Industrial Cluster Path Evolution Based on Particle Swarm Optimization

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Abstract
This paper associates the self-organizing path dependence rules of the industrial cluster with particle swarm optimization (PSO). After an in-depth study of the application of PSO to the industrial cluster, an industrial cluster evolution model based on PSO is put forward. The model is applied to Shandong provincial automobile industrial clusters, with results suggesting that PSO can qualitatively and quantitatively describe the industrial cluster process. Through further solution and analysis of the above case, it is found that, when government's macro-control is proper and competition and cooperation between enterprises reach a balance, the position of the final industrial cluster can converge on the position of the global optimum competitiveness. On the coordinate position of (2.7, 1.4) near the south of Yantai, the competitiveness value of the industrial cluster obtained through convergence reaches the maximum, namely 0.3944. However, if government's macro-control is excessive or inadequate, or competition and cooperation between enterprises lose their balance, the industrial cluster will be located at the local optimal competitiveness. The coordinate position is (0.3, 1.2), which is close to the north of Liaocheng.
Keywords: PATH DEPENDENCE, PARTICLE SWARM, INDUSTRIAL CLUSTER EVOLUTION, COMPETITIVENESS VALUE

1. Introduction

Industrial cluster refers to the economic phenomenon that relevant enterprises of the same kind gather in a specific area [1]. Enterprises within an industrial cluster achieve better development and higher economic profits by relying on the huge competitive edge obtained through the cluster of various enterprises [2]. Therefore, the evolution process and the formation rules of the industrial cluster have become a research focus to current scholars. In terms of the development history of the industrial cluster theories, famous Western economists, including Marshall, Weber, et al. [3-4], paid their attention to the cluster-based development of enterprises in the late 19th century and the early 20th century, expounding on the formation causes and economic profits of the industrial cluster and providing a fundamental research framework for the future study of industrial cluster theories. During the late 1980s and the early 1990s, Krugman studied the industrial cluster from the perspective of New Economic Geography; while Porter [5] conducted a systematic analysis of the industrial cluster from the perspective of New Economics of Competition. Up to date, research into the industrial cluster both at home and abroad has been further diversified. Among the modern scholars, LI Wei, CHEN Jun et al. [6] studied the development path and the industrial cluster effect of the regional new and high-tech industry; while Atienza, Arias et al. [7] conducted an in-depth analysis of the large-scale mine enterprises, and their regional development and cluster, and put forward an ideal cluster evolution process for mine enterprises.

However, at present, research into the formation process and evolution rules of the industrial cluster has still been in a qualitative stage. The research depth is inadequate to quantitatively describe the dynamic changes of the industrial cluster [8-10]. At the same time, the current research has still been focused on the case study of industrial cluster. The conceptual discussion is too much, while the computer-aided simulation of the industrial evolution process is inadequate.

Therefore, this paper focuses on studying the evolution process of the industrial cluster. Based on the path dependence theory and PSO, this paper conducts a detailed analysis of the industrial cluster from the perspective of the self-organizing path dependence, and put forward an algorithm model to solve the evolution formation mechanism of the industrial cluster. Shandong provincial automobile industrial clusters are adopted as an example. The similarity between the industrial cluster and PSO is first expounded. The industrial competitiveness indicators and comprehensive competitiveness value in different areas are clarified. At last, through PSO of different model parameters and iteration-based solution, the author analyzes the path evolution process and rules of the industrial cluster, attempting at providing new analysis perspectives for the academic study of the industrial cluster.

2. The PSO-based industrial cluster evolution algorithm

2.1. Similarity between the industrial cluster evolution and PSO

2.1.1. Standard PSO

POS is a heuristic optimization algorithm model. In terms of an PSO whose objective function is set, it is assumed that there exists a particle swarm containing M particles; the searching space dimensionality of the particle swarm is "D;" Particle "i" is one part of the swarm. Then, at the moment of "t," the status attribute value of Particle "i" is shown in Eq. (1) to Eq. (4).

1: Position status:

$$X_i^t = (X_{i1}^t, X_{i2}^t, X_{i3}^t, ..., X_{id}^t)^T$$
$$X_{id}^t \in (X_{\min}, X_{\max}) \quad (1)$$

Where, $X_{\min}$ stands for the lower limit of the coordinate position, while $X_{\max}$ stands for the upper limit of the coordinate position.

2: Velocity status:

$$V_i^t = (V_{i1}^t, V_{i2}^t, V_{i3}^t, ..., V_{id}^t)^T$$
$$V_{id}^t \in (V_{\min}, V_{\max}) \quad (2)$$

Where, $V_{\min}$ stands for the lower limit of the velocity; while $V_{\max}$ stands for upper limit of the velocity.

3: Local optimum position:

$$P_i^t = (P_{i1}^t, P_{i2}^t, P_{i3}^t, ..., P_{id}^t)^T \quad (3)$$

4: Global optimum position:

$$P_g^t = (P_{g1}^t, P_{g2}^t, P_{g3}^t, ..., P_{gd}^t)^T \quad (4)$$

All the above is the status attribute value of the particle at the moment of "t." At the moment of "t+1," the particle's status attribute value can be updated through iteration according to Eq. (5):

$$V_{id}^{t+1} = wV_{id}^t + c_1 r_1 (P_{id}^t - X_{id}^t) + c_2 r_2 (P_{gd}^t - X_{id}^t)$$
$$X_{id}^{t+1} = X_{id}^t + V_{id}^{t+1} \quad (5)$$

Where, w stands for the inertial weight value of PSO.

When the status attribute value of the particle iterates from "t" to ""'t+1, there are three core parts during the process. First is the velocity of the particle at the former moment. In other words, the velocity of the particle at the latter moment inherits that at the former moment. Second is the self-cognition, meaning that the particle will adjust its flying s status according to its flying experiences and the historical optimum position. Third is the social part. The particle also refers to the flying information of the whole swarm apart from its own, and adjusts its flying status according to the optimum position of the swarm.

2.1.2. Similarity between the industrial cluster and PSO

In fact, industrial cluster is a self-organizing path dependence system. The formation process of the industrial cluster evolves through the open dissipative structure [11].PSO can also be called self-organizing algorithm, whose optimum seeking process is a self-organizing one. If enterprises in an industrial cluster are regarded as particles in a PSO, the cluster is located at the position with the maximum cluster competitiveness. The position can be regarded as the position of the optimal solution of PSO. In this way, the industrial cluster process can be regarded as an optimum seeking process of the particle swarm, and the optimum seeking process of the particle swarm and the process of the industrial cluster have something in common. The following part conducts a thorough analysis from the perspective of the parameters of PSO.

(1) Parameter w

In the particle swarm, the parameter acts as the inertia weight value of PSO. It plays the role of adjusting PSO. The larger the inertia weight coefficient is, the more dependent the algorithm relies on the velocity obtained through the former iteration and the stronger the global searching capacity of the algorithm is. On the contrary, the stronger the local searching capacity of the algorithm is. During the industrial cluster process, the parameter can be regarded as the macro-control of the national government in participating in the industrial cluster activities. When the government intervenes in the cluster economic activities, high w means excessive macro-control, which might goes against the basic rules of the market economy; while *small* will bring irrevocable losses to the unbalanced market.

(2)Parameter c_1

In the particle swarm, the parameter acts as the cognition part of PSO. In other words, when the efficiency of PSO in finding the optimum value is extremely low, it means no information exchange between particles or no sharing of social information during the optimum seeking process. Every particle seeks the optimum value through iteration in its own way. During the industrial cluster process, it is reflected as economic benefits that the industrial cluster is seeking during the evolution process. The benefits are a merely predatory fighting for market shares. There is no competition but cooperation between industries. In the whole process, the industrial cluster conducts economic activities without taking the social environment and its carrying capacity into consideration.

(3)Parameter c_2

In the particle swarm, the parameter acts as the social part of PSO. When PSO just has the social part but lacks the cognition part, the algorithm will lose its global perspective (meaning the algorithm will be easily stuck into the local optimum value), even if there is sound social information sharing between particles, and the particle's convergence velocity is relatively fast, making the convergence of an optimum value easier. During the industrial cluster process, the parameter is reflected as the cooperation between enterprises within the industrial cluster. The cooperation here is a relatively extensive concept. It includes the cooperation between enterprises and the cooperation between enterprises and governments, or between enterprises and scientific research institution or even between governments. Participants or managers of the industrial cluster pays more attention to how the cluster can be guaranteed at a favorable and sustainable state and achieve recycling of the cluster economies of scale.

2.2. Model building of industrial cluster evolution based on PSO

Based on the analysis of the internal relevance between PSO and the industrial cluster, the industrial cluster should undergo microparticulation before being used to modelize the industrial cluster evolution with PSO. To put it more specifically, the comprehensive indicator value of the industrial cluster acts as the objective function value solved by PSO; the geological coordinate position of the industrial cluster acts as the position of the particle in searching the space in PSO; and the competition and cooperation between enterprises in the industrial cluster can be realized through the cognition and social part in PSO.

To sum up, the objective function and the basic velocity and position iteration equations of the industrial cluster evolution model based on PSO are shown in Eq. (6). In Eq. (6), various variables are endowed with the characteristics of the industrial cluster. The iteration process of the algorithm should be calculated according to the standard PSO.

$$\max Z = f(x,y)$$
$$V_{id}^{t+1} = wV_{id}^{t} + c_1 r_1 (P_{id}^{t} - X_{id}^{t}) + c_2 r_2 (P_{gd}^{t} - X_{id}^{t})$$
$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \tag{6}$$

Various variables in Eq. (6) are endowed with the following new meanings:

w stands for the government intervention during the cluster evolution process, such as national policies and macro-control;

X stands for the geological coordinate position of the cluster, namely (x, y);

c_1 and stand for the competition and cooperation degree of the industrial cluster during the economic activities, respectively;

P_{id}^{t} and P_{gd}^{t} stand for the optimum location of the cluster searched by individual particles and the particle swarm;

Z stands for the comprehensive indicator value of the industrial cluster.

3. Model application and result analysis

Shandong has been developed into a major automobile industrial base in China. Up to year 2015, the production scale of the Shandong provincial automobile industry has reached 3.5 million cars, with the overall industrial sales reaching 80 billion RMB. At the same time, eight major automobile industrial sub-bases have been built. Qingdao, Jinan, Yantai and Weifang will be developed into 100-billion industrial sub-bases to annually turn out 500,000 cars. Weihai, Rizhao, Zibo and Liaocheng will be developed into 10-billion automobile production sub-bases with an annual output of 100,000 cars. On the whole, the concentration degree of Shandong's automobile production bases will reach above 90%. Therefore, this paper adopts Shandong's automobile industry as an example to analyze and study its cluster process and rules based on PSO.

3.1. Model hypotheses

To study the industrial cluster evolution through PSO should be based on the following hypotheses:

Hypothesis 1: During the cluster evolution process, the competitiveness of several district and municipal automobile industries in Shandong Province is stable during certain period.

Hypothesis 2: During the cluster evolution process, there are no emergencies which impose a huge influence on clusters, such as earthquake and other disasters.

3.2. Calculation of the comprehensive competitiveness of the industrial cluster

Relevant data of the competitiveness measuring indicator system of the Shandong provincial automobile industry in 2014 are shown in Table 1:

Table 1. Competitiveness indicator value of the automobile industrial clusters in various places of Shandong in 2014

Indicators	Jinan	Qingdao	Yantai	Zibo	Weifang	Linxi
Number of enterprises in cluster	75	89	185	25	45	23
Total industrial output value (unit: 10,000 RMB)	5175808	4724558	7623545	390023	2633211	380911
Sales revenues (unit: 10,000 RMB)	5117679	4166939	7517093	375585	2429111	379039
Fixed assets (unit: 10,000 RMB)	1123792	988629	955728	98725	700135	102347
Overall year-end assets (unit: RMB)	1586968	2500143	1319019	223011	1603788	334562
Number of major devices (unit: set)	11097837	7432444	8564063	510043	4800329	732398
Production area (×100m2)	20411	17034	22267	2031	13045	2257
Sales profits (unit: 10,000 RMB)	102282	110342	110442	5405	80224	11403
Overall net profits (unit: 10,000 RMB)	502311	390024	770401	53201	302122	60521
Industrial added-value (unit: 10,000 RMB)	120764	110543	180054	23091	102201	22036
	1293952	1181139	1905888	97505	658302	95227
Indicators	Liaocheng	Tai’an	Jining	Heze	Rizhao	
Number of enterprises in cluster	32	27	23	31	19	
Total industrial output value (unit: 10,000 RMB)	2823165	512201	560074	430015	596634	
Sales revenues (unit: 10,000 RMB)	2637539	509076	549730	430285	595667	
Fixed assets (unit: 10,000 RMB)	639011	129533	160053	102322	163029	
Overall year-end assets (unit: RMB)	4408611	232289	368801	270018	332081	
Number of major devices (unit: set)	4300791	730925	730842	652036	804523	
Production area (×100m2)	11213	1804	4301	2219	3802	
Sales profits (unit: 10,000 RMB)	77059	21205	33008	33289	45289	
Overall net profits (unit: 10,000 RMB)	270041	99025	87031	66051	79271	
Industrial added-value (unit: 10,000 RMB)	80953	22491	33054	27031	22077	
	705791	128050	140018	107503	149158	

By investigating into Shandong's automobile industry, this paper clarifies the weight value of various competitiveness indicators through the analytic hierarchy process (AHP). The pairwise comparison matrix, A, of the 11 indicators is shown below:

$$A=\begin{bmatrix} 1 & 1/3 & 1/3 & 1/4 & 1 & 1/3 & 2 & 2 & 1/3 & 1/4 & 1/3 \\ 3 & 1 & 1 & 1/3 & 3 & 1 & 4 & 4 & 1 & 1/3 & 1 \\ 3 & 1 & 1 & 1/3 & 3 & 1 & 4 & 4 & 1 & 1/3 & 1 \\ 4 & 3 & 3 & 1 & 4 & 3 & 5 & 5 & 3 & 1 & 3 \\ 1 & 1/3 & 1/3 & 1/4 & 1 & 1/3 & 2 & 2 & 1/3 & 1/4 & 1/3 \\ 3 & 1 & 1 & 1/3 & 3 & 1 & 4 & 4 & 1 & 1/3 & 1 \\ 1/2 & 1/4 & 1/4 & 1/5 & 1/2 & 1/4 & 1 & 1 & 1/4 & 1/5 & 1/4 \\ 1/2 & 1/4 & 1/4 & 1/5 & 1/2 & 1/4 & 1 & 1 & 1/4 & 1/5 & 1/4 \\ 3 & 2 & 2 & 1/3 & 3 & 2 & 4 & 4 & 1 & 1/3 & 1 \\ 4 & 3 & 3 & 1 & 4 & 3 & 5 & 5 & 3 & 1 & 3 \\ 3 & 2 & 2 & 1/3 & 3 & 2 & 4 & 4 & 1 & 1/3 & 1 \end{bmatrix}$$

By solving the matrix, A, this paper obtains the maximum eigenvalue and its corresponding eigenvector, and checks their consistency. The maximum eigenvalue is λ =11.79, CR =0.0521<0.1; while the corresponding eigenvector, or the weight value of various indicators is shown in Table 2:

Table 2. Weight value of competitiveness indicators of the industrial cluster

Indicators	Weight value
Number of enterprises in cluster	0.0364
Total industrial output value (unit: 10,000 RMB)	0.0867
Sales revenues (unit: 10,000 RMB)	0.0867
Fixed assets (unit: 10,000 RMB)	0.2007
Overall year-end assets (unit: RMB)	0.0364
Number of major devices (unit: set)	0.0867
Production area (×100m2)	0.0241
Sales profits (unit: 10,000 RMB)	0.0241
Overall net profits (unit: 10,000 RMB)	0.1088
Industrial added-value (unit: 10,000 RMB)	0.2007
	0.1088

Through the normalization of the value of various competitiveness indicators of the automobile industrial clusters in various places in Shandong, and the weighting summation of various indicators, the comprehensive competitiveness indicator value of the industrial clusters in various places is shown in Table 3 below:

Table 3. Comprehensive competitiveness of the industrial clusters in various places in Shandong

Jinan	Qingdao	Yantai	Zibo	Weifang	Linxi	Liaocheng	Tai'an	Jining	Heze	Rizhao
0.1955	0.1712	0.2443	0.0205	0.1193	0.0215	0.1173	0.0259	0.0312	0.0246	0.0286

Through the fitting of the relative geographical coordinate position and serial number with the comprehensive competitiveness value of the industrial clusters in Table 4 below, the fitting function is shown in Eq. (7) and the fitting results and relevant fitting parameters are shown in Table 5. The overall competitiveness distribution of the industrial clusters in Shandong is shown in Figure 1.

$$f(x,y)=p_1+p_2x+p_3y+p_4x^2+p_5xy+p_6y^2+p_7x^3+p_8x^2y+p_9xy^2+p_{10}y^3 \tag{7}$$

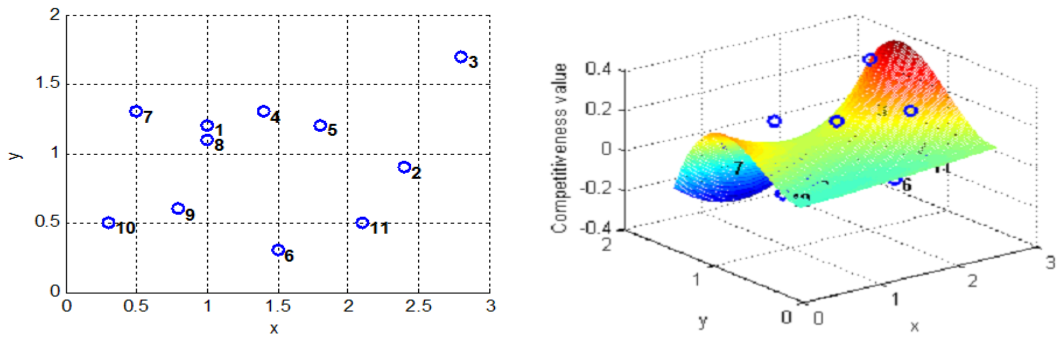
Table 4. Relative geographical coordinate value of various places in Shandong

Place	Jinan	Qingdao	Yantai	Zibo	Weifang	Linxi
Coordinate position,（x,y）	(1.0,1.2)	(2.4,0.9)	(2.8,1.7)	(1.4,1.3)	(1.8,1.2)	(1.5,0.3)
Serial No.	1	2	3	4	5	6
Place	Liaocheng	Tai'an	Jining	Heze	Rizhao	
Coordinate position,（x,y）	(0.5,1.3)	(1.0,1.0)	(0.8,0.6)	（0.3,0.5)	(2.1,0.5)	(0.5,1.3)
Serial No.	7	8	9	10	11	7

Table 5. Fitting results and relevant fitting parameters

Parameters	Parameter value
p1	0.0307
p2	0.1662
p3	-0.4895
p4	-0.0385
p5	-0.5229
p6	1.3578
p7	-0.5661
p8	0.1378
p9	0.0966
p10	-0.0794

Root of Mean Square Error (RMSE):0.1349　　　R-Square: 0.9800
Sum of Square Error (SSE):0.0182



(a)　　　(b)

Figure 1. a: Relative geographical coordinate distribution of various places in Shandong; b: Overall competitiveness value of the automobile industrial clusters in Shandong Province

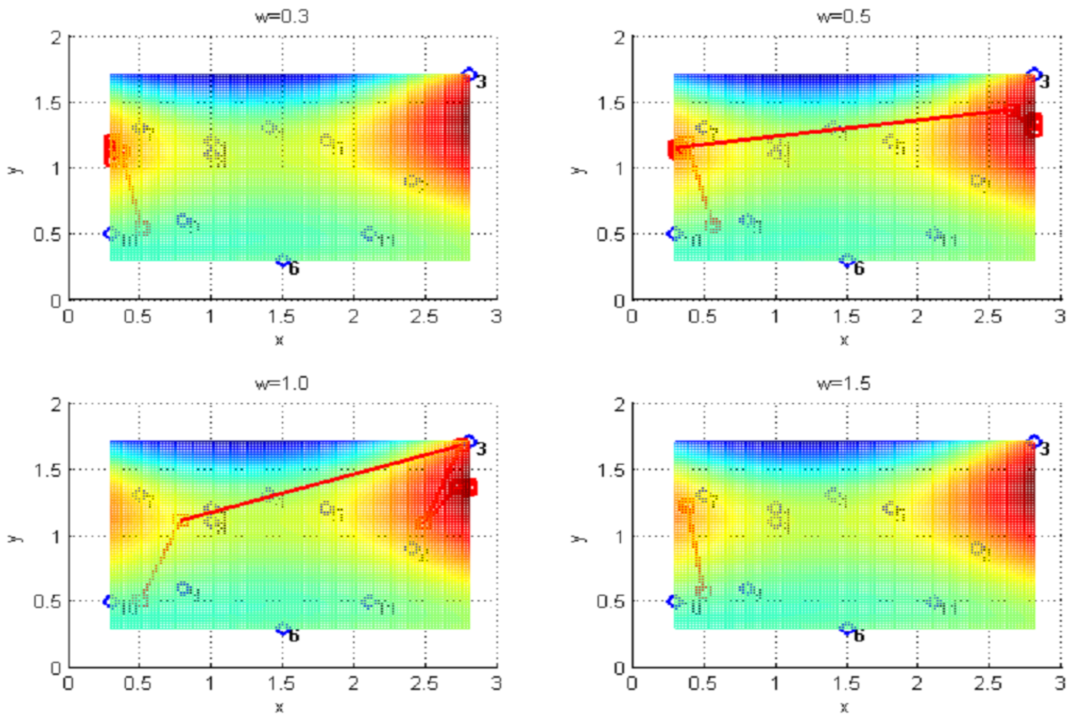
3.3. PSO model analysis

Eq. (7) seeks optimum through iteration and works out its maximum. Assuming the evolution iterations are 100; the number of particles in the swarm is 50; the initial position coordinate of the particle is (0.5, 0.5).

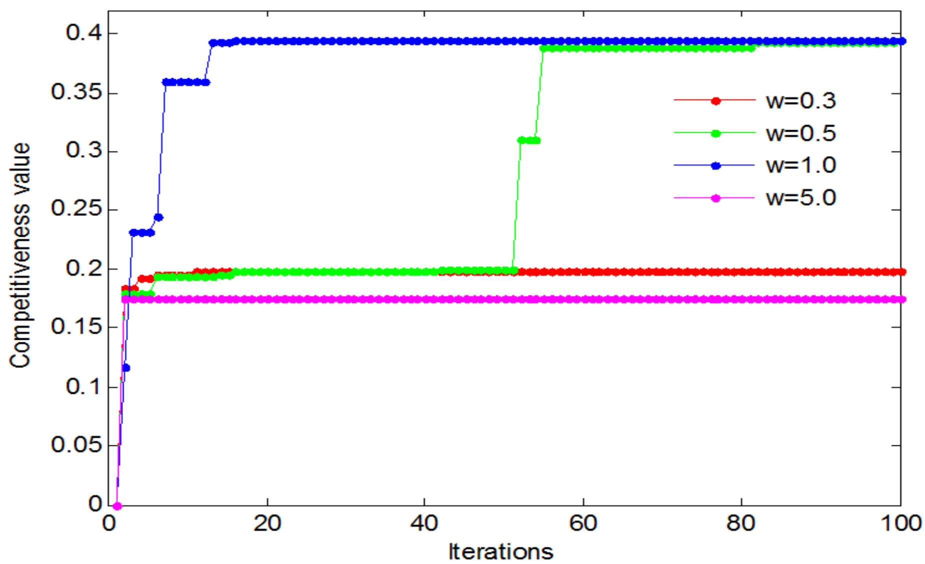
1: When c_1=1 and c_2=1, while w increases gradually, namely that the government plays an increasingly stronger intervening role during the cluster evolution process, the simulation results are shown in Table 6 and Figure 2:

Table 6. Industrial cluster evolution and convergence results as *w* increases gradually

w	Convergence coordinate position/ (x,y)	Convergence of the maximum competitiveness value /maxf
0.3	(0.3060,1.1521)	0.1989
0.5	(2.7992,1.3593)	0.3941
1	(2.7994,1.3408)	0.3944
1.5	(0.3874,1.2161)	0.1753



(a)



(b)

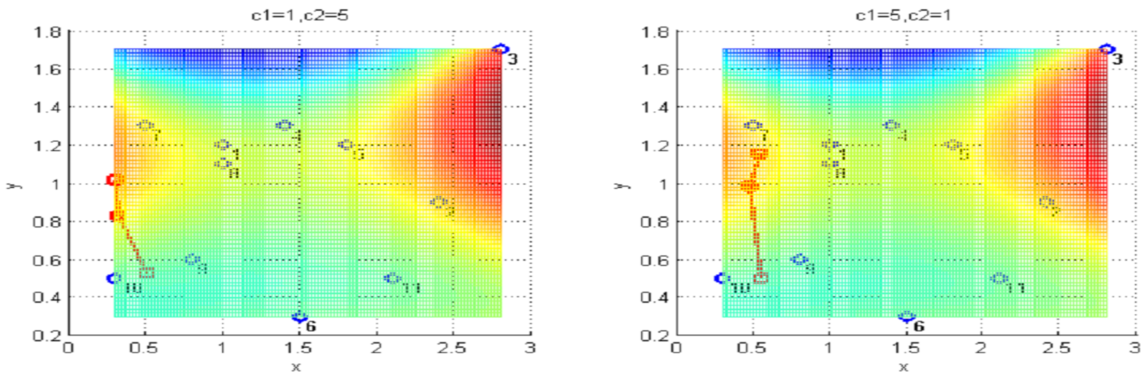
Figure 2. Industrial cluster evolution results as *w* increases gradually; a: Position changes of the industrial cluster along with the value of *w* ; b: Changes of the optimal competitiveness of the industrial cluster along with the value of *w*

Based on the simulation analysis results of Table 6 and Figure 2, it can be seen that, when w is extremely small or large, PSO only converges at the local optimal solution. When the government's macro-control is excessive or inadequate, the industrial cluster evolution path is relatively conservative and can only converge at the position of the local optimal competitiveness, namely (0.3, 1.2) near Liaocheng, but can not form clusters at the position of the global optimal competitiveness. When w is at a moderate value, or when the government's macro-control is proper, the final position of the industrial cluster will converge at the position of the global optimal competitiveness, namely (2.7, 1.4) near Yantai. The maximum competitiveness value is 0.3944.

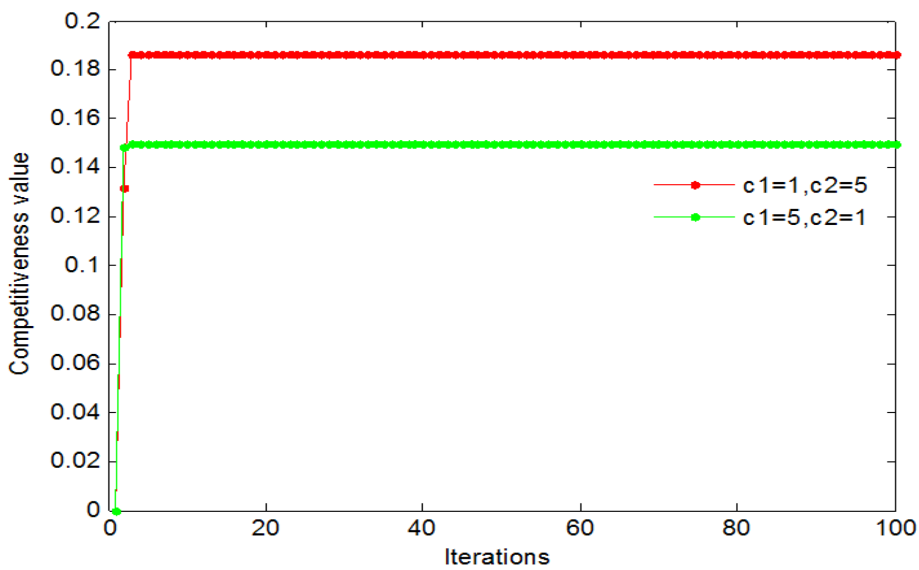
2: When w =1.0, while c_1=1, c_2=5 or c_1=5, c_2=1, namely when the cooperation degree c_2 is far higher than the competition degree, c_1, and when the competition degree, c_1, is far higher than the cooperation degree, c_2, the simulation results of the industrial cluster during cooperated economic activities are shown in Table 7 and Figure 3:

Table 7. Convergence results of the industrial cluster evolution at the different cooperation/competition degree

c_1	c_2	Convergence coordinate position/(x,y)	Convergence of the maximum competitiveness value/maxf
1	5	(0.3059,1.0153)	0.1862
5	1	(0.5456,1.1541)	0.1495



(a)



(b)

Figure 3. Influence of the cooperation and competition degree on the industrial cluster evolution; a: Changes of the industrial cluster position at the different cooperation/competition degree; b: Changes of the optimal competitiveness of the industrial cluster

From the simulated analysis results of Table 7 and Figure 3, it can be seen that, when the cooperation degree between enterprises is far higher than the competition degree, the industrial cluster evolution path is also in a relatively conservative state. When enterprises lose their competitiveness awareness, the final position of the industrial cluster can only stay in its surrounding, namely (0.3, 1.2) near Liaocheng. When the competition degree between enterprises is far higher than the cooperation degree, namely that enterprises lose their win-win objectives and ignore the recyclable benefits of the cluster economy, the final position of the industrial cluster also stay in its surrounding, namely (0.3, 1.2) near Liaocheng.

4. Conclusions

This paper mainly studies the application of PSO to the industrial cluster. Based on the self-organizing path dependence rules of the industrial cluster, the author associates the industrial cluster with PSO and puts forward an industrial cluster evolution model based on PSO. The model is applied to the analysis of Shandong provincial automobile industrial clusters. Results suggest that PSO can quantitatively and qualitatively describe the industrial cluster evolution process. Further solution and analysis of the above case through PSO finds out that, when the government's macro-control is moderate and the cooperation and competition between enterprises strike a balance, the final position of the industrial cluster can converge at the position of the global optimum competitiveness, namely (2.7, 1.4) near the south of Yantai. The maximum competitiveness value of the industrial cluster obtained through convergence is 0.3944.

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