

Hindawi Publishing Corporation
Scientific Programming
Volume 2016, Article ID 2402037, 10 pages
<http://dx.doi.org/10.1155/2016/2402037>



Research Article

Research on the Uncertainty Decision Model of the Regional Collaborative Innovation System Based on an Improved Ant Colony Algorithm

Xiaona Zhang¹ and Fayin Wang²

¹Harbin Normal University, Harbin, Heilongjiang 150025, China

²Harbin Engineering University, Harbin, Heilongjiang 150001, China

Correspondence should be addressed to Xiaona Zhang; xiaonazh@sohu.com

Received 26 June 2016; Revised 14 September 2016; Accepted 28 September 2016

Academic Editor: Xiaofeng Xu

Copyright © 2016 X. Zhang and F. Wang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The regional collaborative innovation system is a nonlinear complex system, which has obvious uncertainty characteristics in the aspects of member selection and evolution. Ant colony algorithm, which can do the uncertainty collaborative optimization decision-making, is an effective tool to solve the uncertainty decision path selection problem. It can improve the cooperation efficiency of each subsystem and achieve the goal of effective cooperation. By analysing the collaborative evolution mechanisms of the regional innovation system, an evaluation index system for the regional collaborative innovation system is established considering the uncertainty of collaborative systems. The collaborative uncertainty decision model is constructed to determine the regional innovation system's collaborative innovation effectiveness. The improved ant colony algorithm with the pheromone evaporation model is applied to traversal optimization to identify the optimal solution of the regional collaborative innovation system. The collaboration capabilities of the ant colony include pheromone diffusion so that local updates are more flexible and the result is more rational. Finally, the method is applied to the regional collaborative innovation system.

1. Introduction

Collaborative innovation is a kind of integrated product development mode, which combines the human design method and the innovative technology. It is not only an individual's innovative behavior but also a kind of collective innovation [1–5]. The result of innovation can be a concept of design object, program, or entity model. Collaborative innovation is conducted to improve the desired function of production, accelerate the product development process, and make it have better economic characteristics. Collaborative innovation needs collaborative decision-making [6]. It is a procedure of multisubject participation. From a number of feasible solutions, it takes the collaborative decision group as the main body and does the quantitative and the qualitative analysis, in the order to choose the best one. There are 4 stages of collaborative decision-making process: (1)

determining the collaborative criteria (target); (2) providing a number of feasibility collaborative programs; (3) doing quantitative treatment; (4) choosing the best plan. To improve reliability and dependability of analysis appraisal, it proposes the methods of grey relative analysis based on Analytic Hierarchy Process and develops the scheme analysis and evaluation system. Most research on collaborative innovation based on model evaluation at home and abroad uses an evaluation decision model based on results, mainly the Production Function Method, Analytic Hierarchy Process, Fuzzy Comprehensive Evaluation, DEA Method, Grey Evaluation Method, Matter-Element Analysis Method, Artificial Neural Network Method, Delphi Method, Comprehensive Index Method, and so forth. The research perspectives mainly concentrate on the national, regional, and other macroscopic evaluation decisions [7–9].

The innovation performance evaluation system of federal research institutions is representative, and the Government Performance and Results Act (GPRA) was formed as the framework and system foundation. It converted the performance evaluation from “input-output” into “target-results” mode. South Korea placed the direction of the development of science and technology as the core and measured the degree of project completion objectively through the inspection of project objective setting. The OECD put forward that the core of collaborative innovation evaluation and decision is inventory investment, technology, knowledge update and spillover effects, and so forth [10–14] from the perspective of the process of knowledge innovation. Pia Hurmelinna-Laukkanen and Pierre Barbaroux et al. researched collaborative innovation evaluation and decision from the angle of innovation main bodies.

On April 24, 2011, comrade Hu Jintao put forward explicitly that collaborative innovation should be promoted actively in a speech marking the one hundredth founding anniversary of Tsinghua University. Subsequently, the Ministry of Education and Ministry of Finance jointly issued a collaborative innovation program in the universities, which is referred to as the 2011 plan [15–17]. Chen Jin, Xiong Li, Xie Xuemei, and other scholars have researched collaborative innovation deeply from the angle of the collaborative evaluation decision of collaborative innovation. The economic competition of contemporary world is mainly manifested as the competition of science and technology. The social economic structure and economic relations and customs have changed dramatically during the era of knowledge economy. Regional innovation system is an effective tool for developing economics. Unlike other tools, regional innovation system is a more flexible policy tool. The evaluation of regional innovation system’s performance can provide scientific basis for the judgment, establishment, and correction of regional policy. A lot of researchers note this. The studies are mainly concerned with the network organization, type, operation, and institutional reform of collaborative innovation based on the mechanisms of collaboration and of improvement. There is no too much work that utilizes mathematical modelling to study the improvement process of collaborative innovation capability [18–22].

In integrated domestic and foreign research, the research methods are mainly confined to the discussion and summary of experience. This research is basically concerned with the strategic objectives, organizational structure, system development, and other aspects of qualitative analysis. There is more qualitative analysis but less quantitative evaluation, and the quantitative evaluation model is only a general fit model. The lack of collaborative innovation design for the industry characteristics of the specialized collaborative innovation decision-making evaluation model is a major drawback. Research on collaborative innovation decision-making through an evaluation model is still rare. The ant colony algorithm has not been introduced into the research on collaborative innovation so far.

2. Uncertainty Decision Model Construction of the Regional Collaborative Innovation System

The regional innovation system is basically the same as the ant colony algorithm in many ways, such as the goal and process of uncertainty collaborative optimization decision-making. However, there is a big difference in the uncertainty of the system optimization decision path caused by the local factors’ alteration [23–25]. Therefore, this paper establishes an ant colony model based on pheromone diffusion to reflect the pheromone. This model can improve the cooperation ability of collaborative innovation system in the direction of evolution path selection, further optimize the balance and load of resources in the regional innovation system, and speed up the process of collaborative decision-making. Under the guidance of ant colony optimization model, it is possible to enhance the value of innovation and improve the regional innovation system’s innovation efficiency.

2.1. Model Building. Members of the regional collaborative innovation system (n universities, m scientific research institutes, p enterprises, and q participating members of other innovative technologies such as government financial institutions) achieved innovation improvement through collaboration, that is, more efficient innovation, shorter innovation cycles, and stronger knowledge transfer capabilities. Collaboration can produce two types of driving modes: first, theoretical innovations are achieved by the internals of universities through collaborative innovation in some subjects. Second, the ultimate goals of more efficient innovation, shorter innovation cycles, and stronger knowledge transfer capabilities are achieved through institutional innovation by the original organization [26–28].

To facilitate the analysis, C is defined as the regional collaborative innovation system, $S = \{S_1, S_2, \dots, S_n\}$ is defined as a subsystem of universities, $R = \{R_1, R_2, \dots, R_m\}$ is defined as a subsystem of scientific research institutes, $E = \{E_1, E_2, \dots, E_p\}$ is defined as a subsystem of enterprises, and $O = \{O_1, O_2, \dots, O_q\}$ is defined as a subsystem of others. The collaborative mechanism of care comprises S , R , E , and O . Because of the characteristics of uncertainty, instability, and nonlinearity in the coordination mechanism, the regional collaborative innovation system C will be influenced by itself and the external environment. The complex changes in overall status, structure, and functional effects in C will happen according to the basic principles of synergetics. Material, energy, information exchange, and collaboration exist in internal subsystems and also between systems and the external environment; therefore, system instability can be used to describe the evolution processes, and evolution regularity can be grasped through identifying the order parameters of the regional collaborative innovation system [29].

To further simplify the discussion, cofactor F is introduced; then, regional collaborative innovation systems are abstracted as in type 1:

$$C = F \{S, R, E, O\}. \quad (1)$$

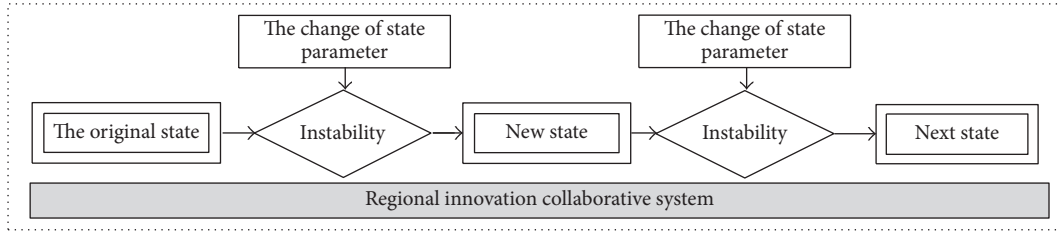


FIGURE 1: Instability analysis of a regional collaborative innovation system.

The essence of collaborative mechanisms is looking for an effective collaborative solution $f_S, f_R, f_E, f_O \in F$ based on the structure functional characteristics of the composite system such that the overall performance $V(C)$ of

the regional collaborative innovation system C is greater than the performance $V(S)$ plus $V(R)$ plus $V(E)$ plus $V(O)$ and $V(C)$ can obtain its maximum:

$$\max \left\{ V^F(C) - \left(\sum_{i=1}^n V^{f_S}(S) + \sum_{i=1}^m V^{f_R}(R) + \sum_{i=1}^p V^{f_E}(E) + \sum_{i=1}^q V^{f_O}(O) \right) \right\}. \quad (2)$$

Q is defined as the status parameter of the complex system, Q_0, Q_1 are defined as the initial state condition of the system and evolution constraints, and the sets of f_S, f_R, f_E, f_O are F ; then, formula (2) is as follows:

$$\text{st. } \begin{cases} q \in Q_0 \\ f_S(q), f_R(q), f_E(q), f_O(q) \in Q_1 \\ f_S, f_R, f_E, f_O \in F. \end{cases} \quad (3)$$

2.2. State Parameter Analysis and Model Evaluation. The instability of the regional innovation system is a general characteristic of a complex system. When the control parameter reaches a critical value, the system will lose stability and transition into an unstable state until the emergence of a new stable state.

Figure 1 shows the evolution processes of the regional innovation system. The critical control parameters are the state parameters of the system, where the state parameters show the nature and extent of order when the system has changed as shown in Figure 1.

A regional collaborative innovation system is a complex system, and, between the various subsystems, there is no simple linear relationship, but rather the mutual influence and mutual restriction of a nonlinear relationship. The evolution direction of the regional innovation system is multidirectional. In terms of its evaluation goal, members of the regional collaborative innovation system focus on different goals.

Universities efficiently use a variety of scientific and technological innovation resources (including personnel, organizations, equipment, facilities, funding, and other tangible resources, an innovative culture, policy mechanisms, and organizational management intangible resources). Many high level scientific and technological innovations (including

papers, books, patents, and awards, as well as the direct results of innovative talents and achievements in the economic and social fields and other indirect results) are obtained through knowledge innovation, technological innovation, transformation and management innovation, and other scientific and technological innovation activities, and competitive advantages in science and technology and an innovation ability are formed.

For the scientific research institutes, technology innovation abilities are based on progress at the scientific research level and the diffusion abilities of innovation. The levels of scientific research are decided by the subject frontier and the visual original and whether there is a major breakthrough with the new discovery, invention, and technology. The diffusion of innovation ability mainly includes the innovation resources, talents, information, equipment, and policy from several aspects.

For the enterprises, technological innovation means improvements of product quality and market share, development of new products and services, and enhancements of profits by applying innovative knowledge and new technologies, processes, production methods, and management mode [30–32].

To a certain extent, universities pay more attention to the progress of innovation and scientific research, institutes pay more attention to the practical transformation of innovation, and enterprises pay more attention to the value of innovation. There are several evaluations for the collaborative innovation centre platform. It can be divided into three levels with dozens of indicator references [33]. Among them, this paper will regard the direct parameter of the influencing innovation index after collaborative optimization as the basis of evaluation. In the regional collaborative innovation system, organic coordination among different subsystems makes innovation more efficient; see Table 1.

TABLE I: Evaluation index of the regional collaborative innovation system.

First-level evaluation index	Weight	Second-level evaluation index	Weight	Third-level evaluation index	Unit	Weight				
Conditions for innovation	20%	Human resources	35%	R&D staff (1)	People	18%				
				Technological staff (2)	People	16%				
				Production and business staff (3)	People	6%				
				Other staff (4)	People	5%				
				Number of senior staff/total staff	%	20%				
				Number of master and doctorate/total staff	%	15%				
		Financial resources	25%	Academic leaders	20%	Project funding	Ten thousand yuan	25%		
						Business funding	Ten thousand yuan	18%		
						Other funding	Ten thousand yuan	15%		
						Per funding	Ten thousand yuan/People	42%		
						Number of scientific research platforms at national, provincial level		35%		
						Innovative devices over 1 million	Ten thousand yuan	25%		
						Use of scientific equipment	%	40%		
						Achievements in scientific research	25%	Achievements in scientific research	100%	Number of research projects completed
Number of scientific and technological awards at provincial level	Item	27%								
Number of invention patents	Item	33%								
Number of SCI/SSCI	Paper	17%								
Innovation benefits	35%	Achievement transformation	30%	Leadership adopted (instructions), patent implementation, and achievements transformation	Item	42%				
				Business income of member enterprise	Ten thousand yuan	11%				
				Percentage share of business income of joint investment of social capital	Ten thousand yuan	6%				
		Public service	30%	Rate of transformation	38%	Service of platform for the public		38%		
						Penetration of public service	%	29%		
						Effective growth rate	%	33%		
						Human input-output ratio	%	33%		
		Efficiency of innovation	40%	Financial input-output ratio	44%	Financial input-output ratio	%	44%		
						Material input-output ratio	%	23%		
						Development planning	45%	Planning and construction of subjects	56%	Implementation of research programs
Establishment of collaborative system		55%								
System implementation		45%								
System construction	25%	Incentives at all levels	67%	Item						67%
				Spiritual rewards	Item					33%
Organizational culture	30%	System implementation	45%	Incentives at all levels	Item	67%				
							Spiritual rewards	Item	33%	
Cooperative level	20%	System construction	25%	System implementation	45%	Incentives at all levels	67%			
								Spiritual rewards	Item	33%

2.3. *Indicator Processing.* For a more detailed description, the evaluation of creative ability is a normalized quantization process; parameters affecting innovation indicators based on collaborative optimization are used for the evaluation basis. Definitions are given below:

- $C'_{ij}(\text{value})$ —evaluation function of innovation value.
- $C'_{ij}(\text{time})$ —evaluation function of innovation cycles.
- $C'_{ij}(\text{efficiency})$ —evaluation function of innovation efficiency.

Without taking into account other relevant factors, the overall performance $V(C)$ of the regional collaborative innovation system C in formula (2) is converted into the following formula:

$$V^F(C) = \xi_1 C'_{ij}(\text{value}) + \xi_2 C'_{ij}(\text{time}) + \xi_3 C'_{ij}(\text{efficiency}). \quad (4)$$

ξ_1, ξ_2, ξ_3 represent the weight functions. Obviously, $C'_{ij}(\text{value})$ and $C'_{ij}(\text{efficiency})$ are positive indicators (the higher the value is, the stronger the capacity is). $C'_{ij}(\text{time})$ is a negative indicator (the higher the value is, the poorer the ability is). Because the dimensions of the evaluation function are not the same, the index matrix $V^F(C)$ must be normalized.

Order

$$x_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m (a_{ij})^2}}. \quad (5)$$

When A is a negative indicator

$$x_{ij} = \frac{-a_{ij}}{\sqrt{\sum_{i=1}^n (a_{ij})^2}}, \quad (6)$$

$$x_j^+ = \max \{x_{ij}\},$$

$$x_j^- = \min \{x_{ij}\}, \quad (7)$$

$$(j = 1, 2, \dots, n).$$

The sets of the optimal values are $V^F(C)^+ = \{x_1^+, x_2^+, \dots, x_n^+\}$.

The sets of the worst values are $V^F(C)^- = \{x_1^-, x_2^-, \dots, x_n^-\}$.

Based on the related principles of the osculation value model, a satisfactory system performance value is the point closest to the sets of optimal values and the maximum distance from the sets of the worst values.

Then, the osculation value of $V^F(C)$ is

$$C_i = \frac{d_i^+}{d^+} - \frac{d_i^-}{d^-}, \quad (8)$$

where

$$\begin{aligned} d_i^+ &= \left[\sum_{j=1}^n (x_{ij} - x_j^+)^2 \right]^{1/2}, \\ d_i^- &= \left[\sum_{j=1}^n (x_{ij} - x_j^-)^2 \right]^{1/2}, \\ d^+ &= \min \{d_i^+\}, \\ d^- &= \max \{d_i^-\}, \end{aligned} \quad (9)$$

and d_i^+ and d_i^- indicate the Euclidean distances between solution A_i and the optimal solution A^+ and worst solution A^- . d^+ is the minimum among the most advantageous m ; d^- is the maximum among the worst m .

C_i reflects the degree of deviation of the performance of regional collaborative innovation system $V^F(C)$ from the most advantageous performance. When $C_i = 0$, $V^F(C)$ is closest to the most advantageous thing. For the range of values of $C_i > 0$, $V^F(C)$ deviates from the most advantageous. The range of values of $C_i > 0$ will be used as a measure. Then, when C_i is a minimum value, the collaborative optimization model is the most satisfactory model [34].

3. Model of Collaborative Uncertainty Decision

To further describe the collaborative optimization mechanism of multiple subsystems and give full play to the institutional innovation system and resource advantages, the improved Ant Colony Algorithm is introduced to improve system performance innovation $V^F(C)$. In the improved ant colony algorithm, a volatilization model is introduced in the process of pheromone partial updates and the number of outstanding ants is increased in the process of the global updates. With this algorithm, the shortcomings of the basic ant colony optimization algorithm, such as slower convergence speed and ease of convergence to a local optimal solution, are improved [35].

3.1. *Pheromone Diffusion Model.* An ant colony algorithm based on the pheromone diffusion model is proposed, and pheromone diffusion rules are given by scholars. The optimization abilities of this algorithm are close to the real behavior of ants, but the pheromone diffusion model construction is relatively complex and the local pheromone update mechanism is missing. In this case, a simplified efficient pheromone diffusion model is constructed as shown in Figure 2.

Pheromones will diffuse within a circle with centre O and radius r , as shown in Figure 2. If there is a point l in the circle, then the pheromone concentration received by l is determined by

$$\frac{\tau_O}{r} = \frac{\tau_l}{r - d_l}. \quad (10)$$

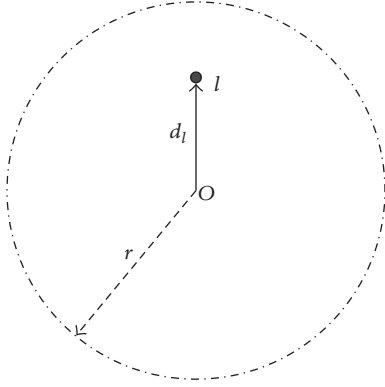


FIGURE 2: The pheromone evaporation model.

Assumptions. The position of the ant is O , and the concentration of the pheromone is τ .

3.2. Local Pheromone Update Mechanism. In the process of crawling, ants will diffuse pheromones to the path nearby through traverse points. If ant k traverses between two points i and j and the distance is d_{ij} , then the ant k will diffuse pheromones according to the pheromone diffusion model in Figure 2. The pheromone diffusion concentration of the paths connecting (i, l) and (j, l) will be changed, and the changes are $\Delta\tau_{il}^k$ and $\Delta\tau_{jl}^k$. The formula derivation is as follows.

The pheromone diffusion concentration of ant m that traverses points i, j is $\tau_O = \mu\Delta\tau_{il}^k$, where $0 < \mu < 1$, diffusion radius $r = d_{ij}^2/\bar{d}$, and the average distance of all traversed points is \bar{d} . According to formula (10), $\Delta\tau_{il}^k$ and $\Delta\tau_{jl}^k$ can be expressed as

$$\Delta\tau_{il}^k = \begin{cases} \mu \cdot \frac{1}{l_{ib}} \cdot \left(1 - \frac{d_{il} \cdot \bar{d}}{d_{ij}^2}\right), & d_{il} < r, \\ 0, & \text{otherwise,} \end{cases} \quad (11)$$

$$\Delta\tau_{jl}^k = \begin{cases} \mu \cdot \frac{1}{l_{jb}} \cdot \left(1 - \frac{d_{jl} \cdot \bar{d}}{d_{ij}^2}\right), & d_{jl} < r, \\ 0, & \text{otherwise.} \end{cases}$$

In the proposed algorithm, formulas (7) and (8) are placed into the pheromone update formula (12):

$$\tau_{ij}(i+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}^k, \quad (12)$$

$$\Delta\tau_{ij}^k = \begin{cases} \frac{1}{l_{jb}}, & \text{when the ant } k \text{ is through the city } ij, \\ 0, & \text{otherwise.} \end{cases} \quad (13)$$

Here, ρ represents the pheromone diffusion factor, $1-\rho$ represents the residual factor, $\rho \in [0, 1]$, and l_{jb} represents the path length travelled from the initial city to the current city.

Thus, compared to the pheromone update mechanism of the basic ant colony algorithm, the new pheromone diffusion

can display better collaboration ability between ants, and the convergence speed is accelerated.

3.3. Collaborative Uncertainty Decision Model Calculations. The collaborative pheromone update methodology is adopted in the moving process of ants, which speeds up the local optimization of the algorithm and simultaneously increases the likelihood of local convergence. To avoid local minima, a random disturbance is introduced and used to change the global pheromone update mechanism of the basic ant colony algorithm and prevent the algorithm from premature convergence or stagnation in the process of ant path finding. The overall algorithm framework is shown in Figure 3.

The specific steps of the algorithm design are as follows.

Step 1 (parameter initialization). Collaborative innovation evaluation index matrix information is read, and the values of the initial evaluation indices are added to the taboo table. $V^F(C)$ and fitness value table of osculation value C_i are obtained.

Step 2 (selection of the next evaluation traverse points according to the probability). The transition probabilities of traverse points are calculated based on formulas (12) and (13), and the next traverse point j is selected based on roulette rules and put into taboo table. Then, the values of $V^F(C)$ and C_i will be calculated, the retention policy based on eliteness will be implemented, and the fitness value table will also be updated.

Step 3 (local pheromone update). The corresponding path pheromone based on formulas (11) will be updated according to the pheromone diffusion model.

Step 4. If the taboo table of ant k is not full, go to Step 2.

Step 5 (global pheromone update). When all of the evaluation matrix is traversed by m ants, $V^F(C)$ and C_i will be calculated and the optimal solution will be updated. The best solution in this cycle is selected and the global pheromone updated.

Step 6. If the termination conditions are met, the calculation will be stopped and the optimal solution will be outputted.

4. Example Verification

To fully validate the science, feasibility, and effectiveness of the model, model analysis and collaborative optimization calculation for "CICOST" have been implemented. The regional collaborative innovation system comprises universities within the industry, research institutes with strong research capabilities, and sizeable enterprises with strong scientific research, and, among them, the universities are the main members and the others general members. The main data of the collaborative innovation model are shown in Table 1.

The three types of osculating value curves indicate that three types of problems increase with increasing number of evaluation indices of innovation efficiency, as shown in Figure 4.

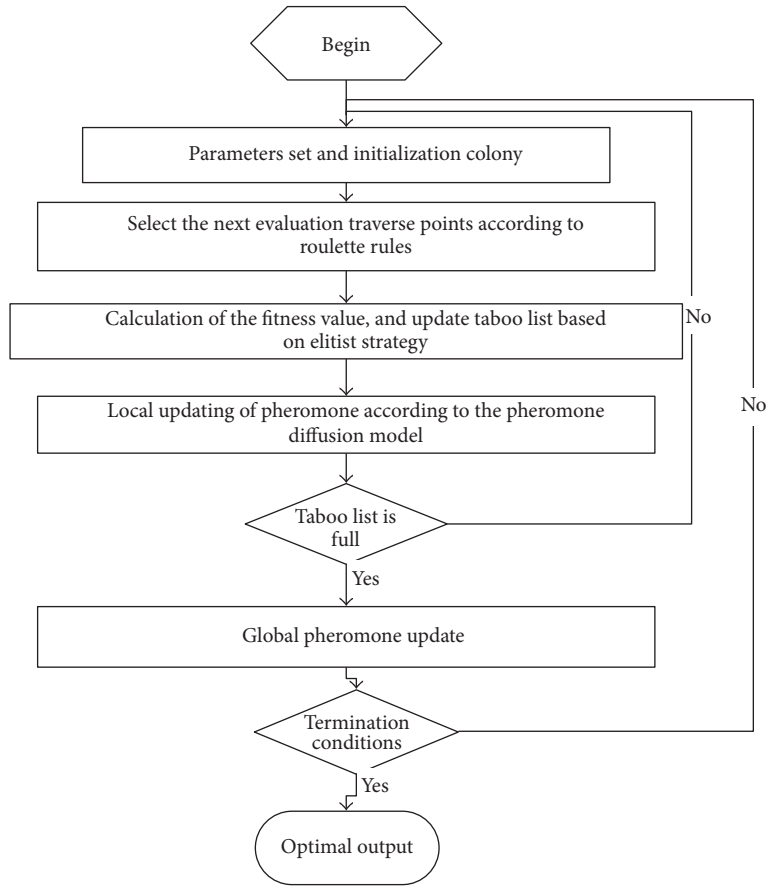


FIGURE 3: Algorithm framework.

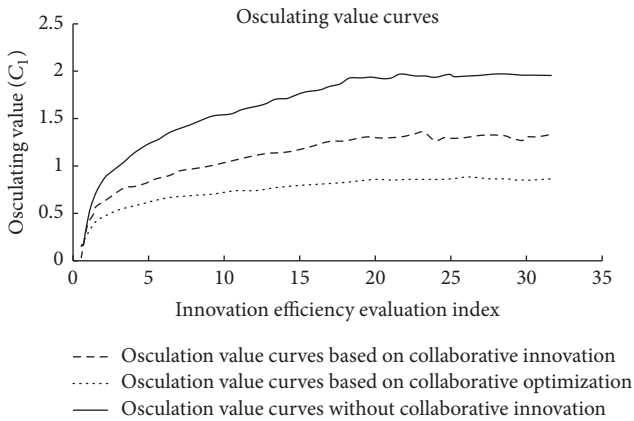


FIGURE 4: Osculation value curve.

The final calculation results are given in Table 2.

Noncollaborative innovation refers to members not integrated to form a regional collaborative innovation system, the collaborative model refers to members who become an innovative collaborative innovation system through mutual cooperation, and the optimized collaborative model refers to each member with the highest efficiency synergies. The

Euclidean distance between the most optimized point and the index evaluation value is expressed as d_i^+ , and the Euclidean distance between the worst point and the index evaluation value is expressed as d_i^- . The osculation value between the most optimized point and innovation evaluation performance $V^F(C)$ is expressed as C_i .

Table 1 shows that the innovation performance of non-collaborative innovation is 0.641, that of the collaborative innovation model is 0.720, and that of the optimized collaborative model is 0.854, which is much better than 0.720. Figure 3 results show that the best performance of the regional collaborative innovation system is obtained when the improved ant colony algorithm is used to solve the collaborative optimization problem in this paper, and as the scale of the problem is larger, the advantage is more obvious.

The effectiveness of the algorithm in optimizing the regional collaborative innovation system is analysed through the iterative curve shown in Figure 5. The basic parameters of the ant colony algorithm are set to $m = 30$, $\lambda = 5$, $\alpha = 1$, $\beta = 2$, $q_0 = 0.96$, $\rho = 0.58$, and $\mu = 0.37$. After 500 iterative calculations, the fitness value converges to 0.854, and the elapsed time is 12150 ms. This shows that a good solution and a good convergence speed of the algorithm can be obtained when solving optimization problems of a collaborative innovation system. Simultaneously, the loads

TABLE 2: The results of the models.

Type	d_i^+	d_i^-	C_i	$V^F(C)$
Noncollaborative innovation	1.825	0.523	1.899	0.641
Collaborative innovation model C	0.728	0.576	1.341	0.720
Optimized collaborative innovation model C'	0.808	0.712	0.598	0.854

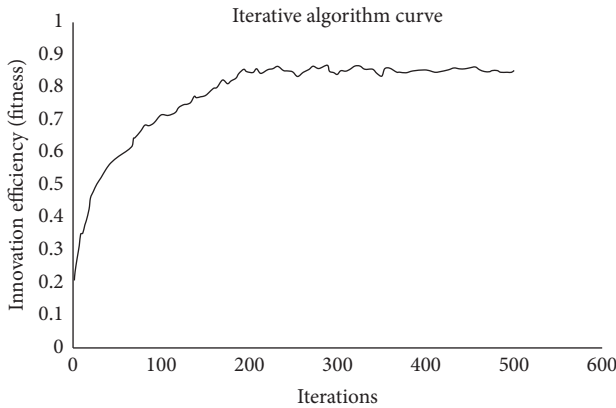


FIGURE 5: Convergence curve of algorithm search optimization.

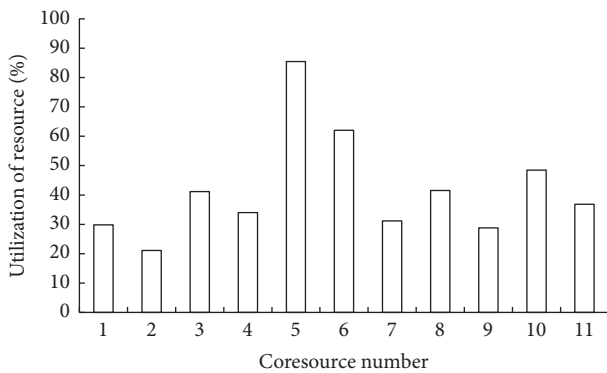


FIGURE 6: Load optimization of 11 class sharing resources of the collaborative innovation system.

used for 11 class sharing resources were compared before and after optimization using the histograms in Figures 6 and 7, which show that the loads used for the resources are more balanced and that the overall resource utilizations are improved after collaborative optimization.

The evaluation results of the regional collaborative innovation system of “CICOST” show that “CICOST” takes leading industry and national development as its own duty and addressing the major needs of the country and the industry as a goal. It brings together domestic first-class universities and large enterprise groups with collaborative members making decisions. According to the significant scientific research task, it has produced a substantial collaboration, formed a collaborative innovation culture with active innovation and exploration and the establishment of a risk and benefit sharing system, and carried out scientific planning around major

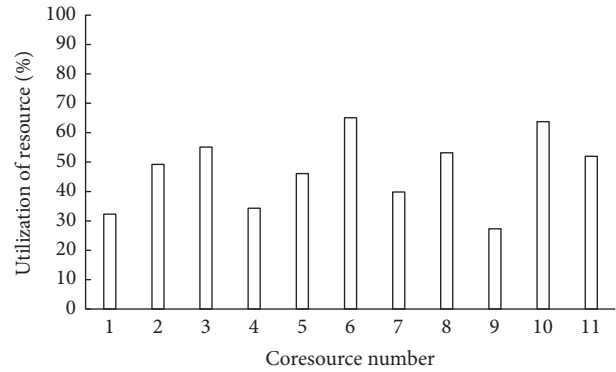


FIGURE 7: Optimized resources of the collaborative innovation system.

innovation tasks. It has made significant progress whether in the high level of team building, personnel training, science and technology awards, intellectual property rights, and so forth or in terms of institutional reform and other aspects, particularly in innovative exploration and reform of talent cultivation. The reform of the system is still in its initial stage, because it is a new innovation system. The aspects of the high level of cooperation in scientific and technological innovation, high level of talent and innovation team management system, high level personnel training system, and so on still need to strengthen.

5. Conclusion

Optimization analysis and an improved ant colony algorithm were implemented for the members of a collaborative innovation system. The algorithm, which improves the pheromone update mechanism and enhances the collaboration ability of ants in path selection, optimizes the balance of resources and loads of the system. Thus, if we select collaborative innovation members based on the ant colony algorithm, the technical strengths of cooperative members selected will be fully utilized, and, through an effective collaborative decision mechanism, the value of innovation will be promoted, the efficiency of innovation will be improved, and a scientific basis for collaborative uncertainty decision of cooperative members will be provided.

Disclosure

The authors declare that this work is the extension of the link paper entitled “A Verification Model of Collaborative Innovation Optimization System Based on Ant colony Algorithm.”

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work was supported by philosophy and social science research projects of Heilongjiang Province (15GLC03) and key research topics of economic and social development in Heilongjiang Province (15119).

References

- [1] H. Yubing, "Theoretical model of production-study-research cooperative innovation," *Studies in Science of Science*, vol. 2, pp. 165–172, 2012.
- [2] C. Jin and Y. Yinjuan, "The theoretical basis and connotation of collaborative innovation," *Studies in Science of Science*, vol. 2, pp. 161–154, 2012.
- [3] L. Junhua, W. Yaode, and Ch. Yueming, "Research on the operation mechanism of collaborative innovation in Regional Innovation Networks," *Science & Technology Progress and Policy*, vol. 7, pp. 32–35, 2012.
- [4] W. Xiangbing, Y. Guangle, and Y. Weizhong, "The game mechanism for dynamic evolution of regional innovation system," *Science Research Management*, vol. 11, no. 33, pp. 1–8, 2011.
- [5] D. Li and M. Chenglin, "Research on the relations of R&D investment and technology innovation performance—an empirical analysis based on panel data in the eastern region," *Journal of Anhui University of Science and Technology (Social Science)*, vol. 2015, no. 7, pp. 36–40, 2015.
- [6] P. Karjalainen, "R&D investments: the effects of different financial environments on firm profitability," *Journal of Multinational Financial Management*, vol. 18, no. 2, pp. 79–93, 2008.
- [7] A. Jaffe, M. Trajtenberg, and M. Fogarty, "Knowledge spillovers and patent citations: evidence from a survey of inventors," *American Economic Review*, no. 90, pp. 215–218, 2000.
- [8] J.-Y. Xu, S.-Y. Li, and P. Li, "Institution quality, institution distance and the motivations of Chinese international intelligence return," *Studies in Science of Science*, vol. 31, no. 3, pp. 350–357, 2013.
- [9] P. Aghion and P. Howitt, "A model of growth through creative destruction," *Econometrics*, vol. 60, no. 2, pp. 323–351, 1992.
- [10] S. Yi and C. Fengyan, "Regional innovation systems based on stochastic frontier analysis: a study on thirty-one provinces in China," *Science, Technology & Society*, vol. 20, no. 2, pp. 204–224, 2015.
- [11] Z. Xiuwu and H. Ridong, "Analysis on innovation driving force of region high-tech industry: based on the view point of industrial cluster," *Journal of Finance and Economics*, no. 4, pp. 37–49, 2008.
- [12] C. De Fuentes and G. Dutrénit, "Best channels of academia-industry interaction for long-term benefit," *Research Policy*, vol. 41, no. 9, pp. 1666–1682, 2012.
- [13] K. Motohashi, "University-industry collaborations in Japan: the role of new technology-based firms in transforming the National Innovation System," *Research Policy*, vol. 34, no. 5, pp. 583–594, 2005.
- [14] R. Bekkers and I. M. Bodas Freitas, "Analysing knowledge transfer channels between universities and industry: to what degree do sectors also matter?" *Research Policy*, vol. 37, no. 10, pp. 1837–1853, 2008.
- [15] P. D'Este and P. Patel, "University–industry linkages in the UK: what are the factors underlying the variety of interactions with industry?" *Research Policy*, vol. 36, no. 9, pp. 1295–1313, 2007.
- [16] L. Gang and L. Yang, "Decision-oriented collaborative innovation intelligence service of think -tank: the functional orientation and system construction," *Library and Information*, no. 1, pp. 36–43, 2016.
- [17] L. Li-Jun, "Research on collaborative innovation mechanism of decision support information security of characteristic think tank," *Researches in Library Science*, no. 7, pp. 62–65, 2014.
- [18] J. Ma and X. Jin, "Selection research on synergistic innovation mode of the 'industry-university' based on the joint-decision perspective," *Soft Science*, vol. 29, no. 2, pp. 61–67, 2015.
- [19] T. Wen-Xian, T. Chun-Chao, and L. Li-Min, "The decision model and grey relative analysis for the collaborative innovation development of products," *Information of Manufacturing Industry in China*, vol. 34, no. 7, pp. 105–107, 2005.
- [20] T. Bui and J. Lee, "An agent-based framework for building decision support systems," *Decision Support Systems*, vol. 25, no. 3, pp. 225–237, 1999.
- [21] B. E. Hansen, "Threshold effects in non-dynamic panels: estimation, testing, and inference," *Journal of Econometrics*, vol. 93, no. 2, pp. 345–368, 1999.
- [22] X. Li, "China's regional innovation capacity in transition: an empirical approach," *Research Policy*, vol. 38, no. 2, pp. 338–357, 2009.
- [23] Z. J. Acs, L. Anselin, and A. Varga, "Patents and innovation counts as measures of regional production of new knowledge," *Research Policy*, vol. 31, no. 7, pp. 1069–1085, 2002.
- [24] J. Wu, Z. Zhou, and L. Liang, "Measuring the performance of Chinese regional innovation systems with two-stage DEA-based model," *International Journal of Sustainable Society*, vol. 2, no. 1, pp. 85–99, 2010.
- [25] S. Yi, J. Xuesong, L. Jiasu, and L. Zhouzhou, "Research on collaborative evolution of regional innovation system based on B-Z reaction," *China Soft Science*, no. 3, pp. 44–61, 2016.
- [26] J. M. Zabala-Iturriagoitia, P. Voigt, A. Gutiérrez-Gracia, and F. Jiménez-Sáez, "Regional innovation systems: how to assess performance," *Regional Studies*, vol. 41, no. 5, pp. 661–672, 2007.
- [27] P. Cooke, "Regional innovation systems: origin of the species," *International Journal of Technological Learning, Innovation and Development*, vol. 1, no. 3, pp. 393–409, 2008.
- [28] C. Renyong, Y. Xiaofen, and L. Zhengwei, "An analysis of differences in innovation efficiency between the eastern & the western regions in China and its causes," *China Soft Science*, no. 8, pp. 128–131, 2004.
- [29] H. Feng and C. Rong, "Corporate governance, managerial incentive and firm efficiency—an empirical analysis of Chinese listed company in several industries," *Journal of Management Sciences in China*, no. 8, pp. 142–152, 2008.
- [30] L. Lingli and L. Jianhua, "Empirical study on the efficiency of regional R&D resource allocation based on stochastic frontier analysis," *Science of Science and Management of S.& T*, no. 12, pp. 39–44, 2007.
- [31] W. Yanbing, "Measurement on R&D output elasticity of China's industrial sector," *China Economic Quarterly*, no. 4, pp. 869–890, 2008.
- [32] J. Junfeng, S. Zhao-Han, and W. Xiula, "Modeling the techno-innovative cooperation between enterprises with asymmetric

- capability," *Journal of Systems Engineering*, no. 3, pp. 335–342, 2009.
- [33] L. Shunzhong and G. Jiancheng, "The evaluation on the innovating performance of regional innovation systems," *Chinese Journal of Management Science*, no. 1, pp. 75–78, 2002.
- [34] W. Weiguo and X. Lanyun, "The empirical research about the relationship of Chinese regional R&D expenditure and economic development," *Research on Financial and Economic Issues*, no. 11, pp. 108–115, 2009.
- [35] G. E. Battese and T. J. Coelli, "A model for technical inefficiency effects in a stochastic frontier production function for panel data," *Empirical Economics*, vol. 20, no. 2, pp. 325–332, 1995.



Hindawi

Submit your manuscripts at
<http://www.hindawi.com>

