well as model-solving procedures in steps. Section 5 presents the cost allocation mechanism of P2P trading. In Section 6, a case study attests to the effectiveness of the suggested approach. Section 7 concludes the article.

## 2. System Modeling

### 2.1. System Architecture

Direct control of diverse DERs has been costly due to their modest size and distributed position in the distribution network. Due to the progress of modern metering and communication technologies, as well as smart terminal devices such as smart meters, the VPP is introduced to manage DERs. Aggregated DERs may be distributed in various but neighboring distribution grid nodes. As a result, without losing generality, VPP is utilized to represent aggregates of DERs. Traditionally, VPPs trade with the grid or retailers with a feed-in tariff,  $\lambda_t^s$ , that is much lower than the electricity purchasing price,  $\lambda_t^b$ . With the decline of RE subsidies, distributed REs benefits are limited and their development is hampered. Thus, an energy-sharing mechanism for P2P trading is proposed to address this issue.

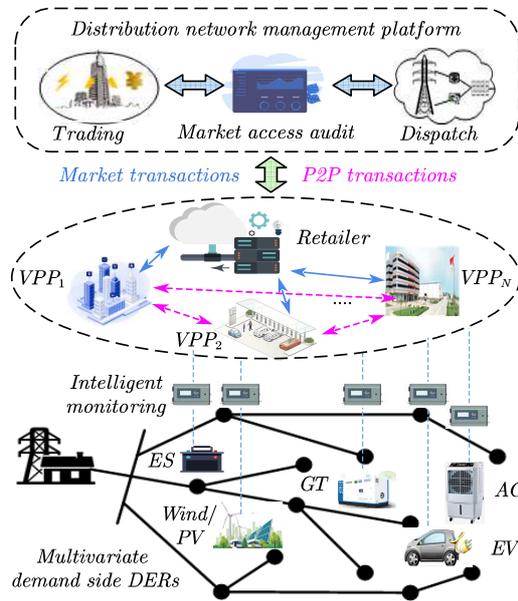


Fig.1. Schematic diagram of energy trading in multi-VPPs.

As shown in Fig.1, the settings of the energy-sharing mechanism via P2P transactions are:

- **Participants:** VPPs, with forecasting, optimization, and management of internal DERs as functions. VPP, as a self-interested stakeholder, seeks to maximize its interests.
- **Platform:** facilitate energy-sharing by recording P2P electricity transactions, assisting cost allocation, sharing network information, and so on.
- The benefits allocation of DER inside each VPP is defined by themselves, which is outside the scope of the P2P electricity transaction platform.
- It is assumed that there is no network congestion and that only the P2P trading distance in the grid is considered.
- While VPPs do not alter the initial physical structure of the network, they may vary their behaviors in response to P2P transactions, such as increasing RE installed capacity, etc., which results in indirect physical changes.

From the perspective of VPP, it can trade with both the grid and other VPPs. VPPs can increase profits or cut operating costs via P2P transactions than trading directly to the grid. Thus, because all VPPs in the P2P transaction

benefit in some way, the energy-sharing mechanism conforms to the economic principle and can improve the social welfare of the system. The detailed modeling of the system is shown in the following parts.

## 2.2. Modeling of the Flexible DERs

(1) *Flexible Load (FL)*. Unlike the unadjustable load, FL can be regulated according to demand response. It will respond to price signals or incentives to change the demand pattern to minimize costs. Assuming the FL within VPP  $i$  can partially transfer the power demand according to the grid price, the FL of VPP  $i$  at time step  $t$  will be as follows.

$$p_{i,t}^{fl} = \tilde{L}_{i,t}^{fl} - u_{i,t}^{fl} L_{i,t}^d + (1 - u_{i,t}^{fl}) L_{i,t}^u, \forall t \in 1:T \quad (1)$$

where  $\tilde{L}_{i,t}^{fl}$  is the original load.  $L_{i,t}^d$  and  $L_{i,t}^u$  are the reduced load and the increased load response, respectively, while  $u_{i,t}^{fl}$  is a binary variable corresponding to state variables.

Besides, the up and down response capacity must not exceed a certain proportion of the reference load, as (2). The difference in response load between adjacent moments should not be greater than its adjustable capacity, as (3). Where  $r_i^{DR}$  is the response capacity's proportion to the reference load, and  $\Delta L_i$  is the maximum power that the response capacity can alter.

$$\begin{cases} 0 \leq L_{i,t}^d \leq u_{i,t}^{fl} r_i^{DR} \tilde{L}_{i,t}^{fl} \\ 0 \leq L_{i,t}^u \leq (1 - u_{i,t}^{fl}) r_i^{DR} \tilde{L}_{i,t}^{fl}, \forall t \in 1:T \end{cases} \quad (2)$$

$$\begin{cases} -\Delta L_i \leq (L_{i,t+1}^d - L_{i,t+1}^u) - (L_{i,t}^d - L_{i,t}^u) \\ (L_{i,t+1}^d - L_{i,t+1}^u) - (L_{i,t}^d - L_{i,t}^u) \leq \Delta L_i \end{cases}, \forall t \in 1:T \quad (3)$$

Finally, (4) sets up a minimum energy consumption over the entire dispatch horizon  $T$ .

$$\sum_{t=1}^T p_{i,t}^{fl} \times \Delta t = \sum_{t=1}^T \tilde{L}_{i,t}^{fl} \times \Delta t \quad (4)$$

All the constraints are convex, and a general denotation is defined for the constraints set,  $\Phi(\mathbf{p}_i^{fl}) := \{(2)\sim(4)\}$ .

(2) *Electric Vehicle (EV)*. There are a large number of floating populations near public buildings. EV drivers can use their work, shopping, and leisure time in the area to charge their vehicles at charging stations. However, the disorderly on-demand charging not only causes load spikes that undermine the security of the distribution network but is also costly<sup>[29]</sup>. Thus, the EV charging behavior needs to be optimized through the following two steps.

*Firstly, the model of arrival and departure patterns of EVs.* Firstly, the focus is on the use of charging piles to control the charging/discharging behavior of private EVs. According to the study, the Poisson distribution can be used to model the process of EVs arriving at charging stations<sup>[30]</sup>. Let  $N_s$  be the total number of EVs that arrived in time  $H_c$ . And  $N_c = N_s/(H_c/h_c)$  will be the average EV number of arrivals in each time interval  $h_c$ . If  $k_h^D$  is considered to be the number of EVs that arrives in each period, it follows the Poisson distribution rules, as (5).

$$K^D = \{k_1^D, k_2^D, \dots, k_h^D\} \sim P(N_c), h = H_c/h_c \quad (5)$$

where  $\sum_h K^D = N_s$ .  $h$  is the period. If  $h_c$  is 15 minutes (0.25 hours), there will be eight periods in two hours ( $h = 8$ ).

*Secondly, the EV charging demand analysis.* The EV state of charge (SOC) when it arrives,  $SoC_n^{Sta}$ , varies depending on the driver's habit. The statistics show that it can be simulated with a normal distribution. Assume that the EV is fully charged when it departs ( $SoC_n^{End} = 100\%$ ). Thus, the number of charging periods is calculated as (6).

$$t_n^d = (SoC_n^{End} - SoC_n^{Sta}) \times E_n^r / p_n^r / h_c \quad (6)$$

where  $E_n^r$  is the rated battery capacity, and  $p_n^r$  is the rated charging power of EV  $n$ . Then, the total charging period for EV  $n$  during its stay at the charging pile is  $H_N$ .  $u_{n,l}^{ev}$  is the charging state of EV  $n$  at time step  $l$ . Then, EV cannot be charged before its arrival time,  $t_a^d$  or after its departure,  $t_d^d$ . Then, the total charging step is equal to  $t_n^d$ . And once it starts to charge, it cannot be interrupted until it is fully charged, as (7).

$$\begin{cases} u_{n,l}^{ev} = 0, l > t_d^d, l < t_a^d, \\ \sum_{l=1}^{H_N} u_{n,l}^{ev} = t_n^d, \quad \forall l \in 1:H_N, \forall n \in N_s \\ \left| \sum_{l=1}^{H_N-1} (u_{n,l+1}^{ev} - u_{n,l}^{ev}) \right| \leq 2, \end{cases} \quad (7)$$

The amount of EV charging power integrated or managed by VPP  $i$  throughout the scheduling time  $t$  can be calculated as (8). The constraints set will be  $\Theta(\mathbf{p}_i^{ev}) := \{(6)\sim(8)\}$ .

$$p_{i,t}^{ev} = \sum_{j=(t-1)/h_c+1}^{j=t/h_c} \sum_{n=1}^{N_s} u_{n,j}^{ev} \times p_n^r, \forall t \in 1:T \quad (8)$$

### (3) Gas Turbine (GT)

As a highly flexible resource, GT will play a major role in the future power system. Each generator  $g$  can be represented by a cost function,  $C_g^{gt}(\mathbf{E}_g^{gt})$ , as (9).

$$\begin{cases} C_{i,g,t}^{gt}(p_{i,g,t}^{gt}) = C_{i,g,t}^{gt,o}(p_{i,g,t}^{gt}) + (c_{i,g,t}^{gt,su} + c_{i,g,t}^{gt,sd}) \times u_{i,g,t}^{gt} \\ C_{i,g,t}^{gt,o}(p_{i,g,t}^{gt}) = a_{i,g} \times (E_{i,g,t}^{gt})^2 + b_{i,g} \times E_{i,g,t}^{gt} + c_{i,g} \end{cases} \quad (9)$$

where  $a_{i,g}$ ,  $b_{i,g}$ , and  $c_{i,g}$  are constant factors associated with the characteristics of each generator  $g$ . The energy produced within the time  $\Delta t$  will be  $E_{i,g,t}^{gt} = p_{i,g,t}^{gt} \times \Delta t$ , which  $p_{i,g,t}^{gt}$  is the power at time  $t$ .  $c_{i,g}^{gt,su}$  is start-up cost and  $c_{i,g}^{gt,sd}$  is shutdown cost.

The operation of GT must adhere to the following constraints. First, the binary variable  $u_{i,g}^{gt}$  is on/off state, as (10). Besides the generation limits, the ramping rate constraints are as (11).

$$u_{i,g,t}^{gt} \times p_{i,g}^{gt,min} \leq p_{i,g,t}^{gt} \leq u_{i,g,t}^{gt} \times p_{i,g}^{gt,max}, \forall t \in 1:T \quad (10)$$

$$\begin{cases} p_{i,g,t}^{gt} - p_{i,g,t-1}^{gt} \leq \Delta_{i,g}^{gt} \times \Delta t \\ p_{i,g,t-1}^{gt} - p_{i,g,t}^{gt} \leq \Delta_{i,g}^{gt} \times \Delta t \end{cases}, \forall t \in 1:T \quad (11)$$

where  $p_{i,g}^{gt,max}$  and  $p_{i,g}^{gt,min}$  are the max and min power limits. where constant  $\Delta_{i,g}^{gt}$  implies the max ramping rate for up/down regulation. Thus, the operating cost of GT in VPP  $i$  will be as in (12). The constraints set of GT will be  $\Psi(\mathbf{p}_i^{gt}) := \{(9)\sim(11)\}$ .

$$C_i^{gt}(\mathbf{p}_i^{gt}) = \sum_{g=1}^G (C_{i,g}^{gt}(\mathbf{p}_{i,g}^{gt})) \quad (12)$$

#### (4) Active PV/Wind generators (AG)

An RE active generator (AG) is defined as solar PV or wind turbines connected to a hybrid energy storage (ES) system. The concept of PV-based AG was introduced in previous work [31]. A local energy management system (EMS) is applied for inner instantaneous power dispatching among the RE and ES. It can not only smooth the power fluctuation and intermittency of RE, limit the disturbance of system fault current, but also improve the static and transient stability of the distribution grid. By combining with short-term prediction, the local controller can control the active and reactive power of the AG, transforming it from an uncontrollable to a controllable power source. Since the ES charging and discharging behavior is a dynamic process, the schedule of AG needs to be quantitatively calculated based on the RE power forecast and the SoC of the ES device.

Firstly, it is assumed that the prediction error of RE can be absorbed by ES, so the predicted value,  $\mathbf{p}_i^{re}$ , can be regarded as the actual output. Since the time scale is supposed to be 15 minutes to 1 hour, only battery constraints are considered, while the ultra-capacitor is auto-controlled by the local EMS. The SoC of ES depends on the state-transition equations (13).

$$E_{i,t+1}^S = E_{i,t}^S + \left( \eta_i^c p_{i,t}^{S,c} - p_{i,t}^{S,d} / \eta_i^d \right) \times \Delta t \quad (13)$$

where  $p_{i,t}^{S,d}$  and  $p_{i,t}^{S,c}$  are discharge/charge powers, respectively.  $\eta_i^c$  and  $\eta_i^d$  are matched efficiencies, respectively. AG can store the RE power when the price is low, and sell it when the price is high. Thus, the AG power of VPP  $i$  will be as (14). To avoid the ES early wear out, the charge/discharge powers have to be restricted by upper bounds,  $p_i^{S,c,max}$  and  $p_i^{S,d,max}$ , respectively, and its SoC limit, as (15)-(16). To avoid frequent charging, ES must adhere to the restriction (17) during the scheduled time.

$$\mathbf{p}_i^{ag} = \mathbf{p}_i^{re} + \mathbf{p}_i^{S,d} - \mathbf{p}_i^{S,c} \quad (14)$$

$$0 \leq p_i^{S,c} \leq p_i^{S,c,max}, 0 \leq p_i^{S,d} \leq p_i^{S,d,max}, \forall i \in 1:T \quad (15)$$

$$E_i^{S,min} \leq E_i^S \leq E_i^{S,max} \quad (16)$$

$$\sum_{t=1}^T \frac{p_{i,t-1}^{S,d} p_{i,t}^{S,c}}{|p_{i,t-1}^S| |p_{i,t}^S|} \geq -k \quad (17)$$

where  $k$  is the max number of charge-discharge cycles in the scheduling period. And its cost function is as (18).

$$C_i^{ag}(\mathbf{p}_i^{ag}) = \sum_{t=1}^T (p_{i,t}^{re,s} \times c^{re,s} + (p_{i,t}^{S,d} - p_{i,t}^{S,c}) \times c^{es}) \quad (18)$$

where  $c^{re,s}$  is the cost of RE curtailment, and  $c^{es}$  is the cost of the ES system. The constraints set is  $\Xi(\mathbf{p}_i^{ag}) := \{(13)\sim(17)\}$ .

### 2.3. Power Trading with Distribution Grid

VPP buys power from the grid at price  $\lambda_t^b$  and sells power to the grid at price  $\lambda_t^s$ . To avoid VPP arbitrage and encourage RE consumption,  $\lambda_t^b$  is higher than  $\lambda_t^s$ . It is the driving force behind P2P trading. If VPP buys power from the grid as  $\mathbf{p}_i^b := \{p_{i,t}^b, \forall t \in T\}$  and sells power to the grid as  $\mathbf{p}_i^s$ , the cost of energy trading between VPP  $i$  and the grid is as (19). The constraint  $Y_i(\mathbf{p}_i^b, \mathbf{p}_i^s) = \{(20)\}$  needs to be satisfied, where  $p_i^{b\_min}$ ,  $p_i^{b\_max}$ ,  $p_i^{s\_min}$ , and  $p_i^{s\_max}$  are the min and max allowed trading power, respectively.

$$C_i^{grid}(\mathbf{p}_i^b, \mathbf{p}_i^s) = \sum_{t \in T} (\lambda_t^b p_{i,t}^b - \lambda_t^s p_{i,t}^s) \Delta t \quad (19)$$

$$p_i^{b\_min} \leq \mathbf{p}_i^b \leq p_i^{b\_max}, p_i^{s\_min} \leq \mathbf{p}_i^s \leq p_i^{s\_max}, \forall i \in I. \quad (20)$$

### 2.4. P2P Energy Transactions among VPPs

VPPs can choose to participate in P2P electricity sharing, or trading with other VPPs. The power of P2P trading of VPP  $i$  with other VPPs at time step  $t$  can be denoted as  $\mathbf{e}_i = \{e_t^{i,j}, \forall t \in T, j \in \chi_i\}$ . The power trading between the VPP  $i$  and VPP  $j$  must be the same size but in the opposite direction, as (21). The P2P transaction price restriction (22) must be satisfied for the balance of payment of shared energy. (23) is to prevent VPP from arbitrage through P2P transactions. (24) is the upper and lower limits of  $\mathbf{e}_i$ , where  $e_{min}^i$  and  $e_{max}^i$  are min and max allowed P2P transaction power, respectively. Thus, (25) is the cost of P2P trading. The cost will be negative if it sells energy and vice versa. Let  $\Lambda_i = \{(21) \sim (24)\}$  be the constraint set for  $\mathbf{e}_i$ .

$$e_t^{i,j} + e_t^{j,i} = 0, \forall t \in T, \forall i \in I, \forall j \in \chi_i. \quad (21)$$

$$\lambda_t^{i,j} = \lambda_t^{j,i}, \forall t \in T, \forall i \in I, \forall j \in \chi_i. \quad (22)$$

$$e_t^{i,j} \times (p_i^b - p_i^s) \geq 0, \forall i \in I, \forall j \in \chi_i, \forall t \in T. \quad (23)$$

$$e_{min}^i \leq \sum_{j \in \chi_i} e_t^{i,j} \leq e_{max}^i, \forall i \in I, \forall t \in T. \quad (24)$$

$$C_i^{et}(\mathbf{e}_i, \lambda_i) = \sum_{j \in \chi_i} \sum_{t \in T} e_t^{i,j} \lambda_t^{i,j} \quad (25)$$

### 2.5. Transmission Costs for P2P Transactions

P2P transactions among VPPs must pay network usage fees to the grid operator<sup>[32]</sup>. There are two reasons. First, the fees will be used for the operation and maintenance of the grid. Second, it encourages VPP to prioritize transactions with nearby VPPs, lowering the risk of grid congestion.  $\gamma^{i,j}$  is the transmission cost factor of VPP  $i$  and VPP  $j$ , as (26).  $c^{dis}$  is the cost of per unit distance set by the grid operator.  $d^{i,j}$  is the electrical distance determined by the grid structure. This cost is borne by each VPP in half. Thus, the P2P trading transmission fee is as (27).

$$\gamma^{i,j} = (c^{dis} d^{i,j}) / 2 \quad (26)$$

$$C_i^{tc}(\mathbf{e}_i) = \sum_{j \in \chi_i} \sum_{t \in T} \gamma^{i,j} |e_t^{i,j}| \quad (27)$$

This paper utilizes Thevenin impedance distance<sup>[33]</sup> to describe the electrical distance:

$$d^{i,j} = |Z_{ii} + Z_{jj} - Z_{ij} - Z_{ji}| \quad (28)$$

where  $Z_{ij}$  is the corresponding impedance between nodes  $i$  and  $j$  in the node impedance matrix  $Z$ . It should be noted that node  $i$  is an approximate center. It could be the location of the DER with the largest capacity in VPP  $i$ .

## 3. General Nash Bargaining Theory Based Model for Multi-VPPs Energy Sharing

### 3.1. Fundamentals of General Nash Bargaining (GNB)

GNB studies how profit (or reductions in operating costs) be shared by establishing appealing axioms that solutions to the bargaining problem must satisfy. It is useful when the parties are willing to cooperate to implement a fair solution. Any GNB solution should satisfy Pareto optimality. The model of an  $i$ -agent GNB optimization problem is shown as (29). It consists of three key features. First, a disagreement, or threat point  $u_i^0$  is the guaranteed payoff to agent  $i$  if no agreements are reached. Second, the feasible agreements typically include all possible joint actions, whose payoffs,  $u_i$ , are better than the threat point for each agent,  $u_i \geq u_i^0$ . Third, a parameter  $\alpha_i$  is introduced to indicate the bargaining power of each individual in the negotiation process based on its contribution. When compared to Nash bargaining theory, GNB eliminates the symmetry axiom, making it more appropriate for instances in which individuals contribute differently to the cooperative process. The basis for benefit distribution is their bargaining power.

$$\max \prod_i (u_i - u_i^0)^{\alpha_i}, s. t. u_i \geq u_i^0, \forall i \in I. \quad (29)$$

### 3.2. VPPs Energy-sharing Model based on GNB Theory

According to (29), as well as the decentralized mechanism, an optimization model of multi-VPPs including P2P transactions is proposed as (30). The objective is to reduce the operational cost of the energy-sharing alliance of  $i$  VPPs.

$$\max \prod_i (C_i^0 - C_i^V)^{\alpha_i}, \text{ s. t. } C_i^0 \geq C_i^V, \forall i \in I. \quad (30)$$

where  $C_i^0$ , the breaking point of GNB, denotes the cost when VPP  $i$  opts out of P2P transactions. Appendix A provides details on the modeling and solution of  $C_i^0$ .  $\alpha_i$  reflects the bargaining power of VPP  $i$ .  $C_i^V$  is the cost of VPP  $i$  when participating in P2P transaction. Thus, the cost reduction,  $(C_i^0 - C_i^V)$ , is not less than. Otherwise, it exits the P2P transaction. The VPP model established in Section 2,  $C_i^V$  is presented as follows

$$\begin{aligned} C_i^V(\mathbf{x}_i, \mathbf{e}_i) &= C_i^{gt} + C_i^{ag} + C_i^{grid} + C_i^{tc} + C_i^{et} \\ \text{s. t. } &\begin{cases} \sum_{g=1}^G \mathbf{p}_{i,g}^{gt} - \mathbf{p}_i^{fl} + \mathbf{p}_i^{ag} + \mathbf{p}_i^b - \mathbf{p}_i^s \\ -\mathbf{p}_i^{ev} + \sum_{j \in \chi_i} \mathbf{e}^{i,j} = \mathbf{p}_i^{bl} \\ \Phi_i, \Theta_i, \Psi_i, \Xi_i, \Upsilon_i, \Lambda_i \end{cases}, \forall i \in I. \end{aligned} \quad (31)$$

where  $\mathbf{x}_i := \{\mathbf{p}_i^{fl}, \mathbf{p}_i^{ag}, \mathbf{p}_i^{ev}, \mathbf{p}_{i,g}^{gt}, \mathbf{p}_i^b, \mathbf{p}_i^s\}$ .

The model objective is to maximize the cost reduction for all VPPs. The variables include the operational status of DERs aggregated by VPPs,  $\mathbf{x}_i$ , and the P2P transaction power,  $\mathbf{e}_i$ .

### 3.3. The Equivalent Transformation for GNB-based Model

It is impossible to solve the model (30)-(31) directly because it is non-convex and nonlinear. Thus, the model is equivalently transformed into two sub-problems: (1) cost minimization of the VPP alliance, and (2) payment allocation of the P2P transactions. Appendix B provides proof of equivalent conversion.

#### (1) Subproblem 1: VPP Alliance Cost Minimization

The overall cost minimization model is shown in (32). The variables include  $\mathbf{x}_i$  and  $\mathbf{e}_i$ . According to Appendix B, the cost of P2P transactions is omitted because their benefits and costs within the VPP alliance offset each other ( $\sum_{i \in I} C_i^{et} = 0$ ). Thus, the convexity of the objective function and constraints makes the model easily solved centrally.

$$\begin{aligned} \text{Min } &\sum_{i=1}^I U_i \\ \text{s. t. } &\begin{cases} U_i(\mathbf{x}_i, \mathbf{e}_i) = C_i^{gt} + C_i^{ag} + C_i^{grid} + C_i^{tc}, \forall i \in I. \\ \Phi_i, \Theta_i, \Psi_i, \Xi_i, \Upsilon_i, \Lambda_i \end{cases} \end{aligned} \quad (32)$$

#### (2) Subproblem 2: Payment Allocation of P2P Transactions

Because the costs of P2P transaction,  $C_i^{et}$ , in *Subproblem 1* cancel each other out, only the P2P trading power is settled. As a result, further study on the allocation of P2P trading costs is required, as shown in (33).

$$\begin{aligned} \text{Min } &\sum_{i=1}^I -\alpha_i \ln(C_i^0 - U_i^* - C_i^{et}(\lambda_i)) \\ \text{s. t. } &\begin{cases} C_i^0 \geq U_i^* + C_i^{et}(\lambda_i) \\ \lambda_t^{i,j} = \lambda_t^{j,i}, \forall t \in T, \forall i \in I, \forall j \in I \setminus i. \end{cases} \end{aligned} \quad (33)$$

where  $U_i^*$  is the value of the function (32) after solving *Subproblem 1*. The variable is the P2P transaction price  $\lambda_i$ .

## 4. Decentralized Solving of Subproblem 1

The aforementioned model (32) and (33) can be solved by a central agency since they are convex. However, the centralized solution is challenging to employ in practice given the various stakeholders of each VPP. Since all VPPs are required to report their detailed operational data to the central agency, there is a risk of privacy leakage. Except for local  $\mathbf{x}_i$ ,  $\mathbf{e}_i^{i,j}$  is a variable of VPP  $i$  in the model (32), but it is coupled to the variable  $\mathbf{e}_i^{j,i}$  of VPP  $j$  by constraint (21). The same holds for the P2P transaction price  $\lambda_i$  in the model (33).

### 4.1. Distributed Algorithm for Subproblem 1

(1) *Augmented Lagrangian Function Based on Multiplier Method*. Fast-ADMM is a method that combines linear and quadratic terms in ADMM into a single augmented Lagrangian term. It has a higher order convergence rate than ADMM<sup>[34]</sup>. Thus, it is used to decompose the objective function of the convex model (32) into the sum of two functions. First, by introducing auxiliary variables and Lagrangian multipliers, an augmented Lagrangian function is developed. It is then solved iteratively until the convergence criteria are met.

(2) *Auxiliary variable.* The function (32) is split into two parts: the local variables  $\mathbf{x}_i$ , and the global variable  $\mathbf{e}^{i,j}$ . The latter is decomposed by introducing an auxiliary variable  $\boldsymbol{\varepsilon}_i = \{\boldsymbol{\varepsilon}_t^{i,j}\}$ .  $\boldsymbol{\varepsilon}_t^{j,i}$ , as shown in (34) and (35), is called the coupled variable, which is the power that VPP  $j$  trades with VPP  $i$ .

$$\mathbf{e}_t^{i,j} - \boldsymbol{\varepsilon}_t^{j,i} = 0, \forall t \in T, \forall i \in I, \forall j \in I \setminus i. \quad (34)$$

$$\boldsymbol{\varepsilon}_t^{i,j} + \boldsymbol{\varepsilon}_t^{j,i} = 0, \forall t \in T, \forall i \in I, \forall j \in I \setminus i. \quad (35)$$

(3) *Dual variables and Augmented Lagrangian Function.* Then, a dual variable  $\boldsymbol{\sigma}_i$  also referred to as the Lagrangian multiplier, is employed to create an augmented Lagrangian function  $\Gamma$ , as (36).  $\tau$  is the iteration penalty factor.

$$\Gamma(\mathbf{p}_i^{fl}, \mathbf{p}_i^{ag}, \mathbf{p}_i^{ev}, \mathbf{p}_{i,g}^{gt}, \mathbf{p}_i^b, \mathbf{p}_i^s, \mathbf{e}_i, \boldsymbol{\varepsilon}_i) = \sum_{i \in I} \left[ \begin{array}{l} U_i (C_i^{gt} + C_i^{ag} + C_i^{grid} + C_i^{tc}) \\ + \tau/2 \sum_{j \in \chi_i} \sum_{t \in T} \left( \mathbf{e}_t^{i,j} - \boldsymbol{\varepsilon}_t^{j,i} + \boldsymbol{\sigma}_t^{i,j} / \tau \right)^2 \end{array} \right] \quad (36)$$

#### 4.2. Fast-ADMM Algorithmic Solution in Steps.

Here, a three-step sequential iterative solution method based on fast-ADMM<sup>[17]</sup> is introduced to solve the function (36). The system variables, such as auxiliary variables, dual variables, and convergence conditions, must be initialized.

- **Step 1.** The optimization objective function (37) of each VPP is solved based on the corresponding constraints. When solving for the first time,  $\boldsymbol{\varepsilon}_i$  and  $\boldsymbol{\sigma}_i$  are initially given. In the subsequent iterative process,  $\boldsymbol{\varepsilon}_i$  is the result of **Step 2**, and  $\boldsymbol{\sigma}_i$  is the update of **Step 3**. Each VPP can be solved in parallel to expedite the solution because the global interaction variables  $\boldsymbol{\varepsilon}_i$  and  $\boldsymbol{\sigma}_i$  are known.

$$\text{Min} \left[ \begin{array}{l} U_i (C_i^{gt} + C_i^{ag} + C_i^{grid} + C_i^{tc}) \\ + \tau/2 \sum_{j \in \chi_i} \sum_{t \in T} \left( \mathbf{e}_t^{i,j} - \boldsymbol{\varepsilon}_{t,(k-1)}^{j,i} + \boldsymbol{\sigma}_{t,(k-1)}^{i,j} / \tau \right)^2 \end{array} \right] \quad (37)$$

Variables:  $\mathbf{x}_i, \mathbf{e}_i$

Given:  $\boldsymbol{\varepsilon}_{t,(k-1)}^{i,j}, \boldsymbol{\sigma}_{t,(k-1)}^{i,j}, \forall j \in \chi_i, \forall i \in I$ .

Subjectto:  $\Phi_i, \theta_i, \Psi_i, \Xi_i, \Upsilon_i, \Lambda_i$ ,

- **Step 2.** Solve and update auxiliary variables  $\boldsymbol{\varepsilon}_i$  with (38).  $\mathbf{e}_{i,(k)}$  is the result of **Step 1**. To realize the fully distributed solution of P2P trading, the analytical solution of coupled variables is obtained by KKT transformation.

$$\boldsymbol{\varepsilon}_t^{i,j} = \frac{\mathbf{e}_{(k)}^{i,j} - \boldsymbol{\varepsilon}_{(k)}^{j,i}}{2} + \frac{\boldsymbol{\sigma}_{(k-1)}^{i,j} - \boldsymbol{\sigma}_{(k-1)}^{j,i}}{2\tau}, \forall i \in I, \forall j \in \chi_i. \quad (38)$$

- **Step 3.** Update the dual variables based on the results of **Step 1**,  $\mathbf{e}_{i,(k)}$  and **Step 2**,  $\boldsymbol{\varepsilon}_{i,(k)}$ , respectively.

$$\boldsymbol{\sigma}_{(k)}^{i,j} = \boldsymbol{\sigma}_{(k-1)}^{i,j} + \tau(\mathbf{e}_{(k)}^{i,j} - \boldsymbol{\varepsilon}_{(k)}^{j,i}) \quad (39)$$

Dualvariables:  $\boldsymbol{\sigma}_i$

Given:  $\boldsymbol{\varepsilon}_{(k)}^{i,j}, \boldsymbol{\varepsilon}_{(k)}^{j,i}, \forall i \in I, \forall j \in \chi_i$ .

- *Condition for iterative convergence.* The iterative stopping condition is that both the norm of primal residual,  $r^{(k)}$ , and norm of dual residual,  $s^{(k)}$ , are less than the stopping threshold,  $\xi$ , which is usually a small positive number.

$$\begin{cases} r^{(k)} = \mathbf{e}_{i,(k)} - \boldsymbol{\varepsilon}_{i,(k)} \\ s^{(k)} = \boldsymbol{\sigma}_{i,(k)} - \boldsymbol{\sigma}_{i,(k-1)} \end{cases} \quad (40)$$

#### 4.3. Algorithm 1 for Subproblem 1

The fast-ADMM-based distributed clearing process of P2P transactions for *Subproblem 1* is presented in *Algorithm 1*. The original problem is first turned into an augmented Lagrangian form by the introduction of auxiliary and dual variables. It is then decomposed and solved iteratively in three steps until the convergence conditions are met. VPP  $i$  only needs to share P2P transaction power with other VPPs. The operation information of DERs managed by VPP  $i$  is only used for its decision-making, which protects the privacy of each VPP and reduces the communication burden of the energy-sharing platform.

**Algorithm 1**


---

Inputs: REs and load forecasts  $(\tilde{p}_i^{re}, \tilde{L}_i^l)$ , electricity price of retailer  $(\lambda^b, \lambda^s)$ , and system preset parameters, etc.  
Initialize  $\varepsilon_i(0) = 0, \sigma_i(0) = 0, \tau = 1.3, \xi = 1e^{-4}, K$   
**for**  $k = 1$  **to**  $K$  **do**  
    (1) **Step 1**: VPP independently optimizes locally in parallel for  $x_i$  and  $e_i$  with  $\varepsilon_{i,(k)}$  and  $\sigma_{i,(k)}$ .  
    (2) **Step 2**: VPP updates coupling variables locally.  
    (3) If the convergence conditions are met?  
        **if**  $\|r^{(k)}\|_2 \leq \xi$ , and  $\|s^{(k)}\|_2 \leq \xi$  **then**  
            **Subproblem 1** is solved, and stop iteration.  
        **else**  
            **if**  $k > K$  **then**  
                The model is unsolvable. The VPPs will have to trade with the grid with  $(\lambda^s, \lambda^b)$ .  
            **end if**  
        **end if**  
    (4) **Step 3**: Update  $\sigma_{i,(k)}$  with  $e_{i,(k)}$  and  $\varepsilon_{i,(k)}$   
    (5)  $k \leftarrow k + 1$ , and return to (1).  
**end for**

---

**5. P2P Transaction Cost Allocation***5.1. Contribution factor*

By solving *Subproblem 1*, the P2P transaction power that minimizes system cost is obtained, as well as the operating cost  $U_i^*$ . Since the costs and benefits of P2P transactions are offset within the VPP alliance, the price of P2P transactions has not been cleared. Thus, *Subproblem 2* needs to be further solved to obtain the clearing price of the P2P transaction.

First, a mapping approach based on an exponential function is proposed to estimate the cooperative contribution of VPP in the energy-sharing alliance, that is, the bargaining power  $\alpha_i$ . Regardless of whether VPP  $i$  sells or buys P2P trading power, both actions contribute to maximizing the alliance's benefit. Thus, calculate the total P2P power purchase and sale of VPP  $i$  in a scheduling period  $T$  respectively.

$$\begin{cases} pb_i = \sum_{j \in \chi_i} \sum_{t \in T} \max(0, e_t^{i,j}) \\ ps_i = - \sum_{j \in \chi_i} \sum_{t \in T} \min(0, e_t^{i,j}) \end{cases}, \forall i \in I. \quad (41)$$

According to (41), define  $p_{\max}^b = \max\{ps_i, \forall i \in I\}$ , and  $p_{\max}^s = \max\{pb_i, \forall i \in I\}$ , so that  $\alpha_i$  can be quantified as

$$\alpha_i = e^{ps_i/p_{\max}^s} - e^{-pb_i/p_{\max}^b} \quad (42)$$

Above (42) is a nonlinear power mapping function based on an exponential function with the Euler–Mascheroni constant as the base. The range of the exponent of the previous item is  $[0, 1]$ , and the range of the value is  $[1, e]$ . While the variation range and value of the latter term are  $[-1, 0]$  and  $[1/e, 1]$ , respectively, as shown in Fig.2. It is clear that  $\alpha_i$  is not smaller than zero. The reasoning for this contribution metric is that it ensures:

- First, any VPP participating in energy-sharing has a positive contribution unless it withdraws from the alliance.
- Second, the behavior of VPP selling energy contributes more than buying electric power. That is, the more electric energy sold, the closer the value of the first term of (42) is to  $e$ , and the closer the value of the second term is to  $1/e$ , thus the larger the difference and the larger the  $\alpha_i$ . This is compatible with the willingness to promote demand-side distributed power generations.
- The bigger the quantity of energy shared by VPP, the greater the contribution and bargaining power it will have.

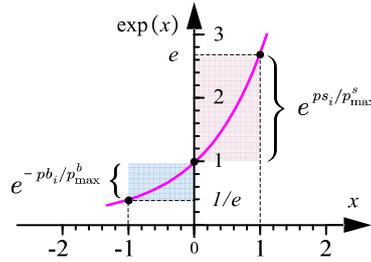


Fig.2. A nonlinear power mapping based on an exponential function.

### 5.2. Solving the Subproblem 2

Next, based on the results of *Subproblem 1*, the price of P2P transactions is cleared by solving the model (33). Since  $C_i^0$ ,  $U_i^*$ , and P2P transaction power  $e_i$  is known, the only variable in the model (33) is P2P transaction price  $\lambda_i$ .

The model can be solved by the energy-sharing platform. Each VPP transmits  $C_i^0$ ,  $U_i^*$ , and  $e_i$  to the platform. The latter initially computes  $\alpha_i$  using (41) and (42). The clearing price and P2P transaction cost are then determined by solving the model (33). This strategy delivers a speedy answer for price clearing by sacrificing some privacy.

### 5.3. Other Cost Allocation Methods

*Subproblem 2* is solved to obtain the P2P transaction pricing and to realize transaction cost allocation. This, however, is not the only option. Three additional methods are described below.

(1) *Shadow Price*. In economics, the Lagrange multiplier in the model (36) has a meaningful explanation. It represents the cost that will be paid if the constraints associated with this dual variable are violated. The optimal solution,  $\sigma_i^*$ , of the dual problem, assuming strong duality, is the shadow price. In our case,  $\sigma_i^*$  can be regarded as the trading price when there are P2P transactions, that is, when the dual variable is valid.

(2) *Middle Price*. The power deficit VPP buying power from the grid at price  $\lambda^b$  and the power surplus VPP selling power to the grid at price  $\lambda^s$  are avoided by P2P transactions. Thus, it is straightforward and acceptable to assume that P2P trading is conducted at intermediate pricing,  $(\lambda^b + \lambda^s)/2$ .

(3) *Shapley Value (SV)*. The SV approach is generally known as a classic way for benefits from allocating multiplayer in cooperative games. The particular rules and formulas will not be repeated in detail here because it is a time-tested and reliable approach. It is important to note that the SV approach merely distributes benefits and cannot provide precise P2P trading prices. Although SV is a fairly fair way to distribute the benefits of cooperative games, as stated in [35], its high computing cost restricts the size of the game.

## 6. Numerical Test with Case Study

### 6.1. Basic Data, Modeling, and Solving

First, VPPs can transact with retailers. The latter determines time-of-use electricity prices, which are as follows: peak 9:00–11:00 and 18:00–23:00, flat 12:00–16:00 and 24:00–1:00 (next day), valley 2:00–8:00. The electricity prices during these periods are 12.9, 10.5 and 6.6 cents/kWh, respectively. The buying price of the retailer from VPPs is usually lower than that of sells, as: flat 9:00–1:00 (next day), and valley 2:00–8:00, with prices of 5.1 and 4 cents/kWh, respectively.

Second, three VPPs are included, as shown in TABLE I.

TABLE I ELECTRICAL DISTANCES BETWEEN VPPS

	DERs Included
Commercial building <b>VPP1</b>	20 EV charge pile of 30kW each; rated rooftop PV of 150 kW, the base load peak of 600 kW (does not include EV, same in VPP2)
Residential building <b>VPP2</b>	20 EV charge pile of 7kW each; rated rooftop PV of 300 kW, the base load peak of 300 kW
Industrial building <b>VPP3</b>	three GTs: rated power of [30,60,60] kW; rated wind of 300 kW, the base load peak of 260 kW

Other parameter settings (Some parameters are given in the following example analysis.):

- RE curtailment penalty factor is 20 cents/kWh;

- ES capacity for AG set to 20% of RE-rated power.
- The transmission cost of P2P trading is 1 cent/km. The electrical distance between VPPs is as in TABLE II.
- Fast-ADMM convergence criterion is  $\xi = 1e^{-3}$ .

TABLE II ELECTRICAL DISTANCES BETWEEN VPPS

Transactions	VPP1-VPP2	VPP2-VPP3	VPP1-VPP3
Electrical distance	0.79	1.11	1.90

Programming and model solving: The proposed GNB-based model and algorithm are modeled in the Yalmip environment in Matlab R2020b. The solver uses for *Subproblem 1* is Gurobi with an academic license and IPOPT for *Subproblem 2*.

### 6.2. Cost Comparison of Different Optimization Methods

First, this part illustrates the operating cost of different trading strategies of the first stage, which is the solution to *Subproblem 1*. TABLE III compares the operating costs of each VPP when P2P transactions are excluded and included. Without taking into account P2P transactions, the system will cost \$1537.6 in total within 24 hours of a scheduling period. In the case of P2P transactions, the cost of the energy-sharing alliance based on the fast-ADMM algorithm is \$1434.7, a drop of 6.7%. However, not all VPP costs are lowered in TABLE III since the P2P transaction cost is not taken into account in *Subproblem 1*. For example, the cost of VPP1 dropped by 17.5% since it replaced a portion of the energy purchased from retailers via P2P transactions, which was not included in the cost. The 14.4% increase in VPP3 cost is due to it replacing part of the electricity formerly sold to retailers via P2P transactions. As a result, the reduction in the operating costs of the energy-sharing alliance is primarily due to lower trading costs with retailers. *Subproblem 2* will deal with the allocation of P2P trading benefit. In addition, TABLE III compares the performance of the centralized solution and the distribution method based on fast-ADMM. The results show the difference between the fast-ADMM and centralized method is about 0.1%. Thus, it can be claimed that the decentralized method gets the global optimal solution and delivers the same result as the centralized method. Furthermore, as indicated in Section 4, the distributed methodology will secure the private information of DERs in VPP while significantly lowering the amount of transmission data.

TABLE III COMPARISON OF OPERATING COSTS

Cost (\$)	Without P2P Transaction	With P2P Transaction	
		Centralized*	Fast-ADMM
VPP1	809.1	667.3	667.5
VPP2	187.6	146.9	148.4
VPP3	541.0	619.6	618.8
Total	1537.6	1433.8	1434.7

\*In the centralized mode, the model is shown in Appendix A.

### 6.3. Effectiveness of fast-ADMM Convergence

Fig.3 illustrates the evolution of the primal residual and dual residual during the iterative solution of the fast-ADMM. The parameter of the convergence condition is set to  $1e^{-4}$ . The primal and dual residuals satisfy the convergence condition after 10 and 33 iterations, respectively. This demonstrates the efficacy of the fast-ADMM-based distributed method used here. The penalty factor  $\tau$  is one of the most critical parameters. If it is set too low, the initial value of P2P transaction power will be less than optimal and will not be able to be raised in the future. If it is too large, the iterations will fail to converge. Usually, starting with a small value and increasing it with the number of iterations helps the algorithm's convergence. However, the delicate study of parameter settings is beyond the scope of this paper.

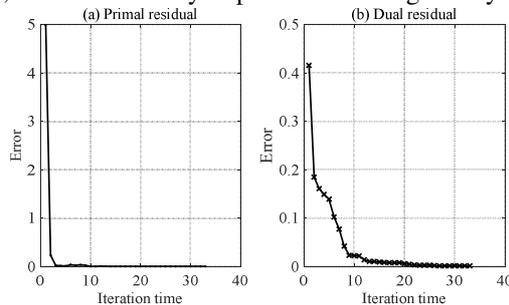


Fig.3. Fast-ADMM iteration convergence.

#### 6.4. Optimal Operation of VPPs

Fig.4 illustrates the optimized operating states of the three VPPs.

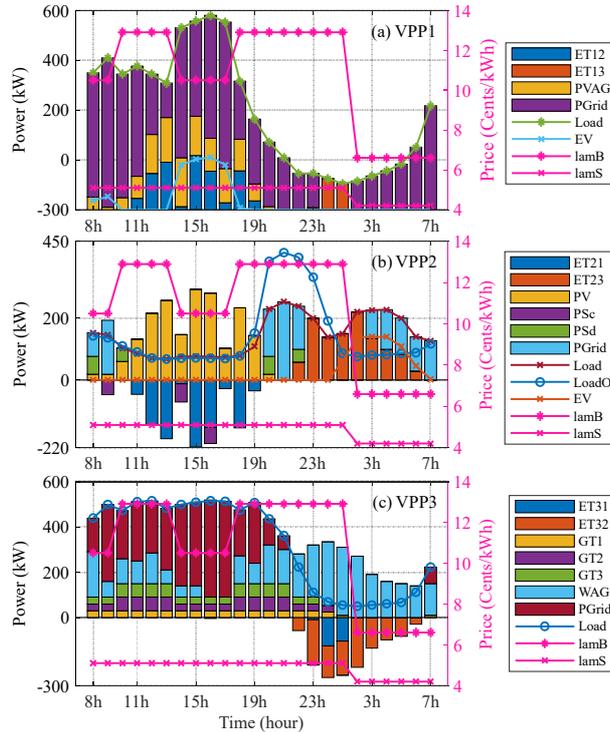


Fig.4. Optimization results of three VPPs.

For the commercial building VPP1 in Fig.4(a), the net load is always positive. In addition to buying electricity from retailers (PGrid), its power sources include the active PV generator (PVAG), and power purchased via P2P transactions, with ET12 and ET13 being power purchased from VPP2 and VPP3, respectively. As can be seen from the y-axis on the right side, in pink, the time-of-use price lamB is significantly higher than the fed-in-tariff lamS. This difference is the motivating cause for the P2P transactions. EV charging loads are in 8–9h and 14–18h when lamB is lower than 10–13h. Details on the charging characteristics of EVs are given later. The residential building VPP2 in Fig.4(b) has a significant PV energy surplus during the day. When the price is low, the battery within the PVAG is charged at 9 h, 14 h, and 16 h, PSc in purple. When the price is high, the battery is discharged at 20 h and 22 h, PSd in green. It is also clear that FL moved the peak of the original load (LoadO) from the higher price period of 20–23h to the lower price period of 2–7h in the evening. The GT operational characteristics are shown in the industrial building VPP3 in Fig.4(c). The GT is turned off during the price is low in the evening, and runs at rated power during the 10–13h and 18–1h (next day) of the price peak. It shows that FL, AG, and GT can be modified to maximize their benefits or minimize costs.

Fig.5 shows the EV charging characteristics. Assume that EVs are all BYD e6 with a battery capacity of 64.5kWh. The charging time for VPP1 is about 2 hours with 30kW charge piles, but the charging time for VPP2 is around 6 hours with 7kW charge piles. Without optimization, the charging power in VPP1 is EVC1. It can be observed that there is a 600kW power spike at 9h, which will cause a significant shock to the power grid. With optimization, its charging power EVC2 is relatively smooth. It avoids not just power shocks but also pricing peak hours. The original EV charging curve EVR1 in VPP2 is at the peak of load at night. By moving its charging period to the lower price period, the improved charging curve EVR2 lowers costs. In fact, at 2–6h, the power source of VPP2 is mainly wind power from VPP3, and its average cost is even lower.

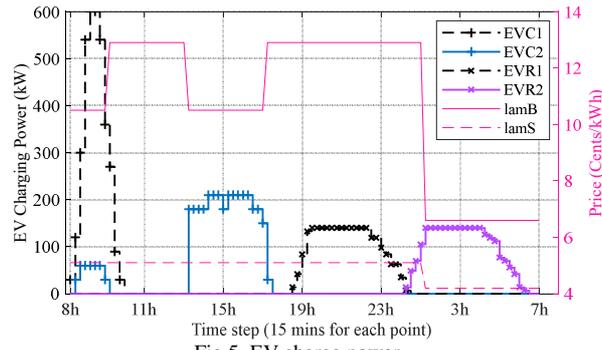


Fig.5. EV charge power.

### 6.5. Optimal P2P Transactions between VPPs

Fig.6 depicts the power transaction of the three VPPs with the decentralized method proposed in Section 4. The electricity traded by VPPs via P2P was originally sold to retailers. VPPs with power surplus will profit more from P2P transactions than from sales to retailers. For example, VPP3 in Fig.6(c) can increase revenues by selling excess wind power at night to VPP1 and VPP2. Simultaneously, VPP1 saves money by purchasing power from VPP3 at a lower price than lamB. The same is true with distributed PV generation in VPP2. It can be observed that P2P electricity trading can promote the utilization of distributed RE power and its development by raising its revenue.

In addition, as shown in TABLE I, the electrical distances between VPP3 and VPP1, and VPP2 are 1.90km and 1.11km, respectively, so VPP3 preferentially sells surplus wind power to VPP2. Similarly, VPP2 also favorably sells surplus PV power during the day to VPP1, which is nearby, rather than VPP3, which also needs to purchase electricity.

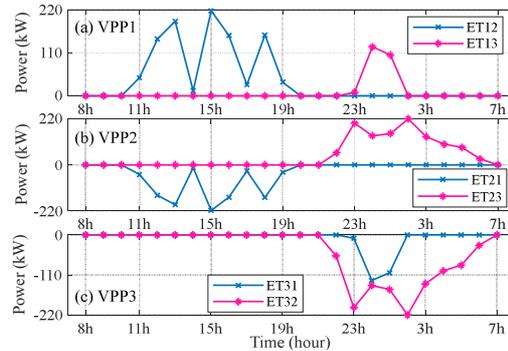


Fig.6. P2P transactions power among three VPPs.

### 6.6. P2P Transaction Benefit Distribution

Fig.7 compares P2P electricity transaction prices based on GNB and Nash bargaining (NB) theory. For example, lam12NB is the NB-based trading price between VPP1 and VPP2, while lam12GNB is the GNB-based transaction price. The difference between them is that the latter considers the contribution factor,  $\alpha_i$ . According to (42), they are 0.63, 1.67, and 1.72, respectively. As can be seen, the GNB-based P2P trading price is higher than that of an NB-based. The higher the price, the more advantageous it is for the power surplus VPP to boost income. This is entirely consistent with the primary purpose of encouraging RE development with energy sharing.

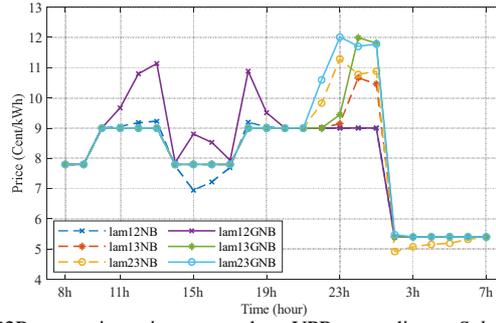
Fig.7. P2P transaction price among three VPPs according to *Subproblem 2*.

TABLE IV shows the final cost of VPPs based on different P2P transaction cost allocation methods, including the shadow price (SP), the middle price (MP), and Shapley value (SV), NB, and GNB. The cost reduction and cost reduction rate of VPPs using those cost allocation strategies are shown in Fig.8. For VPP1, as shown in Fig.8, the SP method provides the smallest cost decline of \$9.1, whereas the MP delivers the biggest cost cut of \$36.3. And it drops by \$18.4 with the SV method. When compared to the previous three approaches, it is clear that the NB method is the most similar to MP because it does not take into account the contribution of VPPs to the cost reduction of the energy-sharing alliance. And the GNB approach is the most identical to SV. This can be further verified with VPP3. The GNB method was able to optimize its gains as an energy provider, achieving \$39.3, which was significantly more than SP's \$27.2 and MP's \$24.9. This fully reflects the role of the contribution factor established in Section 4.1, namely that the distribution of benefits favors the energy provider. VPP2 sells surplus PV during the day and buys excess wind power from VPP3 at night. As a result, its overall contribution is the greatest, which is also consistent with the setting of  $\alpha_i$ . The GNB method reduced the cost by \$41.7, about 22.2%. In conclusion, the P2P trading cost allocation method based on GNB considers the contribution of each VPP to the energy-sharing alliance. It is not only a more equitable strategy, but it also improves the benefits of distributed power sources and encourages RE consumption. Finally, the method here has a significantly lower computing complexity than the intricate SV calculation procedure.

TABLE IV P2P TRANSACTION BENEFIT ALLOCATION

Cost (\$)	Final cost with P2P transactions				
	SP	MP	SV	NB	GNB
VPP1	799.9	772.8	790.6	772.6	788.9
VPP2	119.4	144.2	137.1	154.4	145.9
VPP3	513.9	516.2	506.0	509.3	501.7
Total	1433.2	1433.1	1433.8	1436.3	1436.5

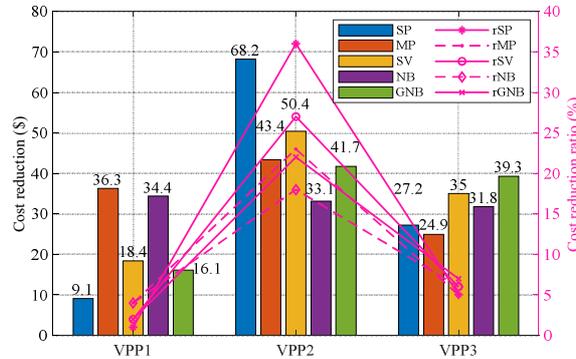


Fig.8. Cost reduction and reduction rate with various cost allocation methods.

## 7. Conclusions

To manage a large number of diverse distributed energy resources on the demand side, this study proposed a general Nash bargaining theory-based energy-sharing mechanism between multiple virtual power plants. The paper addresses the following three issues. First, the non-convex and nonlinear general Nash bargaining-based optimization model is

equivalently transformed into two easy-to-solve subproblems. *Subproblem 1* is solved using fast-ADMM algorithm to protect the privacy. The numerical test demonstrates that after a limited number of iterations, the distributed approach is able to achieve almost the same results as centralized optimization, with an error less than 0.1%. Besides, the neighboring use of renewable energy can be encouraged while lowering the overall cost by roughly 6.7% thanks to the energy sharing system based on peer-to-peer electricity trading. Moreover, the benefit allocation for *Subproblem 2* is addressed using a contribution factor method. The proposed model of the general Nash bargaining theory considering the contribution factors can achieve a fairer benefit distribution and is conducive to promoting the development of the distributed renewable energy resources. When the contribution factor is taken into account, the price of a peer-to-peer trade is higher for the virtual power plant with a surplus of power than it is for one with a deficit. This is completely in line with the main objective of promoting RE development. Finally, the cost distribution will be impacted by the integrity issue, particularly the veracity of the breaking point  $C_i^0$  and the optimal cost  $U_i^*$  reported by virtual power plants for solving *Subproblem 2*. Thus, future work will focus on the reliability of distributed transactions and the sensitivity analysis of risk aversion. The daily renewable energy prediction uncertainty in the virtual power plant will also have an impact on its revenue. Consequently, one of the key objectives for future research is to introduce uncertainty into the method suggested in this paper.

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### Appendix

#### A.1. VPP Cost without P2P Transactions

An optimization model that disregards P2P trading is developed. The objective function is shown as (43).

$$\begin{aligned} \min C_i^0(\mathbf{p}_{i,g}^{gt}, \mathbf{p}_i^{fl}, \mathbf{p}_i^{ag}, \mathbf{p}_i^{ev}, \mathbf{p}_i^b, \mathbf{p}_i^s) &= C_i^{gt} + C_i^{ag} + C_i^{Grid} \\ s.t. \left\{ \begin{array}{l} \sum_{g \in G} p_{i,g,t}^{gt} - p_{i,t}^{fl} + p_{i,t}^{ag} + p_{i,t}^b - p_{i,t}^s - p_{i,t}^{ev} = p_{i,t}^{bl} \\ \mathbf{p}_i^{fl} \in \Phi_i, \mathbf{p}_i^{ev} \in \Theta_i, \mathbf{p}_{i,g}^{gt} \in \Psi_i, \mathbf{p}_i^{ag} \in \Xi_i, \mathbf{p}_i^b, \mathbf{p}_i^s \in \Upsilon_i \\ \forall i \in I, \forall t \in T. \end{array} \right. \end{aligned} \quad (43)$$

#### A.2. Proof of Equivalent Transformation for GNB-based Model

Because it is not convex, the model (30)-(31) is challenging to solve. Thus, this part demonstrates that it can be equivalently transformed into two solvable subproblems under the conditions of the mean inequality, as (44).  $R^+$  represents the positive real number, and the equal sign holds if and only if  $a_1$  to  $a_i$  are equal.

$$a_1 a_2 \dots a_i \leq \left( \frac{a_1 + a_2 + \dots + a_i}{i} \right)^i, \forall a_1, a_2, \dots, a_i \in R^+. \quad (44)$$

According to (49), the function (30) can be transformed into  $\sum_i (C_i^0 - C_i^V)$ ,  $\forall i \in I$ , under the premise of satisfying the following conditions: First,  $C_i^0 - C_i^V \geq 0$ , which is obvious. Secondly,  $\sum_i (C_i^0 - C_i^V)$  is a constant. To prove the second point, let  $U_i = C_i^{gt} + C_i^{ag} + C_i^{grid} + C_i^{tc}$ , then

$$\sum_{i=1}^I (C_i^0 - C_i^V) = \sum_{i=1}^I C_i^0 - \sum_{i=1}^I C_i = \sum_{i \in I} C_i^0 - (\sum_{i \in I} U_i + \sum_{i \in I} C_i^{et}) = \sum_{i \in I} C_i^0 - \sum_{i \in I} U_i \quad (45)$$

In (50), since the P2P transaction costs and benefits within the VPP alliance offset each other, so  $\sum_{i \in I} C_i^{et} = 0$ . Since  $C_i^0$  is a constant and  $U_i$  is also a fixed value, (31) is equivalently transformed into the following as (51).

$$\begin{aligned} \max \prod_i (C_i^0 - C_i^V)^{\alpha_i} &\Leftrightarrow \max \sum_i (-C_i^V) \Leftrightarrow \min \sum_i U_i \\ s.t. \Phi_i, \Theta_i, \Psi_i, \Xi_i, \Upsilon_i, \Lambda_i, \forall i \in I. \end{aligned} \quad (46)$$

When *Subproblem 1* is solved and the optimal value  $U_i^*$  is reset to (30), the model (32) can be obtained.

The natural logarithm is a convex function that increases monotonically. Consequently, taking the natural logarithm and converting the original problem to a minimization problem yields the equivalent model (33).

## References

- [1] J. Guerrero, D. Gebbran, S. Mhanna, A. C. Chapman, and G. Verbič, "Towards a transactive energy system for integration of distributed energy resources: Home energy management, distributed optimal power flow, and peer-to-peer energy trading," *Renewable and Sustainable Energy Reviews*, vol. 132, p. 110000, 2020.
- [2] S. M. Nosratabadi, R.-A. Hooshmand, and E. Gholipour, "A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems," *Renewable and Sustainable Energy Reviews*, vol. 67, pp. 341-363, 2017.
- [3] K. Mahmud, B. Khan, J. Ravishankar, A. Ahmadi, and P. Siano, "An internet of energy framework with distributed energy resources, prosumers and small-scale virtual power plants: An overview," *Renewable and Sustainable Energy Reviews*, vol. 127, p. 109840, 2020.
- [4] Yan X, Gao C, Song M, Chen T, Ding J, Guo M, *et al.*, "An IGDT-based Day-ahead Co-optimization of Energy and Reserve in a VPP Considering Multiple Uncertainties," *IEEE Transactions on Industry Applications*, vol. 58, no. 3, pp. 4037-4049, 2022.
- [5] D. Neves, I. Scott, and C. A. Silva, "Peer-to-peer energy trading potential: An assessment for the residential sector under different technology and tariff availabilities," *Energy*, vol. 205, p. 118023, 2020.
- [6] W.-T. Lin, G. Chen, and C. Li, "Risk-averse energy trading among peer-to-peer based virtual power plants: A stochastic game approach," *International Journal of Electrical Power & Energy Systems*, vol. 132, p. 107145, 2021.
- [7] C. Tan, Z. Tan, Y. Du, Z. He, S. Geng, and Z. Jiang, "Feasibility evaluation of virtual power plants participating in rural Energy Internet under zoning and stratification using prospect theory," *International Journal of Electrical Power & Energy Systems*, vol. 144, p. 108560, 2023.
- [8] Yang C, Du X, Xu D, Tang J, Lin X, Xie K, Li W., "Optimal bidding strategy of renewable-based virtual power plant in the day-ahead market," *International Journal of Electrical Power & Energy Systems*, vol. 144, p. 108557, 2023.
- [9] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nature Energy*, vol. 3, no. 2, pp. 94-101, 2018.
- [10] W. Tushar, C. Yuen, H. Mohsenian-Rad, T. Saha, H. V. Poor, and K. L. Wood, "Transforming energy networks via peer-to-peer energy trading: The potential of game-theoretic approaches," *IEEE Signal Processing Magazine*, vol. 35, no. 4, pp. 90-111, 2018.
- [11] Seven S, Yoldas Y, Soran A, Yalcin Alkan G, Jung J, Ustun TS, Onen A., "Energy Trading on a Peer-to-Peer Basis between Virtual Power Plants Using Decentralized Finance Instruments," *Sustainability*, vol. 14, no. 20, p. 13286, 2022.
- [12] M. Mehdinejad, H. A. Shayanfar, B. Mohammadi-Ivatloo, and H. Nafisi, "Designing a robust decentralized energy transactions framework for active prosumers in peer-to-peer local electricity markets," *IEEE Access*, vol. 10, pp. 26743-26755, 2022.
- [13] E. A. Soto, L. B. Bosman, E. Wollega, and W. D. Leon-Salas, "Peer-to-peer energy trading: A review of the literature," *Applied Energy*, vol. 283, p. 116268, 2021.
- [14] W. Tushar, T. K. Saha, C. Yuen, T. Morstyn, H. V. Poor, and R. Bean, "Grid influenced peer-to-peer energy trading," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1407-1418, 2019.
- [15] Tushar W. Chai B, Yuen C, Huang S, Smith DB, Poor HV, Yang Z., "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1462-1475, 2016.
- [16] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy peer-to-peer trading in virtual microgrids in smart grids: A game-theoretic approach," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1264-1275, 2019.
- [17] S. Cui, Y.-W. Wang, and J.-W. Xiao, "Peer-to-peer energy sharing among smart energy buildings by distributed transaction," *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 6491-6501, 2019.
- [18] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Transactions on Industrial electronics*, vol. 66, no. 8, pp. 6087-6097, 2018.
- [19] C. Long, Y. Zhou, and J. Wu, "A game theoretic approach for peer to peer energy trading," *Energy Procedia*, vol. 159, pp. 454-459, 2019.
- [20] S. Fan, Q. Ai, and L. Piao, "Bargaining-based cooperative energy trading for distribution company and demand response," *Applied energy*, vol. 226, pp. 469-482, 2018.
- [21] C. Wei, Z. Shen, D. Xiao, L. Wang, X. Bai, and H. Chen, "An optimal scheduling strategy for peer-to-peer trading in interconnected microgrids based on RO and Nash bargaining," *Applied Energy*, vol. 295, p. 117024, 2021.
- [22] Y. Wang, X. Wang, C. Shao, and N. Gong, "Distributed energy trading for an integrated energy system and electric vehicle charging stations: A Nash bargaining game approach," *Renewable Energy*, vol. 155, pp. 513-530, 2020.
- [23] J. Ding, C. Gao, M. Song, X. Yan, and T. Chen, "Optimal operation of multi-agent electricity-heat-hydrogen sharing in integrated energy system based on Nash bargaining," *International Journal of Electrical Power & Energy Systems*, vol. 148, p. 108930, 2023.
- [24] S. Cui, Y.-W. Wang, Y. Shi, and J.-W. Xiao, "Community energy cooperation with the presence of cheating behaviors," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 561-573, 2020.
- [25] G. Li, Q. Li, X. Yang, and R. Ding, "General Nash bargaining based direct P2P energy trading among prosumers under multiple uncertainties," *International Journal of Electrical Power & Energy Systems*, vol. 143, p. 108403, 2022.
- [26] Wang Z, Liu F, Ma Z, Chen Y, Jia M, Wei W, Wu Q., "Distributed generalized Nash equilibrium seeking for energy sharing games in prosumers," *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 3973-3986, 2021.
- [27] X. Wang, B. Li, Y. Wang, H. Lu, H. Zhao, and W. Xue, "A bargaining game-based profit allocation method for the wind-hydrogen-storage combined system," *Applied Energy*, vol. 310, p. 118472, 2022.
- [28] B. Houska, J. Frasch, and M. Diehl, "An augmented Lagrangian based algorithm for distributed nonconvex optimization," *SIAM Journal on Optimization*, vol. 26, no. 2, pp. 1101-1127, 2016.
- [29] M. Gilleran *et al.*, "Impact of electric vehicle charging on the power demand of retail buildings," *Advances in Applied Energy*, vol. 4, p. 100062, 2021.
- [30] W. Yang, Y. Xiang, J. Liu, and C. Gu, "Agent-based modeling for scale evolution of plug-in electric vehicles and charging demand," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1915-1925, 2017.
- [31] X. Yan, D. Abbes, and B. Francois, "Uncertainty analysis for day ahead power reserve quantification in an urban microgrid including PV generators," *Renewable Energy*, vol. 106, pp. 288-297, 2017.
- [32] A. Paudel, L. Sampath, J. Yang, and H. B. Gooi, "Peer-to-peer energy trading in smart grid considering power losses and network fees," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 4727-4737, 2020.

- [33] P. Cuffe and A. Keane, "Visualizing the electrical structure of power systems," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1810-1821, 2015.
- [34] T. Goldstein, B. O'Donoghue, S. Setzer, and R. Baraniuk, "Fast alternating direction optimization methods," *SIAM Journal on Imaging Sciences*, vol. 7, no. 3, pp. 1588-1623, 2014.
- [35] L. Han, T. Morstyn, and M. McCulloch, "Estimation of the shapley value of a peer-to-peer energy sharing game using multi-step coalitional stratified sampling," *International Journal of Control, Automation and Systems*, vol. 19, no. 5, pp. 1863-1872, 2021.