

Research on Agricultural Film Recycling Mechanism Based on Intelligent Optimization Algorithms and Game Theory

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Abstract: This study employs an intelligent optimization algorithm model to quantify key factors influencing the cost of agricultural film recycling through multi-dimensional data analysis, optimizing parameters for an economically feasible cost coordination mechanism. Simultaneously, a game theory algorithm model is constructed to systematically elucidate the theoretical framework and technical pathways for agricultural film recycling. Through model solving, the study clarifies the interests and game relationships among the government, production enterprises, and farmers, proposing an optimal mechanism for multi-party interest coordination. This research provides a significant theoretical foundation and practical reference for policy formulation, technology promotion, and operational practices in agricultural film recycling.

Keywords: Agricultural Film Recycling; Intelligent Optimization Algorithms; Game Theory; Sustainable Development.

1. Introduction

Agricultural film mulching technology, as an advanced farmland management method, has demonstrated significant advantages in enhancing the yield-to-efficiency ratio during crop growth cycles, making it an integral component of modern agricultural production systems [1][2]. However, the issue of residual agricultural film has triggered multi-dimensional environmental impacts, including soil structure degradation, nutrient imbalance, and groundwater pollution, necessitating the establishment of a systematic recycling and management system to address this environmental challenge [3][4].

At present, domestic and international researchers have conducted extensive studies on this issue. Wang et al. constructed a tripartite evolutionary game model composed of the government, recyclers, and consumers, and analyzed the initial, intermediate, and mature stages of the development of the electronic waste recycling industry [5]. Shan et al. proposed a tripartite evolutionary game model composed of the government, recyclers, and consumers, exploring the implementation mechanism and influencing factors of China's Extended Producer Responsibility (EPR) system. Additionally, there are evolutionary game studies related to the recycling of other solid wastes [6]. Yang et al. explored the behavioral evolution of multiple stakeholders in the recycling industry chain of discarded takeout packaging [7]. Guo et al. investigated the behavioral evolution of multiple stakeholders in the recycling industry chain of discarded takeout packaging [8]. Wang et al. analyzed the behavioral evolution of the government, collectors, and recyclers in the issue of plastic waste recycling [9]. Among these, game theory models are widely applied by domestic and international researchers, and evolutionary game theory is a tool widely used in economics to study the behavioral evolution of multiple stakeholders. After Smith and Price first proposed this concept in 1973 [10], Taylor and Jonker introduced the concept of replicator dynamics while studying ecological evolution phenomena [11]. Li et al. constructed a

multi-stakeholder evolutionary game model, analyzing the cooperative mechanism in urban solid waste management. They focused on the behavioral evolution of the government, enterprises, and residents in waste classification and recycling, and explored the impact of policy incentives on cooperation among the parties [12]. Zhang et al. proposed a dynamic model based on evolutionary game theory to analyze multi-party interest conflicts and cooperation in electronic product recycling. They studied the behavioral evolution of manufacturers, retailers, and consumers in electronic product recycling and proposed policy recommendations to promote recycling efficiency [13]. Huo et al. developed a tripartite evolutionary game model involving the government, enterprises, and social organizations, studying the synergistic mechanism in the waste paper recycling industry chain. They analyzed the evolutionary patterns of the behaviors of the parties at different stages and proposed strategies to optimize the recycling system [14].

This paper first constructs an intelligent optimization algorithm model, through systematic analysis and calculation of multi-dimensional data, deeply excavates and quantifies the key factors affecting the cost of agricultural film recycling, and then optimizes to obtain the most economically feasible parameters for the recycling cost coordination mechanism. On this basis, secondly, a game theory algorithm model is established, systematically elaborating the theoretical framework and technical path of agricultural film recycling from a perspective combining theory and practice. Through model solving and verification, the interests and game relationships of the government, production enterprises, and farmers in the agricultural film recycling process are clarified, and finally, an optimal mechanism scheme for multi-party interest coordination is proposed. This research provides an important theoretical basis and practical reference for subsequent policy formulation, technology promotion, and practical operation of agricultural film recycling.

2. Agricultural Film Recycling Model Based on Intelligent Algorithms

2.1. Metaheuristic Algorithm Model

The Wolf Pack Algorithm (WPA) is a multi-objective bionic optimization algorithm inspired by the collective hunting behavior of wolf packs. As social animals, wolves exhibit various group behaviors, and the Wolf Pack Algorithm is specifically designed to simulate their hunting strategies. Through hierarchical collaboration, wolf packs can, over time, identify the most optimal locations for survival by making decisions and adjustments. As a swarm intelligence-based optimization method, the Wolf Pack Algorithm effectively simulates the behavior of agricultural film recycling under complex influencing factors. By mimicking the cooperation and competition mechanisms in wolf pack hunting, the algorithm dynamically adjusts key parameters. Based on the different roles in the hunting process, the recycling mechanism can be analogized to the types of wolves in the algorithm, as explained below:

Leader Wolf: In the process of searching for the optimal solution, the leader wolf adopts the best mechanism identified within the current time frame as a guide, meaning the mechanism with the highest recycling efficiency during the search period. It also directs other wolves to move closer, enabling the pack to continuously converge toward the optimal mechanism, dynamically adjusting as the search progresses and time evolves. This process is expressed by Equation (1):

$$z_{id}^p = z_{id} + \sin(2\pi \times \frac{q}{g}) \times step_s^m \quad (1)$$

Scout Wolves: Initially, the wolf pack dispatches a group of scout wolves to search the surrounding environment for prey. If a scout wolf detects a higher concentration of prey scent, it becomes the leader wolf and calls other wolves to encircle the prey. Later, the fitness of the prey found by different scout wolves is compared, and the one with the highest fitness is selected as the leader wolf. This process is expressed by Equation (2):

$$z_{id}^{p+1} = z_{id}^p + step_b^m \cdot \frac{g_m^p - z_{id}^p}{|g_m^p - z_{id}^p|} \quad (2)$$

Fierce Wolves: When fierce wolves sense the call of the leader wolf, they immediately rush toward its position. During this process, if they detect prey with higher fitness, they replace the current leader wolf and take command of the pack. This process is expressed by Equation (3):

$$z_{id}^{p+1} = z_{id}^p + \lambda \cdot step_w^m \cdot |G_m^p - z_{id}^p| \quad (3)$$

The step sizes of the above three intelligent behaviors follow the relationship expressed by Equation (4):

$$step_s^d = \frac{step_b^d}{2} = 2 \cdot step_w^d = \frac{|M_d - m_d|}{C} \quad (4)$$

The bionic schematic of the Wolf Pack Algorithm is shown in Figure 1.

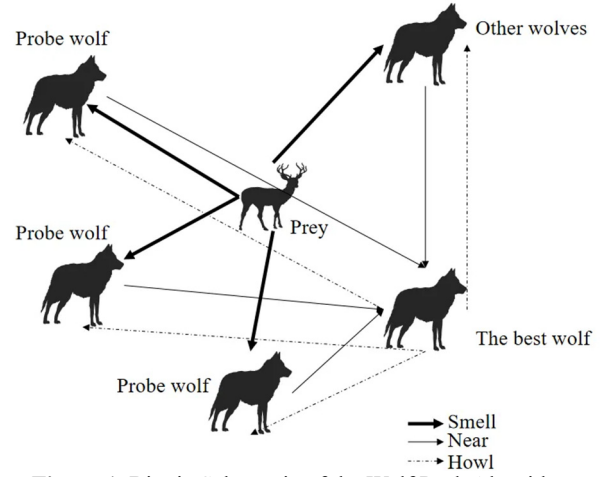


Figure 1. Bionic Schematic of the Wolf Pack Algorithm.

The Wolf Pack Optimization Algorithm is an intelligent optimization algorithm that simulates the foraging behavior of wolf packs, exhibiting strong global search capabilities and fast convergence. This study constructs an agricultural film recycling cost analysis model based on the Wolf Pack Optimization Algorithm, which includes the following steps:

Step 1: Initialization. Determine decision variables and constraints. Decision variables include agricultural film usage, recycling rate, policy subsidies, transportation costs, labor costs, etc. Constraints include data ranges and interrelationships among variables.

Step 2: Fitness Calculation. Calculate the fitness values of each variable. The fitness function is used to evaluate the quality of variable combinations, typically aiming to minimize costs.

Step 3: Pheromone Update. Update pheromones based on fitness values. Pheromones represent the quality of variable combinations, with higher fitness values corresponding to higher pheromone concentrations.

Step 4: Position Update and Boundary Check. Update the positions of the wolves based on pheromone distribution, simulating the foraging behavior of the wolf pack. Adjust the value ranges of variables through pheromone distribution. Perform boundary checks to ensure that the positions of the wolves remain within reasonable limits, avoiding invalid solutions.

Step 5: Iteration Termination. Terminate the iteration when the maximum number of iterations is reached or the fitness value converges. Typically, the iteration stops when the fitness value change falls below a set threshold.

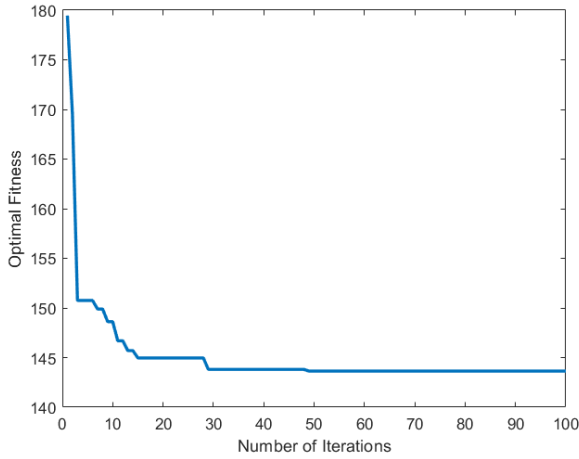
To validate the effectiveness of the model, we employed cross-validation, dividing the dataset into training and testing sets for model training and performance evaluation, respectively. The results show consistent performance across both sets, indicating the model's strong generalization ability.

Building on the model construction, we further optimized parameters such as the number of wolves, iteration count, and pheromone update rate. Through multiple experiments, the optimal parameter combination was determined, improving the model's convergence speed and optimization effectiveness. By running the model, the main factors influencing agricultural film recycling costs and their weights were identified, as shown in Table 1.

Table 1. Main Factors Influencing Agricultural Film Recycling Costs and Their Weights.

Variable	Agricultural Film Usage	Recycling Rate	Policy Subsidies	Transportation Costs	Labor Costs	Other Factors
Weight	0.35	0.25	0.15	0.1	0.05	0.05

The fitness optimization process of the Wolf Pack Algorithm is illustrated in Figure 2.

**Figure 2.** Fitness Optimization Process of the Wolf Pack Algorithm.

Through the Wolf Pack Optimization Algorithm model, the key factors influencing agricultural film recycling costs were systematically analyzed, and economically feasible parameters for the recycling cost coordination mechanism were optimized. The results demonstrate that the Wolf Pack Optimization Algorithm model has significant advantages in handling multi-dimensional data and identifying key factors.

2.2. Game Theory Algorithm Model

In agricultural film recycling activities, the government supports and regulates enterprises through macro-level policies, while enterprises need to actively respond to these policies to maximize policy support and minimize regulatory constraints and penalties. By setting parameters, the benefits and costs can be decomposed into basic variables:

The government's strategy set is $S3 = \{\text{Regulate, Do not regulate}\} = \{z, 1-z\}$, where $z \in [0, 1]$ [8]. Cg: Regulatory cost. K: Reputation improvement under the regulatory strategy. Environmental performance: Environmental benefits of enterprises establishing a recycling system. B: Environmental performance of enterprises not recycling. O: Environmental performance of enterprises not recycling (absolute value $B < O$). T: Tax on enterprises establishing a recycling system under regulation. Q: Tax on enterprises not recycling under regulation ($T < Q$). Q: Tax on enterprises not recycling without regulation. J: Subsidy for enterprises establishing a recycling system. L: Fine for enterprises not recycling.

The farmers' strategy set is $S1 = \{\text{Recycle to enterprises, Do not recycle}\} = \{x, 1-x\}$, where $x \in [0, 1]$. R: Reward given by enterprises to farmers for recycling. Time cost: Cost of recycling to enterprises (E) and cost of not recycling (G), where $E > G$. H: Cost of purchasing mulch film. D: Subsidy for recycling farmers. I: Fine for farmers not recycling.

The enterprises' strategy set is $S2 = \{\text{Establish a recycling system, Do not recycle}\} = \{y, 1-y\}$, where $y \in [0, 1]$. C: Recycling cost when establishing a recycling system. P: Additional cost borne when farmers do not recycle. W: Profit

from recycling. M: Production cost of agricultural film.

Recycling agricultural film benefits enterprises in two ways: (1) enhancing consumer welfare and (2) improving corporate image to attract customers. Product recycling has positive externalities, meaning that choosing recyclable options protects the environment and improves overall consumer welfare, while choosing non-recyclable options negatively impacts the environment and consumer welfare.

By integrating the subjective weight vector set W_1 and the objective weight vector set W_2 , a combined weight vector set is established, and a linear combination of subjective and objective weights is constructed as follows:

$$W = a_1 w_1^T + a_2 w_2^T$$

where a_1 and a_2 are linear combination coefficients representing the proportion of each weighting method.

Subsequently, an optimization combination is implemented with the Nash equilibrium as the reconciliation goal. A compromise model is established to achieve consistency between subjective and objective weight values, specifically minimizing deviations to form an optimal game solution. The objective function is as follows:

$$\min \left\| \sum_{l=1}^2 a_l w_l^T - w_l \right\|$$

Based on the cost-benefit analysis of the game participants, the model parameters are determined. For consumers, the parameters include the willingness-to-return coefficient, willingness-to-purchase coefficient, and recycling cost. For enterprises, the parameters include collection cost, improvement cost under negative consumer recycling, sales profit, and recycling profit. For the government, the parameters include regulatory cost, environmental performance, enterprise taxes, fines, subsidies, and reputation improvement.

The payoff matrix for farmers, enterprises, and the government under different strategy combinations in the game tree is shown in Figure 3.

The replication dynamic equations (4.3–4.5) indicate that the probability of each stakeholder choosing a specific strategy changes over time. When the replication dynamic equations of all three parties simultaneously equal zero, the evolutionary game equilibrium points can be determined. It is evident that the model has eight pure strategy equilibrium solutions: (0,0,0), (0,0,1), (0,1,0), (1,0,0), (1,1,0), (0,1,1), (1,0,1), and (1,1,1). These eight equilibrium points define the boundary of the model's solution space, i.e., $\{(x,y,z) | 0 \leq x \leq 1; 0 \leq y \leq 1; 0 \leq z \leq 1\}$. Additionally, multiple mixed-strategy equilibrium solutions can be derived through calculations. However, the solutions of the mixed-strategy game model do not necessarily imply Nash equilibrium, as the mixed-strategy model assumes that each player makes strategic choices only when aware of the strategies of other players, which is unrealistic under conditions of information asymmetry.

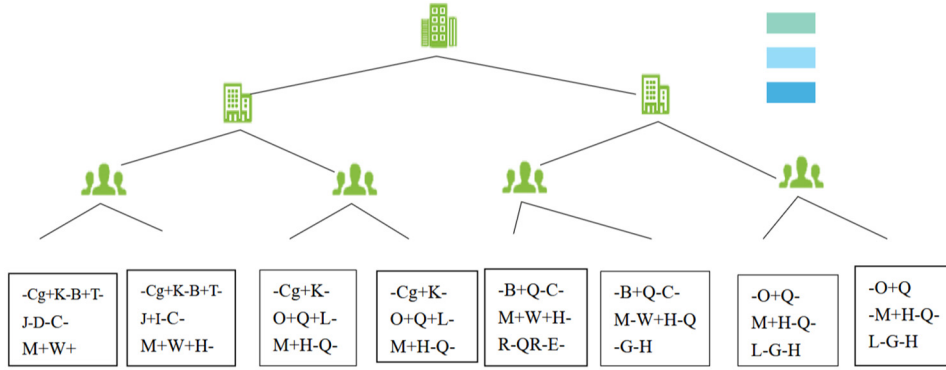


Figure 3. Payoff Matrix for Farmers, Enterprises, and Government Under Different Strategy Combinations in the Game Tree

The analysis shows that when $(x_0, y_0, z_0) = (0.5, 0.5, 0.5)$, neither $(1, 0, 0)$ nor $(1, 0, 1)$ are evolutionarily stable strategies without additional conditions. This indicates that when enterprises adopt traditional recycling methods, consumers will not actively choose to recycle. This is because, in these scenarios, consumers incur time costs for active recycling. In this case, regardless of the value of z , it does not affect consumers' strategic choices, as they are not fined for negative recycling. Therefore, it is locally unstable.

selected: the difference between the time cost of recycling for farmers ($E=8$) and the time cost of not recycling ($G=4$) reflects the additional investment required for recycling behavior. The enterprise recycling reward ($R=15$) and penalty measures ($I=6$) reflect a governance approach that combines incentives and constraints. The government subsidy ($D=12$) demonstrates the level of policy support. These parameter choices not only consider the realistic constraints of each stakeholder but also provide moderate flexibility for system evolution. The results are shown in Figure (4).

3. Simulation Experiment Analysis

3.1. Evolutionary Path Analysis

In this experiment, realistic parameter settings were

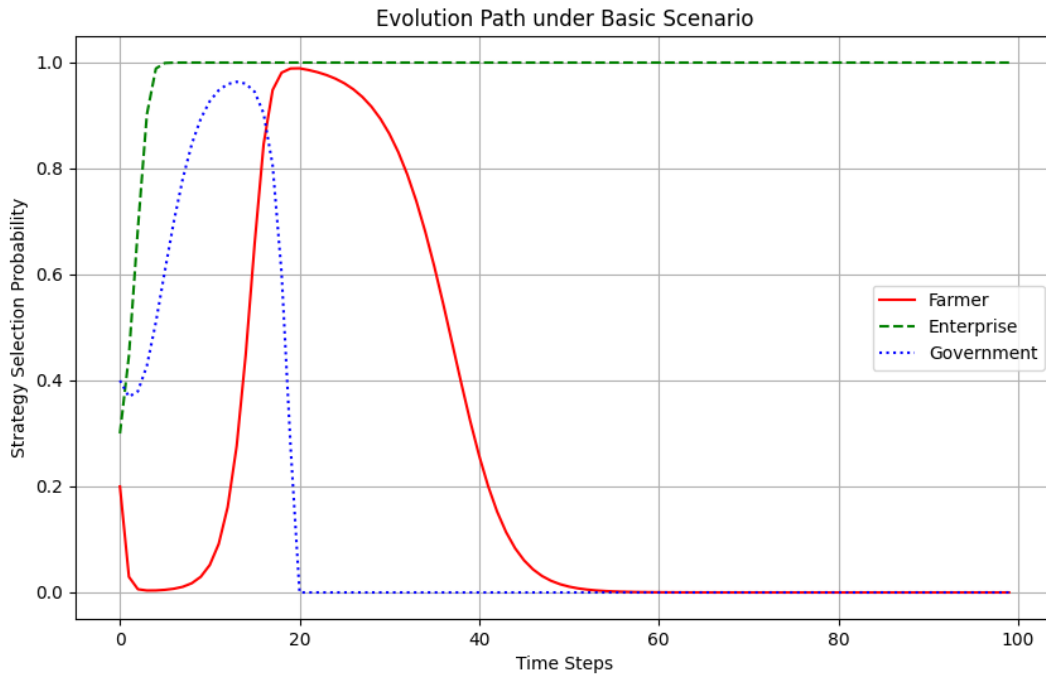


Figure 4. Simulation result diagram

From the figure, it can be observed that under the baseline parameter configuration, the strategy choices of the three stakeholders exhibit distinct stage-specific characteristics:

- Initial Stage ($t < 20$): The strategy choices of all parties fluctuate significantly, reflecting exploration and adaptation during the early policy implementation phase.
- Intermediate Stage ($20 < t < 60$): The system gradually stabilizes, indicating the achievement of a preliminary equilibrium through stakeholder interactions.
- Stable Stage ($t > 60$): The probabilities of strategy

choices converge, reflecting the long-term effects of policy implementation.

3.2. Probability Impact Analysis

By setting five different initial probability groups $\{(0.1, 0.1, 0.1), (0.3, 0.3, 0.3), (0.5, 0.5, 0.5), (0.7, 0.7, 0.7), (0.9, 0.9, 0.9)\}$, the impact of initial conditions on system evolution was investigated. The experimental results are shown in Figure (5).

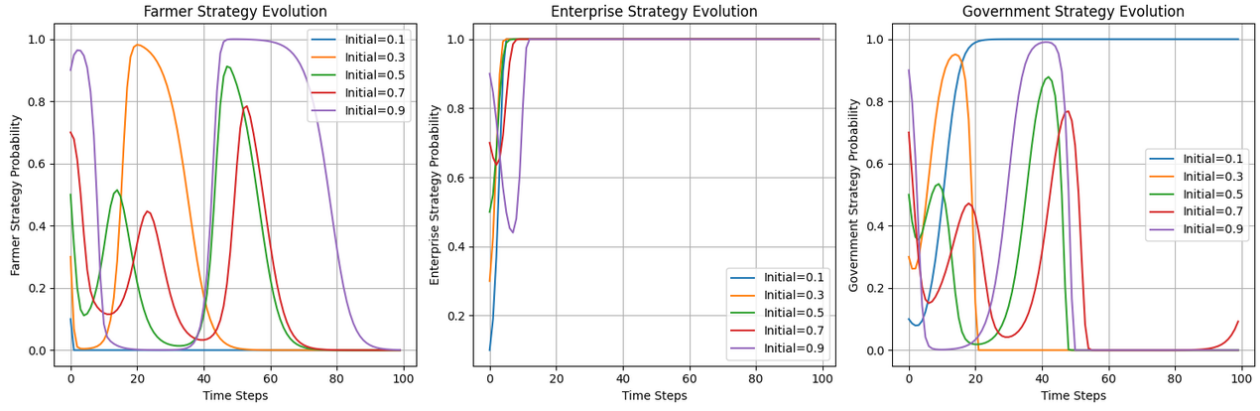


Figure 5. Data graphs under three different scenarios

From the figure, it can be seen that: Low Initial Probability Groups (0.1, 0.3): The evolutionary paths exhibit a "slow start" characteristic, requiring a longer time to reach a steady state, with relatively low final convergence values. Medium Probability Group (0.5): The evolution process is relatively smooth, with moderate convergence speed, ultimately forming an ideal equilibrium state. High Initial Probability Groups (0.7, 0.9): Significant fluctuations occur in the early stages, with fast convergence speeds, stabilizing at higher

levels.

3.3. Parameter Sensitivity Analysis

This experiment focused on the impact of three key parameters: government subsidy (D), enterprise improvement cost (P), and recycling reward (R). By setting five levels within the interval [5,25], the influence of parameter changes on strategy evolution was systematically analyzed. The experimental results are shown in Figure (6).

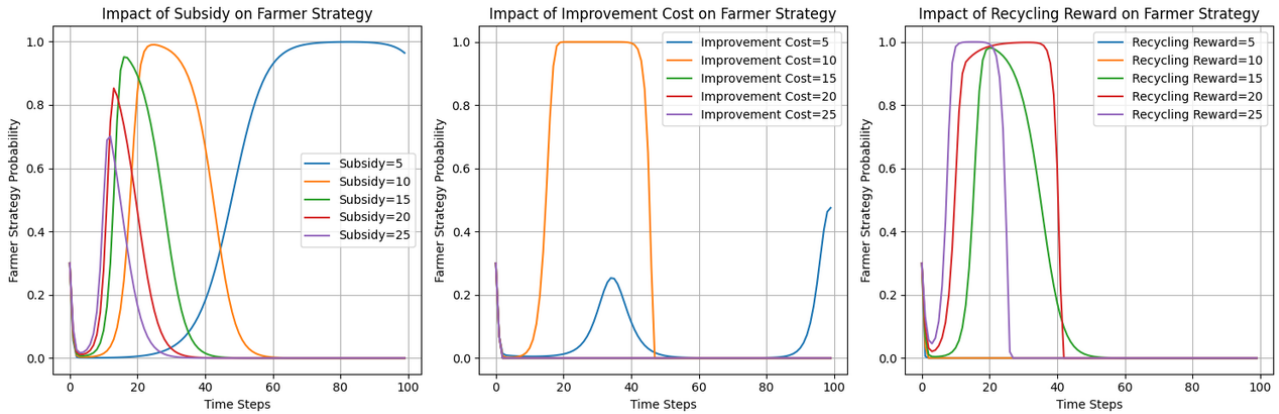


Figure 6. Data graphs under three different scenarios

From the figure, it can be observed that: 1. Impact of Government Subsidy (D): Subsidy levels are positively correlated with farmer participation, exhibiting a clear "threshold effect." Additionally, higher subsidies promote faster system convergence. 2. Impact of Improvement Cost (P): Increased costs inhibit enterprise participation and significantly affect system stability, showing a nonlinear correlation. 3. Impact of Recycling Reward (R): Higher rewards effectively stimulate participation, with an optimal reward range. Excessively high rewards may lead to system instability.

Finally, the optimized mechanism for agricultural film recycling is summarized as follows: 1. Seize the "Window Period" of Policy Implementation: Set initial parameters reasonably. 2. Build a Multi-Level Incentive System: Balance the interests of all stakeholders. 3. Adopt Gradual Policy Adjustment Strategies: Ensure stable system evolution.

4. Conclusion

This study first proposes and establishes an intelligent optimization algorithm model. Through systematic analysis and computation of multi-dimensional data, it thoroughly

explores and quantifies the key factors influencing the cost of agricultural film recycling, ultimately optimizing the parameters for the most economically feasible recycling cost coordination mechanism. Building on this foundation, the research team constructed a game theory algorithm model, systematically elucidating the theoretical framework and technical pathways for agricultural film recycling from a perspective that integrates theory and practice. By solving and validating the model, this study clarifies the interests and game relationships among stakeholders such as the government, production enterprises, and farmers in the agricultural film recycling process, ultimately proposing an optimal mechanism for multi-party interest coordination. This research provides significant theoretical foundations and practical references for subsequent policy formulation, technology promotion, and operational practices in agricultural film recycling.

References

- [1] DING L, GUO Z, XUE Y. Dump or recycle? Consumer's environmental awareness and express package disposal based on an evolutionary game model [J]. Environment, Development and Sustainability, 2023, 25(7): 6963-86.

- [2] DU B, HOU H, XU H, et al. How to solve the problem of irregular recycling of spent lead-acid batteries in China?--An analysis based on evolutionary game theory [J]. *Journal of Cleaner Production*, 2023, 421: 138514.
- [3] WAINWRIGHT J. A dynamical systems approach to Bianchi cosmologies: orthogonal models of class A [J]. *Classical and Quantum Gravity*, 1989, 6(10): 1409.
- [4] LYAPUNOV A M. The general problem of the stability of motion [J]. *International Journal of Control*, 1992, 55(3): 531-4.
- [5] WANG Z, WANG Q, CHEN B, et al. Evolutionary game analysis on behavioral strategies of multiple stakeholders in E-waste recycling industry [J]. *Resources, Conservation and Recycling*, 2020, 155: 104618.
- [6] SHAN H, YANG J. Promoting the implementation of extended producer responsibility systems in China: A behavioral game perspective [J]. *Journal of Cleaner Production*, 2020, 250: 119446.
- [7] YANG J, LONG R, CHEN H, et al. Willingness to participate in take-out packaging waste recycling: Relationship among effort level, advertising effect, subsidy and penalty [J]. *Waste Management*, 2021, 121: 141-52.
- [8] GUO Y, LUO G, HOU G. Research on the Evolution of the Express Packaging Recycling Strategy, Considering Government Subsidies and Synergy Benefits [J/OL] 2021, 18(3):10.3390/ijerph18031144
- [9] WANG Z, HUO J, DUAN Y. The impact of government incentives and penalties on willingness to recycle plastic waste: An evolutionary game theory perspective [J]. *Frontiers of Environmental Science & Engineering*, 2020, 14(2): 29.
- [10] SMITH J M, PRICE G R. The Logic of Animal Conflict [J]. *Nature*, 1973, 246(5427): 15-8.
- [11] FRIEDMAN D. On economic applications of evolutionary game theory [J]. *Journal of Evolutionary Economics*, 1998, 8(1): 15-43.
- [12] Li, X., et al. A multi-stakeholder evolutionary game model for urban solid waste management: cooperation mechanisms among government, enterprises, and residents. *Journal of Environmental Management*, 2020, 261, 109-118.
- [13] Zhang, Y., et al. Dynamic evolutionary game model for analyzing in electronic product recycling. *Resources, Conservation and Recycling*, 2020, 172, 1056-1065.
- [14] Huo, L., et al. A three-party evolutionary game model for waste paper recycling industrial chain: synergy mechanisms among government, enterprises, and organizations. *Journal of Cleaner Production*, 2022, 320, 122-133.