Peer-to-Peer Energy Sharing With Social Attributes: A Stochastic Leader–Follower Game Approach

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***Abstract*—Distributed energy resources bring about challenges related to the participation of an increasing number of prosumers with strong social attributes in peer-to-peer (P2P) energy sharing markets, resulting in the increased complexity of socio-technical systems. Previous research has focused on energy sharing analysis based on rational games without considering the social attributes of prosumers, which are not typically used in real scenarios. In this article, an interdisciplinary P2P energy sharing framework that considers both technical and sociological aspects is proposed. It is based on prospect theory (PT) and stochastic game theory, in which the prosumers work as followers with subjective load strategies, while an energy sharing provider (ESP) serves as the leader with a dynamic pricing scheme. A subjective utility model with risk utility (RU) determined by PT is designed for prosumers, and a profit model for dynamic prices is suggested for ESP. Moreover, a solution algorithm that consists of interpolation and curve fitting to obtain the RU function, the aggregation of prosumers to a Markov decision process, and a differential evolution algorithm to solve the game are proposed to solve the problems of the "curse of dimensionality" and discreteness arising from the social attributes of prosumers. Numerical analysis reveals the results of the Stackelberg equilibrium and demonstrates the effectiveness of this method in terms of the social behavior of prosumers, i.e., radicalness when losing and conservatism when gaining.**

***Index Terms*—Markov decision process (MDP), peer-to-peer (P2P) energy sharing, prospect theory (PT), stochastic leader–follower game, subjective prosumer.**

I. Introduction

A PARADIGM shift of energy generation patterns from centralized methods with traditional power resources to distributed methods with renewable energy sources, such as photovoltaic (PV) and wind energy, is underway to face the challenges of climate change and resource scarcity [1]. Although distributed energy resources (DERs) can serve as a possible low-carbon-emission, low-cost, and high-efficiency solution while satisfying large energy requirements [2], they also complicate the power flow of networks and control strategies due to their distributed allocation, intermittence, and fluctuation [3], [4]. DERs are usually set on the demand side close to users to facilitate consumption, which allows users to produce and consume energy, thus rendering users as prosumers who have multiple methods by which to participate in the energy market, i.e., there is a diversity of market roles [5].

As the use of DERs expands, the number of prosumers is increased, thus enabling the possibility for "greening" the power system. Until recently, the majority of research has focused on the prosumer era, explaining how prosumers could be integrated effectively and efficiently into competitive electricity markets [6], designing the demand response framework among each prosumer as well as between prosumers and operators based on game theory [7]–[9], and developing prosumer community groups to effectively manage prosumers [10], [11]. Peer-to-peer (P2P) models have been considered as one of the most effective methods to coordinate prosumer transactions in the emerging energy markets. Using P2P, prosumers can share energy so that the energy can be balanced to the greatest extent in the sharing area and the energy supply of the utility grid can be reduced [12]. In general, P2P energy sharing can be divided into three categories: Pure P2P without an agent, P2P with agent coordination, and P2P with agent participation. Blockchain technology is a predominant method for pure P2P energy trading, meaning it can be carried out without reliance on a trusted third party due to the distributed control mechanism and autonomy network [13], [14]. Pure P2P can also be realized using a method in which the seller sets the trading prices and the buyer conducts seller selection [12]. For P2P with agent coordination, an agent is required to coordinate the P2P trading platform, provide electricity prices [15], or connect the P2P prosumers to the utility and obtain the profit [16]. Finally, for P2P with agent participation, the agent will participate in the energy trading by maintaining a balance between energy selling and buying, and providing the trading energy that buys from the utility grid based on the obtained energy information [17], [18]. Many existing studies

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relate to game theory, indicating that game theory is efficient for solving prosumer-related problems. As prosumers are increasingly active participants in P2P energy sharing and making profit [18], their subjective initiative should be considered due to their significant impact on the energy sharing system [15]. However, existing research has rarely considered the social attributes of prosumers.

Studies that focus on the social attributes of the smart grid (SG) can be mainly separated into two categories: Data-driven and model-driven research. A data-driven method was proposed by Jain *et al*. [19], with a large number of works that observe samples with significant heterogeneity (prosumers) to obtain the consumption patterns of energy usage behavior of prosumers, which can help to resolve the socio-technical complexities when planning DERs. Model-driven methods rely heavily on prospect theory (PT), which is a behavioral economics theory used to express individual behavior applications under risk or uncertainty conditions [20], thereby explaining prosumer social attributes under economic risk conditions. PT is also superior to other theories because it includes a mathematic model composed of value function and probability weighting function that is suitable for engineering applications. There are four conclusions of PT, namely the confirmation effect, the reflection effect, loss avoidance, and reference dependence. Based on these four conclusions, prosumers will bear great risks when losing and avoid great risks when gaining. The losing and gaining are determined by a reference point. Research exploring social attributes by PT uses a discrete strategy of whether storage batteries work, which considers prosumers engaging in real-life decision-making behavior as a stochastic game (evolution game) due to the uncertainty that comes from the social attributes of each prosumer [21]. Other works have considered the uncertainty of future energy prices on a 1-h time scale (i.e., without time-coupling considerations), focusing on the influence of a PT reference point on energy trading [22].

While PT is already being used together with game theory to study the social attributes of prosumers in SG, a number of P2P energy sharing issues remain. These can be categorized into three aspects: 1) Although the rational game framework has ubiquitous usage in P2P energy sharing, it considers only ideal situations and cannot fix the stochastic problems arising from the uncertainty of subjective prosumer decisions in the current socio-technical era [16]; 2) utility models of the prosumers and utility grid with time-coupled variables and multiple participators under the PT application scenarios still require research [21], [22]; 3) the solution algorithm for the “curse of dimensionality” and discreteness problems arising from the multiple scenarios and probabilities due to social attributes of prosumers must be considered.

Therefore, to address the aforementioned problems, a P2P energy sharing framework using a stochastic leader–follower game with social attributes is proposed in this article. The main contributions are as follows.

1) A stochastic leader–follower game-based P2P energy sharing framework with uncertainty originating from multiple prosumers with social attributes and time-coupled fixed, flexible load is created. In the framework, an energy sharing provider (ESP) is employed to manage the system by providing the dynamic pricing scheme for energy sharing, and the demand response of prosumers is affected by their subjective consideration of economic risk.
2) An optimal utility maximization model based on PT is proposed for prosumers to obtain discrete utility function while considering social attributes under the condition of economic risk [risk utility (RU)], thus enabling prosumers to set load strategies. The profit model is also suggested for ESP operation, which allows the ESP to adjust the uncertain dynamic prices in a day-ahead market affected by the prosumers’ strategies.
3) A solution algorithm composed of interpolation and curve fitting, Markov decision process (MDP), and differential evolutionary (DE) are proposed to transform the problem into a continuous MDP problem, obtain the RU function, and reduce the dimension.

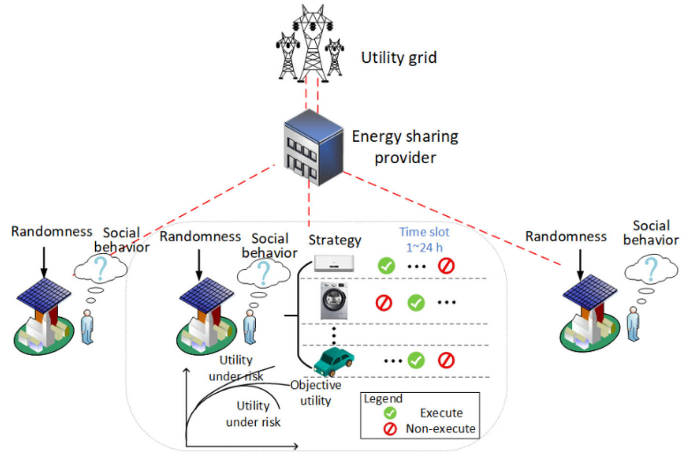

Fig. 1. Framework of P2P energy sharing.

II. System Framework and Sociality Theory

A. Structure of the System

The system framework proposed in this article is a P2P energy sharing framework, in which the main participants are prosumers with a user energy management system and an ESP. Prosumers, who can generate and consume energy, are users equipped with PV panels and serve as buyers or sellers participating in the energy market according to their net energy. The ESP is a third party that manages the P2P energy sharing among each prosumer and coordinates the transactions between prosumers and the utility grid. The system framework is illustrated in Fig. 1.

In this framework, the ESP will maximize its operating profit by implementing dynamic buying and selling electricity prices. Prosumers will also set their strategies of load demand according to the dynamic buying and selling prices to maximize their profits. Benefiting from the buying and selling behavior of prosumers, the local consumption of PV energy will be enhanced. However, in practical situations, prosumers are human beings with subjective initiatives, referred to as social attributes in this

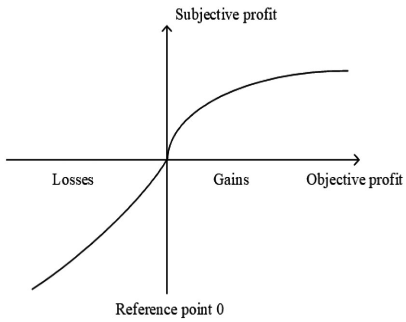

Fig. 2. Value function.

article; they will therefore make strategies not based on rational values, but rather according to their psychological perceptions of the potential values of gains and losses under economic risks [20]. PT provides a good explanation for the social attributes of prosumers in the face of risks.

B. Prospect Theory in P2P Energy Sharing Markets

PT is a behavioral economics theory that can well-explain the social attributes of prosumers in the face of uncertainties. With the increase of the number of prosumers appearing in a P2P energy sharing market, the decisions of the prosumers in the market are no longer completely rational, and general rational decision methods, such as rational game theory [23], will become unsuitable for application to practical situations. Therefore, the profits of prosumers are determined by a mathematical function, called the PT function (utility), which can measure subjective thought when gaining and losing

$$U\left(X\right)=\sum_{k=1}^{K}\omega\left(p_k\right)v\left(x_k\right) \tag{1}$$

where $U(X)$ is the prospect utility in PT, x_k are the possible objective utilities when social attributes are considered, p_k is the corresponding objective probability of each utility, and both x_k and p_k belong to prosumer objective attributes. There will be many possible scenarios (suppose that the number is k) and corresponding probabilities for these scenarios. Additionally, $v(\cdot)$ and $\omega(\cdot)$ are each the value function and the probability weighting function that combine objective attributes with subjective characteristics (i.e., social behavior).

The social behavior of prosumers during decision-making process can be reflected via a mathematical model. Social behavior is represented by the PT utility via the value function and the corresponding probability weighting function based on initial objective utility and probability. The value function $v_i(\cdot)$ represents the relative value of different possible results in the minds of prosumers based on the risk analysis of PT. It is expressed as an s-shaped curve in Fig. 2.

The curve expresses that loss aversion occurs when the loss value is larger than the gain value. Although there are many value functions, the value function proposed by Tversky, the inventor of PT, and proofed by Al-Nowaihi *et al*. [24] is the most widely used for PT [25].

$$v\left(x\right)=\begin{cases}x^{a}, & x\geq 0\\ -b\left(-x\right), & x<0\end{cases} \tag{2}$$

where $0 \leq a \leq 1$ and $b \geq 1$ are constant parameters denoting the loss aversion, x is the objective profit, and the reference point is 0.

Equation (2) and Fig. 2 show the relative value (i.e., subjective profit) under economic risk. Here, the subjective profit will increase less than the objective profit (e.g., x^a) when the objective profit is higher than the reference point, and the subjective profit will decrease similarly to the objective profit (e.g.,$-b(-x)$) when the objective profit is lower than the reference point, reflecting the perspective of risk.

Additionally, $\omega_i(\cdot)$ represents the prosumers' response to probability. In general, prosumers will over-react to low-probability events and under-react to high-probability events. Prelec [26] proposed the following probability weighting function:

$$w\left(p\right)=\exp(-\left(-\ln p\right)^{d}) \tag{3}$$

where $0 \leq d \leq 1$ is a constant denoting the distortion between objective and subjective probability.

III. Stochastic Leader–Follower Game Considering the Social Behavior of Prosumers

Because multiple possible scenarios occur in PT, the decision-making process of prosumers will result in a stochastic process on the prosumer side. In this study, t denotes the stochastic process index (i.e., state), h denotes the time slot index, and i denotes the prosumer index. For prosumer i at each time slot h, a stochastic process can be expressed as the change of state t to the next state $t+1$ accompanied by probabilities $p_{i,k}^{t,h}$ of action k. The action is one of the strategies that can be chosen at each scenario, and the probabilities are the possibility of each strategy being chosen by the prosumers (i.e., load demand $dL_{i,k}^{t,h}$, or energy sales $sL_{i,k}^{t,h}$) [27].

A. Utility Model of Prosumers

Suppose there are N prosumers in the P2P energy sharing framework; among them, the numbers of sellers and buyers are N_s and N_B, respectively. Each prosumer has PV production E_i^h and load consumption $cL_{i,k}^{t,h}$. The load model of the prosumer consists of fixed load $fixL_i^{t,h}$ and flexible load $fL_i^{t,h}$. The fixed load requires high reliability and the time of power supply is immutable, the flexible load includes aspects like electric vehicle charging and washing machines and can be adjusted in the decision-making process to become the strategies of prosumers [7]. Each prosumer will serve as a buyer that sets load demand when $dL_{i,k}^{t,h}=cL_{i,k}^{t,h}-E_i^h\geq 0$ or a seller that sets energy sales when $sL_{i,k}^{t,h}=E_i^h-cL_{i,k}^{t,h}\geq 0$ to participate in P2P energy sharing. Therefore, prosumer decision variables are flexible load. The PV productions of prosumers are random variables with probability u_i^h, and the probability distribution function is denoted by

$$F\left(u_i^h\right) = \int_{-\infty}^{u_i^h} f\left(u_i^h\right) du_i^h. \tag{4}$$

The objective payoff of the prosumer consists of two components: The utility of load consumption and the profit of P2P energy sharing. According to the prosumer's role (seller or buyer), the payoff function can be expressed as follows:

$$f_{i,k}^{t,h} = \begin{cases} \alpha_i^h \ln(1 + cL_{i,k}^{t,h}) + sL_{i,k}^{t,h} * pri_s^{t,h}, & sL_{i,k}^{t,h} \geq 0 \\ \alpha_i^h \ln(1 + cL_{i,k}^{t,h}) - dL_{i,k}^{t,h} * pri_b^{t,h}, & dL_{i,k}^{t,h} \geq 0 \end{cases} \tag{5}$$

where $f_{i,k}^{t,h}$ is the payoff of prosumer i in time slot h, $sL_{i,k}^{t,h} = F(u_i^h) - cL_{i,k}^{t,h}$ is the strategy of the seller, $dL_{i,k}^{t,h} = cL_{i,k}^{t,h} - F(u_i^t)$ is the strategy of the buyer, and $pri_s^{t,h}$ and $pri_b^{t,h}$ are, respectively, the dynamic selling prices and buying prices, which are determined by the ESP. The profit of P2P energy sharing is $sL_{i,k}^{t,h}{*}pri_s^{t,h}$ or $dL_{i,k}^{t,h}{*}pri_b^{t,h}$. The natural logarithm $\ln(\cdot)$ function has been widely used in economics for modeling the preference of users and the decision-making process [28] and has been shown to be suitable for the design of the utility for power consumers [29]. In addition, $\alpha_i^h \ln(1 + cL_{i,k}^{t,h})$ is the utility of producing the energy $cL_{i,k}^{t,h}$ that the prosumer consumes, the format $\ln(1 + (\cdot))$ can avoid the underside utility of $-\infty$, and α_i^h is a constant preference parameter of the prosumer who will consume more energy with a higher value of α_i^h.

The adjustment of the load is not infinite; there exist lower and upper bound constraints and time-coupling constraints

$$cl_i^{h\min} \leq cl_i^h \leq cl_i^{h\max}, \tag{6}$$

$$\sum_{h=1}^{H} fl_i^h = sq_i \tag{7}$$

where the upper and lower bounds are the same at the same time slot for the same prosumer at different states and the lower bound is equal to the fixed load, and sq_i is the sum of the flexible load of prosumer i in the entire time period to satisfy the sum constraint.

Based on the PT, the prosumers with strong social behavior will not participate in the game as rational individuals. Therefore, there are many strategies of prosumers (suppose the number is k) and will generate probabilities according to different decisions when the state changes from t to $t + 1$. The number of k profits and the number of k strategies ($f_{i,k}^{t,h}$ and $cL_{i,k}^{t,h}$) will exist. In addition, the utility of prosumers is changed from the objective payoff (5) to the PT utility. The value function can be expressed as follows:

$$v\left(f\left(cL_{i,k}^{t,h}\right)\right) = \begin{cases} f(cL_{i,k}^{t,h})^a, & f\left(cL_{i,k}^{t,h}\right) \geq 0 \\ -b\left(-f\left(cL_{i,k}^{t,h}\right)\right), & f\left(cL_{i,k}^{t,h}\right) < 0 \end{cases}. \tag{8}$$

The objective probability $p_{i,k}^{t,h}$ of a prosumer's strategy is determined by the Maxwell–Boltzmann distribution, which expresses the relationship between the probability of each system position appearing and the related energy, e.g., the probability that the system will show a certain position can be expressed as the ratio of the energy at that position to the total energy of the system [30]. In the present work, the energy is equivalent to the prosumers' utility, which is added to the minimum utility to keep the positive of probability. Thus, the probability that action k will appear in state t can be determined according to

$$p_{i,k}^{t,h'}\left(cL_{i,k}^{t,h}\right) = \frac{f\left(cL_{i,k}^{t,h}\right)}{\sum_k f\left(cL_{i,k}^{t,h}\right)}. \tag{9}$$

However, the possible strategies that appear in state t should be related to the action before state t, so the objective probability is a conditional probability

$$p_{i,k}^{t,h}\left(cL_{i,k}^{t,h} | S_i^{t-1,h}\right) = \frac{p_{i,k}^{t,h'} \prod_{t=1}^{T-1} p_{i,k}^{t,h}}{\prod_{t=1}^{T-1} p_{i,k}^{t,h}} \tag{10}$$

where $S_i^{t-1,h}$ is the state of prosumers i in time slot h and state $t-1$, the prosumer state is fixed load, flexible load, and PV production, which also shows the iteration process.

Based on the probability weighting function (3) and the probability distribution (10), the objective probability can be expressed as a subjective probability function:

$$w\left(p_{i,k}^{t,h}\right) = \exp\left(-\left(-\ln p_{i,k}^{t,h}\right)^d\right). \tag{11}$$

In general, PT utility is an expected utility considering all possible prosumer decisions and corresponding probabilities, which is used to measure the overall strategy and corresponding possible prosumer utility under uncertain conditions (i.e., risk). However, prosumers can only choose one strategy as their action when they make decisions in practice. In turn, the stochastic problem arises from social attributes, which will directly influence prosumer load strategies. Unlike natural factors, which are not prosumer strategies, PV generation influence on the decision-making process comes from the prosumer effect on netload. Social attributes will result in a mixed strategy with many possible strategies and corresponding probabilities. This mixed strategy is like a comprehensive consideration of all possible scenarios, and it cannot be used directly to make decisions. Therefore, this article focuses on RU, which is one of the PT utility terms that offer the greatest contribution to the expected PT utility. The RU that prosumers use to set actions can be expressed as follows:

$$fPT_{i,k}^{t,h} = \begin{cases} w\left(p_{i,k}^{t,h}\right) \cdot f(cL_{i,k}^{t,h})^a, & sL_{i,k}^{t,h} \geq 0 \\ w\left(p_{i,k}^{t,h}\right) \cdot f(cL_{i,k}^{t,h})^a, & f\left(cL_{i,k}^{t,h}\right) \geq 0 dL_{i,k}^{t,h} \geq 0 \\ w\left(p_{i,k}^{t,h}\right) \cdot -b\left(-f\left(cL_{i,k}^{t,h}\right)\right), & f\left(cL_{i,k}^{t,h}\right) < 0 dL_{i,k}^{t,h} \geq 0 \end{cases}. \tag{12}$$

B. Profit Model of ESP

As a coordinator, the goal of the ESP is to maximize its own profit. The strategy by which to realize this goal is to set the dynamic selling and buying prices based on the strategies of prosumers (i.e., load information) and the utility grid prices $g_{s,h}$ and $g_{b,h}$, which are determined by the feed-in tariffs of some countries. When the total PV energy of the system is greater than the total load demand, the ESP should sell energy to the utility grid, and it should buy energy from the utility grid when the net energy of the system is insufficient. The profit model can be expressed as follows:

$$R^{t,h} = \begin{cases} \mathrm{pri}_b^{t,h} \cdot dE^{t,h} - pri_s^{t,h} \cdot sE^{t,h} + g_s \Delta E^{t,h}, & \Delta E^{t,h} \geq 0 \\ pri_b^{t,h} \cdot dE^{t,h} - pri_s^{t,h} \cdot sE^{t,h} + g_b \Delta E^{t,h}, & \Delta E^{t,h} < 0 \end{cases}, \tag{13}$$

$$dE^{t,h} = \sum_{i \in N_B} dL_i^{t,h}, \tag{14}$$

$$sE^{t,h} = \sum_{i \in N_S} sL_i^{t,h}, \tag{15}$$

$$\Delta E^{t,h} = sE^{t,h} - dE^{t,h} \tag{16}$$

where $dE^{t,h}$, $sE^{t,h}$, and $\Delta E^{t,h}$ are, respectively, the total energy buying, total energy selling, and net energy of the system at time slot *h* and state *t*. The selling and buying energy values are from the perspective of prosumers.

The ESP profit is composed of two parts: As a participant to the prosumers' P2P energy sharing and trading the unbalanced energy with the utility grid. Here, ESP provides the sharing energy from the utility grid based on the obtained energy information of prosumers. The first part is $pri_b^{t,h} \cdot dE^{t,h} - pri_s^{t,h} \cdot sE^{t,h}$, which is the trading with prosumers to provide energy for energy sharing and is determined by the energy information of prosumers and dynamic prices. The second part is $g_s \Delta E^{t,h}$, which is trading with the utility grid, i.e., buying energy when $\Delta E^{t,h} < 0$ and selling energy when $\Delta E^{t,h} \geq 0$, to balance the energy in the system.

Generally, the dynamic prices should be adjusted within the range of the utility grid prices that adopt the feed-in-tariff of some countries. In addition, the profit of the ESP comes from the difference between dynamic prices and utility prices; the dynamic buying prices should be higher than the dynamic selling prices to keep the ESP profitable, which can be expressed as follows:

$$g_s^h \leq \mathrm{pri}_s^{t,h} < \mathrm{pri}_b^{t,h} \leq g_b^h. \tag{17}$$

Due to the social behavior of prosumers, the strategy of the ESP will be different in a rational game, in which the dynamic prices are based on the load information while considering the social attributes of prosumers; thus, the strategy of the ESP will also have sociability.

C. Formulation of Stochastic Leader–Follower Game

The goal of the participants in the P2P energy sharing framework is to maximize their utility (i.e., the prosumer's utility and ESP's profit). It is therefore similar to a multiagent profit optimization problem, which can be analyzed by game theory. The interaction between the prosumers and ESP can be formulated as a leader–follower game, in which ESP is the leader with the strategy of dynamic prices $\mathrm{pri}_b^{t,h}$ and $\mathrm{pri}_s^{t,h}$, and the prosumers are the followers with the strategy of load demand $dL_i^{t,h}$ or energy sales $sL_i^{t,h}$ [5].

The stochastic framework is used in the prosumer side to express the multiple scenarios and probabilities with different prosumer strategies generated by considering their social attributes. Because there are possible actions that each prosumer can choose when they make decisions in each state and because each action corresponds to a certain probability, the decision-making process on the follower side throughout the game is a strategy selection process to attain the optimal utility. Suppose that there is one scenario in the initial state 1, prosumers have *k* possible actions to change to state 2; the possible results (i.e., number of scenarios) of state 2 is then *k*, that of state 3 is k^2, and that of state *t* is k^{t-1}, which is a stochastic process and will generate many possible states. Therefore, the classical leader–follower game is changed to the stochastic leader–follower game, which can be expressed as follows:

$$G = \{G^t | t = 1, 2, \ldots, T\}$$

$$G^t = \begin{Bmatrix} (\mathrm{ESP} \cup N), \{\boldsymbol{S}^t\}, \{\boldsymbol{cL_i^t}\}_{i \in N, t \in T}, \{\boldsymbol{pri_b^t}\}, \{\boldsymbol{pri_s^t}\}, \\ \{\boldsymbol{fPT_i^t}\}, \{\boldsymbol{R}^t\} \end{Bmatrix} \tag{18}$$

where superscript *t* is the state index of the game that appears because the stochastic process is on the prosumer side, and the process of state change is equivalent to the iteration process of a general leader–follower game, ESP and *N* are the respective sets of the ESP and prosumers, $\boldsymbol{S}^t$ is the state set, which includes fixed load, flexible load, and PV production, $\boldsymbol{cL_i^t}$ is the load action set of prosumers, $\boldsymbol{pri_b^t}$ and $\boldsymbol{pri_s^t}$ are internal buying and selling prices, which are also the action set of the ESP, $\boldsymbol{fPT_i^t}$ is the RU of prosumers, and the goal is to maximize utility, and finally $\boldsymbol{R}^t$ is the profit of the ESP, and the goal is to maximize the profit. The process of the stochastic leader–follower game is illustrated in Fig. 3.

During the process of the game *G*, the strategy of prosumers in state *t* will relate to the action in the previous state, which is also explained by the conditional possibility of (10). Therefore, the strategy of the prosumer is a state-coupled variable that should be considered over the entire state scale. The strategies of each prosumer at the same state also affect each other. In addition, due to the element of uncertainty, the strategy of the prosumer is also discrete and is therefore difficult to solve by the general method (e.g., the similar solution method for the problem on the leader side).

With the game occurring, the utility of the prosumers will approach the optimal value, as should the profit of the ESP. Therefore, there exists only one feasible solution of the game, which is the Stackelberg equilibrium (SE).

Definition 1: A strategy set of gamers *i* in time slot *h* can be expressed as $\psi_i^{t,h} := \{cL_i^{t,h}, \mathrm{pri}_b^{t,h}, \mathrm{pri}_s^{t,h}, t = 1, 2, \ldots, T\}$. A set of optimal strategy $\psi_i^{t,h*}$ is the SE of the game, if and only if the following expressions are satisfied:

$$tfPT_i^h\left(\psi_i^{t,h*}\right) \geq tfPT_i^h\left(cL_i^{t,h}, \boldsymbol{cL_{-i}^{t,h*}}, \mathrm{pri}_b^{t,h*}, \mathrm{pri}_s^{t,h*}\right),$$

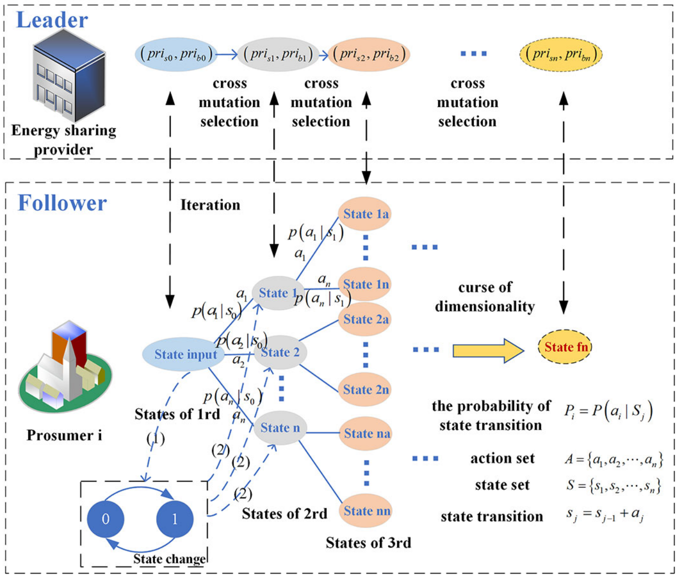

Fig. 3. Iteration process of the stochastic leader–follower game.

$$\forall i \in N, \forall cL_i^{t,h} \in \boldsymbol{cL_i^t} \tag{19}$$

$$R_i^{t,h}\left(\psi_i^{t,h*}\right) \geq R_i^{t,h}\left(cL_i^{t,h*}, \text{pri}_b^{t,h}, \text{pri}_s^{t,h}\right)$$
$$\forall \text{pri}_b^{t,h} \in \boldsymbol{pri_b^t}, \forall \text{pri}_s^{t,h} \in \boldsymbol{pri_s^t} \tag{20}$$

where $\boldsymbol{cL_{-i}^{h*}} = [cL_1^{h*}, cL_2^{h*}, \ldots, cL_{i-1}^{h*}, cL_{i+1}^{h*}, \ldots, cL_n^{h*}]$.

Theorem 1: The unique SE always exists in the proposed stochastic leader–follower game G.

Proof: The detailed proof is available on https://www.researchgate.net/publication/341735276_Proofof_Theorem_1_for_Peer-to-peer_Energy_Sharing_with_Social_Attributes_A_Stochastic_Leader-follower_Game_Approach.

After the game G, the ESP will obtain the optimal profit and corresponding optimal strategy (i.e., action), which is the SE result. However, the utility function of the prosumer that is used to make decisions is the RU, which is particularly used to set the strategy under a condition of risk in a subjective way, and cannot measure the real utility of the prosumer. Therefore, the real utility corresponding to the optimal strategy that considers social behavior is obtained by substituting the optimal strategy under SE into the initial objective utility function (5) of the prosumers. It should be noted that this utility value is only used to display the level of gaining, not the optimal value, because the corresponding optimal strategy is not obtained by the SE of the utility.

IV. Solution Algorithm

Fig. 3 shows that the number of scenarios and corresponding actions will increase exponentially with the iteration of game G. Therefore, the game will face the problem of the "curse of dimensionality," thereby making it mathematically unsolvable. Additionally, according to the preceding analysis, due to prosumer social attributes indicated in the selection action process (i.e., the stochastic process) and each scenario corresponding to a prosumer load distribution, flexible load variables had to be discrete to generate different scenarios, which is difficult to solve and cannot be practically applied.

A. Discrete Problem to a Continuous Problem

To fit the usage in practical situations, in which prosumers set actions continuously, the discrete problem should be transformed into a continuous problem. Interpolation and the curve fitting method are used to realize this transformation [31]. The adjustment range of the flexible load is separated into M equal intervals, and the probability (10) corresponding to each interval is changed from the summation method in a discrete condition to an integral in a continuous condition. The prosumers' utility can then be obtained by calculating the first value of each interval so that the results can be expressed as a set of arrays, which describes the relationship between the flexible load and corresponding PT utility of prosumers. To enable the smooth adjustment of the flexible load and apply it to practical scenarios, the cubic spline interpolation function is used to increase the number of data points. The decision-making process of prosumers is to select the optimal strategy from the strategy set rather than to choose a strategy directly. The action of the ESP is set by optimizing its profit, which is difficult to achieve by combining the continuous solution method with the discrete selection method. Therefore, there should be a continuous utility function of the prosumers that allows the prosumers to set their action according to the RU, and this function is obtained by the fitting method.

B. Segmented Optimization Based on the MDP of Prosumers

Prosumers may have several decision possibilities corresponding to certain probabilities when considering the social attribute, which will result in the stochastic problem on the prosumers' side, i.e., each state is determined by the previous state and prosumer actions; the number of actions and states increase exponentially, resulting in the problem of the "curse of dimensionality." Because the action of each prosumer is affected by the dynamic prices and because the prices are related to the load information of the entire system, the action of each prosumer will affect each other; thus, the decision-making process of each prosumer is relevant. To resolve this problem and transform the interdependent stochastic process into a solvable problem, the overall optimization for all prosumers in each state is adopted, i.e., all prosumers are aggregated to a unified set. All prosumers change states at the same time via the overall optimization, and the state-coupled action of each prosumer is contained in the inner side. Therefore, the decision-making process on the prosumers' side can be formulated as an MDP. The MDP of prosumers can be expressed as follows:

$$M = \left\{\boldsymbol{S_i^t}, \boldsymbol{A_i^t}, \boldsymbol{p}\left(a_{i,k}^{t,h}|s_i^{t-1,h}\right), \boldsymbol{U_i^t}\right\} \tag{21}$$

where $\boldsymbol{S_i^t}$ is the state set of prosumers i in state t, $\boldsymbol{A_i^t}$ is the action set of prosumers i in state t, $\boldsymbol{p}(a_{i,k}^{t,h}|s_i^{t-1,h})$ is the probability of

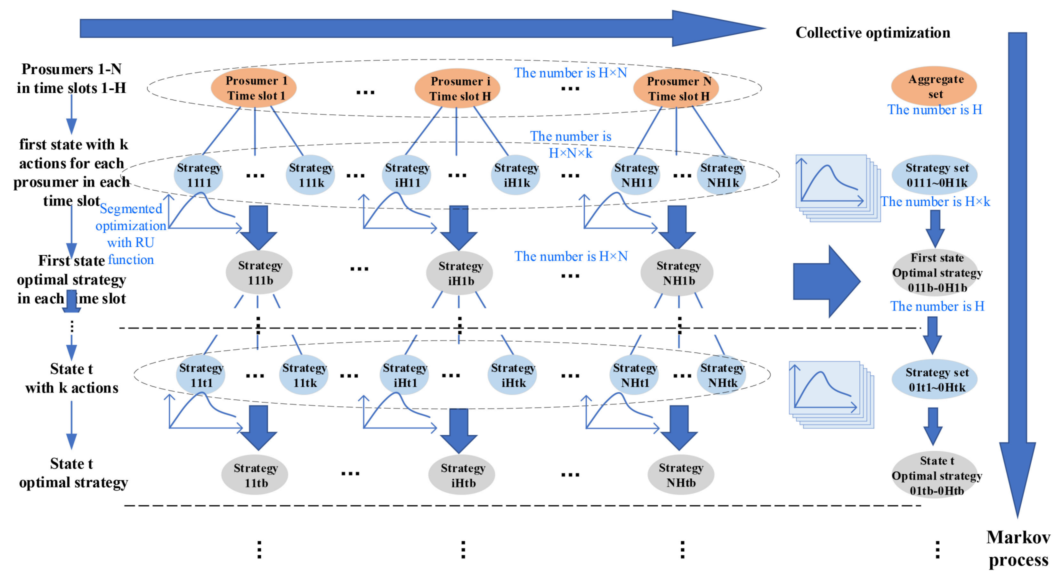

Fig. 4. Stochastic process of MDP with interpolation and curve fitting.

one action happening at the state set $\boldsymbol{S}_i^t$, which is a conditional probability, and $\boldsymbol{U}_i^t$ is the RU of prosumer i in state t.

The state of prosumers i in state t consists of the fixed load, flexible load, and PV production and can be expressed as follows:

$$S_i^{t,h} = \left\{fixL_i^h, fL_i^{t,h}, E_i^h\right\}, h \in [1, \ldots, H]. \tag{22}$$

Prosumer actions come from the prosumer action set, and they can be expressed as follows:

$$A_i^{t,h} = \left\{cL_{i,k}^{t,h}\right\}, h \in [1, \ldots, H], k \in [1, \ldots, K] \tag{23}$$

where the change of load consumption originates from the flexible load.

State change of the MDP is accompanied by iteration of the game; with the change of the dynamic prices set by the leader, the state of the prosumers' side will also change corresponding to a certain probability. The probability of the state change is the same as the subjective probability $w(p_{i,k}^{t,h})$, which indicates that the action appeared in one state and results in the state change.

For a Markov process, according to the optimality principle of dynamic programming, the remaining decisions must constitute an optimal strategy according to the state resulting from the first strategy [32]. Therefore, the overall optimal strategy can be obtained by segmented optimization in each state. The stochastic process of prosumers side shown in Fig. 3 can be changed to a solvable problem and illustrated in Fig. 4.

The encoding method of the strategy in Fig. 4 is the four numbers $\{N, H, t, k\}$, where N denotes the prosumer, H denotes the time slot, t is the state, and k is the number of possible actions in one state. The "0" in each term indicates that this item does not exist and "b" indicates the optimal strategy of k actions. The k actions will serve as the RU function by the fitting method; thus, there are $N \times k$ numbers of RU functions for each time slot in one state and they are aggregated to a unified function to be the utility $\boldsymbol{U}_i^t$ of the MDP. The value of $\boldsymbol{U}_i^t$ will change in every iteration between the leader and follower of the game and acts as the basis for setting strategies.

From Fig. 4, it is evident that the prosumers' optimal strategy of each state can be acquired state-by-state and is accompanied with the optimal strategy of the ESP in each state. The process of the stochastic leader–follower game is then the MDP of the followers' side and the optimization process of the leader's side, and the state change of the MDP is accompanied by the iteration between the leader and follower of the game.

C. Solution Algorithm for Stochastic Leader–Follower Game

Based on the interpolation and curve fitting method, MDP, and segmented optimization, the game is transferred to a dual-side optimization problem, but the optimization problem remains difficult to solve. During the process of solving the game, the ESP (leader) will set dynamic prices according to its profit and load information, and prosumers (followers) will set load distribution based on the RU obtained by the aforementioned methods and dynamic prices. These two types of players have different objectives and affect each other. The DE algorithm is used to solve the dual-side optimization problem by establishing the relationship between the leader and follower sides [33]. A solution algorithm composed of interpolation and curve fitting method, MDP, and DE is then proposed. The process is described as follows.

V. Case Study

A. Basic Data

A P2P energy sharing test system in a day-ahead market was used in the present study to verify the performance of the proposed model. The system consisted of five prosumers

Algorithm 1: Combinational Solution Algorithm for Game G.

1. Set the parameters a, b of the value function (8), d of the probability weighting function (11), α_i^h of the prosumer, and the number of iteration times Iter.
2. Initialize the ESP, set the utility grid prices g_b^h and g_s^h as initial dynamic prices $\mathrm{pri}_b^{t,h}$ and $\mathrm{pri}_s^{t,h}$, respectively, and obtain the initial profit $R^{t,h}$.

For iteration $t = 1$

3. The ESP generates q number of descendants.
4. Broadcast the dynamic prices $\mathrm{pri}_b^{t,h\prime}$ and $\mathrm{pri}_s^{t,h\prime}$ of all descendants to prosumers.
5. Prosumers obtain the RU function by the interpolation and curve fitting methods, and the MDP and segmented optimization for the problems (6), (7), and (12) are conducted based on the new prices. The new load distribution and profits are then obtained and the results are uploaded to the ESP.
6. The ESP calculates the profits based on (13)–(16) and selects the best profit $R^{t,h\prime}$.

If $R^{t,h\prime} > R^{t,h}$
  $R^{t,h} = R^{t,h\prime}$
  $\mathrm{pri}_b^{t,h} = \mathrm{pri}_b^{t,h\prime}$ and $pri_s^{t,h} = pri_s^{t,h\prime}$
Else
  Continue;
If $t <$ Iter
  Take the results of this state as the initial value for the next state and return to step 3.
  $R^{t+1,h} = R^{t,h}$
  $\mathrm{pri}_b^{t+1,h} = \mathrm{pri}_b^{t,h}$ and $\mathrm{pri}_s^{t+1,h} = \mathrm{pri}_s^{t,h}$
  $t = t + 1$
Else
  Stop the solution algorithm.
End for

with PV panels connected to a low-voltage (10 kV) feeder of a distribution network including commercial buildings and factories, and the data of the system was taken from an industrial park in Guangdong Province, China. The prosumers had flexible loads and fixed loads, and the real-time PV production and load information were collected by smart meters installed on the prosumers' side. An ESP was a third party and was in charge of coordinating the prosumers and the utility grid via communication. Each prosumer could choose the role of a seller or buyer to participate in energy sharing according to their netload. The initial data of netload per hour is presented in Fig. 5. It is clear that prosumer 3 was a seller in time slots 8–16 and served as a buyer in the other time slots. Therefore, the P2P energy sharing system is largely dependent on the strategy of prosumers who have strong social attributes and cannot be considered as entirely rational entities. In addition, the PV production with strong randomness was obtained from the probability distribution. The parameter of the prosumers' utility (5) was set as $\alpha_i^h = 55$, the a, b, and d values of the RU function (12) were respectively 0.5, 1, and 0.8, the constraints of the lower bounds and upper bounds of the flexible loads were 0 and 250 kW, and the utility grid selling prices and buying prices are 0.35 and 1.0 kWh/CNY.

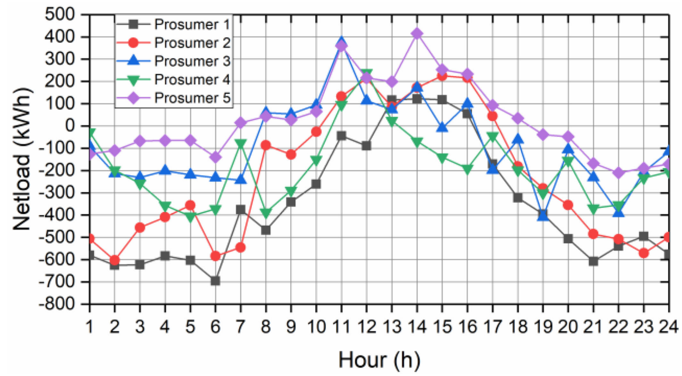

Fig. 5. Netload of PV prosumers in each time slot.

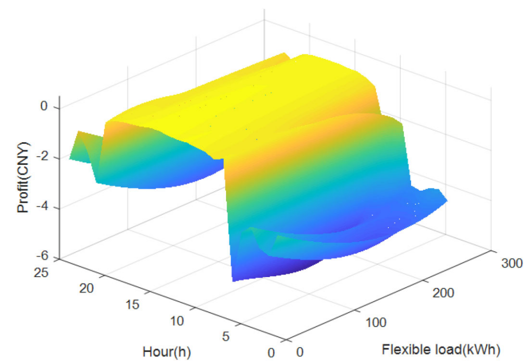

Fig. 6. RU surface of prosumer 1 at the first state.

B. Analysis of the Interpolation and Curve Fitting Results

Each prosumer implements different actions in different states, and each action corresponds to a unique probability and utility. Based on the interpolation and curve fitting method, the continuous RU function of different time slots in the same state can be acquired. According to the test system, there were five prosumers with 24-h load scheduling; thus, 120 continuous RU functions could be obtained in one state. By combining the continuous RU function of each prosumer in 1 d (i.e., 24 h), the RU surface can be obtained. The number of intervals of the flexible load was 250, and the interval of the integral to determine the probability was 1. In addition, the interpolation and curve fitting were implemented by MATLAB, and the error of the method was found to be less than 10^{-4}; it can therefore be used in industrial applications. Fig. 6 shows the RU surface of prosumer 1 in the first states.

The RU surface reflects the correspondence between RU, strategy of prosumers, and time slots in each state. Each state has a unique RU surface because the RU is related to the objective utility (5), which is affected by the dynamic prices set by ESP that will be changed throughout the game process. In general, the RU surface expresses the possible utility of prosumers under different load distributions in 1 d and considers the social attributes of the prosumers. This information is important and requires follow-up study.

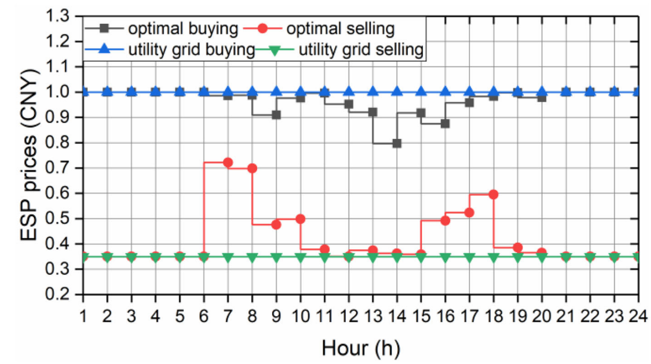

Fig. 7. Dynamic prices set by the ESP and the utility grid prices.

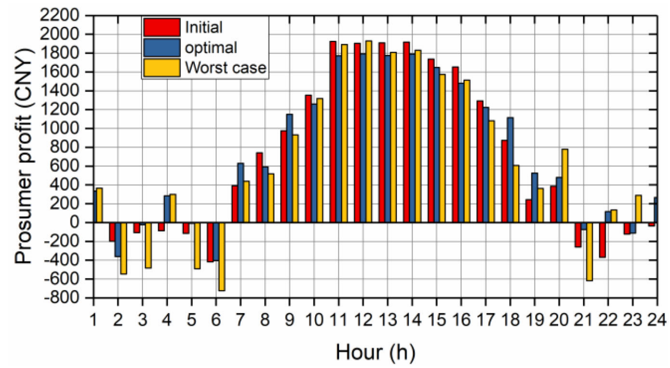

Fig. 9. Profits of prosumers.

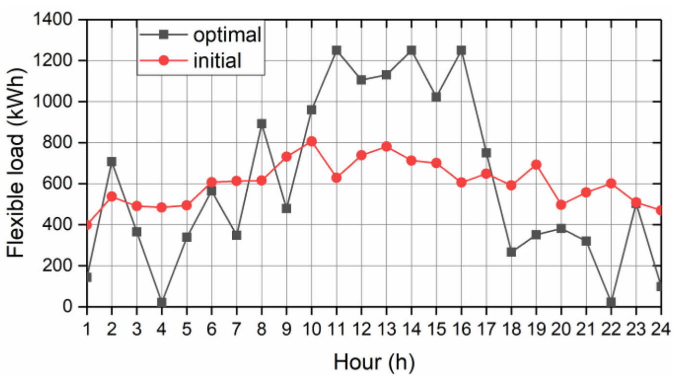

Fig. 8. Optimal flexible load distribution of prosumers.

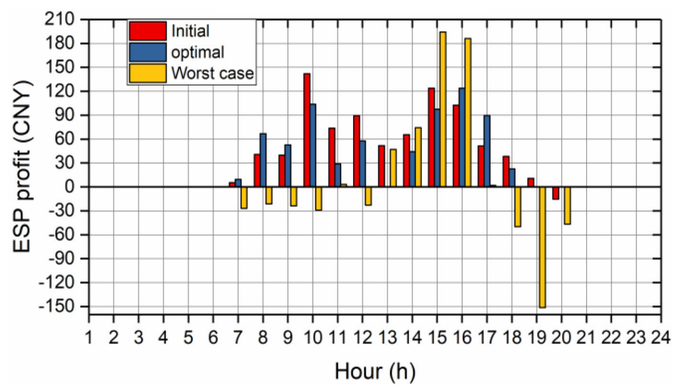

Fig. 10. Profits of ESP.

C. Analysis of the Game Results

1) Action of the ESP: The action of the ESP is the setting of the dynamic selling and buying prices, which is shown in Fig. 7. Due to the social behavior of prosumers, i.e., the multiple strategies and corresponding possibilities, there were minor fluctuations in the dynamic prices. According to Fig. 5, there was no PV production in time slots 0–7 and 21–24, and the buying prices set by the ESP were therefore the same as the prices of the utility grid. However, in time slots 8–20, the ESP set lower buying prices and higher selling prices than the utility grid to stimulate trading with prosumers to obtain more profit via the differential price. It is clear that in time slots 11–15, the buying prices were at the lowest level and the selling prices remained in a lower level to increase the local consumption of PV production and stimulate the buyer to buy energy. In time slots 6–10 and 16–18, the peaks of selling prices originated from the PV production being unable to meet the demand of prosumers; thus, the ESP stimulated prosumers to sell energy by increasing the selling prices. It can also be seen from Fig. 7 that the dynamic buying prices were always higher than the dynamic selling prices, which promoted the local consumption of PV energy.

2) Action of the Prosumers: Fig. 8 presents the flexible load distribution (i.e., the actions) of all prosumers. It is clear that for all prosumers, the peak flexible load was higher than the initial flexible load. From Fig. 7, the buying prices decrease in time slots 10–17, and the PV production is high in these time slots, resulting in the higher peak flexible load of prosumers. Therefore, the flexible load scheduling changed with the PV production and the dynamic prices to get higher profits.

3) Utility of Prosumers and the ESP: To demonstrate the advantages of the proposed game model in terms of increasing prosumer and ESP utility, three scenarios are designed, the initial, optimal, and worst case, when all prosumers implement the same actions during the iteration process of the game.

Fig. 9 provides an hourly comparison of the prosumers' utility in three scenarios. As illustrated in the figure, the sum of utility increases from initial 15 650 CNY to optimal 17 257 CNY and then decreases to 15 145 CNY. It should be noted that the RU that is considered in the game model is the utility with the greatest contribution to the expected PT utility, and the utility of the prosumer in Fig. 9 is the objective utility with optimal and worst load distribution. The hourly profit of the ESP in three scenarios is shown in Fig. 10 and also increases from initial 696 CNY to optimal 819 CNY and decreases to 135 CNY at its lowest. For the optimal scenarios, when the PV production of prosumers is sufficient, the ESP will maintain the dynamic selling prices at a low level and reduce the dynamic buying prices. When the PV production is insufficient, the dynamic buying prices will be closed to the utility grid prices to maximize the profit. Additionally, prosumers set the load distributions to fit the change of dynamic prices, i.e., the flexible load is transferred

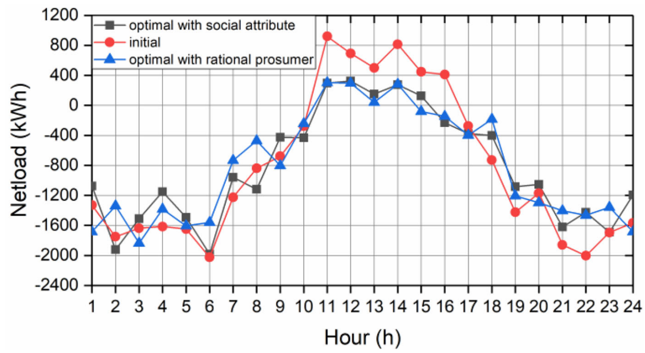

Fig. 11. Comparison of the netload in the scenarios of social and rational prosumers.

to the time with high PV production or low buying prices, thus reducing the buying cost.

For the worst scenario, all prosumers conduct the same actions and the personalized decision-making process of each prosumer has disappeared so that they cannot determine the optimal unique actions. Therefore, the profit of prosumers is decreased and the extreme distribution of ESP's utility is generated.

D. Analysis of the Social Attributes of Prosumers

The PT indicates that the prosumers will take great risks when they are losing and will avoid great risks when they are gaining; this is reflected in the RU function. The game results of the netload of prosumers with RU are presented in Fig. 11 and are accompanied by the rational game results. In time slots 7–20 (i.e., have PV production), the prosumers are gaining according to the reference point; the fluctuation of the netload as compared to the initial value was smaller than the rational scenario, which demonstrates that the prosumers were more conservative than in the rational scenario. The reason is that the prosumers tend to maintain the present status to avoid the risk of dramatically changing the status of participating market transactions. However, in time slots 2–6 and 21–24 (i.e., no PV production), the prosumers are losing according to the reference point, and the fluctuation of the netload (i.e., actions) as compared to the initial netload in the social scenario was larger than the rational scenario, indicating that the prosumers were more likely to participate the P2P energy sharing, undertake the market risk, and take a gamble to make more profit, which is a kind of radical behavior. This phenomenon is similar to the experiment results that Kahneman and Tversky [20] obtained when they proposed the PT by showing the responses of students and university faculty when facing different benefits. Therefore, the method proposed in this article can express the social attributes of prosumers in the process of real decision making.

E. Analysis of Computation Cost and Practical Feasibility

Three larger-scale systems each consisting of 10, 20, and 30 prosumers were established to analyze the computation performance of the proposed algorithm. The designed algorithm was implemented using a computer with Intel Core i5-8250 CPU 1.60 GHz, 16-GB memory, and MATLAB 2018a was used as the testing environment for the algorithm. Table I lists the corresponding average computation time.

TABLE I
COMPUTATION TIME WITH DIFFERENT NUMBERS OF PROSUMERS

Number of prosumers	5	10	20	30
Time cost(s)	2624	4765	9136	12868

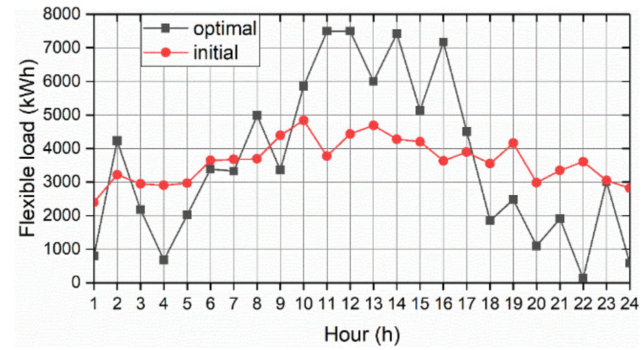

Fig. 12. Actions of prosumers in a 30-prosumer system.

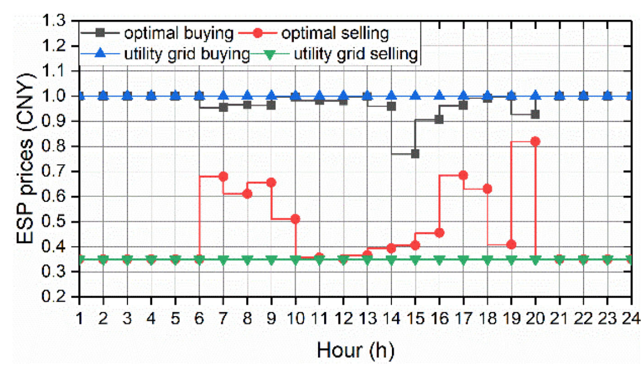

Fig. 13. Actions of ESP in a 30-prosumer system.

Table I shows that computation times are measured in hours, e.g., 0.72, 1.32, 2.53, and 3.57 h, because of the DE algorithm iteration. Moreover, the computation complexity of this algorithm is $O(n)$ due to each prosumer conducting the interpolation and curve fitting when dynamic prices change, which will be influenced by the number of prosumers. However, in day-ahead scheduling, the maximum consumption time required is less than 24 h, and the corresponding maximum number of prosumers is 210. Not many commercial building and factory prosumers exist in one specific system—generally no more than 30. Therefore, the computation time of the proposed algorithm remains within a relatively acceptable degree and the proposed algorithm can be implemented in the system context.

Prosumer and ESP strategies in the 30-prosumer systems are each shown in Figs. 12 and 13. Fig. 12 also shows that the peak flexible load is higher in the time slots 10–17, in which buying prices decrease and PV production is at the high level. Results are similar to the results of a five-prosumer system. Fig. 13 shows that ESP sets lower buying prices and higher selling prices in PV production time, and the changing trend is similar to the five-prosumer system previously analyzed. Therefore, both results show that the 30-prosumer system has similar characteristics to the 5-prosumer system.

VI. Conclusion

In this article, a P2P energy sharing market was developed consisting of an ESP and prosumers with social attributes and time-coupled variables under economic risk based on PT and game theory. A solution algorithm composed of interpolation and curve-fitting method, MDP, and DE was then proposed. The optimal results of dynamic prices and load distributions were shown and can be respectively set by the ESP and prosumers according to the game via numerical verification. The influence of social attributes on the P2P energy sharing market was analyzed according to the differences between prosumers with and without social attributes. It was then concluded that prosumers were conservative when gaining and radical when losing, as previously illustrated by the Kahneman and Tversky sociological experiments. Future research will relate to new methods that reduce computation complexity and distributed computation technologies that can support a larger scale system, e.g., edge computing.

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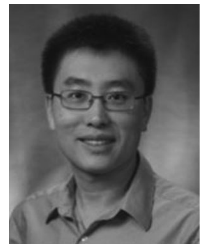

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