Research Article

Prediction of Evolution and Development Trend in Sports Industry Cluster Based on Particle Swarm Optimization

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Sports industry cluster refers to the economic phenomenon that sports related enterprises gather in a large number in a specific area. For the sports enterprises in the cluster, they can obtain huge competitive advantages through enterprise agglomeration, thus obtaining better development and rich economic benefits. The optimization of particle swarm optimization is interlinked with the agglomeration of industrial clusters. Therefore, in view of the limitation of the standard particle swarm optimization (PSO) algorithm, an improved particle swarm optimization algorithm-diaphragm particle swarm optimization (D-PSO) was proposed and used to simulate the formation of sports industry clusters. D-PSO introduces the cell membrane processing mechanism of the biological system into the PSO algorithm, which improves the ability of the PSO algorithm to get rid of local extremum points. The competitiveness value of the sports industry cluster is the value of the objective function solved by the D-PSO algorithm. The geographical coordinates of the industrial cluster were the locations in the particle search space of the D-PSO algorithm. The D-PSO algorithm is used to simulate the aggregation process of enterprises in the cluster. Compared with the standard PSO, the D-PSO algorithm has better convergence performance and optimal rate. The results of case analysis show that the proposed method can effectively predict the development trend of sports industrial clusters.

1. Introduction

Industrial cluster is the mainstream trend of modern industrial development and the main driving force of industrial upgrading. Industrial clusters play an important role in promoting regional industrial development and enhancing regional competitiveness. By reducing transaction costs and sharing facilities, industrial clusters can significantly reduce cost advantages [1–5]. At the same time, knowledge spillovers and diffusion among enterprises in industrial clusters can provide a source for industrial upgrading. Industrial clusters can promote the expansion of the scale of industrial fields and the continuous and rapid development of industries. Industrial cluster is an economic phenomenon based on self-organization structure. Self-organization structure is characterized by self-adaptation and self-organization, which coincides with industrial clusters. Similarly, if the cluster is regarded as a system composed of

many enterprises and institutions, it is also a self-organizing system [6–8]. The formation of industrial clusters is also evolving through the open dissipative structure.

Sports industry cluster is the new highlight and main melody of today's sports industry development, and it is also a distinctive organizational form in social and economic development, which plays an important role in promoting regional economic progress and promoting local industrial competitiveness [9–11]. Sports industrial cluster is the subordinate concept of industrial cluster. Although the research on sports industrial cluster at home and abroad has been gradually enriched in recent years, there is no unified view on the definition of this concept so far.

In recent years, sports industry cluster has become a hot field of academic research; many researchers will be full of research enthusiasm into it and has made many scientific research results. However, there are still the following deficiencies in the current research on sports industrial cluster

[12–16]: (1) the research on the generation process and evolution law of this economic phenomenon, sports industrial cluster, is still in the stage of qualitative discussion, and the research depth is not enough; (2) the current research mainly aims at the existing industrial clusters, carries on the case analysis, carries on the conceptual elaboration to be quite many, and rarely simulates the industrial cluster formation process through the computer.

Particle swarm optimization is interlinked with the agglomeration of sports industry clusters. The formation of sports cluster is actually a self-organizing process. The particle swarm optimization algorithm is a self-organizing algorithm [17–19], and its optimization process is also self-organizing. If the enterprises in the cluster are regarded as the particles in the particle swarm optimization algorithm and the location of the cluster is the location where the cluster has the greatest competitiveness and it is regarded as the location of the optimal solution in the particle swarm optimization algorithm [20], then the aggregation process of industrial clusters can be regarded as the optimization process of particle swarm optimization. It can be seen that the optimization of particle swarm and the agglomeration of sports industry cluster are interlinked.

Therefore, this paper makes a detailed analysis of industrial clusters based on self-organization and PSO algorithm. An improved PSO algorithm-diaphragm particle swarm optimization (D-PSO) is proposed to accurately solve the evolution and formation mechanism of industrial clusters. Studying industrial clusters from the perspective of self-organization provides a new analytical thinking for academic research of industrial clusters.

2. Analysis of Self-Organization Characteristics of Sports Industrial Clusters

2.1. Formation Mechanism of Sports Industry Cluster. Industrial cluster is an important carrier of regional economic development. The emergence of industrial cluster can effectively enhance the competitiveness of regional economy and greatly promote the development of regional economy. Therefore, the evolution process and formation law of industrial clusters are topics worthy of study.

At present, there are two main theories about industrial clusters [17, 18]: one is Marshall's industrial zone theory and the other is Porter's cluster theory. The concept of industrial cluster can be defined in broad sense and narrow sense. He et al. [19] on the basis of Porter's research results on industrial clusters, combined with the characteristics of sports industry, defined sports industrial clusters as a group of geographically adjacent and interrelated enterprises and institutions, which is a broad concept of industrial clusters. Tao et al. [20] mainly studied the main feature of industrial clusters-spatial agglomeration from the perspective of economics and geography. Wei [21] pointed out the important role of innovation network in cluster development. Coordination among enterprises in the network will effectively enhance the overall competitive advantage. The

development of network innovation will be an important driving force for the future growth of industrial clusters.

Researchers have analyzed and discussed the formation mechanism of industrial clusters from different perspectives, and their representative views mainly include four kinds: factor theory, model theory, dynamic theory, and system theory. The formation mechanism of industrial clusters in "Factor Theory" is shown in Figure 1.

The view of industrial cluster formation mechanism of "model theory" is a further extension of "factor theory" [22]. This view not only lists the essential conditions for the formation of industrial mechanism but also logically analyzes in detail how different elements interact to form clusters. However, scholars who hold this view mostly analyze how different elements work from a static point of view. The formation and development of industrial clusters is a dynamic change process, and it is incomplete to analyze the formation mechanism of industrial clusters from a static point of view. "Dynamic theory" is a new viewpoint formed with the rapid development of industrial clusters in recent years, and it is the most advanced theory to analyze the formation mechanism of industrial clusters at present. This view regards the formation of industrial clusters as a dynamic change process and analyzes the formation mechanism of each stage from different stages of industrial clusters formation. The viewpoint of industrial cluster formation mechanism of "dynamic theory" accords with the basic concept of particle swarm.

2.2. Self-Organizing Structure Analysis. Since 1960s, people began to study the theory of self-organization. Self-organization theory plays an important role in the research of complexity science. From the perspective of system science, self-organization can be understood as an orderly system structure in the system environment, in which internal members are orderly without unified leadership and command [23, 24]. The self-organizing system is not formed by external forces. During its birth, internal members interact with each other, which is a spontaneous behavior. On the contrary, in the process of organization formation, the organization formed by external driving force is generally called other organization.

Self-organization structure is characterized by self-adaptation and self-organization, which coincides with industrial clusters. Actually, industrial cluster is a self-organizing system. The formation of industrial clusters is also evolving through the open dissipative structure. The whole process of industrial cluster from the agglomeration of small-scale enterprises to its development and growth to its decline is accompanied by the influence of "fluctuation" factors. In industrial clusters, the emergence of new orderly structure is also completed under the action of fluctuation, which is the expression of catastrophe theory in clusters. Thus, industrial clusters are self-organizing structures, and their evolution process is also self-organizing.

FIGURE 1: The formation mechanism of general industrial clusters.

3. Diaphragm Particle Swarm Optimization (D-PSO) Algorithm

3.1. Principle of PSO Algorithm. In the PSO algorithm, the potential solution of each optimization problem corresponds to the position of a bird in the search space [25–28], which we call “Particle.” Each particle will move in the solution space, and the direction and distance of their flight will be determined by a velocity. There is also a fitness value determined by the optimized function. Then, the particles follow the current optimal particles and search in the solution space.

Suppose that in a D -dimensional target search space, there are N particles representing the potential solutions of the optimization problem to form a group. The position of the particle i is X_i , and the “flying” speed is V_i . The fitness value of X_i can be calculated by substituting it into the objective function, and the advantages and disadvantages can be measured according to its fitness value. The i -th particle determines the next movement through the individual extreme value $pbest$ and the global extreme value $gbest$. The particle updates its own speed and new position according to the following formula:

$$\begin{aligned} v_{id}^{k+1} &= v_{id}^k + c_1 \text{rand}_1^k (pbest_{id}^k - x_{id}^k) + c_2 \text{rand}_2^k (gbest_d^k - x_{id}^k), \\ x_{id}^{k+1} &= x_{id}^k + v_{id}^{k+1}, \end{aligned} \quad (1)$$

where v_{id}^k is the velocity of the D dimension of particle i in the k -th iteration, c_1 and c_2 are learning factors (nonnegative constants), $\text{rand}_{1,2}$ is a random number between (0,1), and x_{id}^k is the position of the D dimension of particle i in the k -th iteration.

3.2. D-PSO Algorithm Design. Cell diaphragm principle [29] is a bionic technology that simulates the intelligent behavior of the biological cell system, and it is a heuristic random search algorithm that combines deterministic and random selection. The diaphragm algorithm is inspired by somatic cell theory and network theory and realizes the self-regulation function similar to biological cells and the function of generating different diaphragms. The diaphragm particle

swarm optimization (D-PSO) model is formed by introducing cell membrane processing mechanism (diversity, self-regulation, diaphragm memory, and so on) into the PSO algorithm. This optimization model combines the advantages of the PSO algorithm and diaphragm algorithm, thus avoiding the disadvantage that the PSO algorithm is easy to fall into local extremum and improving the convergence speed and accuracy of the later evolutionary algorithm. The diversity of septum particles is ensured while keeping individuals with high fitness, thus avoiding the premature phenomenon.

In the process of updating the particle population, the strategy of maintaining diversity based on the concentration mechanism is adopted, which makes the particles (diaphragms) of each fitness level maintain a certain concentration in the new generation particle population. The concentration of the i -th particle (diaphragm) is defined as follows:

$$D(x_i) = \frac{1}{\sum_{j=1}^{N+M} f(x_i) - f(x_j)}, \quad i = 1, 2, \dots, N + M. \quad (2)$$

The probability selection method based on particle concentration is as follows [30]:

$$\begin{aligned} P(x_i) &= \frac{1/D(x_i)}{\sum_{i=1}^{N+M} (1/D(x_i))}, \\ &= \frac{\sum_{j=1}^{N+M} f(x_i) - f(x_j)}{\sum_{i=1}^{N+M} \sum_{j=1}^{N+M} f(x_i) - f(x_j)}, \quad i = 1, 2, \dots, N + M, \end{aligned} \quad (3)$$

where x represents the i -th diaphragm (particle) and $f(x_i)$ represents the fitness value of the i -th diaphragm (particle). It can be seen that the fewer the diaphragms similar to diaphragm i , the greater the probability that diaphragm i will be selected. On the contrary, the more the diaphragms similar to diaphragms, the smaller the probability of diaphragm i being selected. This makes individuals with low fitness also get the opportunity of evolution. Therefore, in theory, the probability selection formula based on antibody concentration can ensure the diversity of diaphragm.

The flowchart of D-PSO is shown in Figure 2.

FIGURE 2: D-PSO algorithm flowchart.

4. Industrial Cluster Evolution Method Based on D-PSO

4.1. Similarity between Industrial Cluster Evolution Mechanism and PSO Algorithm. Through the above discussion, we know that the formation of industrial clusters is actually a self-organization process. However, the PSO algorithm is self-organizing, and its optimization process is also self-organizing. If the enterprises in the cluster are regarded as the particles in the PSO algorithm, the location of the cluster is the most competitive position of the cluster. Considering it as the location of the optimal solution in the PSO algorithm, the clustering process of industrial clusters can be regarded as the optimization process of the particle swarm optimization. It can be seen that the optimization of particle swarm is interlinked with the agglomeration of industrial clusters.

For particle swarm, in the evolution stage, particle swarm performs organized evolution under the domination of “self-consciousness” and “social consciousness” according to certain rules, from an unstable nonlinear system to a stable state mutation. For industrial clusters, enterprises spontaneously move closer to the cluster group under the impetus of self-interest and various external forces.

For particle swarm, particle swarm can find the optimal value under the guidance of specific rules through a lot of iterative learning. For industrial clusters, in the process of evolution, the same industry within the cluster through continuous cooperation and competition to eliminate the lack of competitive enterprises retains the competitive

enterprises. Economies of scale of clusters are reflected. And finally, the cluster achieves a dynamic and stable state.

Therefore, in order to use the PSO algorithm to simulate the formation of industrial clusters, we use particle swarm optimization to solve the problem. The competitiveness value of the industrial cluster is the value of the objective function solved by the PSO algorithm. The geographical coordinates of the industrial cluster are the position in the particle search space in the PSO algorithm. There must be “cooperation” and “competition” between enterprises within the cluster, which can be achieved through the “self-cognition” part and “society” part of the PSO algorithm. Finally, taking the sports industrial cluster as an example, we use the PSO algorithm to simulate the aggregation process of enterprises in the cluster and thus predict the development of the industrial cluster.

4.2. Industrial Cluster Evolution Model Based on D-PSO Algorithm. In order to simulate the formation of industrial clusters with the particle swarm optimization algorithm, we cluster industrial clusters into particles. The competitiveness of industrial clusters is the value of the objective function solved in the particle swarm optimization algorithm. The geographical coordinates of industrial clusters are the positions in particle search space in the D-PSO algorithm. There must be “cooperation” and “competition” among enterprises in the cluster, which can be realized by the “self-awareness” part and “society” part of the D-PSO algorithm.

To sum up, we have established the evolution model of industrial clusters based on particle swarm optimization. The basic speed and location updating formulas in the model are as follows, in which each variable endows the industrial clusters with characteristics. The iterative process is carried out according to the proposed D-PSO algorithm. The following is the update expression:

$$\begin{aligned} v_{id}^{t+1} &= \omega v_{id}^t + c_1 r_1 (P_{id}^t - X_{id}^t) + c_2 r_2 (P_{gd}^t - X_{id}^t), \\ X_{id}^{t+1} &= X_{id}^t + v_{id}^{t+1}. \end{aligned} \quad (4)$$

In this paper, we give new meanings to the quantities in formula (4):

- (1) ω represents the promotion role of the government in the process of cluster evolution, such as the guidance of relevant policies
- (2) X represents the geographical coordinate position of the cluster, here is the position on the coordinate axis

- (3) c_1 and c_2 , respectively, represent the competition and cooperation of industrial clusters in economic activities
- (4) P_i^t and P_g^t , respectively, represent the best cluster positions searched by particle individuals and particle populations
- (5) $Z = f(x, y)$ is the objective function, Z is the value of cluster competitiveness, and (x, y) is the coordinate value

5. Experiment and Result Analysis

5.1. D-PSO Performance Verification

5.1.1. Selection of Test Function. In order to test the performance of the D-PSO algorithm, we use three commonly used test functions, Rastrigin function, Rosenbrock function, and Griewank function, to carry out the experimental test. The three test function expressions are as follows:

$$f_1(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, f_2(x) = \sum_{i=1}^{n-1} \left(100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right), f_3(x) = \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i) + 10). \quad (5)$$

The simulation experiment is realized with the help of MATLAB 2019 b. The CPU of PC is i5-7200U@2.50 GHz, and the memory is 8G. The operating system is Window 10(64 bit), and the software is MATLAB 2019 b. In order to test the performance of the D-PSO algorithm, we choose the standard PSO algorithm for the comparative test. Two algorithms are used to solve the above three test functions, respectively. We set the evolution algebra as 500, the inertia weight ω of the standard PSO as 0.729, the learning factor $c_1 = c_2 = 1.429$, the total number of particles in the population as 100, and the dimensions of the three main test functions as 10.

5.1.2. Analysis of Convergence Results. When testing the performance of the D-PSO algorithm, it is necessary to exclude the influence of random factors on the experiment. Therefore, we have repeated experiments for each algorithm for many times, where the number of times is 10. The average of 10 independent repeated experiments is taken as the final result of the experiment. Griewank function, Rosenbrock function, and Rastrigin function are solved by two algorithms, respectively. The evolution curve when solving the function is shown in Figure 3.

According to the above experiments, the optimal fitness logarithm values of Griewank function, Rosenbrock function, and Rastrigin function corresponding to D-PSO are -0.13, 0.92, and 0.83, respectively. When the standard PSO algorithm is used to solve the above three functions, the

logarithmic values of the optimal fitness are 3.19, 1.42, and 1.05 in turn, and the results of the two algorithms are shown in Table 1.

According to the trend of solving curves, the D-PSO algorithm has achieved good convergence effect within 50 iterations and found the optimal solution. It can be seen that the D-PSO algorithm converges faster. Therefore, compared with the standard PSO algorithm, the D-PSO algorithm has faster convergence speed and higher solution accuracy.

5.2. Example Analysis of Sports Industry Cluster

5.2.1. Evaluation of Cluster Competitiveness. According to the AHP method, the weight distribution table of the competitiveness evaluation index of sports industry cluster can be obtained, as shown in Table 2.

According to the competitiveness values, the competitiveness fitting topographic maps of sports industry clusters in different regions are established, as shown in Figure 4. The larger the value of z in the graph, that is, the higher the protruding part, the greater the cluster competitiveness of this coordinate. If the coordinates of a certain area are (x, y) , the function $Z = f(x, y)$ is a three-dimensional fitting function of geographical coordinates and competitiveness. In order to interpolate the three-dimensional function, the fitting function Z based on 1stopt is adopted. The main parameter values of the fitting function are shown in Table 3.

FIGURE 3: Evolutionary curve when solving function: (a) Griewank; (b) Rosenbrock; (c) Rastrigin.

TABLE 1: Average fitness of two algorithms.

Function	D-PSO-fitness	PSO-fitness
Griewank	1.53	136.07
Rosenbrock	7.64	23.52
Rastrigin	6.28	10.41

TABLE 2: Weight distribution table of the competitiveness evaluation index.

Criterion layer	Index layer	Index weight	
Competitiveness of sports industry cluster	Cluster scale	Number of enterprises (units)	0.0391
		Total industrial output value (ten thousand yuan)	0.0966
		Sales revenue (ten thousand yuan)	0.0966
		Total investment (ten thousand yuan)	0.1744
		Total investment (ten thousand yuan)	0.0326
		Total assets at the end of the year (ten thousand yuan)	0.0966
	Economic benefits	Main equipment ownership (units)	0.0241
		Production area (100 m ²)	0.0241
		Sales profit (ten thousand yuan)	0.0966
		Total net profit (ten thousand yuan)	0.1866
		Industrial added value (ten thousand yuan)	0.1744

FIGURE 4: Fitting topographic map of competitiveness of sports industrial clusters in different regions.

TABLE 3: Main parameter values of fitting function Z.

Parameter	Value
P_1	-0.0001808310780035
P_2	0.00097865676360172
P_3	-0.00012545761310271
P_4	0.000312243741375035
P_5	0.073322666527124324
P_6	-0.0301464618338314
P_7	-0.16584377332312
P_8	1.82335544721859
P_9	0.731132146105326

$$Z = \frac{(p_1 + p_2 \ln(x) + p_3 (\ln(x))^2 + p_4 y)}{1 + p_5 \ln(x) + p_6 (\ln(x))^2 + p_7 (\ln(x))^3 + p_8 y + p_9 y^2}. \quad (6)$$

5.2.2. D-PSO Solution and Analysis. With the help of MATLAB 2019b, the proposed D-PSO algorithm is used to solve the objective function (formula (4)). In the experiment, the evolution algebra is set to 500 times, the number of particles is 100, and the learning factor $c_1 = c_2 = 1.429$ and $w = 0.729$. The result is $(-2.3, -1.1)$. The relative city is a provincial capital city in China, and it is very close to the Yangtze River Delta. The forecast shows that with the development and upgrading of the industry, a super-large-scale sports industry cluster will appear in $(-2.3, -1.1)$ several years later.

Therefore, appropriate suggestions for cluster development can be given according to the predicted coordinates. (1) From the government's point of view, the government plays a role in promoting and assisting the cluster development. If the local government appropriately adjusts various policies according to the trend of cluster development and continuously improves the symbiotic environment within the cluster, it will continuously promote the upgrading of the cluster and effectively prevent the cluster from declining. (2) At the enterprise level, enterprises are the most important members in the cluster and the largest number. The overall development of clusters is good, which

will inevitably promote the development of internal enterprises. Similarly, the good operation of internal enterprises will inevitably promote the development of the whole cluster, which is a virtuous circle.

6. Conclusions

Because particle swarm optimization is interlinked with the agglomeration of industrial clusters, this paper proposes to use the particle swarm optimization algorithm to predict the formation position of industrial clusters. An improved PSO algorithm-diaphragm particle swarm optimization (D-PSO) is proposed to accurately solve the evolution and formation mechanism of industrial clusters. The competitiveness value of industrial clusters is the value of the objective function solved in the PSO algorithm. The geographical coordinates of industrial clusters are the positions in particle search space in the PSO algorithm. Finally, taking the sports industrial cluster as an example, the D-PSO algorithm is used to simulate the aggregation process of enterprises in the cluster, and the development of the industrial cluster is predicted. We will try to use other swarm intelligence algorithms to simulate the aggregation process of enterprises in the cluster such as artificial fish swarm optimization algorithm.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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