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# A Dynamic Incentive Mechanism for Smart Grid Data Sharing Based on Evolutionary Game Theory

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**Abstract:** With the increasing popularization and application of the smart grid, the harm of the data silo issue in the smart grid is more and more prominent. Therefore, it is especially critical to promote data interoperability and sharing in the smart grid. Existing data-sharing schemes generally lack effective incentive mechanisms, and data holders are reluctant to share data due to privacy and security issues. Because of the above issues, a dynamic incentive mechanism for smart grid data sharing based on evolutionary game theory is proposed. Firstly, several basic assumptions about the evolutionary game model are given, and the evolutionary game payoff matrix is established. Then, we analyze the stabilization strategy of the evolutionary game based on the payoff matrix, and propose a dynamic incentive mechanism for smart grid data sharing based on evolutionary game theory according to the analysis results, aiming to encourage user participation in data sharing. We further write the above evolutionary game model into a smart contract that can be invoked by the two parties involved in data sharing. Finally, several factors affecting the sharing of data between two users are simulated, and the impact of different factors on the evolutionary stabilization strategy is discussed. The simulation results verify the positive or negative incentives of these parameters in the data-sharing game process, and several factors influencing the users' data sharing are specifically analyzed. This dynamic incentive mechanism scheme for smart grid data sharing based on evolutionary game theory provides new insights into effective incentives for current smart grid data sharing.

**Keywords:** evolutionary game theory; smart grid; smart contract; data sharing

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## 1. Introduction

In the current era of big data, with the massive growth of data, data have very important strategic significance for any industry. However, the big data industry is currently facing a very serious challenge, which is the dilemma of data silos. With the popularization and application of the concept of the smart grid, the danger of the data silo issue in the smart grid has become more and more prominent, and an effective way to solve this issue is to establish a reasonable and effective data-sharing model [1]. In today's society, with the rapid development of science and technology, the interconnection of data has become an important measure with which to enhance scientific and technological innovation in all walks of life and even the country, and many studies have shown that the interoperability and sharing of data can improve the utilization rate of data resources [2–5], accelerate the dissemination of data resources, and provide a very convenient way for people's work, life, and travel. However, in the process of data sharing, users' unwillingness to share data is affected by the formation of a mutual trust relationship and economic utility. Therefore, cross-system data fusion can only be truly realized by breaking through data silos [6,7].

Previous studies on data sharing have been based on the premise that data holders are willing to participate in data sharing, but, in practice, data holders are often reluctant to share their data when taking into consideration privacy and security issues [8–10]. Therefore, to enhance users' willingness to share data, it is necessary not only to study various cryptographic techniques to ensure the realization of secure sharing, but also to design an effective incentive mechanism, to fully promote the flow of data and address the data silo issue [11]. Evolutionary game theory is an important mathematical tool for studying and analyzing individual behaviors and strategic choices in social systems. The object of evolutionary game theory is the study of a certain group of people changing over time. The purpose of theoretical exploration is to understand the dynamic process of group evolution and to explain why and how the group will reach this current state. Through model building and mathematical analysis, evolutionary game theory can help explain and predict human behavior, and is important for revealing the principles and laws of group behavior evolution. In the process of data sharing, evolutionary game theory can provide an effective framework for analyzing the strategy selection and outcome evolution among participants, in addition to helping to design reasonable incentive mechanisms to motivate data providers to share data and participate in co-operation. By analyzing the benefits and stability of individuals under different strategies, incentives can be designed to encourage data sharing and effectively solve the incentive problem in the data-sharing process [12].

An incentive mechanism based on an evolutionary-game-theoretic approach to realize data sharing in smart grid data centers is proposed, which can effectively increase the willingness of participants to share data while safeguarding the interests of each participant in the smart grid. Generally speaking, data owners can obtain greater benefits by sharing high-value data, but they will also face higher risks. Therefore, the evolutionary game theory viewpoint is adopted here to plan the data-sharing process, allowing both parties in data sharing to continuously improve their sharing strategies in the game until reaching an equilibrium state. Firstly, several basic assumptions of the evolutionary game model are given, and the payoff matrix of the evolutionary game model is established. Then, the analysis of the stable strategy of the evolutionary game is carried out. Based on the analysis results, a dynamic incentive mechanism for smart grid data based on the evolutionary game theory is given to illustrate how the incentive mechanism proposed in this paper can dynamically adjust the incentive parameter and the cost of participation in the smart grid to encourage user participation in data sharing. Finally, the above evolutionary-game-based model is written into a smart contract for invocation by both data-sharing parties, thereby encouraging more users in the smart grid system to participate in data sharing. The main contributions of this paper are as follows:

1. An evolutionary game model based on the smart grid between two data centers is constructed, several basic assumptions of the evolutionary game model are put forward, an evolutionary game payoff matrix is established, and an analysis of the stable strategies of the evolutionary game in the data centers is conducted based on the payoff matrix to describe the strategy choices and the evolution process among the participants, as well as the results of different strategy choices.
2. Based on the analysis results, a dynamic incentive mechanism for smart grid data based on evolutionary game theory is proposed to illustrate how the incentive mechanism proposed in this paper can dynamically adjust the incentive parameters and participation costs in smart grids to promote user participation in data sharing.
3. A smart contract based on evolutionary game data sharing incentives is designed, which automatically executes to provide incentives for both sharing parties when the conditions are met, and, due to the characteristics of the smart contract, the incentive mechanism that excludes the third party is more secure and trustworthy.

The remainder of the paper is organized as follows. Section 2 briefly summarizes the relevant research results and describes the research directions explored in the related work. The current state of the theoretical and technological research is presented and our specific innovations are outlined. Section 3 presents the system model. In Section 4, an evolutionary game model between two data centers is described, including the mathematical derivation and analysis, and a smart contract mechanism is designed. Section 5 describes the simulation experiments performed on the model and its analysis.

## 2. Related Work

### 2.1. Evolutionary Game Theory

Evolutionary game theory (EGT) is an important mathematical tool for studying and analyzing individual behavior and strategic choices in social systems. Evolutionary game theory is the study of a particular group of people changing over time. The purpose of the theoretical inquiry is to understand the dynamic process of group evolution and to explain why the group will reach this current state and how it will get there. In evolutionary game theory, individuals are assumed to be rational, pursuing their own interests and interacting with others by choosing different strategies [13]. In evolutionary game theory, there is a core concept called the "Evolutionary Stable Strategy" (ESS), which is similar to the Nash equilibrium in traditional game theory, but emphasizes the long-term stability of individual strategies in the evolutionary process. Evolutionary game theory focuses on dynamic equilibrium, while general game theory focuses on static equilibrium and comparative static equilibrium. Evolutionary game theory also introduces the concept of replicator dynamics (RD) and a mathematical model of competitive growth dynamics. Replicator dynamics provides a way to understand the evolutionary trend of individual strategic choices from a population level perspective. By analyzing the results of the replicator dynamics model, we can predict the change in the frequency of different strategies in a population over time, thus revealing the evolutionary trend of population behavior. The mathematical model of competitive growth dynamics, on the other hand, can use differential equations to describe the trend of rational behavior of individuals in a population, further revealing the dynamic changes in the evolutionary process [14].

The modeling and mathematical analysis process of evolutionary game theory usually involves several key steps in order to study and understand the strategic evolution, competition, and co-operation of individuals in groups. These steps can be summarized as follows:

1. Identify the participants and strategy space: Firstly, it is necessary to identify the individuals or groups involved in the evolutionary game and specify the available strategies.
2. Determine the payoff function: A payoff function is defined for each combination of strategies, which can be used to quantify the payoffs or utilities that each participant obtains under different combinations of strategies.
3. Construct a dynamic evolutionary model: The evolution of individual strategies over time is simulated by means of different mathematical models.
4. Analyzing evolutionarily stable strategies: Finding and analyzing evolutionarily stable strategies (ESSs), i.e., strategies that are difficult to be violated by other strategies during long-term evolution. This usually involves an analysis of model stability and the stability of equilibria, as well as the use of dynamical systems, steady-state analysis, and other methods to reveal the nature of these strategies [15].
5. Perform mathematical analyses and simulation experiments: Evaluate and validate the accuracy and utility of the model through mathematical analysis methods (e.g., stability analyses, property derivations, etc.) and computer simulation experiments. We can use the results of the model to predict the evolutionary trends of individual strategies.

### 2.2. Data Incentives

Research on incentive schemes for data sharing in different scenarios has been conducted by numerous scholars. This paper analyzes the current research status of data sharing and incentive programs from the data-sharing incentive programs, as well as the application of game theory in the field of energy data incentives in two aspects.

#### 2.2.1. Data-Sharing Incentive Aspects

In terms of evolutionary game theory incentives, An et al. [16] proposed an incentive mechanism for data sharing in science and technology services, where three strategies for science and technology service organizations to participate in data sharing were designed through evolutionary game theory. Subsequently, a safe and adjustable incentive mechanism for smart contracts was constructed based on the sharing strategies. However, the scheme has not yet unified the data complementary indicators, thus lacking empirical modeling and analysis. Cai et al. [17] proposed a blockchain-supported IoT data-sharing incentive framework, ShareBC, which adopts an efficient consensus mechanism and sharding technology to improve the data-sharing efficiency. They also designed a data-sharing incentive mechanism based on a hierarchical data auction-sharing model implemented by smart contracts. However, they did not consider how to realize node balancing in dynamic IoT environments, nor did they address member node reward and punishment management. Shen et al. [18] proposed a reliable collaboration model consisting of data owners, miners, and third parties in which data is shared via blockchain and recorded by smart contracts. However, the authors only analyzed the topological relationships among the participants and developed some Shapley's value models from simple to complex in the revenue distribution process. Li et al [19] proposed a blockchain-based incentive mechanism for blockchain vehicle perception, which incorporates each user into a reputation management system to improve the quality of perception data, adopts a genetic algorithm to solve the selection problem of the winning vehicle and allocates rewards based on task completion, and designs smart contracts to realize non-deterministic vehicles to perform the perception process automatically. However, it is not applicable to the mutual incentive and revenue scenarios among users in the smart grid. Wang et al. [20] proposed an incentive mechanism for data sharing in science and technology service, designed three strategies for science and technology service organizations to participate in data sharing through evolutionary game theory, then constructed a safe and adjustable smart contract incentive mechanism based on the sharing strategy, and, finally, analyzed the factors affecting the sharing strategy. However, the program has not yet unified the data complementary indicators, and, thus, the model cannot be empirically analyzed.

In terms of blockchain and smart contract incentive aspect. Zhang et al. [21] combined the distributed architecture and decentralization of the blockchain, and designed a microgrid data security sharing scheme using points to replace the tokens in the traditional blockchain consensus mechanism to circulate. This scheme stores the data packets in the database under the chain after the nodes reach a consensus, and returns its storage address to the chain for storage. However, this scheme only proposes a sharing scheme for microgrid data, and does not study the aspect of incentivizing users to share data. In scenarios with large amounts of data in the smart grid, the scale of microgrid users and the quality of data also need to be considered to determine the reliability of this scheme. Xu et al. [22] proposed a user-impact-weighted scoring algorithm to analyze the behavior of the user, and established a user impact model, and designed a blockchain-based rating incentive mechanism that links users' rating behavior with their interests. However, the model has a limited scope of consideration and may have a large impact on the effect of data of the magnitude of the smart grid. Shi et al. [23] proposed a blockchain-based competitive platform for SME intelligence sharing, which introduced a credit score system to incentivize data-sharing behavior among users. However, a simulation experiment lacks an analysis of the performance, and it provides a vague discussion on the consensus mechanism. Wang et al. [24] propose a data trust incentive model supported by blockchain by involving equipment providers, data trustees, and general users. They also offer a trusted data transaction scheme. In addition, homomorphic encryption is utilized to achieve fine-grained data querying and device matching with privacy protection for device providers and general users. Xuan et al. [25] propose a data-sharing incentive mechanism based on blockchain and smart contract to encourage users to actively contribute data by dynamically adjusting the incentive level and participation cost. However, the scheme does not consider the effects of shared data size and data quality on the dynamic adjustment of incentives, thus exhibiting certain limitations. Li et al. [26] constructed a blockchain-based privacy-preserving and rewarding private data sharing scheme (BPRPDS) with the help of deniable ring signatures and Monero, which achieves the behavioral feature construction prevention and non-trapability of BPRPDS. At the same time, a licensing technique enforced by smart contracts is utilized to ensure flexible access control for multi-person sharing. However, the main target of the article is for private data, and it is worth considering possible application scenarios for data from massive smart grids.

In terms of other forms of data-sharing incentives: Tay et al. [27] propose a novel collaborative generative modeling (CGM) framework that incentivizes self-interested parties to collaborate in providing data for training generative models (e.g., GANs), from which synthetic data are extracted and distributed to the parties as rewards commensurate to their contributions, and distributing synthetic data as rewards. Vakilinia et al. [28] model the storage service as a non-co-operative repetitive dynamic game and set the players' payoffs such that the dominant strategy of the storage provider is to honestly follow the storage contract. They also utilize smart contracts and oracle networks to effectively manage the storage agreement between customers and storage providers. However, the application scope of this non-co-operative repetitive game is limited, and it is worth investigating whether the scheme can be effective for scenarios such as smart grids, which need to be shared and have a huge sharing scope, as well as a huge scale in the number of users and the amount of data. Khalid et al. [29] proposed a blockchain-based data storage system to overcome the traditional data management issues of data storage mechanisms involving third parties; the proposed system utilizes the advantages of the interplanetary file system (IPFS). An incentive mechanism is also proposed to provide monetary rewards to the respondent vehicles for responding to event messages. However, the analysis of the incentive mechanism and the specific process in the paper is not comprehensive enough, as it mainly focuses on the proposed data storage system.

#### 2.2.2. Game Theory in Energy Data Incentive Applications

In terms of power data incentives, Tang et al. [30] proposed a smart grid dynamic pricing interaction demand-side management scheme based on game theory, which used the game to develop an interaction strategy between the grid and the users, with the grid optimizing the price and the users using the power reasonably to reduce the fluctuation of the demand in order to achieve the Nash equilibrium. However, the indicators that specifically affect the game process, as well as the influencing factors, were not analyzed. Li et al. [31] proposed a dynamic game model for power market transactions based on blockchain technology, applying Stackelberg game theory to address the interaction strategy between market supply and demand parties in the pursuit of the optimal objective of electricity price and power, which effectively incentivizes the integration of distributed clean energy sources into the grid. However, the article is mainly aimed at the game of the power transaction process rather than promoting the sharing of data between power users. Doan et al. [32] studied a P2P energy-trading system based on double auction game theory, where the buyer adjusts the purchase quantity based on different electricity prices, while the auctioneer controls the game, and the seller does not participate in the game, hiding the transaction information to maximize the benefits after a unique game equilibrium. However, the reliability of this scheme for handling massive data in the smart grid was not demonstrated. Apostolopoulos et al. [33] proposed a smart grid demand response management method based on the two-stage game theory to study the demand response management problem in the multi-electric utility and multi-customer coalition, which describes the relationship between the electric utility and the customer as a two-stage game, in which the electric utility and the customer Nash equilibrium point is reached, determining the optimal pricing of the electric utility and the optimal electricity consumption of the customers, iteratively based on reinforcement learning algorithms. Stai et al. [34] modeled the data incentive problem as a non-co-operative game and investigated the existence of a mixed-strategy Nash equilibrium under the adopted proportional allocation policy when the total demand for renewable energy exceeds the available energy. Alsalloum et al. [35] proposed a game theory based on the game-theoretic energy hierarchy management system model for smart grids that considers multiple constraints among multiple suppliers and producers. A Stackelberg game was established to simulate supplier–producer and supplier–consumer interactions, proving the existence of a unique equilibrium solution.

In the area of telematics and other industrial data incentives: Tan et al. [36] proposed a citywide vehicle data-sharing platform based on digital twins, designing out an incentive mechanism based on a game-theoretic approach to eliminate mutual distrust among vehicles and encourage them to contribute to data sharing. However, this paper mainly targets the effect of the direction of trust on the game, as well as the incentive process, which is too homogeneous to consider the factor indicators. Moafi et al. [37] proposed a three-tier intelligent structure based on game theory to evaluate the individual and co-operative strategies of the power manufacturers that this paper targets the direction of. Moniruzzaman et al. [38] proposed a novel system combining the co-operative game theory and blockchain technology to stimulate profit maximization and secure energy transactions for users. However, the research direction of this paper is biased toward the specific application process, and various indicators of factors affecting data sharing are not fully analyzed. Amini et al. [39] utilize game theory to explore the circumstances under which multiple self-interested firms can invest in vulnerability discovery and share their cyberthreats and share their cyberthreat information, which is algorithmically applied to a public cloud computing platform. However, the scheme through game theory targets the cybersecurity and threat aspects and is not applicable to the user dynamic incentive scenarios of smart grids. Pandey et al. [40] proposed a framework for bi-level decision making within the scope of multiple demand response providers in retail competition. It is formulated as a multi-leader–multi-follower game that interacts strategically to optimize the cost of the load-serving entity at the upper level and its cost at the lower level. However, the authors' bi-level decision-making framework addresses the interaction of a multi-leader–multi-follower game without mentioning the specific incentive process and dynamic incentive schemes. Gelhaar et al. [41] bridge the research gap of insufficient matching between data sharing by adopting a conceptual model for motivation and incentive issues in data sharing and applying it to the industrial data ecosystem Catena-X. However, the author's perspective is only on the issue of the matching of data sharing, and other aspects related to the dynamic impact of the incentive process between data-sharing parties have not been studied.

### *2.3. Summary and Analysis*

Existing data-sharing incentive schemes based on smart grid application scenarios generally lack effective incentive mechanisms, and some of the schemes are unable to realize node balancing in dynamic incentives, and there is no punishment and reward management for member nodes. Some data-sharing incentive schemes based on game theory are not unified for the complementary indicators of data, which cannot be empirically analyzed in the model, and some schemes are based on small-scale data incentives, which do not take into account the impact of the shared data size and data quality on the dynamic adjustment of incentives for the massive data of smart grids.

Aiming at the existing data-sharing schemes, smart grid data sharing generally lacks an effective incentive mechanism, data holders are reluctant to share data due to privacy and security issues, and the sharing incentive scheme cannot meet the dynamic demand; a dynamic incentive mechanism for smart grid data sharing based on game theory is proposed. According to several basic assumptions of the evolutionary game model, the evolutionary game payoff matrix is established; based on the payoff matrix, the evolutionary game stabilization strategy analysis is carried out, and several factors affecting the sharing of data between the two sides of the user are simulated and analyzed by using

MATLAB, and the effects of different factors on the evolutionary stabilization strategy of the data-sharing incentive process are discussed.

## 3. System Model

A dynamic incentive model for smart grid data sharing based on evolutionary game theory [25] proposed in this paper is shown in Figure 1.

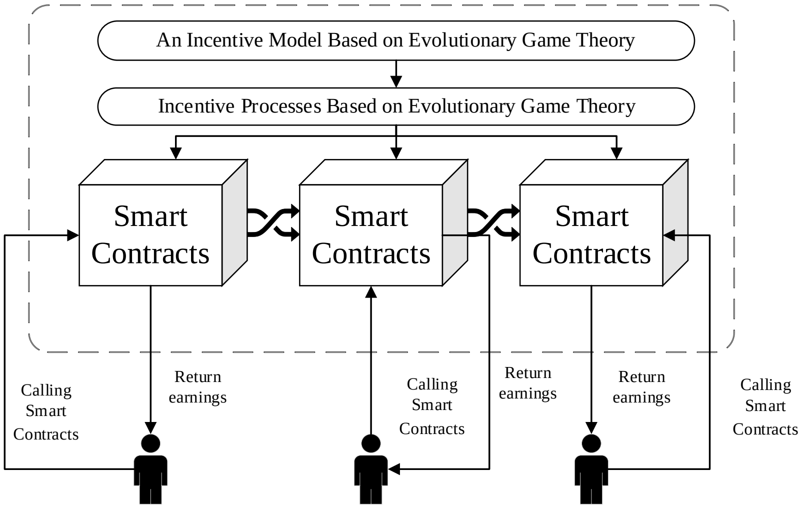



**Figure 1.** System model.

The model consists of three parts: the data provider, the data user, and the smart contract. Among them, the data provider is responsible for sharing the data throughout the system and therefore obtains the benefit of sharing the data. Data users and data providers achieve their own purposes by getting the data provided by the data providers. The smart contract part is responsible for automatically executing the scheme proposed in this paper in the system, which dynamically performs inter-system incentives by invoking smart contracts by judging the incentives in the current state.

The model function can be divided into two parts: the data-sharing incentive mechanism based on evolutionary game theory and the design of a smart contract based on an incentive mechanism. An evolutionary game model is established between data users and analyzed to stabilize the evolutionary strategy, and a smart contract is designed to dynamically adjust the incentive benefits of user participation in sharing.

## 4. Program Description

The construction of a smart grid data dynamic incentive mechanism based on evolutionary game theory is described in detail in this section and a stability analysis of the mechanism is carried out. For each round of data sharing, the data holders can choose to participate or not participate in the sharing process, and the focus of the research in this section is to find the stability point of the data users' stable participation in the data sharing. The model assumes that both parties involved in data sharing have finite rationality, and dynamically adjust their strategies according to the benefits of each sharing, in order to maximize the benefits in the pursuit of the goal.

In evolutionary game theory, repeated strategies refer to players adopting the same decision or strategy in multiple games. Repeated strategies are often used to analyze the outcome of long-term games because they can reflect the decision-making behavior of players at different points in time and their impact on the outcome. In the model of this paper, repeated strategies are the behaviors of Data Centers A and B that consistently choose either shared or unshared data over a certain period of time. A dominant strategy is a strategy by which one party in a game is able to obtain a better outcome than any other strategy. This strategy will dominate the other strategies because the other players will be more inclined to adopt the dominant strategy to obtain better results. In the model of this paper, the dominant strategy means that a certain data-sharing or non-sharing strategy can steadily dominate and become the strategy that Data Centers A and B consistently adopt. A nomination strategy, on the other hand, means that, in a multi-player game, a participant must publicly nominate the other participants with whom he or she will play the game. This strategy can influence the outcome of the game as it involves interaction and mutual selection between participants. In the model of this paper, a dominant strategy means that a certain data-sharing strategy performs well in a specific environment or against a certain reward mechanism, but whether it can become a dominant strategy needs further observation and analysis. The flow chart of the evolutionary game process is shown in Figure 2.

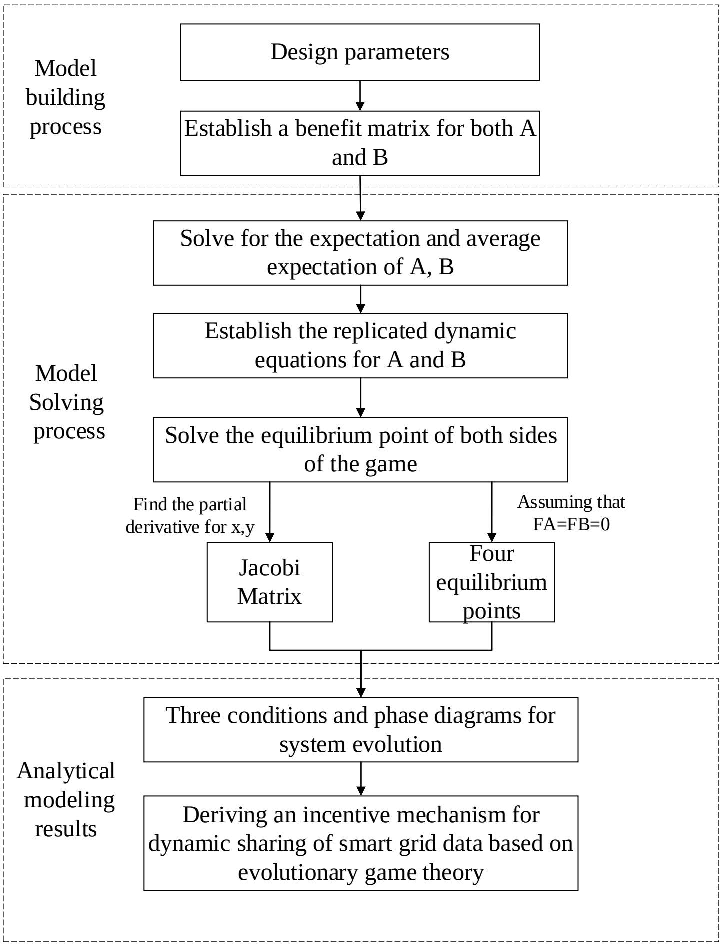



**Figure 2.** Flowchart of the evolutionary game process.

### *4.1. Model Building*

This model constructs an evolutionary game model for data-sharing incentives between two data centers. Evolutionary game theory suggests that game participants are always in a state of finite rationality, and need to learn and imitate the environment in which they are located, and dynamically adjust the data-sharing strategy $P$ in order to achieve the optimal and stable solution. Suppose that $x$ denotes the probability that Data Center A chooses to share the data, and $1 - x$ denotes the probability that Data Center A chooses not to share the data, $x \in (0, 1)$. Similarly, $y$ denotes the probability that Data Center B chooses to share the data, and $1 - y$ denotes the probability that Data Center B chooses not to share the data, $y \in (0, 1)$. $x, y$ will be continuously adjusted during the game, and the following assumptions are made about the model:

**Assumption 1:** *The two parties involved in the evolutionary game are Data Center A and Data Center B. Data Center A's data-sharing behavior strategy is* $P_A$ = {$x$, $1 - x$} = {Sharing data, Not sharing data}, *and Data Center B's data sharing behavior strategy is* $P_B$ = {$y$, $1 - y$} = {Sharing data, Not sharing data}.

**Assumption 2:** *Analysis of direct benefits of data sharing. The direct benefit obtained when data centers share data is related to two factors: one is the size of the shared data E, and the other is the complementary coefficient of the shared data a. Generally speaking, the larger the amount of shared data and the more high-value data, the more benefit it obtains, and the benefit is also related to the complementary nature of the shared data. Therefore, after analysis, it can be seen that the direct gain after sharing Data Centers A and B is* $a_1E_2$, $a_2E_1$.

**Assumption 3:** *Data-sharing reputation gain analysis. Data center parties can reduce the trust cost if they have a high reputation value when sharing data, so a certain reputation gain should be allocated to the sharing parties, denoted by N. The reputation gain obtained by Data Centers A and B is denoted as* $N_1$, $N_2$.

**Assumption 4:** *Data-sharing cost analysis. The execution of data sharing will produce an economic cost and privacy cost. Economic cost refers to the idea that the data-holding party needs to carry out data collection, cleaning, encryption, and other operations; both sides of the game, as long as one party initiated the sharing operation, will produce an economic cost. Privacy cost refers to the idea that the data-holding party in the completion of the data sharing needs to bear the consequences of the possible leakage of data caused by the data; here, Data Centers A and B choose to share data when consumed, and the cost is* $C_1$, $C_2$.

**Assumption 5:** *Data-sharing platform revenue analysis. In order to incentivize both data centers to participate in sharing high-quality data, a certain amount of revenue is rewarded by the platform to the party that chooses to share, and the platform revenue is related to the cost of sharing data by the participant C and the subsidy coefficient k. Here, the platform revenue obtained by Data Centers A and B is* $kC_1$, $kC_2$.

**Assumption 6:** *When Data Center A or Data Center B chooses not to share data as a strategy, it is stipulated that their revenues are both 0.*

According to the assumptions, the gain matrix of the two parties of the game when smart grid data centers are shared is derived, as shown in Table 1.

**Table 1.** Benefit matrix for two-party gaming in smart grid data center sharing.

| **Strategy for Data Center A Selection** | **Strategy for Data Center B Selection** | |
|---|---|---|
| | **Select Share $y$** | **Select Not to Share $1 - y$** |
| Select Share $x$ | $a_1E_2 + N_1 + kC_1 - C_1$<br>$a_2E_1 + N_1 + kC_1 - C_1$ | $N_1 + kC_1 - C_1$,<br>0 |
| Select not to share $1 - x$ | 0,<br>$N_2 + kC_2 - C_2$ | 0, 0 |

*4.2. Analysis of Model Stabilization Evolution Strategies*

From the game payoff matrix in Table 1, the expected payoffs of both parties are analyzed.

Data Center A chooses to share the data with an expected gain of:

$$\begin{aligned} &E_{A1} = y(a_1E_2 + N_1 + kC_1 - C_1) + (1 - y)(N_1 + kC_1 - C_1) \\ &= y(a_1E_2 + N_1 + kC_1 - C_1 - N_1 - kC_1 + C_1) + N_1 + kC_1 - C_1 \\ &= y \cdot a_1E_2 + N_1 + kC_1 - C_1 \end{aligned}$$

Data Center A expects a gain the following of when it chooses not to share data:

$$E_{A2} = 0$$

The average expected return is:

$$\begin{aligned} E_A &= xE_{A1} + (1-x)E_{A2} \\ &= xy \cdot a_1E_2 + x(N_1 + kC_1 - C_1) \end{aligned}$$

Data Center B expects a gain of the following when it chooses to share data:

$$\begin{aligned} &E_{B1} = x(a_2E_1 + N_2 + kC_2 - C_2) + (1-x)(N_2 + kC_2 - C_2) \\ &= x(a_2E_1 + N_2 + kC_2 - C_2 - N_2 - kC_2 + C_2) \\ &= x \cdot a_2E_1 + N_2 + kC_2 - C_2 \end{aligned}$$

Data Center B chooses not to share the data in anticipation of a gain of:

$$E_{B2} = 0$$

The average expected return is:

$$\begin{aligned} &E_B = yE_{B1} + (1-y)E_{B2} \\ &= xy \cdot a_2E_1 + y(N_2 + kC_2 - C_2) \end{aligned}$$

The resulting equation for the replication dynamics between Data Centers A and B is established as:

$$\begin{aligned} &F_A(x) = x(E_{A1} - E_A) = x[y \cdot a_1E_2 + N_1 + kC_1 - C_1 - xy \cdot a_1E_2 - x(N_1 + kC_1 - C_1)] \\ &= x[y(1-x) \cdot a_1E_2 + (1-x) \cdot (N_1 + kC_1 - C_1)] \\ &= x(1-x)(y \cdot a_1E_2 + N_1 + kC_1 - C_1) \end{aligned}$$

$$\begin{aligned} &F_B(y) = y(E_{B1} - E_B) = y[x \cdot a_2E_1 + N_2 + kC_2 - C_2 - xy \cdot a_2E_1 - y(N_2 + kC_2 - C_2)] \\ &= y[x(1-y) \cdot a_2E_1 + (1-y) \cdot (N_2 + kC_2 - C_2)] \\ &= y(1-y)(x \cdot a_2E_1 + N_2 + kC_2 - C_2) \end{aligned}$$

*Let*: $F_A(x) = F_B(y) = 0$; the equilibrium point of both sides of the data-sharing game can be found as $O(0,0)$,$P_1(0,1)$, $P_2(1,0)$, $P_3(1,1)$, $P_4\left(\frac{C_2-kC_2-N_2}{a_2E_1}, \frac{C_1-kC_1-N_1}{a_1E_2}\right) = (x^*, y^*)$.

Next, construct the Jacobi matrix by taking the partial derivation of the above equation:

$$J = \begin{bmatrix} (1-2x)(ya_1E_2 + N_1 + kC_1 - C_1) & x(1-x)a_1E_2 \\ y(1-y)a_2E_1 & (1-2y)(xa_2E_1 + N_2 + kC_2 - C_2) \end{bmatrix}$$

The above matrices and equations are used to determine whether the equilibrium is in a steady state or not. We only need to bring the equilibrium point into the Jacobian matrix, in turn, to calculate this; if the determinant is greater than 0 while the trace is less than 0, it can be determined that the point has equilibrium stability, and satisfies the stabilization strategy during the evolution, from the following three cases to start the analysis:

**Condition 1:** *When $C_2 - kC_2 - N_2 > a_2E_1$, $C_1 - kC_1 - N_1 > a_1E_2$, at this point, the cost of user participation in data sharing is higher than the benefits received, and the system incentive is at a low level. A simple analysis shows that the point $P_4$ does not meet the requirements, the remaining points will be brought into the matrix to calculate the determinant and traces, and the results of the system evolutionary stability analysis are shown in Table 2.*

**Table 2.** Analysis of local evolutionary stabilization results on both sides of data sharing.

| Balance Point | Matrix Determinant Notation | Matrix Trace Symbols | Evolutionary Results |
|---|---|---|---|
| $O(0, 0)$ | >0 | <0 | Evolutionary stabilization strategy |
| $P_1(0, 1)$ | <0 | Uncertain | Saddle point |
| $P_2(1, 0)$ | <0 | Uncertain | Saddle point |
| $P_3(1, 1)$ | >0 | >0 | Unstable |

As can be seen from Table 2, among the four local equilibrium points, only point $O(0,0)$ is a stable evolutionary strategy, indicating that both data-sharing parties choose not to participate in the sharing, $P_3(1,1)$ is an unstable point, and $P_1(0,1)$, $P_2(1,0)$ is a system saddle point.

The phase evolution diagram was used to describe the data-sharing evolutionary process as shown in Figure 3a. The analysis shows that when the system incentive is small, the sharing cost is greater than the gain, and the data-sharing parties after the rational game all chose not to participate in the data sharing, so the parties in the phase diagram are converging to $O(0,0)$.

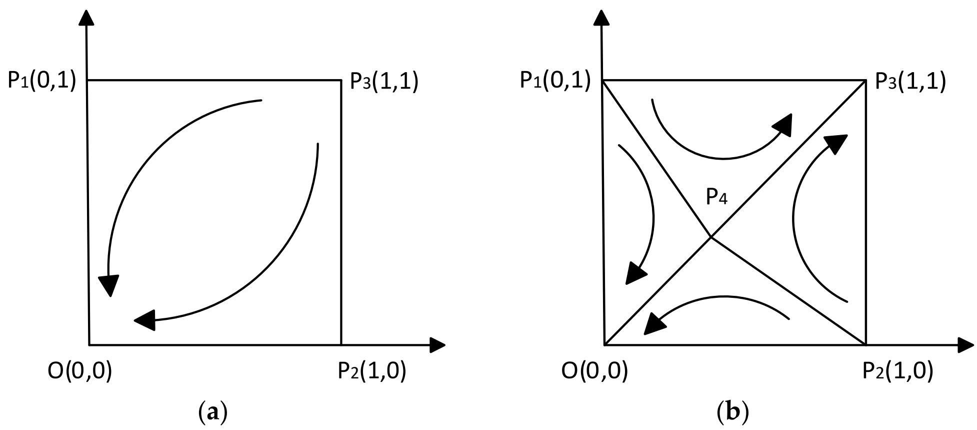



**Figure 3.** (**a**) Phase diagram of the system in the first case; and (**b**) phase diagram of the system in the second case.

**Condition 2:** *When $C_2 - kC_2 - N_2 < a_2E_1, C_1 - kC_1 - N_1 < a_1E_2$ and $N_2 + kC_2 < C_2$, $N_1 + kC_1 < C_1$, the benefits gained from user participation in data sharing are greater than the costs, and all points are brought into the matrix to calculate the determinant and traces, it can be seen that $O(0,0)$ and $P_3(1,1)$ are stable evolutionary points in the system, and the results of the stable evolutionary analysis of the system are shown in Table 3.*

**Table 3.** Results of local evolutionary stability analysis for both sides of data sharing.

| Balance Point | Matrix Determinant Notation | Matrix Trace Symbols | Evolutionary Results |
|---|---|---|---|
| $O(0, 0)$ | >0 | <0 | Evolutionary stabilization strategy |
| $P_1(0, 1)$ | >0 | >0 | Unstable |
| $P_2(1, 0)$ | >0 | >0 | Unstable |
| $P_3(1, 1)$ | >0 | <0 | Evolutionary stabilization strategy |
| $P_4(x^*, y^*)$ | <0 | Uncertain | Saddle point |

According to the analysis in Table 3, it can be seen that $O(0,0), P_3(1,1)$ is an evolutionary stable strategy, $P_1(0,1), P_2(1,0)$ is an evolutionary unstable strategy, and $P_4(x^*, y^*)$

is a saddle point. Only $O(0,0)$ and $P_3(1,1)$ show stable evolution when data users share, which correspond to the two cases when data-sharing parties choose to share data and not share, respectively.

The phase evolution diagram is shown in Figure 3b. Data users choose to share or not share data depending on the initial state of the system, linking the points in the figure; when the initial state of both data-sharing parties falls below, after evolution, the system will converge to point $O$, which indicates the strategy where the sharing parties will tend to choose not to share data; when the initial state of both sharing parties falls above, after evolution, the system will converge to point $P_3$, which indicates the strategy where the sharing parties will tend to choose to share data. The area of the region surrounded by points $P_1P_2P_3P_4$ can be used to indicate the probability of user participation in sharing.

$$S_{P_1P_2P_3P_4} = 1 - \frac{1}{2}\left(\frac{C_2 - kC_2 - N_2}{a_2E_1} + \frac{C_1 - kC_1 - N_1}{a_1E_2}\right)$$

**Condition 3:** *When $C_2 - kC_2 - N_2 < a_2E_1$, $C_1 - kC_1 - N_1 < a_1E_2$, and $N_2 + kC_2 > C_2$, $N_1 + kC_1 > C_1$, the benefits gained from user participation in data sharing are greater than the costs, and the system incentive level is high. A simple analysis shows that point $P_4$ does not meet the requirements, the remaining points are brought into the matrix to calculate the determinant and traces, and the results of the system stability evolution analysis are shown in Table 4.*

**Table 4.** Results of local evolutionary stability analysis of data-sharing parties.

| Balance Point | Matrix Determinant Notation | Matrix Trace Symbols | Evolutionary Results |
|---|---|---|---|
| $O(0,0)$ | >0 | >0 | Unstable |
| $P_1(0,1)$ | <0 | Uncertain | Saddle point |
| $P_2(1,0)$ | <0 | Uncertain | Saddle point |
| $P_3(1,1)$ | >0 | <0 | Evolutionary stabilization strategy |

From Table 4, it can be seen that, among the four equilibrium points, only $P_3(1,1)$ is an evolutionary stable point, indicating that both data-sharing parties adopt sharing strategies, $O(0,0)$ is an unstable point of system evolution, and $P_1(0,1)$, $P_2(1,0)$ is a saddle point.

The phase evolution diagram is shown in Figure 4a, and the analysis shows that, when the incentive strength is in the interval, the data-sharing users all choose to share the data after a long-term game, indicating that the system incentive is at a high level at this time.

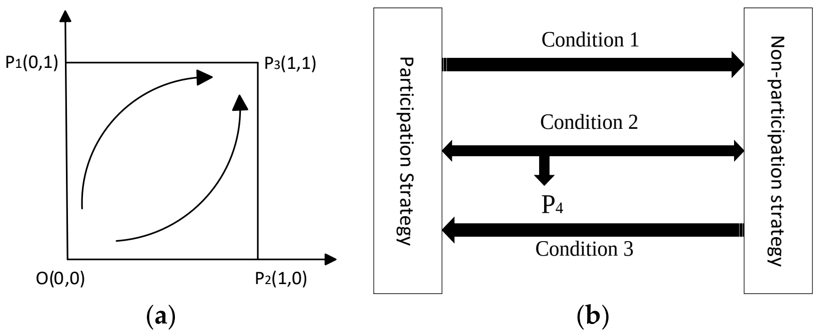



**Figure 4.** (**a**) Phase diagram of the system during the third case; and (**b**) direction of system evolution under different conditions.

The above study analyzes three cases of evolutionary stability in the process of data sharing. Figure 4b summarizes the direction of evolution under different conditions; in fact, affected by a variety of factors to share, the two sides choosing to share the data is not necessarily able to achieve a stable evolutionary strategy. The user who chooses the {sharing, sharing} or {not sharing, not sharing} strategy may reach a stable state of evolution. The state parameter, to a large extent, determines whether the user in the long term after the game should select the sharing of the data, in practice, in order for the two sides to converge to share the need to make the area in the formula larger, as much as possible.

An incentive mechanism based on evolutionary game theory for the dynamic sharing of smart grid data is derived by us and used to encourage more users within the smart grid system to come and participate in data sharing. The motivation process is shown in Figure 4b.

Firstly, in the initial stage of the whole evolutionary gaming process, the proportion of users in the system who choose to participate in data sharing as a whole is small; according to the analysis, using Condition 3, the proportion of participating users can be increased by improving the subsidy coefficient, increasing the size of the shared data, and reducing the cost to incentivize more users to turn to the participation strategy. Once the proportion of users participating in data sharing exceeds a certain threshold, i.e., the state of $P_4$ point, users can spontaneously participate in data sharing without additional incentives from the system. When the current incentive ratio has reached the maximum before the end of a round of the game, the system can spontaneously determine whether it is necessary to use Condition 1, and reduce the proportion of users participating in data sharing in the system at this time by increasing the cost or reducing the subsidies in the system to make the users choose not to participate in data sharing after the evolutionary game; at this time, the blockchain data-sharing platform, with the increasing proportion of sharing users, may bring additional costs to users, and, as the proportion of shared users rises, it may lead to higher loads within the system, resulting in higher maintenance costs. Therefore, it is necessary to dynamically reduce the proportion of partially shared users to ensure that the benefits of the entire system are maximized.

After a round of the game, the system will keep repeating the incentive process described above, charging users for participation through an iterative process of data sharing for inaccessible users, until the system revenue reaches the maximum value of the game stage.

The dynamic incentive mechanism can maximize the user participation rate by dynamically adjusting the parameters and constantly adjusting the conditions of the game phase so that more users can participate in data sharing and experience the benefits of data sharing. In addition, the whole process is designed as a smart contract that automatically executes to provide incentives for both sharing parties when the conditions are met, and the incentive mechanism that excludes third parties is more secure and trustworthy due to the characteristics of the smart contract. The flowchart of the system motivation is shown in Figure 5.

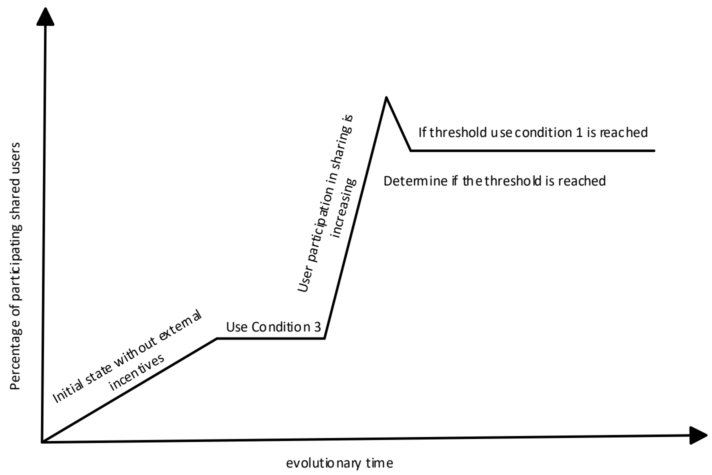



**Figure 5.** System incentive flowchart.

### 4.3. Smart Contract Incentive Mechanism Design

In order to encourage more users to participate in data sharing, a dynamic incentive mechanism based on the evolutionary game is proposed by us, through the design of a smart contract that simulates the whole incentive process, and through the characteristics of the smart contract to achieve the mutual integration of the data-sharing process and the users of the blockchain platform. Meanwhile, smart contracts are deployed on the blockchain platform to ensure privacy and security in data sharing. The decentralized nature of blockchain makes it more secure because data and transaction information are distributed throughout the network and are less susceptible to single-point attacks. Moreover, blockchain uses cryptography to ensure data security, including mechanisms such as the encryption of transaction information and digital signatures. Finally, the consensus mechanism of blockchain ensures consistency between participants in the blockchain network, protecting the integrity and security of data.

First, in the initial stage of the evolutionary game, the number of users participating in data sharing in the system is very small. Using the scenario in Condition 3, taking one incentive for users to participate in sharing motivates more users to shift to the strategy of participating in data sharing. When the proportion of data sharing exceeds a threshold, using Condition 1 ensures that the blockchain can be used without external incentives in the current state, ensuring that the current system is in a normal incentive state. In addition, the blockchain data-sharing platform may impose specific fees on users. The system will keep repeating the above incentive process by charging users for participation through an iterative process of data sharing for different users until the system revenue reaches the maximum value in the game phase.

Smart contracts can be automatically executed according to pre-set rules and trigger conditions, and their program code is deployed on the blockchain with a tamper-proof function, so the sharing incentive mechanism can be written to the smart contract for users to invoke on the smart grid data center, and it is automatically executed to provide incentives for both sharing parties when the conditions are met; this kind of incentive mechanism that excludes the third party is safer and more trustworthy. This section designs a data-sharing incentive contract based on the evolutionary game, which contains five functions, and the specific roles are explained as follows:

(1) GetTotalusers(): Counts the number of data holders participating in data sharing in the system over a period of time, and sets this number to the total number of shared users.
(2) GetParticipatingusers(): Counts the number of data holders participating in data sharing in the system over a period of time, and sets this number to the total number of shared users.
(3) GetCurparaset(): Obtain the set of parameters for the current phase from the parameter set.
(4) GetThreshold(): Calculate the threshold for the current state of the system based on the data in the current set of parameters.
(5) GetIncentive(): Incentivize the system of the evolutionary game by changing, for example, the parameters of the current parameter set.

Tables 5 and 6 show the data names and types of the main functions and parameter sets.

The deployment process of the smart contract is as follows: First, initialize the global parameters; and stipulate that after the proportion of users participating in sharing exceeds 90 percent, end the incentive process and return the incentive rewards and incentive costs automatically. After that, obtain the specific parameters of the current parameter set through the GetCurparaset method, and then compute the proportion of users participating in sharing to the whole set of users $x$. Then, compute the threshold value $x^*$ for the current gamble phase by the GetThreshold() method. Use GetThreshold() method to calculate the threshold $x^*$ for the parameter set of the current game stage; if the proportion $x$ of users participating in sharing is less than the threshold $x^*$, the incentive within the system is enhanced by changing the value of the current parameter set Curparaset, and a new threshold is formed dynamically, and the external incentive is canceled if the proportion of users participating in sharing is greater than the threshold $x_1$*, indicating that the system's own incentive is sufficient, after which the users are made to enter the next stage of the evolutionary game. Finally, the corresponding results are returned, including the cost of data sharing and the incentive benefits in the game stage.

**Table 5.** Names and data types of functions and variables.

| Name | Data Type |
|---|---|
| Participatingusers | int |
| Totalusers | int |
| GetIncentive() | double |
| GetTotalusers() | int |
| GetParticipatingusers() | int |
| GetCurparaset() | double |
| GetThreshold() | double |

**Table 6.** The data name and data type in the parameter set.

| Name | Data type |
|---|---|
| data size | double |
| data complementarity | double |
| user reputation | double |
| sharing cost | double |
| sharing cost | double |

The pseudo-code of the smart contract for smart grid data sharing incentives is shown in Algorithm 1.

**Algorithm 1:** Data-Sharing Incentive Mechanism Smart Contracts

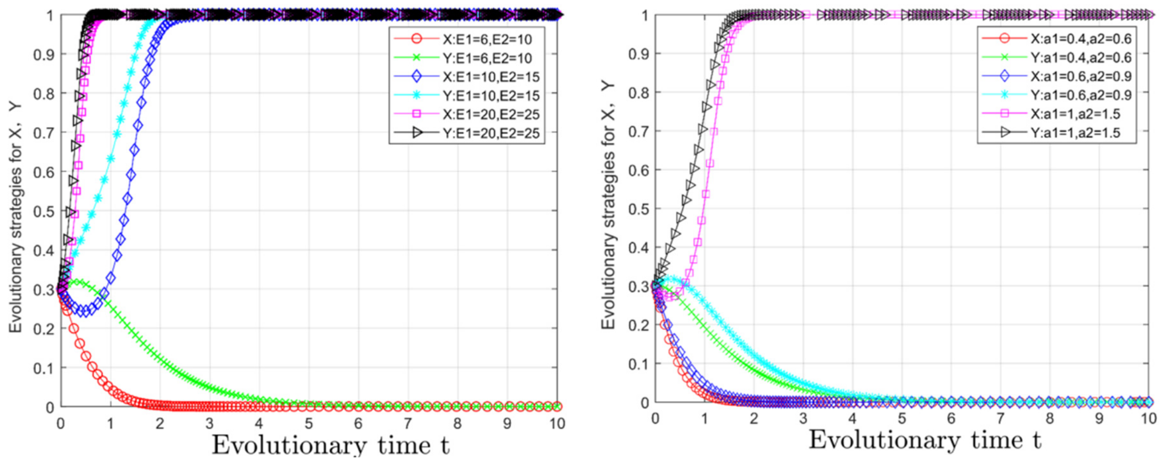
**Input: Totalusers, Userparticipating, Curparaset**
**Output: results**
**Function** GetSystembenefits()
    $N$ = GetTotalusers($P$)
    $n$ = GetParticipatingusers($N$)
    $S$ = GetCurparaset(parameterset)
    $x = n/N$
  **If** $x > 0.9$ **then//**When $x$ is greater than 0.9, it automatically ends the game phase
    Participatingusers = 0
    Totalusers = 0//Reset all parameters of this process
    Curparaset = 0
  **End if**
    $x$* = GetThreshold($S$)//Calculate the threshold assignment for the current parameter set to $x$*
  **While** ($x < x$*)
    $S$* = GetCurparaset(parameterset1)
    GetIncentive($S$*)//Adjust the parameters in the current parameter set for incentive
    $x_1$* = GetThreshold($S$*)//Dynamically adjust the set of parameters and thresholds
    **If** ($x > x_1$*)
    Return results//End this phase of the incentive process
    **Break**
**End Function**

## 5. Simulation Results and Analysis

To discuss the influence of different factors on users' evolutionary strategies, this section uses the MATLAB software (9.5.0.944444 (R2018b)) for simulation analysis. By setting different values of $E$, $N$, $k$, and $C$, the effects of different factors on data incentives are measured by the proportion and speed of users' participation in data sharing, and the role of these parameters in the incentive mechanism in the data-sharing evolutionary game is verified. The control variable method is used to solve the differential equations using the ode45 function to verify the role of a single condition on the stabilization strategy of sharing evolution by setting different parameter values.

### *5.1. Impact of Data Complementarity on Stabilization Evolution*

Data complementarity is an important parameter that affects the user's benefit. In the control of other parameters remaining unchanged, change the parameter $a$ to determine the data complementarity on the evolutionary game stabilization role; the results are shown in Figure 6a. The other parameter assignments are specified as follows: $E_1 = 6, E_2 = 10$, $N_1 = 6,\ N_2 = 6,\ C_1 = 25,\ C_2 = 30,\ k = 0.6$. The initial user sharing ratio in the system is set to 0.3.




(**a**) (**b**)

**Figure 6.** (**a**) Curve of data complementarity on system stability evolution; and (**b**) curve of shared data size on system stability evolution.

Analyzing Figure 6a shows that data complementarity plays a positive role in the system game stabilization strategy. With the increase of data complementarity in the system, the above curve shifts from converging to 0 to converging to 1, and the convergence speed is gradually accelerated, which indicates that the user shifts from not sharing data to sharing data, and the greater the data complementarity between the two sharing parties, the greater the willingness to share data, and the improvement of data complementarity can effectively enhance the system incentive strength.

### *5.2. Effect of Shared Data Size on Stabilization Evolution*

Data-sharing size is also an important parameter that affects the user's benefit; the larger the data shared between the two sides, the more the benefit. In the control of other parameters remaining unchanged, change the parameter $E$ to determine the data complementarity on the evolution of the game stabilization role; the results are shown in Figure 6b. The other parameters assigned specific values are as follows: $a_1 = 0.6, a_2 = 0.9$, $N_1 = 6, N_2 = 6,\ C_1 = 25,\ C_2 = 30,\ k = 0.6$. The initial user sharing ratio in the system is set to 0.3.

An analysis of Figure 6b shows that the data-sharing size plays a positive role in promoting the evolutionary stabilization strategy; as the data shared by both parties in the system increases, the curve in the figure shifts from converging at 0 to converging at 1, and the convergence speed is gradually accelerated. Comparing the same set of curves, the more the data sharing, the faster the convergence speed; the user's willingness to share data in the enhancement, which indicates that the size of the data shared by both parties, is also an important factor affecting the sharing.

### *5.3. User Reputation Impact on Stable Evolution*

Considering that credibility in the calculation of user benefits is an important means to ensure safe sharing, in the control of other parameters remaining unchanged, change the parameter $N$ to determine the impact of user credibility on the stable evolution strategy; the results are shown in Figure 7a. The other parameter assignments are as follows:

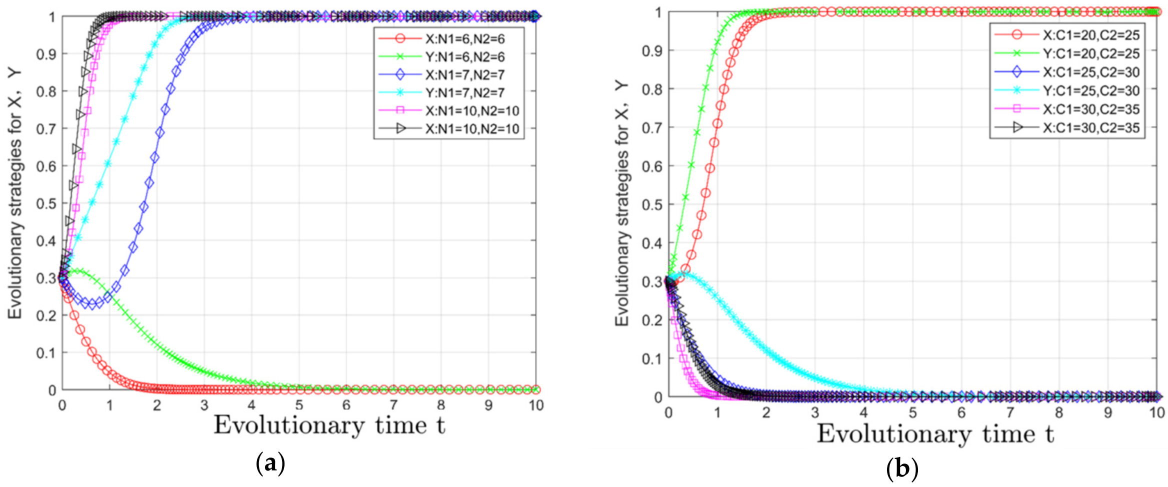



**Figure 7.** (**a**) Influence curve of user reputation on system stable evolution; and (**b**) influence curve of sharing cost on system stable evolution strategy.

$a_1 = 0.6$, $a_2 = 0.9$, $E_1 = 6$, $E_2 = 10$, $C_1 = 25$, $C_2 = 30$, $k = 0.6$. The initial proportion of users in the system is set to 0.3.

An analysis of Figure 7a shows that user credibility positively affects the stabilization strategy of the evolutionary game between the sharing parties, and, as the user credibility parameter increases, the curve in the figure converges to 1 rapidly, and the probability that the user chooses to share the data becomes larger.

### *5.4. Impact of Sharing Cost on Stabilization Evolution*

Users have to consume a certain amount of computational cost in the process of sharing data, and also face the risk of data leakage, so the sharing cost is also an important parameter that affects the user's revenue. Under the control of other parameters remaining unchanged, the parameters $C$ are changed to determine the impact of the sharing cost on the evolutionary game strategy; the results are shown in Figure 7b. The other parameters are assigned as follows: $a_1 = 0.6$, $a_2 = 0.9$, $E_1 = 6$, $E_2 = 10$, $N_1 = 6$, $N_2 = 6$, $k = 0.6$. The initial user ratio in the system is set to 0.3.

An analysis of Figure 7b shows that the size of the sharing cost plays an inverse role in stabilizing the evolutionary strategy. The smaller the sharing cost is, the faster the curve in the graph converges to 1; the probability of user participation in data sharing increases, and, when the sharing cost is greater than the gain obtained, the user will choose not to participate in sharing.

### *5.5. Impact of Platform Subsidies on Stability Evolution*

The factors discussed above are all fixed values, and, when the user sharing cost is greater than the above benefits, a certain amount of subsidy must be given by the platform to incentivize users to share data. Under the control of other parameters remaining unchanged, change the parameters $k$ to determine the impact of platform subsidies on the evolution of the game strategy; the results are shown in Figure 8. The other parameters are assigned as follows: $a_1 = 0.6$, $a_2 = 0.9$, $E_1 = 6$, $E_2 = 10$, $N_1 = 6$, $N_2 = 6$, $C_1 = 25$, $C_2 = 30$. The initial user ratio in the system is set to 0.3.

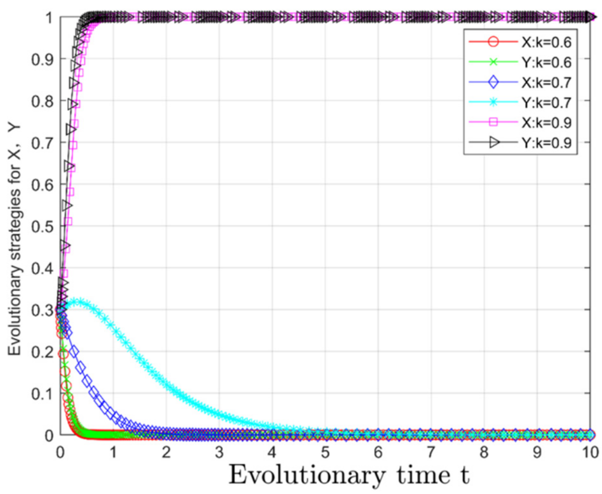



**Figure 8.** Curve of the influence of the platform subsidy on the stable evolution strategy of the system.

An analysis of Figure 8 shows that the platform subsidy plays a positive incentive role in stabilizing the evolutionary strategy. When $k$ = 0.3, the system user chooses not to share data and converges to 0 faster; when $k$ = 0.6, the user still chooses not to share but the converging to 0 slows down; and, when $k$ = 0.9, the user chooses to share and converges to 1, which indicates that the incentive is sufficient at this time. The system adopts the subsidy method with the sharing cost as the credential, standardizes the subsidy standard, and has obvious incentives to promote the sharing of data.

### *5.6. Analysis of Simulation Results*

Synthesize the above simulation and analysis results, and, specifically, analyze several factors that affect the user sharing data.

The larger the size of the data shared by both parties $E$, the larger the complementary coefficient $a$ between the data, and the higher the probability of sharing. The purpose of sharing data is to find differentiated data, so the greater the complementary coefficient between the data, the greater the value generated by sharing, and the higher the willingness of both parties to share.

The greater the reputation value of both parties $N$, the greater the probability of sharing. The reputation value reflects the user's performance in the past sharing: the higher the reputation value, the higher the trust between the two parties to share, and the higher the willingness to share.

The larger the platform subsidy coefficient $k$, the greater the probability of sharing occurring. Here, the overall reward of the platform is positively correlated with the subsidy coefficient and the sharing cost, and, usually, the higher the cost of the sharing party is, the more the platform reward is harvested, and this platform subsidy–cost correlation setup is more in line with reality.

Other things being equal, the higher the cost of data sharing $C$, the lower the probability of sharing occurring. This is due to the fact that the data-sharing party needs to bear the data economic cost and privacy cost, and only when the benefit of data sharing is greater than the cost can it create positive incentives for the sharing process.

The incentive mechanism proposed in this paper can dynamically adjust the incentive parameters and participation costs in smart grids to promote user participation in data sharing. When the number of users participating in data sharing starts to decrease, without the incentive adjustment mechanism, users are likely to continue to decrease, which, ultimately, leads to the failure of the data-sharing network. The incentive adjustment mechanism increases user participation by adding incentives and maintains a balance between the size of the users and the cost of the activity.

When the smart grid system is in the first case or the second case where the initial proportion of participating users is low and the level of system incentives is low, the above experiments can dynamically adjust the incentive parameters such as data complementarity between the two parties, the size of the shared data, the user credibility, the increase of the smart grid's platform subsidy to the sharing users, and the reduction of the sharing cost to incentivize the active participation of the users in the system in the sharing of data, thus expanding the proportion of participating sharing users in the system to maximize the benefits for the users, as well as the entire smart grid system. When the system is in the third situation, the system incentive level is relatively high; at this time, the proportion of shared users in the system is already large, and there is no need for additional incentives from the system. When the proportion of shared users reaches a certain threshold, the proportion of participating users can even be dynamically adjusted by increasing the cost of sharing, so as to achieve the maximization of the revenue of the entire smart grid system.

## 6. Conclusions and Outlook

Based on the game theory on smart grid data-sharing incentive scheme was our study. Because of the lack of an incentive mechanism for the data-sharing problem, we put forward a game-theory-based smart grid data-sharing incentive mechanism. First, we establish the data-sharing stage evolution game model, based on the model analysis of the sharing parties' benefit matrix, and then we discuss the stability of the evolution strategy under different conditions, according to the results of the analysis, to give a kind of model based on the evolutionary game. A dynamic incentive mechanism for smart grid data based on game theory is given based on the analysis results, which illustrates how the incentive mechanism proposed in this paper can dynamically adjust the incentive parameters and participation costs in the smart grid to promote users' participation in data sharing. Accordingly, a smart contract module is designed, and, finally, the effects of different factors on the evolutionary stabilization strategy are discussed through simulation analysis, and the simulation results verify the role of these parameters in the incentive mechanism in the evolutionary game of data sharing.

The incentive model proposed by us uses a two-party evolutionary game to construct a sharing model between data holders and data requesters; in fact, there are also multiple roles in data sharing, such as platform agents. In the future, the incentive mechanism can be improved by investigating the users' behavior in data sharing and testing the applicability and effectiveness of the model in the real smart grid environment to increase the complexity of the gaming process, such as conducting the evolutionary game among the data-sharing users, the management part, and the platform agent, and so on. From there, refinements of this incentive are made to bring the model closer to reality.

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