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Optimization Research on Evaluation Indicators of Corporate Culture Management Based on Improved Particle Swarm Algorithm

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Abstract: *With the advancement of the knowledge economy, corporate culture has become pivotal for enhancing innovation, development, and soft power within enterprises. This study addresses the optimization of corporate culture management indicators using an innovative approach based on improved multi-objective particle swarm optimization (IMOPSO). Firstly, a comprehensive corporate culture evaluation system was established, integrating multiple key evaluation indicators weighted using the entropy weight method. Secondly, the IMOPSO method was enhanced by incorporating strategies such as Grey Wolf encirclement optimization, competitive variation, and inertia weight optimization. Lastly, the IMOPSO was applied to model and optimize the corporate culture management indicators, thereby enhancing management efficiency. Simulation results validated the effectiveness and feasibility of the proposed method in optimizing corporate culture management indicators.*

Keywords: *Evaluation Indicators of Corporate Culture Management; Entropy Weight Law; Improved Particle Swarm Algorithm; Gray Wolf Algorithm; Multi-objective Optimization*

1. Introduction

In recent years, the intensification of market competition and the complexity of the internal and external environment of enterprises have made corporate culture management particularly important in the development of enterprises [1-2]. A good corporate culture can not only enhance employees' sense of belonging and cohesion, but also promote innovation and teamwork, significantly improve corporate performance and competitiveness, and promote the innovation and development of enterprises [3-4]. Therefore, how to scientifically and effectively build corporate culture has become one of the hot spots in current enterprise management research [5].

Most of the research on optimizing corporate culture management at home and abroad relies on empirical governance, which lacks the support of mathematical theory and logical reasoning [6]. The establishment of an evaluation index system for corporate culture [7] is an effective means to transform the abstract concept of corporate culture into concrete digital standards and indicators. However, how to accurately and comprehensively consider the interaction and weight allocation between multiple indicators is still a key issue. Traditional methods often make it difficult to comprehensively assess the importance of various indicators, which can easily lead to bias and uncertainty in decision-making results. Therefore, the multi-indicator decision-making model based on the entropy weight method is regarded as an effective way to solve this problem [8-9]. The entropy weight method determines the weight of each index by analyzing the information entropy of the data, so as to provide an objective basis for multi-objective decision-making.

In order to optimize the corporate culture management indicators, this paper first introduces the Particle Swarm Optimization (PSO) algorithm, which was proposed by Kennedy [10] in 1995 to simulate the information interaction during the foraging process of birds, and has been widely used in multi-domain optimization problems because of its simple principle and easy implementation [11-15]. However, the PSO algorithm has problems such as slow convergence speed and low accuracy. In order to solve these problems, existing studies have improved the performance of the PSO algorithm and improved its diversity and convergence speed by introducing methods such as full perception strategy, comprehensive

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learning strategy, adaptive value-distance-proportionality strategy, and dynamic multi-group strategy [16-17]. Based on these research results, this paper proposes an Improved Multi-Objective Particle Swarm Optimization (IMOPSO) algorithm that integrates multiple strategies. The algorithm is combined with the gray wolf algorithm to optimize the particle position update strategy, which enhances the local search ability and improves the convergence accuracy. The competitive variation algorithm is introduced to reduce the probability of "precocious" convergence and avoid the algorithm falling into local optimum. By dynamically adjusting the inertia weight, the operation efficiency and convergence of the algorithm are improved.

The purpose of this paper is to establish a scientific and reasonable optimization model of corporate culture management indicators through the combination of entropy weight method and IMOPSO algorithm. The model can scientifically allocate and optimize the weights of multiple indicators, help enterprises continuously improve cultural management, and provide theoretical and methodological support for their sustainable development.

2. Construction of corporate culture management index model

2.1. Corporate culture evaluation index system

On the basis of the evaluation index established by Xia Liming [7] and combined with the needs of actual corporate culture management, this paper constructs an evaluation index system of corporate culture from four aspects: enterprise spirit culture, enterprise system culture, corporate behavior culture, and corporate material culture, as shown in Figure 1.

2.2. Comprehensive evaluation methodology

According to the characteristics of the above index system, combined with the research results of relevant scholars in the early stage, this paper comprehensively evaluates corporate culture through the entropy weight method.

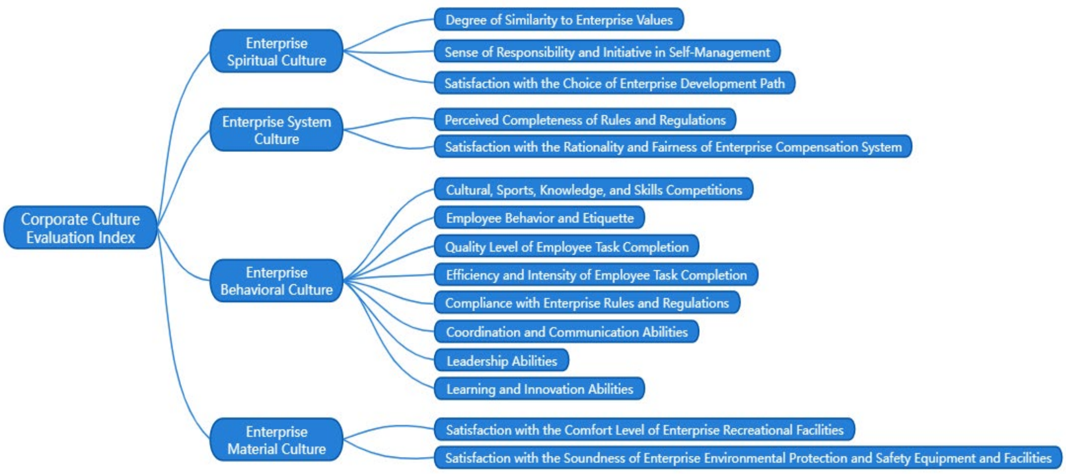

Figure 1: Evaluation Indicator Diagram for Corporate Culture

The value of the evaluation index can be obtained by the evaluation object through questionnaire scoring or other means. Answers to the questionnaire are on a 10-point scale (9-10 indicates excellent; A score of 7-8 indicates good; A score of 5-6 indicates a pass; A score of 1-4 indicates a disqualification). In the process of scoring, the evaluation object shall objectively and fairly judge the occurrence degree of each evaluation index according to the actual situation. Using the entropy weight method, the index weight calculation and the comprehensive evaluation of corporate culture are carried out, and the specific steps are as follows:

(1)Constructing the sample evaluation data matrix $X_{n\times m}$:

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$$(X_{ij})_{n\times m}=\begin{bmatrix} X_{11} & X_{12} & \dots & X_{1m} \\ X_{21} & X_{22} & \dots & X_{2m} \\ \dots & \dots & \dots & \dots \\ X_{n1} & X_{n2} & \dots & X_{nm} \end{bmatrix} \tag{1}$$

Where m represents the evaluation indicator system, n represents the number of evaluation subjects, and X_{ij} denotes the value of the j-th evaluation indicator for the i-th evaluation subject.

(2)Due to the inconsistent units of measurement for each indicator, it is necessary to standardize all indicators to obtain a unit-standardized matrix $(X_{ij}^{'})_{n\times m}$, thereby eliminating inconsistencies in magnitude and units of measurement. Specifically,

$$x_{ij}'=\frac{x_{ij}-\min(\sum x_j)}{\max(\sum x_j)-\min(\sum x_j)} \tag{2}$$

(3)Determine the entropy value of each indicator. The entropy value E_j of the j-th indicator is:

$$E_j=-k\sum_{i=1}^{n}p_{ij}\ln\left(p_{ij}\right) \tag{3}$$

Where,

$$p_{ij}=\frac{x_{ij}'}{\sum_{i=1}^{n}x_{ij}'},i=1,\dots,n,j=1,\dots,m \tag{4}$$

$$k=\frac{1}{\ln(n)}>0,E_j\geq 0 \tag{5}$$

p_{ij} represents the characteristic proportion of the i-th evaluation subject under the j-th indicator, x'_{ij} represents the standardized value of the j-th indicator data for the i-th evaluation subject$(j=1,2,3,\dots,n)$; $\sum_{i=1}^{n}x'_{ij}$ represents the sum of the standardized data of all sample objects for the j-th indicator. Specifically, when $p_{ij}=0$, we stipulate $p_{ij}\ln(p_{ij})=0$ to ensure $E_j\in[0,1]$;

(4)Calculate the redundancy (difference). Based on the entropy value from equation (3), the difference coefficient d_j of the indicator is calculated as $d_j=1-E_j$;

(5)The weight w_j to be assigned to a certain indicator is determined by the proportion of its d_j value in the sum of all d_j values;

$$w_j=\frac{d_j}{\sum_j d_j} \tag{6}$$

(6)Calculate the comprehensive score for each evaluation subject.

$$s_i=\sum_j w_j x_{ij}^{'} \tag{7}$$

Through equations (1)~(7), it can be seen that the entropy weight method considers the correlation between the indicators, and can accurately reflect the performance of the evaluation object on different indicators. By calculating the weight of each index, the degree of corporate culture construction can be more accurately evaluated, the limitation of evaluation based on subjective experience alone is avoided, and the objectivity and scientificity of the evaluation results are ensured.

2.3. Mathematical Model

2.3.1. Objective Functions

With the optimization goal of maximizing the contribution of corporate culture management, the optimization objective function is established:

$$f_1(x)=\frac{(F-E)}{E}\times 100\% \tag{8}$$

$$f_2(x)=s*150 \tag{9}$$

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Where: $f_1(x)$represents the year-on-year growth rate of the cultural construction contribution value for the current period; F represents the total cultural construction contribution for the current period; Erepresents the total cultural construction contribution for the previous period; $f_2(x)$ represents the degree of contribution of corporate culture management; s represents the sum of the comprehensive evaluation scores of corporate culture management calculated using the entropy weight method.

2.3.2. Constraint Conditions

Constraints on the comprehensive evaluation scores of outstanding evaluation subjects:

$$s_{i,min}^t \leq s_i^t \leq s_{i,max}^t \tag{10}$$

Where, s_i^t , $s_{i,min}^t$, and $s_{i,max}^t$ represent the comprehensive evaluation score, the highest comprehensive evaluation score, and the lowest comprehensive evaluation score of the i-th evaluation subject in the t-th period, respectively.

3. Improvement of the MOPSO Algorithm

3.1. Improvement Strategies for the MOPSO Algorithm

3.1.1. Grey Wolf Surrounding Optimization Strategy

In this paper, the update formula is improved in combination with the gray wolf algorithm, the main reason is that the gray wolf algorithm adopts the elite group guidance strategy in the iterative update, that is, the three optimal elite individuals in the group are selected for the guided update, and the optimal individual in the particle swarm algorithm is no longer used for guidance. Moreover, the gray wolf algorithm adopts an enveloping guidance strategy, that is, in the process of searching for pairs, other particles will approach the elite group in an enveloping manner. Therefore, the combination of particle swarm optimization and gray wolf algorithm can further improve the search ability of the algorithm.

The most crucial search strategy in the grey wolf algorithm is the surrounding search strategy. Its mathematical model is as follows:

$$X(t+1) = X_p(t) - A \times D \tag{11}$$

$$D = \left|C \times X_p(t) - X(t)\right| \tag{12}$$

Where, t represents the number of iterations, $X_p(t)$ is the position vector of the prey, and $X(t)$ is the position vector of the grey wolf. The schematic diagram of the surrounding strategy is illustrated in Figure 2.

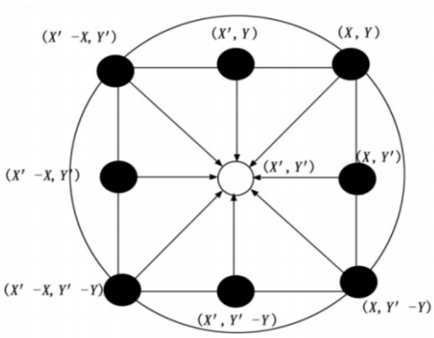

Figure 2: Schematic Diagram of the Surrounding Strategy in the Grey Wolf Algorithm

As shown in Figure 2, assuming the prey's position is (X^*, Y^*) and the grey wolf's position is (X, Y), when $\vec{A} = (1,0)$ and $\vec{C} = (1,1)$, the grey wolf will move towards $(X^* - X, Y^*)$ based on the prey's position. When the values of the vectors $\vec{A}$ and $\vec{C}$ are different, the surrounding effect shown in Figure 2 will occur. Here, $\vec{A}$ and $\vec{C}$ are coefficient vectors that can be expressed by equations (13) and (14):

$$C = 2r_1 \tag{13}$$

$$A = 2ar_2 - a \tag{14}$$

Where, r_1 and r_2 are random numbers between [0,1], and a is a control parameter that linearly

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decreases within [0,2] as the number of iterations increases, following the decrement formula in equation (15):

$$a = 2\left(1 - \frac{t}{T_{\max}}\right) \tag{15}$$

From the above introduction of the gray wolf algorithm, it can be seen that when the gray wolf algorithm is guided, it uses the elite group to guide the population, that is, the optimal three elite individuals are selected to guide the population. The three optimal individuals in the gray wolf population are the optimal solution α, the suboptimal solution β and the third optimal solution δ, and the three elite individuals will guide the whole population according to (11) and (12), and the specific guidance strategy is as follows:

$$D_\alpha = |C_1 \times X_\alpha(t) - X(t)| \tag{16}$$

$$D_\beta = |C_1 \times X_\beta(t) - X(t)| \tag{17}$$

$$D_\delta = |C_1 \times X_\delta(t) - X(t)| \tag{18}$$

Where equations (16) to (18) represent the distances of the grey wolves in the population from the first three optimal solutions α, β, and δ, respectively. Equations (19) to (21) represent the directions in which the grey wolf population moves towards each of the three elite individuals. Finally, equation (22) represents the updated formula of the grey wolf algorithm after combining the guidance from the three elite individuals:

$$X_1(t) = X_\alpha(t) - A_1 \times D_\alpha \tag{19}$$

$$X_2(t) = X_\beta(t) - A_2 \times D_\beta \tag{20}$$

$$X_3(t) = X_\delta(t) - A_3 \times D_\delta \tag{21}$$

$$X(t+1) = \frac{X_1(t) + X_2(t) + X_3(t)}{3} \tag{22}$$

In order to introduce the advantages of the strong global search ability of the gray wolf algorithm, the update formula of the multi-objective particle swarm algorithm is changed to equation (23), that is, the enveloping update strategy of the gray wolf algorithm is added to the update formula of the multi-objective particle swarm algorithm:

$$v_{i,j}^{t+1} = w\left(X_{i,j}^t - x_{i,j}^t\right) + c_1 r_1\left(p_{besti,j}^t - x_{i,j}^t\right) + c_2 r_2\left(g_{bestj}^t - x_{i,j}^t\right) \tag{23}$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \tag{24}$$

Through equation (23), it can be seen that in the position update process of the multi-objective particle swarm algorithm, the original individual experience of the multi-objective particle swarm optimization algorithm and the guidance of the optimal particles are retained, and the gray wolf algorithm update strategy $X(t)$ is introduced, which not only includes the guidance strategy of the elite group of the gray wolf algorithm but also includes the enveloping search strategy of the gray wolf algorithm. By taking advantage of the global search of the gray wolf algorithm, the convergence of IMOPSO can be guaranteed.

3.1.2. Competition Mutation Strategy

In order to solve the precocious problem of traditional multi-objective particle swarm optimization algorithm, the competitive mutation strategy was introduced into the multi-objective particle swarm optimization algorithm. The use of competitive mutation depends on specific conditions, that is, after the iteration is completed, no new particles are generated, indicating that the algorithm is likely to have a "precocious" convergence, and the method of competitive mutation can avoid falling into local optimum and ensure the diversity of the population. Take the t-th iteration as an example: first, N_m particles are selected from the population after the t-th iteration as the losers. Then, the corresponding number of particles is randomly generated as the winner, and the winner guides the evolutionary direction for the loser, and the total number of particles in the population is N, then the position and velocity of the winner are recorded as $x_{w,h}^t(i,j)$, $v_{w,h}^t(i,j)$ $(h = 1,2,\dots,N/2)$, respectively, and the position and velocity of the loser are recorded as $x_{l,h}^t(i,j)$, $v_{l,h}^t(i,j)$, respectively. Then the updated formula for the hth loser is as follows:

$$\overline{x^t} = \frac{\sum_{h=1}^{N_m} x_{l,h} + \sum_{h=1}^{N_m} x_{w,h}}{2 * N_m} \tag{25}$$

$$v_{l,h}^{t+1}(i,j) = R_1 * v_{l,h}^{t}(i,j) + R_2 * (x_{w,h}^{t}(i,j) - x_{l,h}^{t}(i,j)) + \phi R_3 * (\overline{x_k^t}(j) - x_{l,h}^{t}(i,j)) \quad (26)$$

$$x_{l,h}^{t+1}(i,j) = x_{l,h}^{t}(i,j) + v_{l,h}^{t+1}(i,j) \quad (27)$$

$$\begin{cases} \phi(N) = 0 & if\ N \le 100 \\ \phi(N) \in [\phi_L(N), \phi_U(N)] & otherwise \end{cases} \quad (28)$$

$$\begin{cases} \phi_L(N) = 0.14\, log(N) - 0.30 \\ \phi_U(N) = 0.27\, log(N) - 0.51 \\ \quad \phi_L(N), \phi_U(N) \ge 0 \end{cases} \quad (29)$$

3.1.3. Inertial weight optimization strategy

The inertia weight w reflects the degree of influence that the current particle's velocity is affected by the previous generation's particle, and it is an essential parameter in the MOPSO algorithm. Controlling its value can adjust the global and local optimization capabilities of the MOPSO algorithm. A larger w value enhances the global search ability but weakens the local search ability, and vice versa. This paper proposes an inertia weight function to balance the global and local search capabilities, and the specific formula is as follows:

$$w = w_{\min} - (w_{\max} - w_{\min}) \times \exp(-20 \times (iter/iter_{\max})^6) \quad (30)$$

Given $w_{\max}$=0.9 and $w_{\min}$=0, the variation curve of the inertia weight function w is shown in Figure 3.

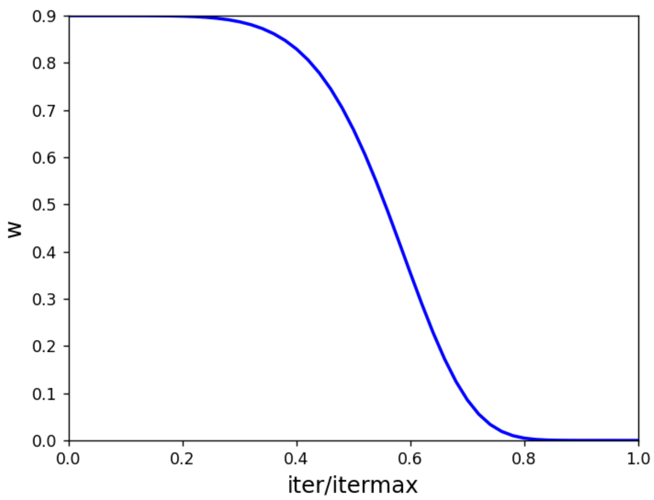

Figure 3: Variation Curve of Inertia Weight

It can be seen from the inertia weight change curve in Figure 3 that the inertia weight function proposed in this paper keeps the inertia weight w at a large value for a long time at the beginning of the iteration and a small value for a long time at the late iteration, thereby increasing the global search time at the beginning of the iteration and the local search time at the end of the iteration, strengthening the global search intensity at the beginning of the iteration and the local search intensity at the later stage of the iteration, so that the global search ability and the local search ability are well balanced. The proposed inertia weight function can effectively improve the operation efficiency and convergence of the algorithm.

3.2. Implementation of the IMOPSO Algorithm

The specific steps for optimizing corporate culture management indicators using the proposed IMOPSO algorithm in this study are as follows:

1)Initialize the algorithm parameters, including the maximum number of iterations, population size N, external archive size M, learning factors c_1 and c_2, the maximum inertia weights w_{max} and the minimum inertia weights w_{min}, and the initial value of the coefficient vector a.

2)Input the initial evaluation index scores, which represent the initial positions of the particle swarm. Randomly generate the initial velocities of the particle swarm, calculate the fitness values of the initial positions, store the non-dominated solutions in the external archive, and determine the initial personal

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best p_{best} and global best g_{best} for each particle.

3)Update the inertia weight, coefficient vector, particle positions, and particle velocities.

4)Calculate the fitness values of each particle, adjust each particle's p_{best}, update the external archive, and if no new particles enter the external archive, perform the competition mutation operation on the particles using equations (25) to (29). Select a new g_{best} from the external archive.

5)Determine if the current iteration count has reached the maximum number of iterations. If so, terminate the algorithm; otherwise, return to step 3.

4. Simulation Test Analysis

In order to verify the optimization performance of the IMOPSO algorithm proposed in this paper to solve the optimization problem of corporate culture management indicators under different iteration times, the simulation experiment was carried out by using PyCharm software to maximize the contribution of corporate culture management. The experimental evaluation indicators include the growth rate of corporate culture management contribution (the percentage of the difference between the optimal corporate culture management contribution calculated by the IMOPSO algorithm and the MOPSO algorithm), the algorithm convergence speed (the number of optimization iterations) and the algorithm time.

The MOPSO algorithm and IMOPSO algorithm were used to optimize the corporate culture management indicators in five cases with 30, 50, 60, 80 and 100 iterations, respectively, and the results are shown in Table 1. Set the particle size to 100; In the IMOPSO algorithm, $w_{max} = 0.9$, $w_{min} = 0$, and in the MOPSO algorithm, $w = 0.8$, $c_1 = 1.49445$, $c_2 = 1.49445$. The MOPSO algorithm belongs to probabilistic optimization, and the optimization result is different each time. Therefore, the average of the results of the 5 runs is taken as the final optimization result for each case. As can be seen from Table 1, for the five different iterations selected, under the same experimental conditions, the contribution value of IMOPSO algorithm to corporate culture management is greater than that of MOPSO algorithm. Compared with the MOPSO algorithm, the time taken by the IMOPSO algorithm is reduced by about $1.0\sim2.5\text{s}$ on average, and the maximum contribution of corporate culture management can be found, and the growth rate of corporate culture management contribution is $5.90\%\sim20.29\%$.

Table 1 Optimization results of MOPSO and IMOPSO algorithms under different iterations

Iteration Count	Contribution to Corporate Culture Management		Optimization Iteration Count		Algorithm Duration / s		Growth Rate of Contribution to Corporate Culture Management / %
	IMOPSO	MOPSO	IMOPSO	MOPSO	IMOPSO	MOPSO	
30	8011.8	7565.4	6	9	35.65	36.94	5.90%
50	8211.4	7576.4	14	34	62.59	64.42	8.38%
60	8532	7726.8	25	46	75.32	77.64	10.42%
80	8861.4	7813	42.4	36	104.28	106.51	13.42%
100	9356	7777.8	28	33	134.07	136.50	20.29%

To further compare the optimization performance, we selected three scenarios with iteration counts of 50, 80, and 100 and plotted the average results in Figure 4. Both the MOPSO and IMOPSO algorithms exhibited stable performance during the optimization process, ultimately converging to the maximum contribution to corporate culture management after multiple iterations. During the iteration process, the IMOPSO algorithm converged slower, but its final optimization results were superior to those of the MOPSO algorithm. Additionally, increasing the iteration count led to a greater increase in the corporate culture management contribution achieved by the IMOPSO algorithm.

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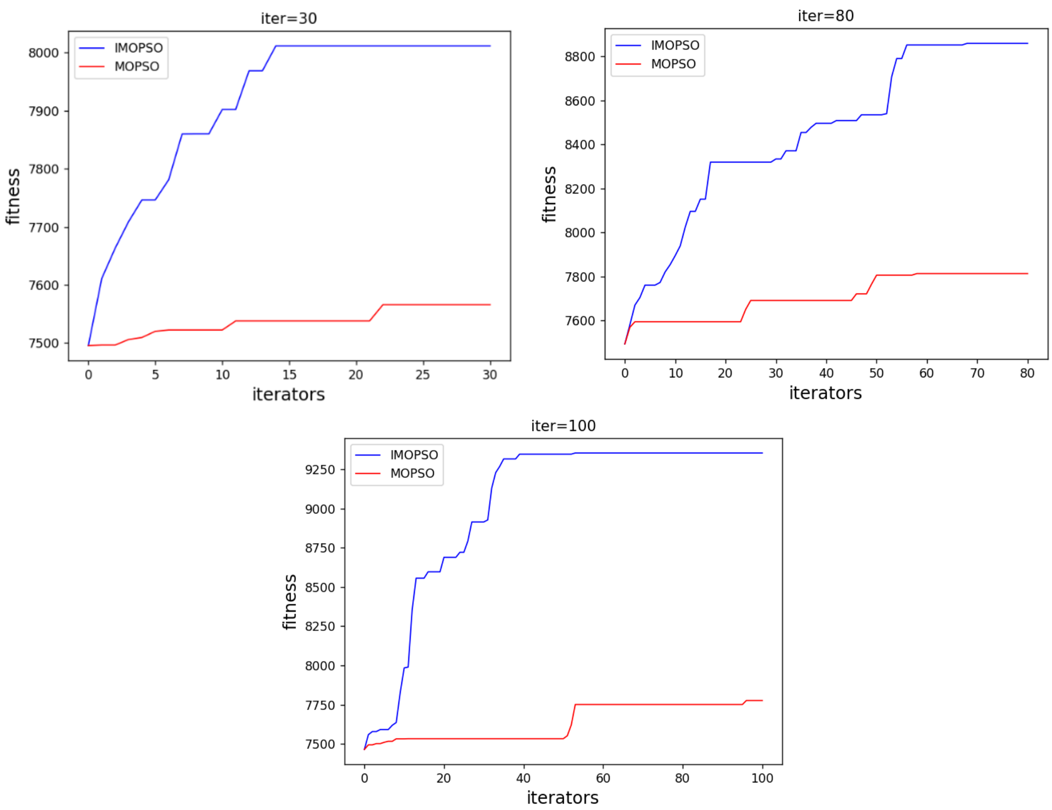

Figure 4: Comparison of Optimization Process between MOPSO and IMOPSO Algorithms

As the number of iterations increases, the difficulty of finding the optimal contribution value for corporate culture management increases exponentially. The IMOPSO algorithm employs the gray wolf algorithm to optimize the particle position update strategy, enhancing the local search ability of the algorithm, improving convergence accuracy, and modifying the inertia weight. It also introduces competitive mutation when no new particles are generated after iterations, enabling the particle swarm to search the solution space more extensively and avoiding premature convergence to local optima. Compared to the MOPSO algorithm, the IMOPSO algorithm, though slower in convergence, is able to find better optimal solutions for large-scale search problems.

The simulation experiments above demonstrate the effectiveness and feasibility of the IMOPSO algorithm in solving the optimization problem of corporate culture management.

5. Conclusion

In order to solve the problem of digital presentation and management optimization of corporate culture, this paper proposes a research method that combines the entropy weight method and the improved multi-objective particle swarm algorithm. First of all, the evaluation index system of corporate culture was established to transform corporate culture into quantifiable numerical indicators. Secondly, the entropy weight method is used to distribute weights to ensure the objectivity and rationality of the evaluation system. Finally, the optimization model of corporate culture management indicators is constructed, and the IMOPSO algorithm is used to solve the maximum contribution of corporate culture management, and the conclusions are drawn.

In order to solve the problem that the traditional multi-objective particle swarm optimization is easy to fall into the local optimal solution, the algorithm is improved in this paper. Firstly, the gray wolf algorithm was introduced to optimize the particle position update strategy to enhance the local search ability of the algorithm and improve the convergence accuracy. Secondly, the competitive variation strategy is used to reduce the probability of "precocious" convergence and avoid the algorithm falling into local optimum. Finally, the inertia weight function is introduced to dynamically adjust the inertia weight to improve the operation efficiency and convergence of the algorithm.

The simulation results show that the proposed method has achieved remarkable results in the optimization of corporate culture management indicators. Compared with the traditional method, this method can better balance the relationship between various indicators, and improve the overall efficiency and competitiveness of corporate culture management. Therefore, this study has certain theoretical and practical value for enterprises to improve the level of cultural management and promote the sustainable development of enterprises. Future research directions can include further optimizing the performance of algorithms, expanding the application fields, and exploring the combination with other optimization methods, so as to further improve the effect and application scope of corporate culture management optimization.

Acknowledgments

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