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Research on the Dynamic Characteristics of Photovoltaic Power Production and Sales Based on Game Theory

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Abstract: This paper mainly studies the dynamic characteristics of production and sales of distributed photovoltaic power. This is beneficial for the construction and development of a green power system, and it promotes the sustainable development of the social economy. First, the production and sales laws of the photovoltaic power are analyzed, and the trade process between photovoltaic power producers (PVPs) and photovoltaic power demanders (PVDs) is modeled as a game. Different from the existing relevant literature, two kinds of payoff bimatrices are provided, which correspond to the PVD market and PVP market, respectively. Then, the dynamic characteristics of the model are revealed by using the semitensor product method. The results present a more reliable theoretical basis for the sustainable development of the green electricity market. Finally, through an illustrative example, it can be seen that the strategies of all participants are constantly changing to obtain more profits rather than stable at a traditional Nash equilibrium point. It is worth pointing out that the method and results are applicable to other distributed low-carbon energies, contributing to the development of sustainable energy systems.

Keywords: sustainable development; distributed photovoltaic power; game theory; semitensor product of matrices (STP); Nash equilibrium

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1. Introduction

In recent decades, the continuous growth of fossil fuel consumption has led to high carbon emissions and exacerbated global warming. Carbon reduction has become a focus of global attention. It is now more urgent than ever to seek sustainable development measures. In order to achieve the dual carbon goal, countries usually choose to change their high-carbon power generation structure, promote green and low-carbon energy transformation in an orderly way, and accelerate the construction of a new type of power system dominated by new energies [1,2]. In fact, green power with zero (or approaching zero) carbon emissions has become the only way to complete the low-carbon transformation of energy structures and promote sustainable social development [3,4].

At present, microgrids have become the main force for the rapid development of renewable energy [5–13]. The energy blockchain injects new vitality into distributed energy and smart microgrids [14–18]. Distributed low-carbon energy, mainly including photovoltaic, wind, nuclear, geothermal energy, and so on, as a supplement to traditional power solutions, can optimize the capacity configuration of electricity and alleviate some issues, such as capacity expansion and renovation. These advantages drive scholars to explore the trading methods of distributed photovoltaic power in the market [19–22]. This not only improves the returns of distributed green power investors but also encourages flexible social capital investment in the development of distributed photovoltaic power, thereby assisting in the green and low-carbon transformation of energy.

Through third-party agents, small- and medium-sized photovoltaic users, not directly dispatched by the power grid, can obtain a reasonable allocation of power resources, and multienergy collaborative trade can be carried out normally [23–26]. However, the trading prices of photovoltaic electricity fluctuate frequently. This is because of (1) the strong volatility and high uncertainty of photovoltaic energy and (2) the transaction price being closely related to the supply and demand relationship of photovoltaic power.

Considering the interest correlation and information privacy among multiagents, many scholars prefer to use game theory to model distributed systems, since game theory proves to be a good choice for decentralized (or distributed) multiagent decision-making problems [27].

For the case of multiple microgrids, cooperative game theory was adopted to model the energy transaction. For example, ref. [28] considered the behavior of energy transactions between multiple operators in microgrids, proposed a distributed coordinated control scheme, and developed a joint optimization strategy for multiple microgrids. The operating costs of the system was effectively reduced by this strategy. A consensus algorithm was proposed to obtain an optimal demand management scheme for multiagent smart microgrids; see [29]. The algorithm depended on the information and data transfer among the neighbors in the smart microgrid. Aimed at the problem of the decentralized scheduling of microgrids, reference [30] presented a two-stage framework in which the distribution feeder reconfiguration was implemented to satisfy technical and security constraints, and microgrids day-ahead scheduling was performed by a game-theoretic approach to avoid market power. A distributed power-sharing framework is considered in [31]. And the method to optimize its performance was formulated as a repeated game between households in a microgrid. Because the ownership complexity feature of distributed energy resources (DERs) greatly impacts peer-to-peer (P2P) energy trading, Luo et al. developed a game-theory-based decentralized trading scheme to examine the effects of DER ownership on the benefit of each participant in the P2P trading market [32]. In [33], a new method was proposed to form microgrid coalitions. Compared with the relevant existing results, the proposed method took into account both power losses and service charges in the bidding strategy of microgrids and calculation of their utility.

A cooperative game is the study of how people allocate the benefits of cooperation when reaching a goal, which is known as the problem of income distribution. A non-cooperative game is a study of how people make decisions to maximize their own profits in situations where interests interact, namely the problem of strategy selection. Due to the fact that the theoretical maturity of cooperative games is much lower than that of non-cooperative games, the latter has a wider application. Stackelberg's game is a common model for analyzing energy transaction problems. For example, in order to analyze the economic optimization method of multiple stakeholders in a distributed energy system, ref. [34] proposed a multistakeholder benefit optimization method and established a local market energy transaction model. The model used the master–slave game method to solve the optimization strategy. A day-ahead economic dispatch strategy which can solve mixed-integer programming problems based on game theory was proposed [35]. This strategy ensured utility and made the users gain maximum benefits. For microgrids with multiparties, a Stackelberg game model was established in [36] to solve the energy trading management problem. In this model, authors took the energy management trading system as the leader and all the distributed generators in the microgrid as the followers. The results indicate that this method can reduce the dependence of microgrids on the upper level of the power grid while obtaining more profits. Amin et al. proposed a framework in [37] that combines the non-cooperative and cooperative game to facilitate P2P electricity trading while maintaining the stability of the contract. In the method proposed above, a pivotal player was determined with the Shapely–Shubik power index to distribute the shared revenue in a fair manner.

The Nash bargaining method, proposed by Nash [38], was used in [39] to describe the economic interaction between community energy managers and photovoltaic consumers. Mohseni et al. developed an asymmetric Nash bargaining game model with a new index, named fuzzy bargaining power, to fairly allocate trading benefits to microgrids [40]. The fuzzy index incentivized microgrids to proactively trade energy throughout the entire day and not just when energy selling or buying was in their interest. A novel demand-side management method was developed in [41] whose results confirm the compatibility between this method and game theory to find the Nash equilibrium point. Ref. [42] proposed an optimal multiagent-based market algorithm for smart multimicrogrid systems. In this algorithm, a game-theoretic double-auction mechanism was proposed for the day-ahead market, while a hierarchical optimization algorithm was developed for the hour-ahead market and real-time market to minimize the energy mismatch and the dependency on the utility by performing an optimal intermicrogrid market. Reference [43] introduced a demand-side integration framework. This framework was based on a prepaid orderly energy consumption strategy. The interaction between aggregators and end-use customers was captured as a Nash bargaining game.

In addition to the typical game models mentioned above, the networked evolutionary game model has recently been used to investigate energy trading problems. Ref. [44] modeled the transaction between green power operators and green power producers as a networked evolutionary game. Based on this model, the dynamic characteristics of the green power transaction were revealed by using the STP method.

However, the existing research methods all have problems: (1) In cooperative games, the information between internal members can be exchanged, and the agreements reached must be enforced. But the reflected real economic problems have incomplete information, and the method cannot provide a clear standard to analyze the competition in real society. (2) The Stackelberg game model can better describe the leader–follower relationship in actual decision making, as well as take into account the time series and causal relationships between participants. But there is information asymmetry and the irrational behavior of decision makers. (3) Although both parties in the Nash bargaining game model have their own strategies at their disposal to achieve the maximum interests within a certain range, they are unwilling to adjust their own strategies according to that of the other party. Thus, the result is not the best one that both parties want, and it may be a slightly less favorable one. (4) In the networked evolutionary game model, the strategy can be updated according to certain rules, and the updated strategy's rules for all players are the same. Players can choose and adjust the next update based on whether the previous update strategy was successful or not. However, the updated strategy's rules may be influenced by the topology of the network where the players are located. The above information is summarized in Table 1.

Therefore , to obtain the dynamic characteristics of photovoltaic power production and sales, this paper takes into account the competition phenomenon in the market-oriented trading process. The fact that the transaction price is always influenced by the supply and demand relationship of green electricity is comprehensively considered. And then an attempt is made to model and analyze the trading process of photovoltaic power producers (PVPs) and photovoltaic power demanders (PVDs) by the game theory and semitensor product (STP) method. The contributions of this paper are as follows:

1. In the dynamic game model for trading between PVPs and PVDs, the payoff bimatrices provided for the PVD market and PVP market reflect the impact of the supply and demand relationship of green electricity on transaction pricing.
2. A game can be transformed into its algebraic form by using the STP. This algebraic form makes it more convenient for us to study the game. Therefore, the STP is an effective method for analyzing the dynamic characteristics of game models.
3. During the trading process, the strategies of all participants are constantly changing to obtain more profits rather than stable at a traditional Nash equilibrium point.

Table 1. Summary of research on game theory to model distributed systems.

Method		Related Achievements	The Characteristics of the Method
Cooperative game		[28–33]	• Information between internal members can be exchanged, and the agreements reached must be enforced. • The reflected real economic problems have incomplete information, and it cannot provide a clear standard to analyze the competition in a real society
Non-cooperative game	Stackelberg game	[34–37]	• It can better describe the leader–follower relationship in actual decision making and take into account the time series and causal relationships between participants. • There is information asymmetry and the irrational behavior of decision makers.
	Nash bargaining game	[38–43]	• Both parties have their own strategies at their disposal to achieve the maximum interests within a certain range. • Both parties are unwilling to adjust their own strategies according to that of the other party. Thus, the result is not the best one that both parties want, and it may be a slightly less favorable one.
	Networked evolutionary game	[44]	• The strategy can be updated according to certain rules, and the updated strategy's rules for all players are the same. Players can choose and adjust the next update based on whether the previously updated strategy was successful or not. • The updated strategy's rules may be influenced by the topology of the network where the players are located.

The rest of this paper is organized as follows. In Section 2, some preliminaries are introduced and the problem analysis of photovoltaic energy trading networks as well as some assumptions are given for the convenience of modeling. Then, the production and sales laws of photovoltaic power generation are analyzed, and the transaction process between PVPs and PVDs is modeled as a game in Section 3. This section also presents the main results. These results include the strategy-updating rule, payoff bimatrix, and two algorithms for calculating all attractors of the system to reveal the dynamic characteristics of the game model. An illustrative example is designed in Section 4. It shows that the strategies of all participants are constantly changing to achieve more profits, rather than stabilizing at the traditional Nash equilibrium point. Finally, a brief conclusion is provided in Section 5.

2. Materials and Methods

2.1. Preliminaries

For ease of expression, some notations are first introduced.

- $\mathbb{R}^n$: the set of all n-dimensional real vectors;
- $\mathbb{M}_{m\times n}$ ($\mathbb{L}_{m\times n}$): the set of $m \times n$-dimensional real (logical) matrices;
- $Col_i(M)$ ($Row_i(M)$): the ith column (row) of matrix M;
- I_n: the $n \times n$ dimensional identity matrix;
- $\delta_n^i := Col_i(I_n)$, the ith column of I_n;
- $\Delta_n := Col(I_n) = \{\delta_n^i \mid i = 1, 2, \cdots, n\}$, the set of all columns of I_n;
- $\delta_n[i_1, i_2, \cdots, i_s] := [\delta_n^{i_1}\ \delta_n^{i_2} \cdots \delta_n^{i_s}]$, a logical matrix.

As analyzed in the introduction, the photovoltaic energy transaction of PVPs and PVDs is modeled as a dynamic game. Here are the four elements of the game [45]:

(1) $N = \{1, 2, \cdots, n\}$ denotes n players;

(2) $S_i = \{1, 2, \cdots, k_i\}, i = 1, 2, \cdots, n$, expresses the strategy set of player i, and $S = \prod_{i=1}^{n} S_i$ is the set of strategy profiles;
(3) $c_i : S \to \mathbb{R}^n, i = 1, 2, \cdots, n$ is the payoff function of player i;
(4) In a multiround game, the players follow the ultimate goal of maximizing their own profits and use this goal as a guiding principle for adjusting their strategies.

A game can be transformed into its algebraic form by using STP technology [46–48]. This form makes it more convenient to study the game. So, it is necessary to recall the STP here.

Definition 1 ([48])**.** *Let $A \in \mathbb{M}_{m\times n}$, $B \in \mathbb{M}_{p\times q}$, and denote the least common multiplier $lcm(n, p)$ of n and p by l. Then, the STP of A and B is*

$$A \ltimes B := (A \otimes I_{\frac{l}{n}})(B \otimes I_{\frac{l}{p}}) \in \mathbb{M}_{\frac{ml}{n}\times\frac{ql}{p}},$$

where $\otimes$ is the Kronecker product of matrices.

Some basic properties of the STP used in this paper are listed as follows. Readers may refer to [49] for more details.

- For any matrix M, n-dimensional column vector X, and n-dimensional row vector Y, the following two equalities hold
$$X \ltimes M = (I_n \otimes M) \ltimes X$$
and
$$M \ltimes Y = Y \ltimes (I_n \otimes M).$$
- For any two column vectors $X \in \mathbb{R}^m$ and $Y \in \mathbb{R}^n$, the following equality holds:
$$W_{[m,n]} \ltimes X \ltimes Y = Y \ltimes X,$$
where
$$\begin{aligned} W_{[m,n]} := \delta_{mn}[&1, m+1, 2m+1, \cdots, (n-1)m+1,\\ &2, m+2, 2m+2, \cdots, (n-1)m+2,\\ &\cdots,\\ &(m-1), m+(m-1), 2m+(m-1), \cdots, (n-1)m+(m-1),\\ &m, m+m, 2m+m, \cdots, nm] \in \mathbb{M}_{mn\times mn} \end{aligned}$$
is a swap matrix.
- For any $\delta_{2^n}^i \in \Delta_{2^n}$, the following equality holds:
$$\delta_{2^n}^i \ltimes \delta_{2^n}^i = \Phi_n \delta_{2^n}^i,$$
where $\Phi_n = \prod_{i=1}^{k} I_{2^{i-1}} \otimes [(I_2 \otimes W_{[2,2^{k-i}]})M_r] \in \mathbb{L}_{2^{2n}\times 2^n}$, and $M_r = \delta_4[1,4]$ is a power-reducing matrix.

It is noted that the STP has properties similar to the conventional matrix product. Especially, when $n = p$, the STP happens to be the conventional matrix product. Therefore, STP is a generalization of the conventional matrix product. Throughout this paper, the matrix products are assumed to be the STP, and the symbol $\ltimes$ is usually omitted.

2.2. Problem Analysis

The users participating in the photovoltaic power transaction include individual users, enterprise users, and energy companies.

- Individual users can become both suppliers and demanders of photovoltaic power in the transactions. As the suppliers, individual users produce sufficient electricity by installing photovoltaic power generation systems, which can not only meet household requirements but also sell their remaining electricity to energy companies and earn profits. On the demand side, individual users need to purchase green electricity when their production is insufficient.
- Enterprise users often appear as demanders. With the increasing awareness of corporate social responsibility and regulatory restrictions on energy consumption, more and more enterprises are purchasing green electricity to reduce their dependence on traditional energy and improve their sustainable development level.
- Energy companies obtain green power through construction and operation of renewable energy generation projects and then sell the green power to individual users and/or enterprise users to obtain profits.

From the above analysis, it can be found that PVPs usually appear in the form of energy companies or individuals, while PVDs are mostly individuals or electricity-consuming enterprises. In addition, there are usually multiple PVPs and PVDs in a photovoltaic energy-trading network. For the convenience of modeling, some assumptions are given here.

Assumption 1. *All players are rational and choose their strategies to obtain as much profit as possible every time.*

Assumption 2. *A PVP can only sell its photovoltaic electricity to a PVD but cannot trade with other PVPs. And a PVD can only buy photovoltaic electricity from a PVP.*

Assumption 3. *PVPs (PVDs) cannot cooperate with each other and must bid independently.*

3. Results

3.1. Transaction Process

Due to the impact of market supply and demand on photovoltaic trading prices, there are two cases that need to be discussed: (1) When there is sufficient photovoltaic power, PVPs compete to sell off. The price of photovoltaic power is showing a downward trend. PVDs have more opportunities to choose PVPs. This is called a PVDs' market. (2) When the supply of photovoltaic power is far less than demand, PVDs compete with each other to obtain as much green electricity as possible and engage in panic buying. The price is on the rise. PVPs are in a favorable market position and have the initiative to sell their green electricity. This is called a PVPs' market.

The trading process of PVPs and PVDs is roughly as follows:

(1) All PVPs and PVDs engage in bidding transactions on the same third-party platform.
(2) According to the real-time market conditions, all participants bid once a day.
(3) For a given PVP, if there is at least a PVD whose quotation is not lower than that of the PVP, then a transaction will be conducted. Otherwise, the deal fails and they wait for the next bidding. When conducting transactions, an introduction is given in the following section about how to determine the transaction price.
    (1) In a PVDs' market, the lowest quotation from the above PVPs will be used as the transaction price.
    (2) In a PVPs' market, the transaction price is the highest quotation of the above PVDs.

3.2. Strategy-Updating Rule

It is natural that the strategy of player i in the next round should be influenced by its neighbors' strategies in this round. Here, player i will learn from the most profitable one among all neighbors to update their next strategy. Therefore, Unconditional Imitation With Fixed Priority [50] is adopted as the strategy-updating rule. That is, if

$$j^* = \arg\max_{j \in \mathrm{U}(i)} c_j(x(t)),$$

then

$$x_i(t+1) = x_{j^*}(t),$$

where $x(t) = (x_1(t), x_2(t), \cdots, x_n(t))$ is the strategy profile of all players at time t; $x_i(t)$ is the strategy of player i at time t; and $\mathrm{U}(i)$ is the set of neighbors of player i.

When there is more than one neighbor with the highest profit, say

$$\arg\max_{j \in \mathrm{U}(i)} c_j(x(t)) = \{j_1^*, \ldots, j_k^*\}, k > 1,$$

the following strategies are chosen:

1. If player i is a PVD, their neighbor players $j_1^*, \ldots, j_k^*$ are PVPs. The PVD prefers to make the next deal with one of the PVPs at the lowest possible price. So,

$$x_i(t+1) = \min\{x_{j_1^*}(t), \ldots, x_{j_k^*}(t)\}.$$

2. If player i is a PVP, all of their neighbors $j_1^*, \ldots, j_k^*$ are PVDs. The PVP tends to make the next transaction with one of the PVDs at the highest price. Then,

$$x_i(t+1) = \max\{x_{j_1^*}(t), \ldots, x_{j_k^*}(t)\}.$$

For ease of understanding, the strategy-updating rule above is rewritten in the form of a flowchart; see Figure 1.

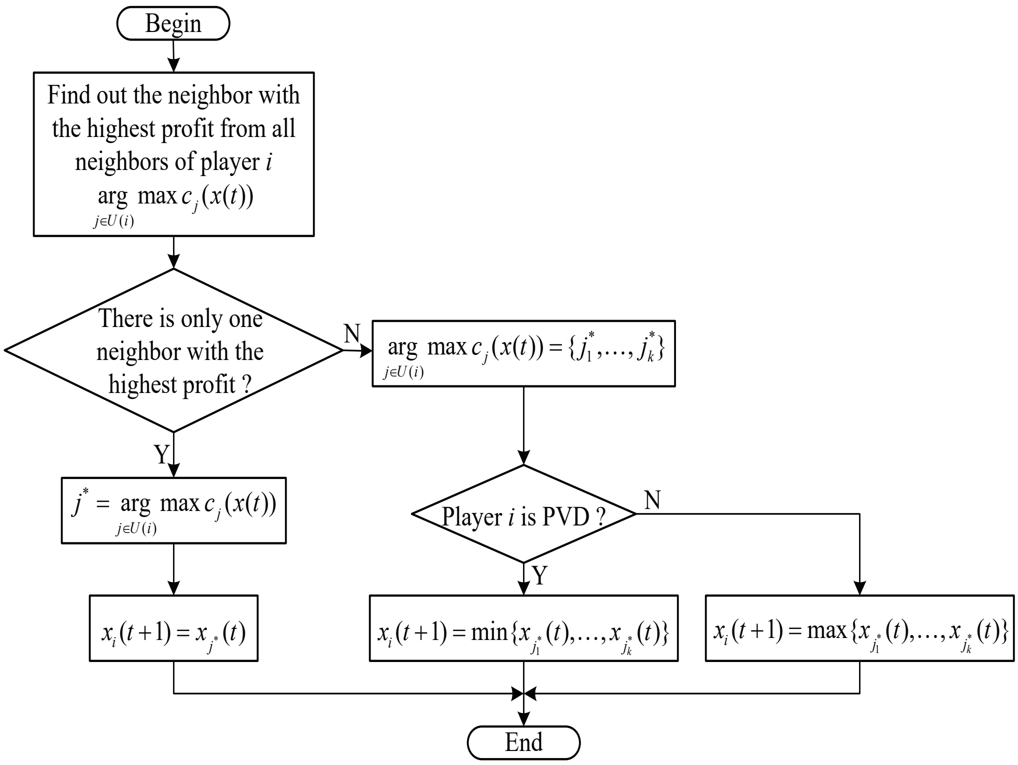

Figure 1. Flowchart for the strategy-updating rule of the photovoltaic energy transaction model.

3.3. Payoff Bimatrix

From the actual current situation, the cost of photovoltaic power is much higher than that of traditional electricity. In order to promote the development of low-carbon or zero-carbon power systems and build a new type of power system with new energy as the main body, the government should provide subsidies to low-carbon or zero-carbon power production enterprises and individuals. Therefore, the transaction price P_{deal} must not be less than the difference between the production price $P_{produce}$ and the government subsidy $P_{subsidy}$ to make PVPs have profits, namely

$$P_{produce} - P_{subsidy} \leq P_{deal}. \tag{1}$$

On the other hand, the use of nongreen energy causes a large amount of carbon emissions. Under the "dual carbon" goal, the state penalizes enterprises with high carbon emissions. Therefore, these enterprises are under increasing pressure. Compared with traditional electricity prices, the transaction price P_{deal} should not be more than the sum of the traditional electricity price $P_{traditional}$ and the compensation costs $P_{compensation}$ to ensure that photovoltaic electricity is more attractive. That is to say, the following inequality holds:

$$P_{deal} \leq P_{traditional} + P_{compensation}. \tag{2}$$

From (1) and (2), the inequality

$$P_{produce} - P_{subsidy} \leq P_{deal} \leq P_{traditional} + P_{compensation}$$

holds.

Let $A = P_{produce} - P_{subsidy}$ and $B = P_{traditional} + P_{compensation}$. Divide the difference between A and B equally into $n+1$ parts: A, $A + \frac{B-A}{n+1}, A + \frac{2(B-A)}{n+1}, \cdots, A + \frac{n(B-A)}{n+1}$, and B.

It is worth noting that no player wants to choose the extreme strategy A or B to achieve a successful transaction as soon as possible. Therefore, for any player, their strategy set is $\{A + \frac{i(B-A)}{n+1}, i = 1, 2, \cdots, n\}$. Without loss of generality, it can be assumed that the strategy sets of all players are the same. In fact, even if there are two players whose strategy sets are different, the same method can be used for subsequent processing. Now, according to the trading process introduced in Section 3.1, the payoff bimatrices of the PVDs' market and PVPs' market are given in Table 2 and Table 3, respectively.

Table 2. Payoff bimatrix of the PVDs' market.

PVP╲PVD	**1**	**2**	$\cdots$	$\boldsymbol{n-1}$	$\boldsymbol{n}$
1	$(1, n)$	$(1, n)$	$\cdots$	$(1, n)$	$(1, n)$
2	$(0, 0)$	$(2, n-1)$	$\cdots$	$(2, n-1)$	$(2, n-1)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$n-1$	$(0, 0)$	$(0, 0)$	$\cdots$	$(n-1, 2)$	$(n-1, 2)$
n	$(0, 0)$	$(0, 0)$	$\cdots$	$(0, 0)$	$(n, 1)$

Table 3. Payoff bimatrix of the PVPs' market.

PVP╲PVD	**1**	**2**	$\cdots$	$\boldsymbol{n-1}$	$\boldsymbol{n}$
1	$(1, n)$	$(2, n-1)$	$\cdots$	$(n-1, 2)$	$(n, 1)$
2	$(0, 0)$	$(2, n-1)$	$\cdots$	$(n-1, 2)$	$(n, 1)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$n-1$	$(0, 0)$	$(0, 0)$	$\cdots$	$(n-1, 2)$	$(n, 1)$
n	$(0, 0)$	$(0, 0)$	$\cdots$	$(0, 0)$	$(n, 1)$

From Tables 2 and 3, it is easy to see that these two payoff bimatrices are both asymmetric and upper triangular. This characteristic is determined by the trading process.

3.4. Dynamic Characteristic Analysis

Now, δ_n^k is identified with k, $k = 1, 2, \cdots, n$; then, each strategy profile $(k_1, k_2, \cdots, k_m)$ can be replaced by $(\delta_n^{k_1}, \delta_n^{k_2}, \cdots, \delta_n^{k_m})$. From [49], $(\delta_n^{k_1}, \delta_n^{k_2}, \cdots, \delta_n^{k_m})$ is equivalent to $\delta_{n^m}^r$, where $r = (k_1 - 1)n^{m-1} + (k_2 - 1)n^{m-2} + \cdots + (k_{m-1} - 1)n + k_m$.

The vector form of strategy variables is utilized to define $x(t) = \ltimes_{i=1}^m x_i(t) \in \Delta_{n^m}$. Then, based on the STP technology provided in [48], the above photovoltaic energy transaction model can be equivalently transformed into its algebraic form

$$x(t+1) = Mx(t), \tag{3}$$

where $M \in \mathbb{L}_{n^m \times n^m}$ is the structure matrix of system (3).

Obviously, (3) has a linear form. So, it is very convenient to investigate the photovoltaic energy transaction by analyzing (3). Besides, as everyone knows, the attractors of (3), including fixed points and limit cycles, are important, where a fixed point corresponds to one Nash equilibrium of the game model. Through these attractors, a comprehensive overview of the photovoltaic energy transaction can be obtained.

Theorem 1. *The system (3), which is equivalent to the photovoltaic energy transaction model, has an attractor C with length k, if and only if:*

1. *For any state $\delta_{n^m}^i \in C$, $Col_i(Row_i(M^k))$ = 1 holds;*
2. *for any integer l ($l < k$), there is a state $\delta_{n^m}^i \in C$, such that $Col_i(Row_i(M^l)) = 0$.*

Proof of Theorem 1. (Necessity) By known conditions, the system (3) has an attractor C with length k. If $k = 1$, C is a fixed point, and Necessity naturally holds. Otherwise, C is a limit cycle with length k. Then, for any state $\delta_{n^m}^i \in C$, (4) holds

$$\delta_{n^m}^i = M^k \delta_{n^m}^i, \quad \delta_{n^m}^i \neq M^l \delta_{n^m}^i, \tag{4}$$

where $l < k$. It is noted that M is a logical matrix. So, (4) leads to $\text{Col}_i(\text{Row}_i(M^k))$ = 1 and $\text{Col}_i(\text{Row}_i(M^l)) = 0$.

(Sufficiency) The proof process of Necessity can be derived in reverse, which completes the proof of Sufficiency. □

As we know, attractors are very important because they can reveal the dynamic characteristics of system (3). Theorem 1 gives a necessary and sufficient criterion for attractors. In the following, based on this criterion, Algorithms 1 and 2 are provided to calculate all attractors of system (3).

Algorithm 1: Compute the set Ω_k of states contained in all limit cycles of length k.

```
Ω_0 = Φ.
for k = 1 to n^m do
    initialize: Ω_k = Φ.
    for i = 1 to n^m do
        if Col_i(Row_i(M^k))=1 holds, then
            Ω_k = Ω_k ∪ {δ^i_{n^m}}.
        end if
    end for
    return Ω_k = Ω_k \ Ω_{k−1}, and the length of attractor Ω_k = k.
end for
```

Algorithm 2: Compute the attractor C of (3) with length k.

for $k = 1$ to n^m do
  denote the potential of Ω_k as r.
  for $j = 1$ to r do
    return $C_{kj} = \{\Omega_k(j), M\Omega_k(j), \cdots, M^{k-1}\Omega_k(j)\}$,
    $\Omega_k = \Omega_k \setminus C_{kj}$.
  end for
end for

Finally, the process of solving the dynamic characteristics of the photovoltaic energy transaction can be demonstrated through a flowchart; see Figure 2.

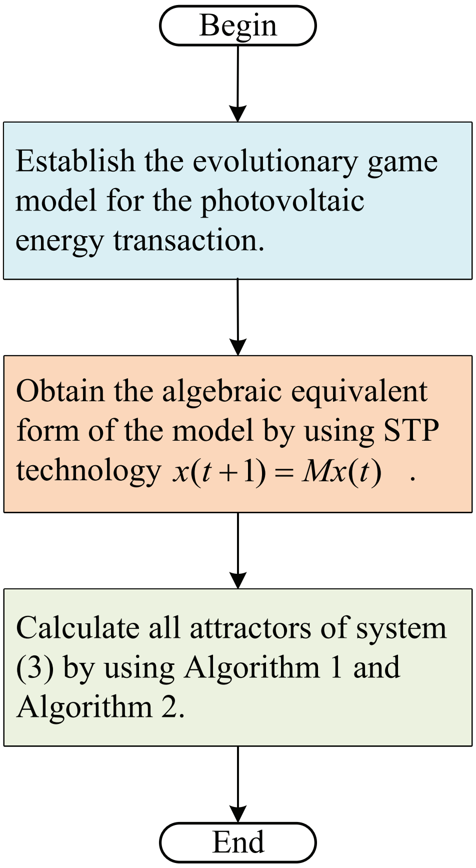

Figure 2. Flowchart for solving the dynamic characteristics of the photovoltaic energy transaction.

4. Discussion

In the following, an example is given to show the effectiveness of the method developed in this paper. To simplify the problem, it is supposed that there are three PVPs (PVP1, PVP2, PVP3) and two PVDs (PVD1, PVD2) in the network, numbered x_1, x_2, x_3, x_4, x_5. Their structure topology is depicted in Figure 3.

Firstly, a trading model in the PVDs' market is established. Setting n = 2, Table 2 becomes Table 4.

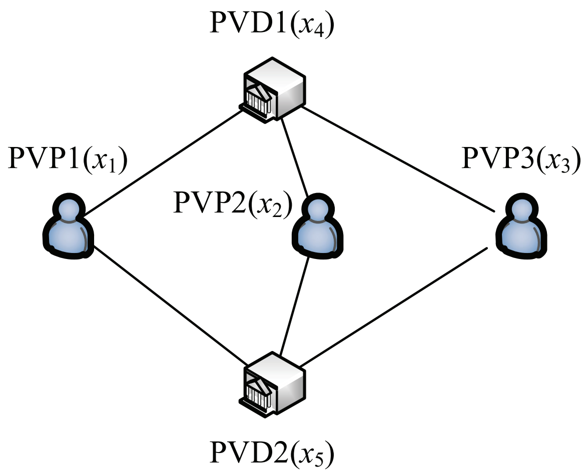

Figure 3. A Topological diagram for the photovoltaic power trade with three PVPs and two PVDs.

Table 4. Payoff bimatrix of the PVDs' market for the case of n = 2.

PVP╲PVD	1	2
1	$(1, 2)$	$(1, 2)$
2	$(0, 0)$	$(2, 1)$

According to Table 4, all the payoffs and next strategies of all players can be calculated. For instance, set $[x_1(t), x_2(t), x_3(t), x_4(t), x_5(t)] = [2, 1, 2, 1, 2]$. For PVP1 ($x_1$), there are two neighbors: PVD1 (x_4) and PVD2 (x_5). Then, the following equalities hold:

$$\begin{aligned}
& c_{1,4}(x_1(t), x_4(t)) = 0, c_{1,5}(x_1(t), x_5(t)) = 2 \\
& \Rightarrow c_1(t) = \max(c_{1,4}, c_{1,5}) = 2, x_1(t+1) = x_5(t) = 2; \\
& c_{2,4}(x_2(t), x_4(t)) = 1, c_{2,5}(x_2(t), x_5(t)) = 1 \\
& \Rightarrow c_2(t) = \max(c_{2,4}, c_{2,5}) = 1, x_2(t+1) = \max(x_4(t), x_5(t)) = x_5(t) = 2; \\
& c_{3,4}(x_3(t), x_4(t)) = 0, c_{3,5}(x_3(t), x_5(t)) = 2 \\
& \Rightarrow c_3(t) = \max(c_{3,4}, c_{3,5}) = 2, x_3(t+1) = x_5(t) = 2; \\
& c_{4,1}(x_4(t), x_1(t)) = 0, c_{4,2}(x_4(t), x_2(t)) = 2, c_{4,3}(x_4(t), x_3(t)) = 0 \\
& \Rightarrow c_4(t) = \max(c_{4,1}, c_{4,2}, c_{4,3}) = 2, x_4(t+1) = x_2(t) = 1; \\
& c_{5,1}(x_5(t), x_1(t)) = 1, c_{5,2}(x_5(t), x_2(t)) = 2, c_{5,3}(x_5(t), x_3(t)) = 1 \\
& \Rightarrow c_5(t) = \max(c_{5,1}, c_{5,2}, c_{5,3}) = 2, x_5(t+1) = x_2(t) = 1.
\end{aligned}$$

The same argument is used for other profiles $[x_1(t), x_2(t), x_3(t), x_4(t), x_5(t)]$, and the next action is computed for every player, as shown in Table 5.

Table 5. Payoffs and dynamics of photovoltaic power trade with three PVPs and two PVDs.

Profile	11111	11112	11121	11122	11211	11212	11221	11222
$c_1(t)$	1	1	1	1	1	1	1	1
$c_2(t)$	1	1	1	1	1	1	1	1
$c_3(t)$	1	1	1	1	0	2	2	2
$c_4(t)$	2	2	2	2	2	2	2	2
$c_5(t)$	2	2	2	2	2	2	2	2

Table 5. *Cont.*

Profile	**11111**	**11112**	**11121**	**11122**	**11211**	**11212**	**11221**	**11222**
$x_1(t+1)$	1	2	2	2	1	2	2	2
$x_2(t+1)$	1	2	2	2	1	2	2	2
$x_3(t+1)$	1	2	2	2	1	2	2	2
$x_4(t+1)$	1	1	1	1	1	1	1	1
$x_5(t+1)$	1	1	1	1	1	1	1	1
Profile	**12111**	**12112**	**12121**	**12122**	**12211**	**12212**	**12221**	**12222**
$c_1(t)$	1	1	1	1	1	1	1	1
$c_2(t)$	0	2	2	2	0	2	2	2
$c_3(t)$	1	1	1	1	0	2	2	2
$c_4(t)$	2	2	2	2	2	2	2	2
$c_5(t)$	2	2	2	2	2	2	2	2
$x_1(t+1)$	1	2	2	2	1	2	2	2
$x_2(t+1)$	1	2	2	2	1	2	2	2
$x_3(t+1)$	1	2	2	2	1	2	2	2
$x_4(t+1)$	1	1	1	1	1	1	1	1
$x_5(t+1)$	1	1	1	1	1	1	1	1
Profile	**21111**	**21112**	**21121**	**21122**	**21211**	**21212**	**21221**	**21222**
$c_1(t)$	0	2	2	2	0	2	2	2
$c_2(t)$	1	1	1	1	1	1	1	1
$c_3(t)$	1	1	1	1	0	2	2	2
$c_4(t)$	2	2	2	2	2	2	2	2
$c_5(t)$	2	2	2	2	2	2	2	2
$x_1(t+1)$	1	2	2	2	1	2	2	2
$x_2(t+1)$	1	2	2	2	1	2	2	2
$x_3(t+1)$	1	2	2	2	1	2	2	2
$x_4(t+1)$	1	1	1	1	1	1	1	1
$x_5(t+1)$	1	1	1	1	1	1	1	1
Profile	**22111**	**22112**	**22121**	**22122**	**22211**	**22212**	**22221**	**22222**
$c_1(t)$	0	2	2	2	0	2	2	2
$c_2(t)$	0	2	2	2	0	2	2	2
$c_3(t)$	1	1	1	1	0	2	2	2
$c_4(t)$	2	2	2	2	0	0	1	1
$c_5(t)$	2	2	2	2	0	1	0	1
$x_1(t+1)$	1	2	2	2	1	2	2	2
$x_2(t+1)$	1	2	2	2	1	2	2	2
$x_3(t+1)$	1	1	2	2	1	2	2	2
$x_4(t+1)$	1	1	1	1	2	2	2	2
$x_5(t+1)$	1	1	1	1	2	2	2	2

Identify action k with $\delta_2^{2-k}, k = 1, 2$. Then, using the method provided by [46], the algebraic form of the evolutionary strategy can be figured out for each player:

$$x_i(t+1) = M_i x(t), i = 1, 2, 3, 4, 5, \tag{5}$$

where $x_i(t) \in \Delta_2, x(t) = \ltimes_{i=1}^{5} x_i(t)$, and

$$\begin{aligned}
M_1 &= \delta_2[1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2], \\
M_2 &= \delta_2[1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2], \\
M_3 &= \delta_2[1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2,1,2,2,2], \\
M_4 &= \delta_2[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,2,2,2], \\
M_5 &= \delta_2[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,2,2,2].
\end{aligned}$$

Utilizing the properties of the STP, equality (5) is transformed as follows:

$$\begin{aligned}
x(t+1) =& \ x_1(t+1)x_2(t+1)x_3(t+1)x_4(t+1)x_5(t+1)\\
=& \ M_1x(t)M_2x(t)M_3x(t)M_4x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2x(t)x(t)M_3x(t)M_4x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5x(t)M_3x(t)M_4x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3x(t)x(t)M_4x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5x(t)M_4x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5W_{[2,32]}M_4x(t)x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5W_{[2,32]}M_4\Phi_5x(t)M_5x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5W_{[2,32]}M_4\Phi_5W_{[2,32]}M_5x(t)x(t)\\
=& \ M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5W_{[2,32]}M_4\Phi_5W_{[2,32]}M_5\Phi_5x(t)\\
=& \ Mx(t).
\end{aligned}$$

Therefore, the algebraic form of the evolutionary game is

$$x(t+1) = Mx(t), \tag{6}$$

where

$$\begin{aligned}
M =& M_1W_{[2,32]}M_2\Phi_5W_{[2,32]}M_3\Phi_5W_{[2,32]}M_4\Phi_5W_{[2,32]}M_5\Phi_5\\
=& \delta_{32}[1,29,29,29,1,29,29,29,1,29,29,29,1,29,29,29,\\
& 1,29,29,29,1,29,29,29,1,29,29,29,4,32,32,32].
\end{aligned}$$

It is easy to see that there are two nonzero elements on the diagonal of matrix M. So, there are two fixed points, δ_{32}^1 and δ_{32}^{32}, namely the Nash equilibria. Furthermore, through simple calculations, a limit cycle $C: \delta_{32}^4 \to \delta_{32}^{29} \to \delta_{32}^4$ can be obtained. And its attraction domains are

$$\begin{aligned}
D(\delta_{32}^1) =& \{\delta_{32}^1, \delta_{32}^5, \delta_{32}^9, \delta_{32}^{13}, \delta_{32}^{17}, \delta_{32}^{21}, \delta_{32}^{25}\}\\
& \sim \{(1,1,1,1,1),(1,1,2,1,1),(1,2,1,1,1),(1,2,2,1,1),\\
& (2,1,1,1,1),(2,1,2,1,1),(2,2,1,1,1)\}\\
D(\delta_{32}^{32}) =& \{\delta_{32}^{30}, \delta_{32}^{31}, \delta_{32}^{32}\}\\
& \sim \{(2,2,2,1,2),(2,2,2,2,1),(2,2,2,2,2)\}\\
D(C) =& \{\delta_{32}^2, \delta_{32}^3, \delta_{32}^4, \delta_{32}^6, \delta_{32}^7, \delta_{32}^8, \delta_{32}^{10}, \delta_{32}^{11}, \delta_{32}^{12}, \delta_{32}^{14}, \delta_{32}^{15}, \delta_{32}^{16}, \delta_{32}^{18}, \delta_{32}^{19}, \delta_{32}^{20},\\
& \delta_{32}^{22}, \delta_{32}^{23}, \delta_{32}^{24}, \delta_{32}^{26}, \delta_{32}^{27}, \delta_{32}^{28}, \delta_{32}^{29}\}\\
& \sim \{(1,1,1,1,2),(1,1,1,2,1),(1,1,1,2,2),(1,1,2,1,2),(1,1,2,2,1),\\
& (1,1,2,2,2),(1,2,1,1,2),(1,2,1,2,1),(1,2,1,2,2),(1,2,2,1,2),\\
& (1,2,2,2,1),(1,2,2,2,2),(2,1,1,1,2),(2,1,1,2,1),(2,1,1,2,2),\\
& (2,1,2,1,2),(2,1,2,2,1),(2,1,2,2,2),(2,2,1,1,2),(2,2,1,2,1),\\
& (2,2,1,2,2),(2,2,2,1,1)\}
\end{aligned}$$

In order to better demonstrate the state motion process of the system (6), the initial states are chosen from sets $D(\delta_{32}^1)$, $D(\delta_{32}^{32})$, and $D(C)$, respectively.

- When the initial state is chosen from $D(\delta_{32}^1)$, for example, the initial state is taken as $x(0) = \delta_{32}^{13}$, which is equivalent to $[1,2,2,1,1]$, according to Table 5, and it is updated to $[1,1,1,1,1]$, which is equivalent to $x(1) = \delta_{32}^1$. Similarly, the follow-up actions can be obtained $x(2) = x(3) = x(4) = \cdots = \delta_{32}^1$. The system (6) will be stable at the

Nash equilibrium δ_{32}^{1} (meaning strategy profile $(1,1,1,1,1)$). Figure 4 gives the state trajectories for all players.

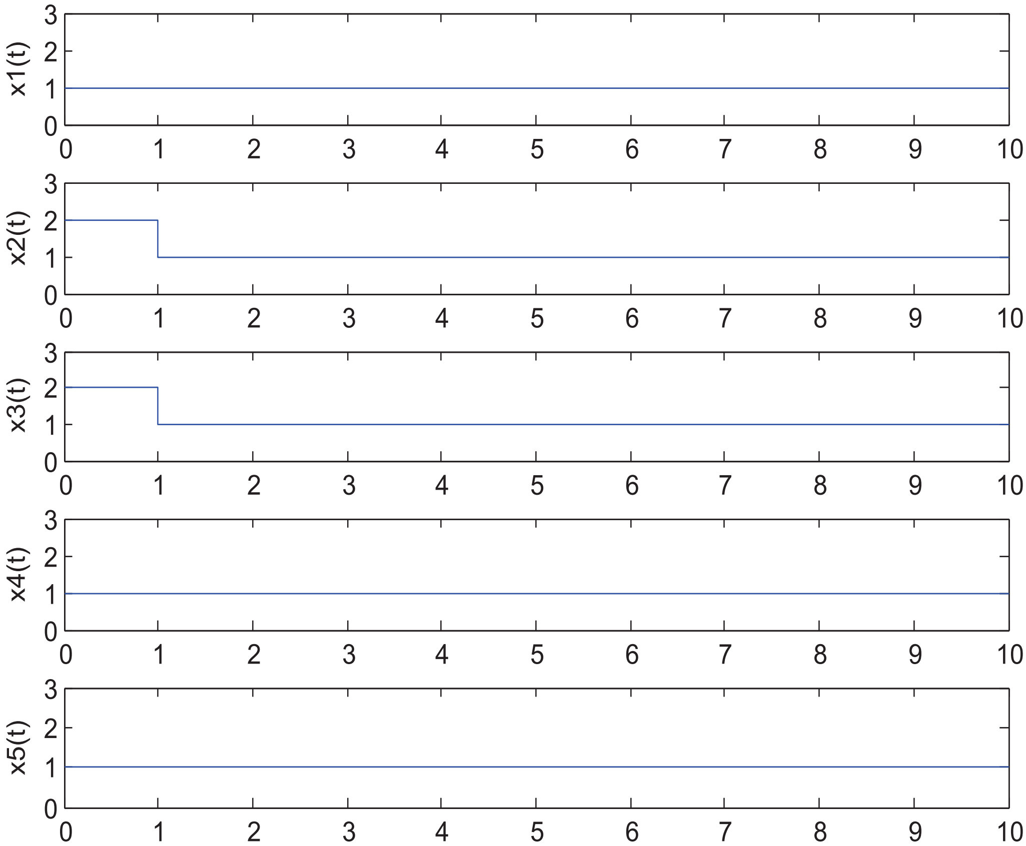

Figure 4. State trajectory of (6) when the initial state $x(0) = \delta_{32}^{13}$.

- When the initial state is chosen from $D(\delta_{32}^{32})$, for instance, $x(0) = \delta_{32}^{30}$, a similar analysis leads to $x(1) = x(2) = x(3) = x(4) = \cdots = \delta_{32}^{32}$. The system (6) will be stable at the Nash equilibrium δ_{32}^{32} (meaning strategy profile $(2,2,2,2,2)$). The state trajectories of all players are shown in Figure 5.
- When the initial state belongs to $D(C)$, say $x(0) = \delta_{32}^{22}$, it is derived that $x(1) = \delta_{32}^{29}$, $x(2) = \delta_{32}^{4}$, $x(3) = \delta_{32}^{29}$, $x(4) = \delta_{32}^{4}, \cdots$. The system (6) will oscillate between δ_{32}^{4} (meaning strategy profile $(1,1,1,2,2)$) and δ_{32}^{29} (meaning strategy profile $(2,2,2,1,1)$). Figure 6 shows the corresponding state trajectories.

The state transition diagram of system (6) is given in Figure 7. From this figure, it can be found that only when the initial state is taken from $D(\delta_{32}^{1})$ or $D(\delta_{32}^{32})$ will system (6) be stable at Nash equilibrium δ_{32}^{1} or δ_{32}^{32}, respectively. If the initial state is taken from $D(C)$, the system (6) will oscillate between δ_{32}^{4} and δ_{32}^{29}.

According to the STP technique, δ_{32}^{4} is equivalent to the strategy profile $(\delta_2^1, \delta_2^1, \delta_2^1, \delta_2^2, \delta_2^2)$, and then to $(1,1,1,2,2)$ and $(A + \frac{B-A}{3}, A + \frac{B-A}{3}, A + \frac{B-A}{3}, A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3})$, where $A = P_{produce} - P_{subsidy}$ and $B = P_{traditional} + P_{compensation}$. Similarly, δ_{32}^{29} is equivalent to $(\delta_2^2, \delta_2^2, \delta_2^2, \delta_2^1, \delta_2^1)$ and $(2,2,2,1,1)$. So, this means the strategy profile $(A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3}, A + \frac{B-A}{3}, A + \frac{B-A}{3})$. And the Nash equilibria δ_{32}^{1} and δ_{32}^{32} express strategy profiles $(A + \frac{B-A}{3}, A + \frac{B-A}{3}, A + \frac{B-A}{3}, A + \frac{B-A}{3}, A + \frac{B-A}{3})$ and $(A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3}, A + \frac{2(B-A)}{3})$, respectively. In addition, an interesting phenomenon can be found that all strategies chosen by PVPs (PVDs) are the same in the strategy profiles mentioned above. Therefore, their strategies will eventually reach consensus without prior agreement.

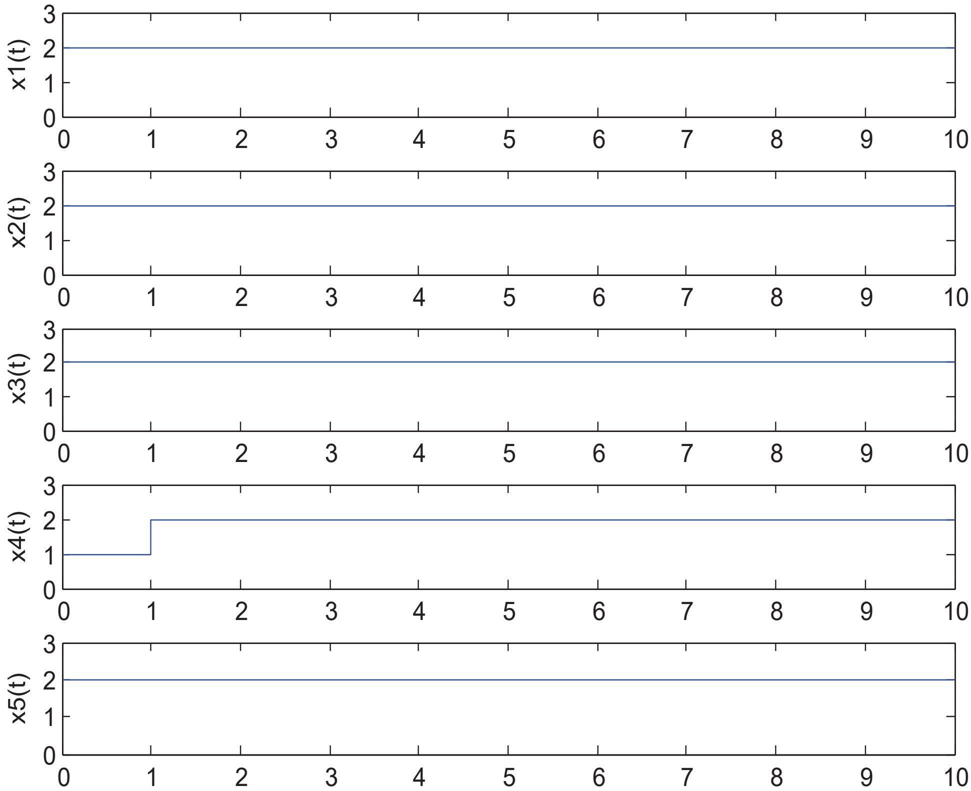

Figure 5. State trajectory of (6) when the initial state $x(0) = \delta_{32}^{30}$.

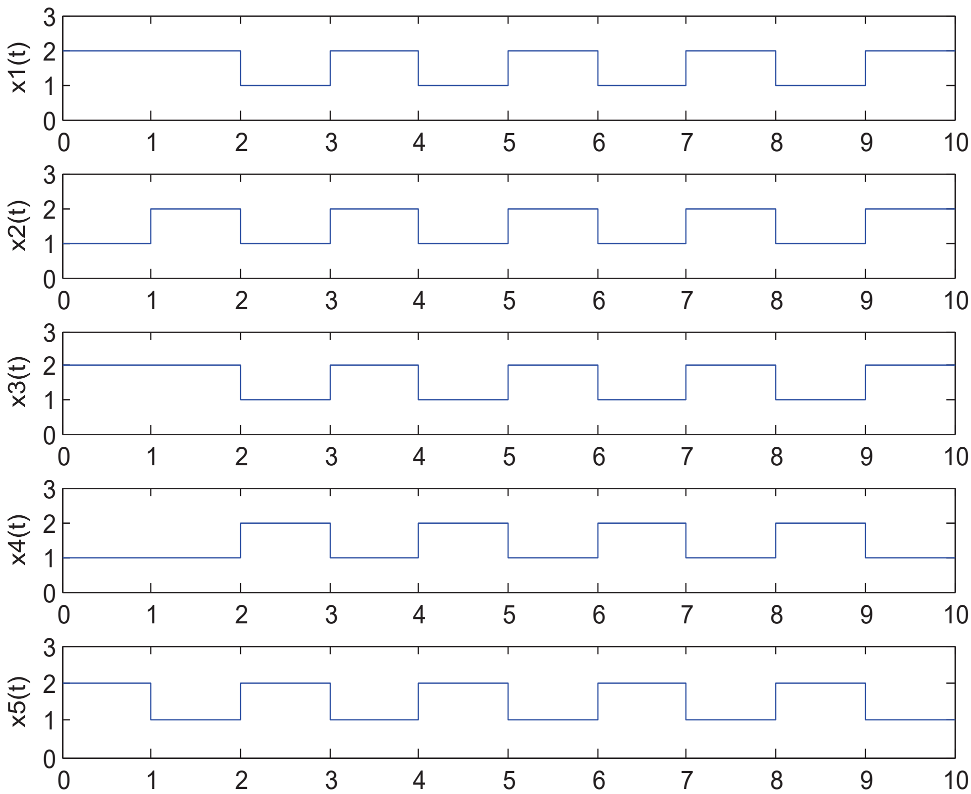

Figure 6. State trajectory of (6) when the initial state $x(0) = \delta_{32}^{22}$.

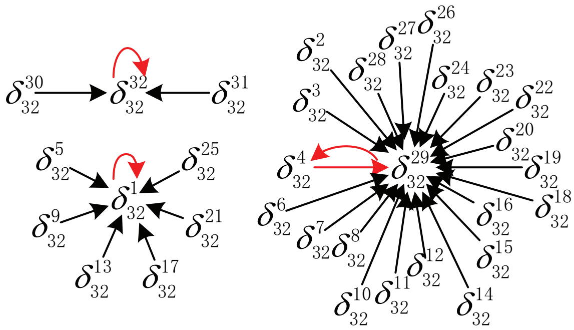

Figure 7. The state transition diagram of system (6).

In summary, the trade results can be divided into the following three situations:

- If players choose an initial strategy profile from $\{(1,1,1,1,1),(1,1,2,1,1),(1,2,1,1,1),(1,2,2,1,1),(2,1,1,1,1),(2,1,2,1,1),(2,2,1,1,1)\}$, the strategy profile will be stable at $(1,1,1,1,1)$ (meaning strategy profile $(A+\frac{B-A}{3}, A+\frac{B-A}{3}, A+\frac{B-A}{3}, A+\frac{B-A}{3}, A+\frac{B-A}{3})$) to achieve the maximum revenue.
- If the initial strategy profile is chosen from $\{(2,2,2,1,2),(2,2,2,2,1),(2,2,2,2,2)\}$, it will reach and be stable at $(2,2,2,2,2)$ (meaning strategy profile $(A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3})$) to make as much profit as possible.
- For other strategy profiles, they are not stable at any state but oscillate between two states: $(1,1,1,2,2)$ (meaning strategy profile $(A+\frac{B-A}{3}, A+\frac{B-A}{3}, A+\frac{B-A}{3}, A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3})$) and $(2,2,2,1,1)$ (meaning strategy profile $(A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3}, A+\frac{2(B-A)}{3}, A+\frac{B-A}{3}, A+\frac{B-A}{3})$). To a certain extent, it can also be considered stable on a limit cycle.

Here, a PVDs' market was used as an example to introduce how to construct a game model for transactions between PVPs and PVDs, and the dynamic characteristics of the model were analyzed. Similar methods can be applied to a PVPs' market with only a modification to the payoff bimatrix according to Table 3. To avoid repetition, it is not described in this paper.

5. Conclusions

This paper focused on the competition phenomenon in the market-oriented trading process of distributed photovoltaic energy. The supply and demand relationship of photovoltaic power, which affects transaction pricing, was comprehensively considered. And the trading processes of PVPs and PVDs were modeled and analyzed using game theory and the STP method. These results provide a reliable theoretical basis for the sustainable development of the photovoltaic power market. The conclusions obtained are as follows:

1. Different from the existing relevant literature, two kinds of payoff bimatrices were provided in the dynamic game model for trading between PVPs and PVDs. One corresponds to a PVDs' market and the other to a PVPs' market. They reflect the impact of photovoltaic power supply and demand on transaction pricing.
2. The game model established above was equivalently transformed into its algebraic form using the STP method. This algebraic form makes it more convenient to study the game. Therefore, the STP is an effective method for analyzing the dynamic characteristics of game models.
3. During the trading process, the strategies of all participants are mostly changing to obtain more profits rather than stable at a traditional Nash equilibrium point.
4. The method and results are applicable to other distributed low-carbon energies, contributing to the development of sustainable energy systems.

It is worth noting that the method used in this paper is universal and can be applied to the research of all distributed low-carbon energy-trading problems, for example, wind, nuclear, geothermal energy, bioenergy, etc. Of course, they can also be applied to distributed systems composed of different types of renewables-based generators.

This paper models the low-carbon energy-trading problem as a discrete system using the STP method. However, in reality, transaction participants can make any bid, and the bid may even appear as continuous. Therefore, how to establish a continuous model for the carbon energy-trading problem and how to use the STP method to address the continuous model are our future research topics.

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Nomenclature

Sets	
$\mathbb{R}^n$	Set of all n-dimensional real vectors
$\mathbb{M}_{m\times n}$	Set of $m \times n$ dimensional real matrices
$\mathbb{L}_{m\times n}$	Set of $m \times n$ dimensional logical matrices
Δ_n	Set of all columns of I_n
$S = \prod_{i=1}^{n} S_i$	Set of profiles
$N = \{1, 2, \cdots, n\}$	Set of n players
$\mathrm{U}(i)$	Set of neighbors of player i
S_i	Strategy set of player i
Parameters	
P_{deal}	Transaction price
$P_{produce}$	Production price
$P_{subsidy}$	Government subsidy
$P_{traditional}$	Traditional electricity price
$P_{compensation}$	Compensation costs
Variables and Functions	
c_i	Payoff function of player i
$x_i(t)$	Strategy of player i at time t
$x(t)$	Strategy of all players at time t
Notations	
I_n	$n \times n$ dimensional identity matrix
$Col_i(M)$	ith column of matrix M
$Row_i(M)$	ith row of matrix M
δ_n^i	ith column of I_n
$\delta_n[i_1, i_2, \cdots, i_n]$	Logical matrix
$(\delta_n^{k_1}, \delta_n^{k_2}, \cdots, \delta_n^{k_m})$	Strategy profile
$lcm(n, p)$	Least common multiplier of n and p
$\otimes$	Kronecker product of matrices
$\ltimes$	STP of matrices
$W_{[m,n]}$	Swap matrix
Φ_n	Power-reducing matrix
C	Limit cycle

Acronyms	
PVP	Photovoltaic power producer
PVD	Photovoltaic power demander
STP	Semitensor product
DER	Distributed energy resource
P2P	Peer-to-peer

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