A Self-determined Evaluation Method for Science Popularization Based on IOWA Operator and Particle Swarm Optimization

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Abstract. With the increase of science popularization, evaluation of science popularization has become an urgent demand. Considering science popularization bases as independent agents, a self-determined evaluation approach for science popularization using induced ordered weighted averaging (IOWA) operator and particle swarm optimization (PSO) is proposed in this paper. Firstly, six factors including science popularization personnel, space, fund, media, activity and influence are selected to construct an index system for science popularization evaluation. On this basis, the absolute dominance and relative dominance of evaluation indexes are used as induced components, and the prior order of the evaluation indexes is determined. Besides, the optimization model of index weighted vectors is established by IOWA operator, index weighted vectors are calculated by particle swarm optimization algorithm, and index weighted vectors and evaluation value vectors are obtain. Finally, the optimal evaluation vectors and evaluation results are given according to the Perron-Frobenius decision eigenvalve theorem .

Keywords: Science popularization · Self-determined evaluation · Induced Ordered Weighted Averaging operator · Particle swarm optimization · Perron-Frobenius decision eigenvalve theorem

1 Introduction

With the rapid development of science and technology, the industry deeply aware that to promote the marketization process of the science and technology, they need to further strengthen the science popularization work and improve public response speed for new technology products. With the increasing of the popularization, it has become an urgent demand to carry out evaluation work to measure the effect and to promote the quality of the science popularization work. The evaluation method for science popularization has gradually become one of the research hotspots in social computing.

In the world, the study on science popularization evaluation is mostly a summary of the practice method. The evaluation indexes mainly consider the universal surface, influence on the attitude and behavior of the public. Information collection is the first step, which mainly include the field interviews, questionnaires survey and Internet feedbacks [1–3]. In China, science popularization evaluation has made some achievements.

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Li Zhaohui et al. evaluated the science popularization infrastructure development from the scale, structure, and effect 3 aspects, employed the Delphi method to determine the weights of the index [4]. Ren Rongrong et al. established the evaluation index system of regional science popularization ability in 5 aspects including investment, facilities, personnel, creation and activity organization. They also combined the entropy weight method with GEM to determine the index weight [5]. Zuo Qingfu et al. established the effect evaluation index system of the project on science popularization benefiting peasants and prospering the rural, employed analytic hierarchy process method to calculate index weight [6]. Wu Huagang established the evaluation index system of science popularization resources construction, employed the global principal component analysis method to evaluate the science popularization resource construction level in 31 provinces / autonomous regions / municipalities in China [7].

It can be seen from the research status on science popularization evaluation that the existing science popularization evaluation methods are all considered evaluation target as passive "evaluation object", which has no "discourse right" in the evaluation. While the views of the evaluation target should be adopted comprehensively in the actual evaluation, carry out self-determined evaluation with "fair competition" concept [8]. In view of this, this paper give full independence to the science popularization base and introduce the Induced Ordered Weighted Averaging (IOWA) operator into the science popularization level evaluation to construct the self-determined evaluation model. The model is solved by particle swarm optimization algorithm, and then the self-determined evaluation results of science popularization are given.

2 The Evaluation Index System of Science Popularization

The primary task of science popularization evaluation is to establish a scientific evaluation index system. This paper refer to science popularization statistic survey which made by the Ministry of Science and Technology in the People's Republic of China. The science popularization personnel, space, fund, media, activity and influence six first level indexes are selected, and be subdivided into twenty-two second level indexes, establishing a science popularization evaluation index system, as shown in Table 1.

3 A Self-determined Evaluation Model for Science Popularization Based on IOWA

3.1 Formation of Decision Matrix for Science Popularization Evaluation

The n science popularization base to be evaluated is $E_i(i = 1, 2, \cdots, n \in N)$, where the j-th evaluation index is $x_j(j = 1, 2, \cdots, m \in M)$, then the indexes set of science popularization base is $I_i = \{x_{i1}, x_{i2}, \cdots, x_{ij}, \cdots, x_{im}\}$, where x_{ij} represents the value of the j-th evaluation index for the i-th science popularization base. All x_{ij} consist of the evaluation index matrix.

Table 1. Evaluation index system for science popularization

First-level index	Second-level index
Science popularization personnel	Full-time personnel I_1
	Part-time personnel I_2
	Volunteers I_3
Science popularization space	Area of exhibition hall I_4
	The number of exhibits I_5
	Equipment I_6
Science popularization fund	Annual funds raised I_7
	Annual amount used I_8
	Special funds I_9
Science popularization media	Annual number of science popularization books published I_{10}
	Annual number of science popularization periodicals published I_{11}
	Annual total page view of science popularization website I_{12}
	Other science popularization readings I_{13}
Science popularization activity	Person-time of participants in science popularization lectures and training I_{14}
	Person-time of visitors for science popularization exhibitions I_{15}
	Person-time of participants in science popularization competitions I_{16}
	Person-time of participants in international communication of science popularization I_{17}
	Person-time of young participants in science popularization I_{18}
	Person-time of participants in science and technology activity week I_{19}
Science popularization influence	Affirmation and naming I_{20}
	Science popularization award I_{21}
	Media coverage I_{22}

$$\mathbf{X} = (x_{ij})_{n \times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix}. \quad (1)$$

Since the dimension of the evaluation index is not consistent, $\boldsymbol{X}$ should be normalized before the evaluation, and the normalized matrix is called the evaluation decision matrix $\boldsymbol{X}' = \left(x'_{ij}\right)_{n \times m}$. Because all the evaluation indexes selected in this paper are the benefit indexes, so they can be standardized as follows:

$$x'_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}}. \quad (2)$$

3.2 Absolute and Relative Dominance Calculation of Evaluation Index

In the self-determined evaluation, the competition field of the evaluation subject should be determined at first. For science popularization base E_i, the determination method of its competition field as follows:

(1) For $\forall j \in M$, if $x_{ij} \geq x_{kj}(k \in N, k \neq i)$, then science popularization base E_i is better than E_k, not form a competitive relationship.
(2) For $\forall j \in M$, if $x_{ij} \leq x_{kj}(k \in N, k \neq i)$, then science popularization base E_i is worse than E_k, not form a competitive relationship.
(3) For $\forall j \in M$, if both $x_{ij} \geq x_{kj}$ and $x_{ij} \leq x_{kj}(k \in N, k \neq i)$ existing, then science popularization base E_i and E_k form a competitive relationship.

For science popularization base E_i, the set of the science popularization bases which form the competitive relationship with it is called competition field of E_i, as $H_i = \left\{E_1^{(i)}, E_2^{(i)}, \cdots, E_{n_i}^{(i)}\right\}$, where n_i represents the number of the science popularization bases which form the competitive relationship with E_i.

Set the competition intensity of the j-th evaluation index x_i of popularization science base E_i relative to E_k in the competition field [8].

$$d_{ik}^{(j)} = x_{ij} - x_{kj}(i, k \in N; j \in M). \tag{3}$$

For science popularization base E_i, the absolute dominance and relative dominance of the evaluation indexes are:

$$\lambda_i^{(j)} = \frac{\sum_{m=1}^{P_i} d_{im}^{(j)}}{\sum_{m=1}^{n_i} \left| d_{ik}^{(j)} \right|}. \tag{4}$$

$$\lambda_i'^{(j)} = \frac{\exp(\sum_{k=1}^{n_i} d_{ik}^{(j)})}{\sum_{j=1}^{m} \exp(\sum_{k=1}^{n_i} d_{ik}^{(j)})}. \tag{5}$$

Where, P_i is the number of the non-negative value of the competition strength of science popularization base E_i relative to all the science popularization bases in the competition field.

3.3 Determination of Position Weight Vector

For science popularization base E_i, the position weight vector of the evaluation index is $\boldsymbol{w} = \left(w_1, w_2, \cdots w_j, \cdots, w_m\right)^T$, where

$$w_j = \frac{q^{\sum_{l=1}^{j} \eta_l}}{\sum_{j=1}^{m} q^{\sum_{l=1}^{j} \eta_l}}. \tag{6}$$

In Eq. (6), $\eta_1 = 1 - \left(\alpha\lambda_i^{(l)} + \beta\lambda_i'^{(l)}\right), (l \in M), 0 < q < 1, \alpha\lambda_i^{(l)} + \beta\lambda_i'^{(l)}$, is the overall competitive advantage of the l-th index, α and β are the preference of the absolute and relative dominance of the evaluation expert respectively, $\alpha + \beta = 1$, $\alpha, \beta \in [0, 1]$, this paper set $\alpha = \beta = 0.5$.

Take the absolute and relative preference dominance as the induced components, the evaluation value of the science popularization base E_k with E_i as the evaluation subject is [9]

$$\begin{aligned} & Y_k[(\lambda_1^{(1)}, \lambda_1^{'(1)}, x_{1m}), (\lambda_2^{(2)}, \lambda_2^{'(2)}, x_{2m}), \cdots, (\lambda_i^{(k)}, \lambda_i^{'(k)}, x_{km})] \\ & = \sum_{j=1}^{m} w_j a_{kj} (k \in N). \end{aligned} \tag{7}$$

Where, a_{kj} is the value of the j-th ranked evaluation index of the science popularization base E_k.

According to the ordered weight averaging operator, the following optimization model can be used to solve the position weight vector:

$$\max \quad orness(w) = \frac{1}{m-1} \sum_{j=1}^{m} [(m-j) w_j]$$
$$s.t. \begin{cases} w_j = \dfrac{q^{\sum_{l=1}^{j} \eta_l}}{\sum_{j=1}^{m} q^{\sum_{l=1}^{j} \eta_l}}, j \in M \\ 0 < q < 1, 0 < w_1 \le 0.5. \end{cases} \tag{8}$$

3.4 Aggregation of Self-determined Evaluation Values

If science popularization base E_i is the evaluation subject, whose given evaluation values of all the science popularization bases are $y^{(i)} = \left(y_1^{(i)}, y_2^{(i)}, \cdots, y_n^{(i)}\right)^T$, the evaluation value vector of all the science popularization bases is recorded as $\boldsymbol{Y} = \left(y^{(1)}, y^{(2)}, \cdots, y^{(n)}\right)$. The sum of the angle between the optimal self-determined evaluation vector $\boldsymbol{y}^* = \left(y_1^*, y_2^*, \cdots, y_n^*\right)^T$ and the vector $y_1^{(i)}, y_2^{(i)}, \cdots, y_n^{(i)}$ should be the smallest, so that $\boldsymbol{y}^*$ can be obtained according to the Perron-Frobenius decision eigenvalve theorem [10].

Theorem 1. For $\forall y \in R^n, \max\limits_{\|y\|_2} \sum\limits_{i=1}^{n} \left(y^T, y^{(i)}\right)^2 = \sum\limits_{i=1}^{n} \left((y^*)^T, y^{(i)}\right)^2 = \lambda_{\max}$, where $\lambda_{\max}$ is the largest eigenvalve of $\boldsymbol{YY}^T, \boldsymbol{Y} = \left(y^{(1)}, y^{(2)}, \cdots, y^{(n)}\right)$ is the positive eigenvectors of $\lambda_{\max}$ correspond to $\boldsymbol{YY}^T$, and $\|\boldsymbol{y}^*\|_2 = 1$.

4 Optimal Evaluation Value Solve Based on Particle Swarm Optimization Algorithm

4.1 Particle Swarm Optimization Algorithm

Particle swarm optimization algorithm is an intelligent iterative optimization algorithm based on group oriented search, which is easy to implement, and has good robustness and fast convergence speed [11–14]. In the previous iteration of the standard particle swarm optimization algorithm, the particle i is updated according to the velocity v and position x:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (p_g^k - x_i^k). \tag{9}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}. \tag{10}$$

Where, k is the number of iterations, p_i^k is the history optimal position of the i-th individual particle in the k-th iteration; p_g^k is the history optimal position of group in the k-th iteration; ω is inertial weight; c_1 and c_2 is the learning factor which controlling the maximum step size; r_1 and r_2 are the random number between [0,1]; to ensure the search efficiency of the particle, usually limited velocity $v_i = [-v_{\min}, v_{\max}]$.

4.2 Solving Process of Optimal Evaluation Value

For the optimization model of Eq. (8), the PSO algorithm is employed to solve the optimal position weight vector, the optimal evaluation value vector, and then obtain the evaluation result. The calculation flow is shown in Fig. 1.

5 Case Analysis

Through the issuance of science popularization survey, collected the operational data of annual Guangzhou new energy and renewable energy science popularization base, Beijing new energy automobile exhibition center, smart grid demonstration hall of Sichuan electric power company of state grid, Yancheng new energy automobile industrial park and the Xin'ao group energy innovation experience center 5 science popularization bases ($E_1 \sim E_5$), as shown in Table 2, where p-t means person-times.

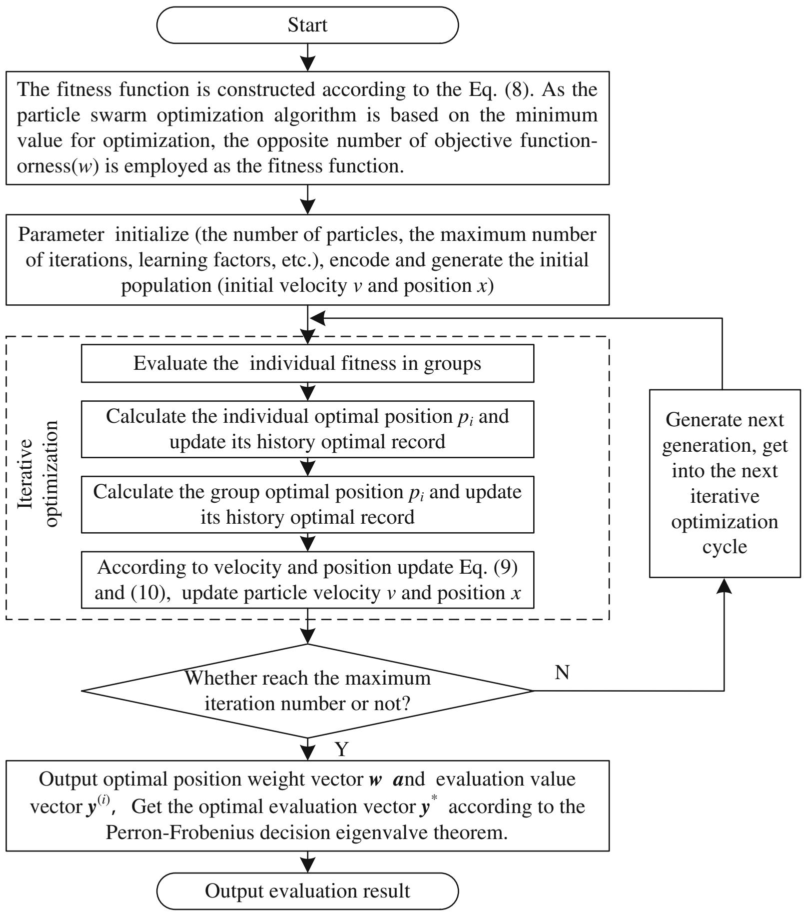

Fig. 1. The calculation process of optimal evaluation value and evaluation result

Table 2. Operation data from science popularization bases

Index	E_1	E_2	E_3	E_4	E_5
I_1	2	1	5	2	2
I_2	16	15	7	45	0
I_3	0	80	28	60	0
I_4	450 m^2	1100 m^2	900 m^2	600 m^2	660 m^2
I_5	17 pcs.	6 pcs.	20 pcs.	200 pcs.	4 pcs.
I_6	10 sets	51 sets	20 sets	15 sets	30 sets
I_7	280000	215000	800000	200000	8000000
I_8	260000	215000	500000	200000	8000000
I_9	0	0	200000	100000	2000000

(*Continued*)

Table 2. (*Continued*)

Index	E_1	E_2	E_3	E_4	E_5
I_{10}	0	0	600	0	10000
I_{11}	0	0	0	0	12000
I_{12}	8000	0	0	4000	0
I_{13}	1000	5847	500	5000	0
I_{14}	1000 p-t	0	400 p-t	200 p-t	6000 p-t
I_{15}	5000 p-t	5847 p-t	1200 p-t	5000 p-t	3099 p-t
I_{16}	200 p-t	0	0	0	300 p-t
I_{17}	0	503 p-t	0	20 p-t	576 p-t
I_{18}	2500 p-t	1671 p-t	400 p-t	300 p-t	500 p-t
I_{19}	2000 p-t	0	200 p-t	100 p-t	0
I_{20}	3	6	2	1	2
I_{21}	0	0	0	3	0
I_{22}	3 times	23 times	18 times	27 times	100 times

The evaluation process of this method is as follows:

STEP1. Form the science popularization evaluation decision matrix.

According to Table 2 and Eq. (2), normalized the index data of the science popularization evaluation, obtain the decision matrix $\boldsymbol{X}$.

STEP2. Calculate the absolute and relative dominance of the index.

According to Eq. (3)−(5), ensure the evaluation index priority order of the 5 science popularization base, and calculate the absolute and relative dominance, as shown in Table 3.

STEP3. Solve evaluation value vector.

In this paper, the PSO algorithm is employed to solve the optimization model of position weight vector. In order to find a PSO algorithm which has more advantage for solving, the accuracy, speed and stability of the standard particle swarm optimization (SPSO) [11], modified particle swarm optimization (MPSO) [12], improved particle swarm optimization algorithm (IPSO) [13] and time-varying acceleration coefficients particle swarm optimization algorithm (TACPSO) [14] are tested respectively. The object E_5 is chosen as an example to be evaluated, set the number of particles 10, 20 and 50 respectively, statistical data of fitness values and convergence iteration numbers are given of the four PSO algorithms for the 20 times continuous operation. The results are shown in Tables 4 and 5; when the number of particles is 50 and the maximum iteration number is 100, the convergence curve of the average fitness changing with the iteration number is shown in Fig. 2.

It can be seen from the figure and tables, the accuracy of the four PSO algorithms are very high, and the convergence speeds are very fast. In general, the performance of the four algorithms ranked as: TACPSO>IPSO>MPSO>SPSO.

The optimal q value and the minimum fitness are obtained by particle swarm optimization, and the corresponding evaluation value vector $\boldsymbol{y}^{(i)}$ is shown in Table 6.

Table 3. The evaluation index priority order and dominance of the science popularization base

E_1			E_2			E_3			E_4			E_5		
x_j	$\lambda_1^{(j)}$	$\lambda_1'^{(j)}$	x_j	$\lambda_2^{(j)}$	$\lambda_2'^{(j)}$	x_j	$\lambda_3^{(j)}$	$\lambda_3'^{(j)}$	x_j	$\lambda_4^{(j)}$	$\lambda_4'^{(j)}$	x_j	$\lambda_5^{(j)}$	$\lambda_5'^{(j)}$
x_{19}	0.2500	0.0050	x_{20}	0.0000	0.0014	x_1	1.0000	0.5337	x_{21}	0.2500	0.0040	x_{11}	0.2500	0.0017
x_{12}	0.4727	0.0078	x_6	0.4259	0.0066	x_9	0.1129	0.0071	x_5	1.0000	0.1565	x_8	0.0000	0.0005
x_{18}	0.0000	0.0010	x_3	1.0000	0.1431	x_4	0.4000	0.0146	x_2	0.8837	0.0347	x_{10}	0.0000	0.0004
x_{16}	0.0000	0.0009	x_{13}	1.0000	0.1236	x_3	0.8319	0.0698	x_{13}	0.1485	0.0022	x_7	0.2842	0.0015
x_{15}	0.1143	0.0036	x_4	0.0090	0.0026	x_6	0.1549	0.0098	x_3	1.0000	0.3109	x_{14}	0.0000	0.0009
x_{20}	0.0000	0.0013	x_{15}	1.0000	0.1830	x_{19}	0.2679	0.0110	x_{15}	0.0820	0.0019	x_{22}	0.6818	0.0052
x_2	0.0173	0.0029	x_{17}	0.0018	0.0027	x_7	0.1915	0.0102	x_{12}	0.0000	0.0022	x_{16}	1.0000	0.1438
x_{14}	0.0130	0.0030	x_{18}	0.0018	0.0028	x_{20}	0.0991	0.0088	x_9	0.0000	0.0023	x_{17}	1.0000	0.1498
x_1	0.0000	0.0007	x_2	0.0000	0.0006	x_{10}	1.0000	0.2521	x_{22}	0.5000	0.0067	x_9	1.0000	0.0351
x_{13}	0.0000	0.0029	x_{22}	0.0000	0.0027	x_5	0.1607	0.0097	x_1	0.0000	0.0023	x_6	1.0000	0.1480
x_5	0.0000	0.0031	x_5	0.0000	0.0029	x_{22}	0.0000	0.0076	x_4	0.0000	0.0025	x_4	1.0000	0.1572
x_7	1.0000	0.2747	x_8	0.0000	0.0018	x_2	0.0000	0.0046	x_{19}	0.7500	0.0181	x_1	0.0000	0.0006
x_8	0.1450	0.0024	x_7	1.0000	0.1414	x_8	0.0461	0.0038	x_6	0.9410	0.0581	x_{15}	0.0000	0.0003
x_{11}	0.3243	0.0054	x_{11}	0.0000	0.0022	x_{14}	0.0882	0.0081	x_{17}	0.0286	0.0022	x_{20}	1.0000	0.1204
x_{21}	0.8706	0.0236	x_{21}	1.0000	0.0557	x_{13}	0.0000	0.0010	x_{14}	0.8706	0.0190	x_{18}	0.2248	0.0011
x_{10}	0.8571	0.0439	x_{10}	0.0000	0.0015	x_{18}	0.0000	0.0039	x_{11}	0.0000	0.0013	x_{21}	1.0000	0.0807
x_{22}	0.0000	0.0012	x_{19}	0.9533	0.0920	x_{11}	0.0000	0.0031	x_8	0.0371	0.0012	x_{19}	1.0000	0.0634
x_6	1.0000	0.2119	x_{14}	0.8214	0.0306	x_{21}	0.0280	0.0045	x_{10}	0.0000	0.0011	x_5	0.0864	0.0008
x_{17}	1.0000	0.3899	x_{12}	0.0000	0.0025	x_{12}	0.2174	0.0108	x_7	0.0909	0.0027	x_{12}	0.0000	0.0009
x_3	0.5714	0.0101	x_{16}	1.0000	0.1931	x_{16}	0.1667	0.0093	x_{16}	0.0000	0.0011	x_2	0.1667	0.0013
x_4	0.0000	0.0031	x_1	0.0000	0.0029	x_{17}	0.0000	0.0076	x_{18}	1.0000	0.3642	x_3	0.0000	0.0011
x_9	0.0000	0.0017	x_9	0.2358	0.0044	x_{15}	0.1351	0.0090	x_{20}	0.3364	0.0046	x_{13}	1.0000	0.0855

Table 4. The statistical data of fitness values for convergence

Number of particles	Optimization algorithm	Fitness values for convergence			
		Optimal value	Worst value	Mean value	Standard deviation
10	SPSO	−0.9534409174	−0.9534373473	−0.9534403495	8.3018E-07
	MPSO	−0.9534409298	−0.9534409257	−0.9534409293	9.0273E-10
	IPSO	**−0.9534409298**	−0.9534409288	−0.9534409296	2.3167E-10
	TACPSO	**−0.9534409298**	**−0.9534409295**	**−0.9534409297**	**8.7945E-11**
20	SPSO	−0.9534409295	−0.9534386345	−0.9534404503	6.0019E-07
	MPSO	**−0.9534409298**	−0.9534409288	−0.9534409296	2.1754E-10
	IPSO	**−0.9534409298**	−0.9534409291	−0.9534409296	1.9105E-10
	TACPSO	**−0.9534409298**	**−0.9534409296**	**−0.9534409297**	**3.9564E-11**
50	SPSO	−0.9534409293	−0.9534404423	−0.9534408261	1.2766E-07
	MPSO	**−0.9534409298**	**−0.9534409297**	**−0.9534409297**	1.2102E-11
	IPSO	**−0.9534409298**	**−0.9534409297**	**−0.9534409297**	3.3404E-11
	TACPSO	**−0.9534409298**	**−0.9534409297**	**−0.9534409297**	**1.0032E-11**

Table 5. The statistical data of iteration numbers for convergence

Number of particles	Optimization algorithm	Iteration numbers for convergence			
		Maximum value	Minimum value	Mean value	Standard deviation
10	SPSO	96	47	75.00	13.9812
	MPSO	67	**11**	51.10	14.4801
	IPSO	68	37	54.45	**8.0163**
	TACPSO	**65**	21	**49.85**	12.7497
20	SPSO	85	37	67.25	13.0015
	MPSO	65	**20**	46.35	11.5953
	IPSO	**57**	23	**46.00**	**8.9736**
	TACPSO	66	22	46.70	9.7877
50	SPSO	77	10	50.15	19.4970
	MPSO	55	8	39.10	**10.9299**
	IPSO	**51**	7	36.75	12.8345
	TACPSO	53	**1**	**32.30**	12.7159

STEP4. Solve the self-determined evaluation value, give the evaluation results

According to the Table 6, $\boldsymbol{y}^{(i)}$ is constructed to evaluate the matrix $\boldsymbol{Y}$, get the characteristic root diagonal matrix $\boldsymbol{D}$ and its corresponding eigenvectors matrix $\boldsymbol{V}$.

$$\mathbf{D} = \begin{bmatrix} 0.4316 & & & & \\ & 0.6358 & & & \\ & & 0.7586 & & \\ & & & 1.0772 & \\ & & & & 2.5229 \end{bmatrix}. \tag{11}$$

$$\mathbf{V} = \begin{bmatrix} 0.1258 & 0.4023 & 0.7196 & -0.4176 & 0.3608 \\ -0.2434 & -0.8126 & 0.1601 & -0.1695 & 0.4755 \\ 0.8412 & -0.0708 & -0.2310 & 0.1763 & 0.4504 \\ -0.2957 & 0.3288 & -0.6242 & -0.4505 & 0.4602 \\ -0.3602 & 0.2544 & 0.1161 & 0.7502 & 0.4787 \end{bmatrix}. \quad (12)$$

The largest eigenvalve of $\boldsymbol{YY}^T$ is $\lambda_{\max} = 2.5229$, by the Perron-Frobenius decision eigenvalve theorem, its corresponding eigenvalve column vector is the optimal

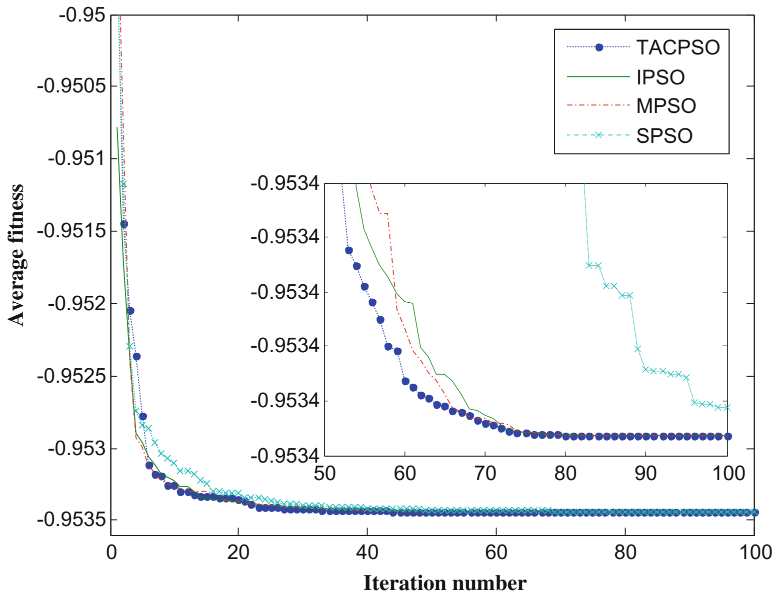

Fig. 2. The convergence curve of the average fitness (the number of particles is 50) (Color figure online)

Table 6. The evaluation value vector of science popularization bases

Science popularization base	q value	Minimum fitness	Evaluation value vector $\boldsymbol{y}^{(i)}$
E_1	0.1869	−0.9590986825	$(0.9716,0.1171,0.0582,0.1811,0.0796)^T$
E_2	0.1941	−0.9545581273	$(0.2250,0.9976,0.2336,0.1995,0.2473)^T$
E_3	0.2480	−0.9621242911	$(0.1291,0.1979,0.9124,0.3415,0.4745)^T$
E_4	0.1781	−0.9587023359	$(0.0852,0.1341,0.0567,0.9827,0.0045)^T$
E_5	0.1988	−0.9534409298	$(0.0125,0.0072,0.0283,0.0057,0.9996)^T$

self-determined evaluation value $y^* = (0.3608, 0.4755, 0.4504, 0.4602, 0.4787)^T$. So far, the science popularization level of the 5 science popularization bases are ranked as $E_5 > E_2 > E_4 > E_3 > E_1$.

6 Conclusion

(1) Overall considered science popularization personnel, space, fund, media, activity and influence these 6 aspects, established a science popularization evaluation index system, which ensure the systematicness of the evaluation.
(2) Combined the IOWA operator and PSO algorithm, studied the science popularization level self-determined method, fully considered the index value differences of the science popularization bases, and provided a new scientific quantitative analysis method for the science popularization evaluation.
(3) The PSO algorithm was employed to solve the position weight vector, which having the advantages of fast computation speed, high accuracy and good stability, could ensure the accuracy of the evaluation value vector.

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