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Optimize the Industrial Ecological Chain of Circular Economy Management in African Enterprises

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Abstract: The development of circular economy and the construction of industrial circular economy are specific and important practical tools to achieve sustainable development, which are rapidly spreading around the world. It is reported that the industrial chain of circular economy is facing more and more practical problems. This paper aimed to study how to apply artificial intelligence to propose optimization strategies for the industrial ecological chain. This paper put forward the optimization strategy of business circular economy management industrial ecological chain. Ant colony algorithm is an intelligent optimization algorithm based on artificial intelligence. This algorithm can not only solve the problem of path optimization, but also apply to the optimization problem of industrial ecological chain. The experiments in this paper's results showed that: when the ant colony algorithm's iterations were 150, the lowest convergence time was 0.49 seconds, and the highest convergence time was 0.56 seconds, as well as the highest convergence rate was 60%; when the iterations were 150, the lowest convergence time was 0.13 seconds, and the highest convergence time was 0.18 seconds, as well as the highest convergence rate was 95%. It was observed that the enhanced ant colony algorithm had the best ability to search for the global optimum and the fastest convergence time, indicating that it could be used to optimize the strategy of locating the ecological chain.

1. Introduction

With the development of economy, the ecological environment has also been damaged to varying degrees, and many non-renewable energy sources have become increasingly scarce. Therefore, a circular economy emerges in this context. With the continuous improvement of green economy and circular economy theory, the development of circular economy and green economy industrial chain is a major opportunity for today's industrial development, which also provides a new development direction for regional strategic deployment. On the basis of summarizing the theory and practice of circular economy and green economy, scientists have conducted corresponding research on green industrial parks and regional cooperation, and the concepts of green Gross Domestic Product (GDP) and sustainable development have been continuously improved. The new concept of implementing new regional cooperation and seeking regional sustainable development based on the construction of green industrial chain in the 1960s has also attracted more and more attention of students.

According to ecological laws, the traditional linear economic model of "one-way flow of resources" is abandoned, and economic activities are organized in a circular feedback model. In order to improve the goal of resource utilization, and reduce the environmental burden, as well as obtain economic benefits and realize the coordinated development of economy, environment and resources, circular economy is rapidly spreading all over the world as a reliable way. Due to the limitations of the current technology level and the pollutants and other factors generated in the industrial circulation chain, it cannot be completely reused or recyclable, and part of it is always discharged into the ecological environment, which requires the ecological environment of the ecosystem to continuously contribute to the industrial cycle chain. Therefore, in order to supplement resources or raw materials, the stable supply of resources in the ecological environment is an important condition for the stable operation of the industrial circular economy chain. The innovation of this paper is to propose an optimization strategy for the business circular economy management industry ecological chain based on artificial intelligence algorithms. This not only proposes but also improves the ant colony algorithm with strong global optimal solution search ability.

2. Related Work

The construction of circular economy industrial chain is an important form and content of circular economy development. All countries in the world have developed industrial circular economy in different industries and sectors with large enterprise groups, eco-industrial parks or circular economy demonstration parks as carriers. Desousajabbour A B L provided a case for the integration of the increasingly popular and largely independent themes of the circular economy. He found that advanced digital manufacturing technology could release the circularity of resources in the supply chain [1]. Liu G Y believed that the Internet, through the reintegration of massive resources, inevitably optimized China's cultural and creative industry and promoted its sustainable innovation to form a new industrial chain. In other words, the ecosystem of China's cultural and creative industries was established in this way [2]. Iacovidou E found that established assessment methodologies focused on the recovery of resources from waste in the context of a circular economy, which only took into account a few important areas. For those who made decisions about policies, this biased approach frequently resulted in inaccurate information [3]. In an effort to establish consensus on the fundamental framework of the circular economy and highlight its connection to ecological innovation, Prieto-Sandoval V observed that the concept of the circular economy was becoming increasingly significant as a means of achieving sustainable development [4]. Parajuly K found that the Circular Economy (CE) was considered as the foundation of sustainable production and consumption and an alternative to today's linear economic models, but the actual potential of CE in many business areas was still not well understood [5].Scholars believe that circular economy and ecological development complement each other, and good ecological development can promote the formation of circular economy, as well as strong circular economy promotes the sustainable development of ecology.

When faced with the pressure of resources, environment and population, green industrial chain is an effective way to coordinate the development of economy and environment and an inevitable choice to promote inter-regional cooperation. DENG found that with the rapid development of national characteristic towns, some problems began to emerge, such as unreasonable spatial structure, industrial disharmony, and inconspicuous industrial clusters. In order to solve these uncoordinated problems, it was very important to rationally arrange the industrial structure and build an industrial ecological chain according to local conditions [6]. Yun Z pointed out that while positive benefits was achieved in politics, economy, culture, etc, the negative problems of the ecological environment also attracted widespread attention. Starting from the principle of ecological art, he established the concept of sustainable development, and made it develop along a healthy and benign track through self-innovation and ecological awareness [7]. Fan W found that land transfer was an important way for China's cultivated land management and intensive production, which was also the government's primary strategy to promote regional development. These transfers would not only generate social, economic and ecological benefits, but also promote regional development in a more efficient and sustainable way [8]. Fang L discovered that as ecological economics advanced, academia and business gave green supply chain management a lot of attention. He looked into a bank and a manufacturing with limited capital that financed a green supply chain. According to the analysis and numerical findings, manufacturers were eager to make green investments, but retailers fared better when asked to contribute to the upfront payment [9]. According to academics, environmentally friendly supply chains can support business growth and should draw people's attention. The detrimental effects of the ecological environment cannot be disregarded as the economy develops.

3. Ant Colony Algorithm Based on Artificial Intelligence Algorithm

The industrial cycle of circular economy is the cycle system shown in Figure 1. The application of these principles facilitates the exchange of materials and energy, including the exchange of information between raw materials, products, by-products, waste and natural enterprises or sectors [10]. The structure of the industrial circular economy chain is similar to the organic stable structure of circular cells composed of producers, consumers and distributors in the natural ecosystem, which has the following characteristics:

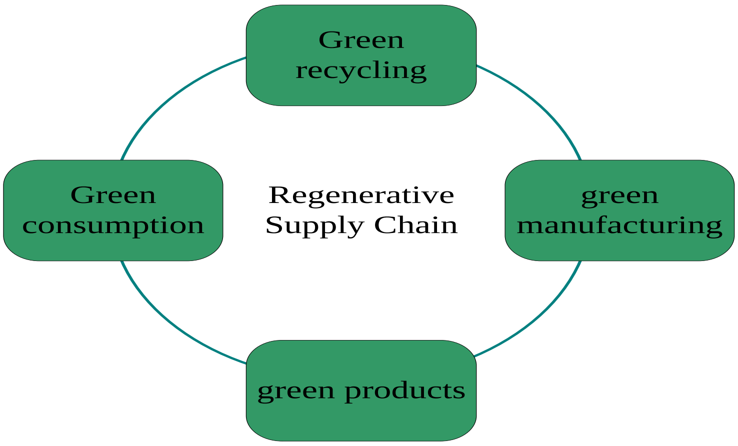

Figure 1. Framework diagram of circular economy industry chain

As shown in Figure 1: The circular economy principle is defined as the "3R" emission reduction principle, which requires the use of less raw materials and energy inputs at the end of the entry to achieve the intended purpose of production or consumption, and control of resources from the entry of the product. Once the life cycle is extended, excessive waste can be avoided. The recycling principle requires that the raw materials and finished products used in the output can be converted into usable resources and returned to the reproduction or re-consumption process, rather than non-recyclable pollutants [11].

3.1 Basic Ant Colony Algorithm

The ant colony optimization method in the artificial intelligence algorithm can be used to swiftly determine the optimization strategy of the industrial chain. The Traveling Salesman Problem (TSP) and scheduling issues have been solved by using the ant colony method, which has produced positive experimental findings [12]. The schematic diagram of the ant colony approach is given in Figure 2.

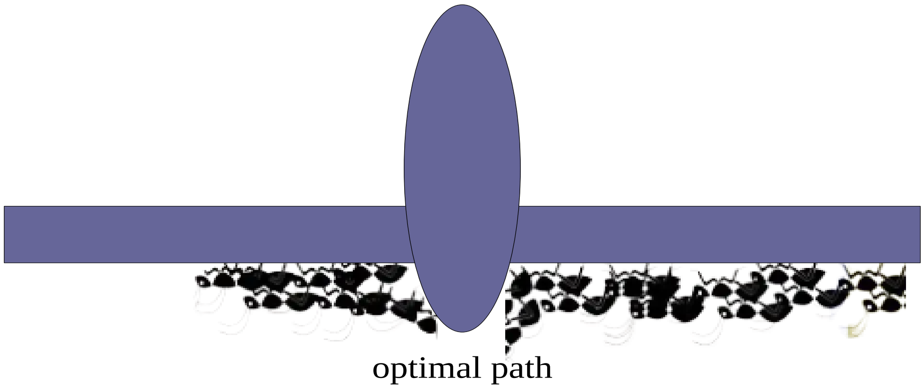

Figure 2. Schematic diagram of the ant colony algorithm

As seen in Figure 2, it can not only perform intelligent searches and global optimization, but also has the advantages of strong implantability and easy combination with other intelligent algorithms. Therefore, since the birth of ant colony algorithm, it has solved complex optimization problems in many fields [13].

It is assumed that there are m artificial ants, and each ant has the following characteristics: The ant determines the next city to pass through according to the transition probability, which is composed of the distance between the two cities [14]. When an ant has experienced a city, the city is added to the taboo list. Unless the traversal is completed, the ant is not allowed to jump to the city that has been visited.

When the ant completes the traversal, it leaves pheromone on each edge it has experienced, so that the frequently experienced pheromone is continuously strengthened. That is $\tau_{ij}(0)=C$ (C is a constant), and the transition probability of ant k (k=1,2...,m) is represented by $\rho_{ij}^{k}(t)$, as shown in Formula 1:

$$\rho_{ij}^{k}(t)=\frac{[\tau_{ij}(t)]^{\alpha}[1/d_{ij}]^{\beta}}{\sum_{s\in allowed_k}[\tau_{iu}(t)]^{\alpha}[1/d_{iu}]^{\beta}} \quad (1)$$

Among them, α and β are related parameters, and d_{iu} represents the expected degree of jumping from city i to city j, which is generally represented by $1/d_{ij}$.

If there are fewer ants on the path, the concentration of pheromone would be lower, which would cause the role of pheromone to mask the role of heuristic information when calculating the transition probability and cause the algorithm to fall into a precocious state (also known as local convergence) [15]. Therefore, the pheromone volatilization mechanism should be added to the ant colony algorithm, and this is also a simulation of the natural volatilization process of ant pheromone in nature [16]. Through the volatilization mechanism, this paper updates the residual pheromone in the ant colony algorithm, and the update rules are as follows:

$$\tau_{ij}(t+n)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij} \quad (2)$$

In the previous formula, the residual coefficient of pheromone and the value range of ρ are (0~1), and pheromone update strategies are not unique. Some scientists have proposed three ant colony algorithm models [17], and the ant week model is:

$$\Delta\tau_{ij}^{k}=\frac{Q}{L_k} \quad (3)$$

L_k represents the total length of the path traversed by ant k in this cycle. It is obvious from the previous formula that the longer the ants move, the lower the amount of pheromone released by each trajectory, and the ant dense model is:

$$\Delta\tau_{ij}^{k}=Q \quad (4)$$

The ant residue model is:

$$\Delta\tau_{ij}^{k}=\frac{Q}{d_{ij}} \quad (5)$$

In the previous formula, d_{ij} represents the residual amount of pheromone. In other words, the residual amount of pheromone would increase as the distance decreases, so ants tend to choose a path with a shorter distance [18].

Although ant colony algorithm has advantages, it is more prone to stagnation. That is, when the algorithm runs to a certain extent, all the solutions tend to be consistent, and the individual search paths are basically the same, as well as the solution space cannot be searched more widely, which is not conducive to finding better solutions. In the ant colony algorithm, ants choose their own search paths according to the pheromone left by other ants. They do not consider their own search experience, and such blind obedience leads to the premature phenomenon of ant colony algorithm [19].

3.2 Improved Ant Colony Algorithm

Through comprehensive analysis, this paper believes that when designing and solving ant colony system algorithm, how to effectively realize path selection and pheromone update (including global pheromone update and local information number) are two core issues in algorithm design [20].

The problem can be subdivided into the following two sub-problems: Determination of path nodes: In the design of ant colony system algorithm for production decision-making in hybrid systems, foraging nodes can be regarded as decision variable combination points. However, how to make the model decision variables correspond to the path nodes of the ant colony system algorithm is one of the key points to be solved; the choice of the path direction: Regarding the choice of the ant's foraging direction, that is, how to choose the next node from one node, this step directly affects the operation result and operation efficiency of the ant colony algorithm. Therefore, this problem is one of the difficulties in the design of the algorithm in this paper, and the way the ants choose the path is shown in Figure 3:

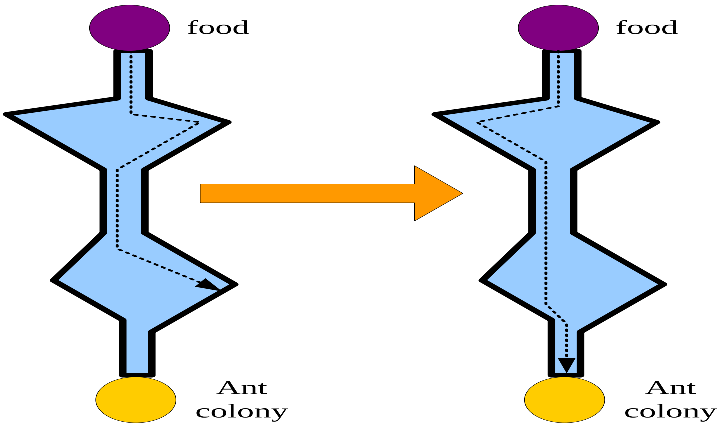

Figure 3. Schematic diagram of path selection in the ant colony system algorithm

As shown in Figure 3: For the determination of the path node, the variable combination is used to solve the t-th path node in the ant colony system algorithm. At this time, the i-th optimization scheme consists of the foraging path sequence of the i-th ant, which transforms the process of seeking optimization strategies into the process of ants seeking the shortest path.

By adopting the principle of pseudo-random proportion to achieve path selection, it can not only ensure the continuous iteration and update of the optimal solution, but also avoid falling into the local optimal solution, which is of great help to improve the solution speed and solution quality, as shown in Formula 6:

$$j = \begin{cases} \arg\max\left(\tau_{ij}(t)^{\alpha}\eta_{ij}(t)^{\beta}\right), q \le q_0 \\ J, q \succ q_0 \end{cases} \quad (6)$$

In the Formula 6, q is a random variable in the interval [0,1]; q_0 is a certain parameter value. Through the cyclic calculation of the ant colony algorithm, multiple paths would be obtained. The global pheromone update means that after obtaining multiple paths, only the pheromone on the optimal path is updated, and the update is performed according to Formula 7:

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}^{bs} \quad (7)$$

Among them, τ is the optimal solution obtained so far, τ_{ij}^{bs} is the number of pheromones released in the last algorithm cycle, and $\tau_{ij}(t)$ is the total cost value of the obtained optimal path.

The size of the ant colony is set to m, and the algorithm adds a down-regulation coefficient of q_1 when the pheromone is initialized, with $q_1 \in [0,1]$. The initial pheromone value in CS_1 is set to q_1 times that of CS_1, so that the initial pheromone concentration in CS_1 is significantly higher than that of other ant colonies, which is beneficial for ants to choose better pheromone at the beginning, as shown in Formula 8:

$$\tau_{ij}(0) = \begin{cases} \tau_0, j \in CS_1 \\ q_1 * \tau_0 \end{cases} \quad (8)$$

During the searching process, the ants record the node capability vector and calculate the alliance vector value. When the τ_{ij} requirement is reached, the searching stops. With the passage of time, the intimacy between ants gradually decreases. ρ represents the degree of intimacy reduction in each time period, and the intimacy adjustment rule is Formula 9:

$$\tau_{ij} = (1-\rho)\cdot\tau_{ij}(t) + \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \quad (9)$$

τ_{ij}^{k} represents the increase of the intimacy between ant i and ant j by the k-th ant in this cycle, as shown in Formula 10:

$$\Delta\tau_{ij}^{k} = \frac{V(C_k)}{\sum_{k=1}^{m} V(C_k)} \quad (10)$$

Among them, α, β and ρ determine the optimal combination according to the experimental value, and the calculation stop until the fixed evolution algebra is reached or the evolution trend is not obvious.

The optimal path probability expression adopts Formula 11:

$$j = \arg\max\left\{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}\right\}, q \le q^{0} \quad (11)$$

With q^{0}, the good path can be selected. When $q \le q^{0}$, the optimal way can be selected.

Ant colony algorithm is a mathematical model established gradually according to the behavior characteristics of ants, and then the process of ant colony algorithm is proposed. Therefore, the local update pheromone strategy proposed in this paper is also proposed according to the action rules of ants and the distribution characteristics of pheromone, and the local update pheromone formula is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\cdot\frac{Q_1}{d_{ij}} \quad (12)$$

The update of the global pheromone is based on the local update, which has an effect of enhancing the concentration of the pheromone on the optimal path and also has a stronger guiding effect on the next generation of ants. The next generation of ants seeks a path in the direction of the shortest path, which has a good impact on the pathfinding of the next generation of ants, and the global update pheromone expression is Formula 13:

$$\tau_{ij}(t+1) = (1-\rho)\times\tau_{ij}(t) + \Delta\tau_{ij} \quad (13)$$

In order to improve the global search ability of the algorithm and enable the algorithm to find the optimal solution, the number of pheromone on the selected path should be reduced accordingly, that is, the number of pheromone in the ant colony should be reduced accordingly, as shown in Formula 14:

$$\tau_{ij}(t+1) = \mu(t)(1-\rho)\times\tau_{ij}(t) + \Delta\tau_{ij} \quad (14)$$

The improved ant colony algorithm adopts the strategy of combining local and global pheromone update, and further improves the information residual factor of global pheromone update, so as to ensure the optimal solution and speed up the convergence.

3.3 Cultural Algorithm Based on Multi-layer Belief Space

Culture algorithm is a new global optimization algorithm that can be used to solve complex optimization problems. The culture algorithm is a two-layer evolutionary algorithm based on culture, which includes two levels of evolution: One is the evolution of the population space, which is iteratively solved through performance evaluation and cultural guidance; the other layer is the evolution of belief space, which preserves the excellent experience of individual evolution in population space. The two layers of evolution simulate biological evolution from the macro and micro levels respectively, and the two levels depend on and influence each other, thus realizing the guiding effect of culture on evolution and improving the speed of evolution, and the basic framework of the culture algorithm is shown in Figure 4:

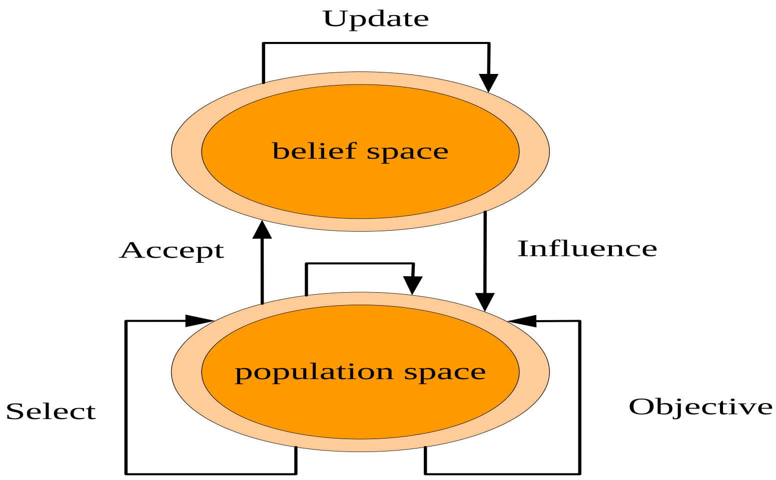

Figure 4. The basic framework of the culture algorithm

As shown in Figure 4: The cultural algorithm surpasses the limitations of traditional evolutionary algorithms. Its two-layer evolutionary model can more accurately reflect the real evolution process of the population, and it can achieve better evolutionary effects than traditional evolutionary algorithms on some problems.

The basic cultural algorithm is not enough to simulate the complex process of enterprise evolution, so this paper proposes to establish a multi-layer belief space in the cultural algorithm. The advantage of this method is that the excellent experience generated in the process of population evolution and individual evolution can be saved separately, so as to achieve effective simulation of individual and environment co-evolution.

For a single enterprise, the enterprise evolution problem is that for the product set C, the enterprise seeks the optimal capability set and output set according to its own production capacity, so as to make the enterprise profit as large as possible. Enterprise income refers to the sum of the income of all products produced by the enterprise, and the income of a certain production cycle 11 is as Formula 15:

$$V^t(A_i) = \sum_{j=1}^{m} V_{ij}^t \quad (15)$$

Sets P_{ij} and F_{ij} can form a constrained optimization problem, as shown in Formula 16:

$$\max z = \sum_{j=0}^{m} s_j^i \cdot (P_{ij} - F_{ij}) \quad (16)$$

In the process of enterprise evolution, sets P_{ij} and F_{ij} also evolve correspondingly, and the enterprise evolution process can be embodied by the evolution process of sets P_{ij} and F_{ij}. The process through which every member of the population finds a better solution to the constrained optimization problem is known as the evolution of the entire population.

Considering the population space's evolutionary properties, this paper divides the belief space into three layers, and the expression of individual fitness is shown in Formula 17:

$$f_i = \frac{V^t(A_i)}{\sum_{b=1}^{r} k_i^b}, 1 \le i \le n \quad (17)$$

After the belief space forms knowledge and experience, it modifies the behavior rules of individuals in the group space through the influence function, and the process is as follows:

The excellent knowledge in the belief space is used to exert an influence on each individual of the current population, so as to generate the next generation population, that is, the elements in the individual are randomly combined to obtain a new individual s, as shown in Formula 18:

$$s = s + \Delta t, if V(c_j) \phi\, V_{aver} \cdot rand = 1 \quad (18)$$

When an enterprise evolves to a certain extent, capability becomes the bottleneck restricting the growth of enterprise benefit. At this time, the situation of uneven utilization of enterprise capacity is easy to occur, resulting in waste of capital and unreasonable product structure. Therefore, this paper needs to make dynamic adjustments to enterprise capabilities to balance the utilization of various capabilities, so that enterprises can achieve greater benefits. The dynamic adjustment method of enterprise capability combined with learning capability is as follows:

$$k_i^{'p} = k_i^p + \frac{1}{1+e^{-\frac{1+\alpha}{1-\alpha}}} \cdot \beta \cdot k_i^q \quad (19)$$

k_i^p and k_i^q are a pair of mutually transformable abilities; $k_i^{'p}$ represents the new ability generated; α is the learning ability factor; β is the gain coefficient.

4. Experiment of Intelligent Optimization Algorithm Based on Artificial Intelligence

4.1 Comparison of Basic Cultural Algorithms and Multi-Belief Space Cultural Algorithms

This paper chooses Matlab software, whose functions include matrix operation, algorithm implementation, user interface generation, compatibility with other programming languages, etc. It is usually used in communication and signal processing, image processing, financial modeling analysis, signal detection and other fields. The data set selects Ylysses22.tsp and Ell51.tsp examples to conduct simulation experiments on the improved ant colony algorithm in this paper.

A simulation comparison experiment between the basic culture algorithm (which uses only one layer of belief space) and the multi-layer belief space culture algorithm is constructed. The experiment uses the same data and enterprise model, and Figure 5 compares the evolution using the two methods.

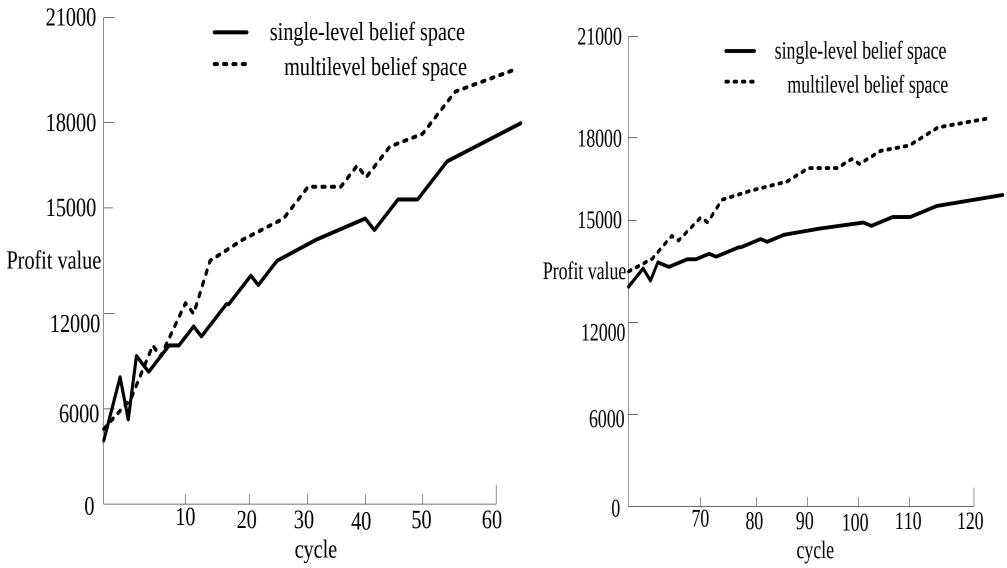

Figure 5. Comparison of income values during the evolution of the two algorithms

As shown in Figure 5: The multi-layer belief space culture algorithm greatly speeds up the evolution process of the individual. When the optimal solution is searched, the production cycle is less. Although the multi-layer belief space culture algorithm has a slow increase in revenue in the early stage of program operation, it can effectively jump out of the local optimal solution. Therefore, the multi-layer belief space culture algorithm can effectively guide individual evolution.

In order to compare the impact of the two algorithms on the evolution of the population, this paper compares the four indicators of average income, average capacity utilization, optimal income, and optimal capacity utilization. The average benefit and average capacity utilization rate refer to the average value of the optimal benefits of each enterprise in the environment and optimal capacity utilization rate. They are the optimal benefit of the optimal enterprise in the environment and the optimal value of the capacity utilization obtained by the optimal enterprise, respectively.

Table 1. Comparison of the benefits and capacity utilization of the two algorithms

index	Multibelief Spatial Culture Algorithm	Basic Culture Algorithm
average return	26545	25389
average capacity utilization	78.88%	70.21%
optimal return	30851	29620
optimal capacity utilization	89.02%	75.66%

According to Table 1, the entire people in the environment can achieve higher average incomes and capacity utilization by simulating the evolution of businesses using the algorithm presented in this work. This is because the algorithm in this paper's multi-layer belief space structure can more accurately replicate the interaction between businesses. Businesses can improve their resource allocation strategies by using belief space to learn from the outstanding experience of other businesses in the environment. Learning enables the realization of the relationship between the enterprise, the environment, and other firms in the environment.

4.2 Comparison of Optimization Performance of Ant Colony Algorithm before and after Improvement

It typically plays a significant role since the ant colony algorithm's major parameter settings have a significant impact on the algorithm's performance. Effective parameter adjustments can decrease the algorithm's calculation time while also increase the global algorithm's convergence speed and acquisition capability.

This study examines the evolution of businesses in $\alpha = 0.4$ (strong learning) and $\alpha = 0.2$ (weak learning) for the best businesses in the environment in order to compare the various outcomes of the enterprise ecological chain. In Figure 6, the comparison findings are displayed.

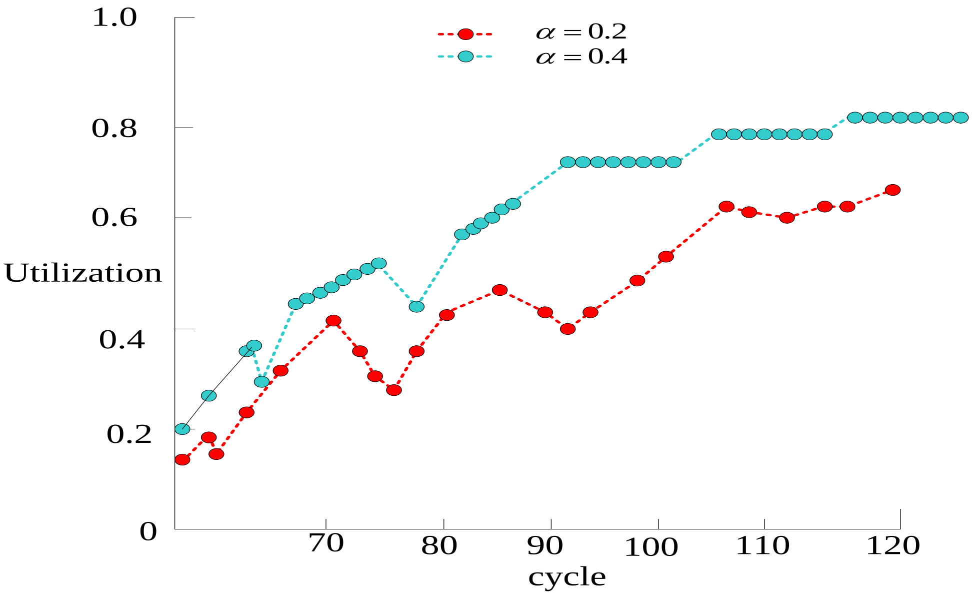

Figure 6. α *Capacity utilization at different values*

As shown in Figure 6: When $\alpha = 0.4$ and the industrial ecological chain is strong, the utilization rate of circular economy continues to grow and fluctuates less; when $\alpha = 0.2$ and the industrial ecological chain is weak, the change in the utilization rate is a more random and fluctuating process. The above analysis shows that the utilization rate of enterprises has a strong purpose when the ecological chain is strong. When the ecological chain is weak, the sustainable development of enterprises is random, unstable, and sometimes even reverses.

Some examples in the data set are tested, and the minimum number of iterations before and after the improvement of the algorithm is compared, as well as the test results are shown in Table 2 and 3:

Table 2. Performance comparison of ant colony algorithm before improvement

number of experiments	number of iterations	convergence time	convergence speed
1	150	0.56s	57%
2	150	0.52s	55%
3	150	0.55s	56%
4	150	0.49s	60%
5	150	0.50s	59%

Table 3. Performance comparison of improved ant colony algorithm

number of experiments	number of iterations	convergence time	convergence speed
1	150	0.13s	95%
2	150	0.16s	92%
3	150	0.15s	93%
4	150	0.18s	87%
5	150	0.17s	89%

As shown in Table 2 and 3: The reason why the exact solution method is rarely used to solve the data set is because the exact solution method takes almost the same time as the heuristic algorithm when the amount of data is small, and sometimes it may take less time. However, when the amount of data increases exponentially, the time-consuming of traditional Ant Colony Optimization (ACO) would increase exponentially. From the above test results, it can be found that the convergence time of the improved algorithm is reduced, and the performance of the algorithm has been well improved.

The convergence effect of the ACO method before and after the improvement is shown in Figure 7:

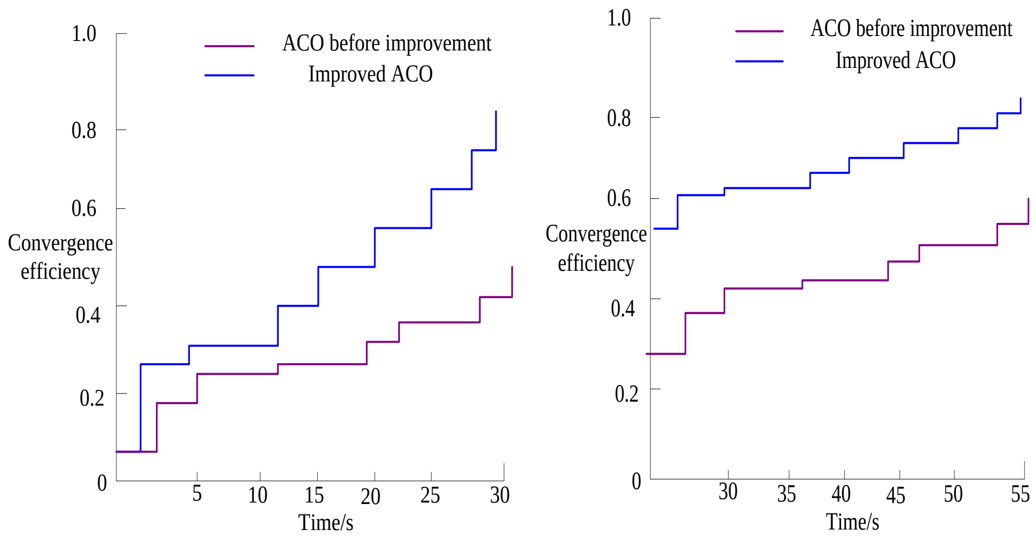

Figure 7. Comparison of algorithm convergence effect before and after improvement

As shown in Figure 7: In the final typical environment, the improved algorithm can generate multiple search spaces efficiently and in time for convergence. In terms of computational feasibility, when the improved algorithm completes the first convergence task, the search time becomes shorter and the amount of computation becomes smaller and smaller.

The analysis of the search ability of the algorithm from the beginning of the operation to the final result is shown in Figure 8:

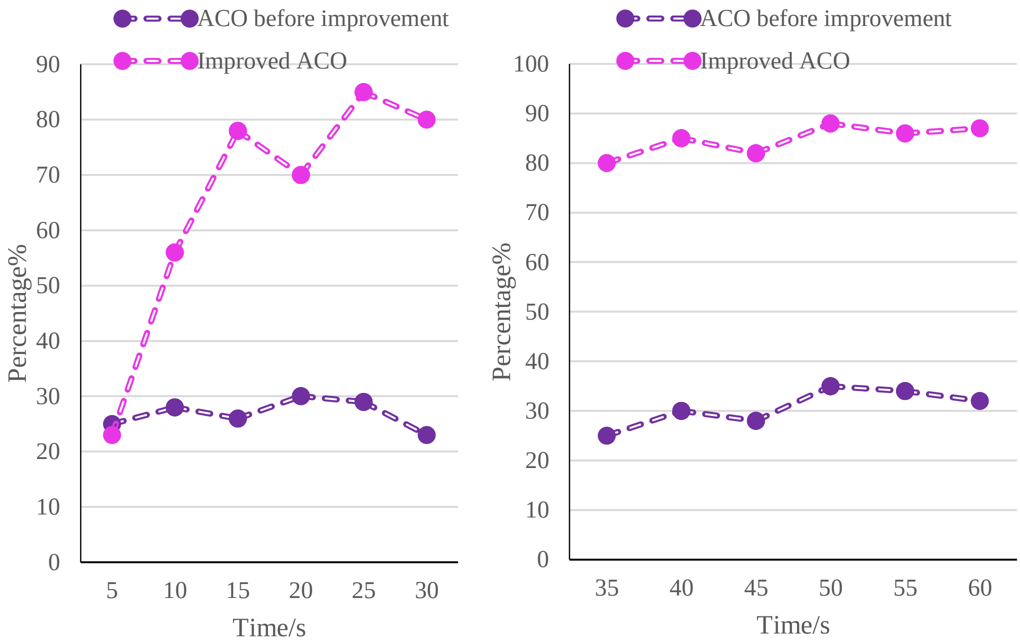

Figure 8. Comparison of search capabilities of the ACO algorithm before and after improvement

(a). The search ability of the two algorithms in a short time

(b). The search ability of the two algorithms for a long time

According to Figure 8: As observed in Figure 8(a), the enhanced ant colony algorithm initially has similar optimal solution search capabilities to the algorithm prior to the modification. However, over time, the improved ant colony algorithm steadily closes the gap with the prior algorithm. Figure 8(b) illustrates how the enhanced ant colony algorithm becomes extremely stable and has a search ability of 80% when the time exceeds 35 seconds. Compared to the method's pre-improvement, the range is from 20% to 35%. It is clear that the enhanced ant colony algorithm consumes considerably less time and has more advantages in search capability.

4.3 Optimization Strategy of Industrial Ecological Chain

(1) Improve people's awareness of ecological environment

The education and popularization of ecological environmental protection is strengthened, and the ecological environment awareness of various groups of people is improved, which can effectively improve the stability of the circular economy industrial chain and improve the ecological environment awareness of producers. Producers refer to the cadres and ordinary employees of various links in the circular economy industrial chain, such as cadres and ordinary employees of pulping enterprises, and paper-making enterprises, as well as waste paper recycling enterprises. The improvement of producers' awareness of ecological environment can prompt them to consciously choose advanced technology and clean renewable resources. For example, waste paper is used as a raw material to produce low-toxicity, low-consumption, low-pollution, reusable and recyclable paper products. The monitoring of the entire production process is strengthened and the undesirable phenomena in the production process are reduced or even eliminated to realize the recycling and comprehensive utilization of resources and wastes.

(2) Establish an ecological industry system

As a way of sustainable development, industrial greening is a new industrial model in which people realize a virtuous circle based on economic development, resource and environmental construction, which is an advanced form of industrial development. Generally speaking, the ideas for ecological transformation of industries and construction of ecological industries are as follows: First, technologies should be developed and selected and enterprises should be created in accordance with ecological principles. According to the principle of ecological operation, the production and operation methods of enterprises as well as the quality of products are standardized; the second is to establish an ecological connection of material flow between industries and within industries according to the overall development strategy and long-term goals of the national economy; through the ecological chain relationship of the industry, the ecological balance relationship and operation mechanism between regions are established; thirdly, according to ecological principles and sustainable standards, waste recovery, treatment and recycling systems are introduced to enable the operation of industrial systems to meet production and consumption. At the same time, the damage to human living conditions and the natural environment is minimized.

(3) Adjust and optimize the internal structure of the industry

The adjustment of agricultural internal structure is to optimize the allocation of agricultural product structure, technical structure and factor input structure, so as to achieve a win-win situation of ecological and economic benefits. This means that it is necessary to reconstruct and integrate agro-ecosystems and agro-economic systems according to the ecological principles of all aspects of agricultural areas to maximize the overall environmental and economic benefits. The agricultural economic system requires the coordinated development of agriculture with its resources, environment and related departments. The focus is on taking measures under local and temporal conditions to rationally distribute agricultural productivity, and adapt to the best environment, as well as achieve high quality, high yield and high efficiency. It can rationally develop and reproduce agricultural natural resources, and focus on improving solar energy utilization and biomass energy conversion efficiency, as well as optimize the distribution between organisms and the environment. This has an appropriate agricultural green economic structure, and realizes a positive environmental and economic cycle, as well as improves the ability to cope with natural disasters.

5. Conclusions

Since the reform and opening up, the rapid development of China's economy has also brought a series of environmental and environmental problems. The frequent occurrence of natural disasters, environmental pollution and low resource utilization efficiency not only destroys the original goal of healthy and rapid development of the national economy, but also endangers daily life and human health. Eco-industry is a new direction of industrial development, which helps to achieve low emission and low pollution and is also the main way of circular economy in the future. As a key element of the green industry, the operation mechanism and structure of the green industry chain affect the stability and sustainability of the green industry system. In order to propose the corresponding optimization strategy, this paper proposed and improved the ant colony optimization algorithm in the artificial intelligence algorithm. The improved algorithm not only converged faster, but also had stronger search ability, which was very important in the setting of parameters in the ant colony algorithm. However, due to the limited experimental conditions, the selection of parameters is not further explained in the experiment, which needs to be improved in future work.

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If any, should be placed before the references section without numbering.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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