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An improved particle swarm optimization algorithm for enterprise informatization maturity evaluation

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ABSTRACT

In order to overcome the problems of premature convergence and high dimension complex function optimization in conventional particle swarm optimization algorithm, the paper presents an improved particle swarm optimization algorithm and applies it to evaluate enterprise informatization maturity. First, the working principle and current problems of original particle swarm optimization algorithm are analyzed; Then, the methods of late random inertia weight and non-linear dynamic inertia weight are advanced to seek for proper inertia weight; Third, the calculation flows of the presented algorithm are redesigned to reduce iteration times; Finally, the evaluation indicators of enterprise informatization maturity are analyzed and the improved algorithm is realized. The simulation results illustrates that the algorithm has better self-adaptability and can simplify model structure, increase algorithm efficiency, and improve evaluation accuracy when used for evaluating enterprise informatization maturity.

KEYWORDS

Particle swarm optimization algorithm; Performance evaluation; Enterprise informatization maturity; Inertia weight; Calculation flows.

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INTRODUCTION

Particle swarm optimization algorithm (PSO) which was proposed by Eberhart and Kennedy in 1995 is a new global optimization algorithm. PSO is originated from the simulation of the behavior of bird predation, and uses speed-location search model. The PSO algorithm, which is an efficient parallel optimization method, is wildly used to solve a large number of non-linear, non-differentiable and multi-peak complex optimization problems. Procedure is relatively simple and few parameters need to be adjusted, so the PSO algorithm developed rapidly and has been applied to the field of science and engineering. At the same time, many improved PSO algorithms are appeared. Due to the relatively short history of the PSO, there are still some problems need to be solved on the theoretical basis and its application[1].

At the same time, enterprise informatization is the fundamental and important constitute part of the nation informatization and society informatization, is the strategic measure to raise the level of enterprise management, to strengthen the enterprise's competition ability in global informatization tide. Now in the process of Enterprise informatization, the widespread and existent phenomenon is unilateral to pursue the high, new and whole techniques, but ignores its present informatization level, so result in that investments for informatization of many enterprises can't get the reasonable repay. In order to avoid blind construction of enterprise information and to solve the problems exposed in the current enterprise information construction process, the enterprise information maturity model and its evaluation system is necessary to be in depth studied. At present, many scholars from various countries in this field have done a lot of research and achieved lots, but the evaluation model and evaluation indicator system for the topic is still not satisfactory and need further research for the researchers in the field related.

So this paper try to improve PSO algorithm and use it to evaluate enterprise informatization maturity.

MATERIALS AND METHODS

Literature review

At present, the evaluation methods of enterprises competitiveness at home and abroad are mainly the following four categories[2-4].

① AHP (Analytic Hierarchy Process), a practical multi-scheme or multi-target decision making method, first makes the problem to be analyzed hierarchical, divides the problem into different components according to the nature of the problem and total target to be achieved, composes the components in different hierarchies according to correlations and subordinations among components, forming a multi-hierarchy analysis and evaluation structure model;

② TOPSIS (Technique for Order Preference Similarity to Ideal Solution) ranks the order of solutions according to each appraised scheme and the distance between ideal solution and negative ideal solution. Ideal solution is the best solution assumed, each attribute value of which reaches the optimal value among all the appraised schemes. Negative ideal solution is the worst solution assumed, each attribute value of which is the worst value among all the appraised schemes. While conducting overall evaluation, the overall situation of appraised object is always reflected by confirming indicators at all hierarchies.

③ Factor analysis is a multi-variable statistical analysis technique that starting from the study on dependence among correlation matrix, some variables with complicated relations come down to a few comprehensive factors. Factor analysis among variables (r-type factor analysis) is the promotion of principal component analysis, the basic idea of which is to group variables according to the size of correlation, so as to obtain a relatively high correlation among variables in the same group; but variables in different groups have low correlation, every group of variables represent a basic structure—common factor.

④ DEA (Data Envelopment Analysis) is a new method for statistic analysis. From the perspective of production function, the model is used for the study of "production department" with multiple inputs, especially with multiple outputs, also, system evaluation deemed as "Scale Efficiency" and "Technical Efficiency" is a very ideal and effective method;

⑤. BP neural network evaluation method makes use of its strong capability in processing nonlinear problems to carry out performance evaluation; the method has advantages like self-learning, strong fault tolerance and adaptability; however, the algorithm is easy to be trapped into defects like local minimum, over-learning, strong operation specialization.

The performance evaluation of enterprise informatization maturity is a multi-indicator complicated evaluation process, among which lots of indicators are involved in. The paper improves particle swarm optimization algorithm to overcome the question of slow convergence. In so doing, not only the problem of convergence speed of ordinary PSO algorithm has been solved, but also the simplicity of the model structure and the accuracy of the evaluation are ensured.

Working principles of particle swarm optimization algorithm

In PSO algorithm, every optimization solution is one particle in search space, all the particles have fitness value decided by optimized function, and each particle has a speed determining their flying direction and distance. Then, particles follow the current optimal article to search in solution space. The algorithm initializes to be a group of random particles (random solution), then finding the optimal solution via iteration. In each time of iteration, particles update themselves via two "extreme values". One is the optimal solution find by the particle itself, which is called personal best value $pBest_i$; the other is the optimal solution found by the entire population currently, which is called global best value $gBest$. After finding two optimal values, particles update their speed and position according to Formula 1 and Formula 2.

$$V_{id}^{(t+1)} = V_{id}^{(t)} + c_1 \cdot rand() \cdot (pBest_{id}^{(t)} - V_{id}^{(t)}) + c_2 \cdot rand() \cdot (gBest_{id}^{(t)} - V_{id}^{(t)}) \quad (1)$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t+1)} \qquad 1 \le i \le N, 1 \le d \le D \quad (2)$$

The search space is D dimension, total number of particles is N, the position of the ith particle is expressed as vector $P_i = (P_{i1}, P_{i2}, ..., P_{iD})$, the flying position change rate of the ith particle (i.e. "speed") is expressed as vector $V_i = (V_{i1}, V_{i2}, ..., V_{iD})$, the optimal position that the ith particle had gone to in the flying history (i.e. the personal best value of the particle) is expressed as vector $pBest_i = (P_{i1}, P_{i2}, ..., P_{iD})$, the optimal position of all the particles while flying of the current population (i.e. global best value) is expressed as $gBest$ (the value is the best value among all the $pBest_i$). Therefore, the position and speed of each particle in the population carry out flying change according to the following formula, expressed as Formula 1 and Formula 2.

In which, C_1 and C_2 are acceleration factors, which are two positive real numbers, respectively called cognitive learning rate and social learning rate, representing the weight of acceleration pushing each particle into personal best and global best, generally valued as $C_1 = C_2 = 2$, $rand()$ is the separate random number within the scope of [0,1]. The position change range of the $d(1 \le d \le D)$ th dimensionality is speed change range being $[X_{\min d}, X_{\max d}]$, speed change range being $[V_{\min d}, V_{\max d}]$; in the process of iteration, if the values of position and speed exceed the boundaries, it is valued as boundary value. The iteration process of $pBest_i$ and $gBest$ in each generation of population are shown as Formula 3 and Formula 4.

$$pBest_i^{(t+1)} = \begin{cases} pBest_i^{(t)}, & F(pBest_i^{(t+1)}) \ge F(pBest_i^{(t)}) \\ P_i^{(t=1)}, & F(pBest_i^{(t+1)}) \prec F(pBest_i^{(t)}) \end{cases} \quad (3)$$

$$\mathrm{g}Best^{(t+1)} = \min(F(pBest_1^{(t+1)}), F(pBest_2^{(t+1)}), ..., F(pBest_D^{(t+1)})) \quad (4)$$

In which, $F(\cdot)$ is fitness function, i.e. first updating the personal best value $pBest_i$ of all the particles according to fitness function, then updating global best value with the optimal personal best value $gBest$.

The defect analysis of PSO algorithm

The main problems of the PSO algorithm can be listed as follows. ① The theoretical research of PSO algorithm isn't deep enough; it is difficult for the algorithm to establish convergence model and analyze the convergence. ② In most cases, PSO algorithm will have the problems of premature convergence easy to fall into local extreme values while solving high-dimensional or ultra high-dimensional complicated problems.③The operation process of PSO algorithm is largely related to the parameter values adopted by it, so the parameter of the algorithm will influence the performance and effectiveness of the algorithm.④ PSO algorithm has limitation in the application field. Any algorithm has the limitation, so does the PSO[5].

Improving inertia weight of PSO algorithm

Inertia weight w makes particles maintain the motion inertia, with the tendency of expanding search space, able to develop new region. It is used to control the impact of the speed of previous iteration on the current speed of this iteration, so the balance between global search and local search is maintained via adjusting the value of w, so as to achieve the purpose of improving algorithm performance. Research shows that if the value of w is large, the exploration ability of particles in the population will be strong, and its local development ability will be weakened, beneficial to global search and easy to avoid local extreme value, but not easy to get accurate solution; if the value of w is small, the development ability of particles in the population will be enhanced, and its global search ability will be weakened; at this time, it tends to local search; although beneficial to the convergence of algorithm, but slow in convergence speed, sometimes it may fall into local extreme value, but easy to get more accurate solution; therefore, proper inertia weight value can improve the optimizing performance of algorithm, and reduce the times of iteration. Hence, it is the key point of the research in this thesis how to seek for proper inertia weight value to make it properly coordinate the balance between search accuracy and search speed[6].

Late random inertia weight

In the formula of PSO algorithm speed updating, the first part $w * v_i(t)$ is used for guaranteeing the global convergence ability of the algorithm, the second and third parts are used for balancing the contradictions between global search and local search to enhance the local convergence performance of algorithm, and the introduction of inertia weight w can balance the relationship between global convergence and local convergence to improve the algorithm performance.

In general, in the process of global search, particles hope to have strong development ability in the early phase of evolution to guarantee the diversity of particles, and strong ability of excavation is hoped to have in the late phase of evolution to reduce the times of iteration and accelerate the convergence.

In the standard PSO algorithm, inertia weight is linearly decreased from 0.9 to 0.4, and such kind of value method has certain limitation. As there are difference optimization problems while solving actual problems, and problems solved by each optimization are different, linearly decreased inertia weight w takes effect on part of the problems. If we can't find the best point in the beginning of evolution, with the decreasing of inertia weight w and the strengthening of local search ability, the algorithm is easy to prematurely converged, falling into local best and failing to get out of it; if we find a relatively good point in the beginning of evolution, and the inertia weight w is decreasing, the smaller w can make the algorithm fast find the best point. Meanwhile, the linear decrease of w slows the convergence speed of the algorithm, making the diversity of particles weaken, leading to decreasing global search ability, easy to fall into local extreme value. Therefore, adopt random inertia weight with (0.4, 0.7) even distribution in the late phase of population search to substitute linearly decreased inertia weight, making particles have larger w in the beginning of the search to maintain the diversity of particles, and enhance global search ability; have the opportunity to obtain larger w in the late phase of the search to jump out of local extreme value.

According to the above analysis, late random inertia weight (LRIW) is put forward, in which the value of random inertia weight w obeying to even distribution changes according to the different times of iteration. When the time of iteration is less than $0.7 * iter_{\max}$, Formula 5 is satisfied; otherwise, Formula 6 shall be adopted.

$$w = w_{\max} - ((w_{\max} - w_{\min}) / iter_{\max}) \times iter \quad \textbf{(5)}$$

$$w = 0.4 + 0.3 * rand \quad \textbf{(6)}$$

In the formula, $iter_{\max}$ is the largest iteration time, $iter$ is the iteration time and $w_{\max}$ is the largest inertia weight.

Late random inertia weight

It is found via analyzing the inertia weight in the standard PSO algorithm speed updating formula that the larger the value of w is, the smaller the opportunity that speed $v_i(t)$ gets close to global best point $gBest$ and personal best point $p_i Best$ is, the particle will skip the current optimal point, and the probability for searching better and optimal point will be increased. It is beneficial in the early phase of algorithm evolution search, as the current optimal point in the early phase of evolution is not necessarily the final global optimal point; while larger value of w can enhance the search ability of particles, so as to maintain the diversity of particles in the population. However, it is unfavorable for the late phase of algorithm evolution, as the late phase of evolution is easy to make particles skip global optimal point, which influences the convergence performance of the algorithm, bad for the convergence of global optimal point. While the smaller of value of w is, the larger the opportunity that speed $v_i(t)$ gets close to global optimal point $gBest$ and personal optimal point $p_i Best$ is, and the particles will get close to current global optimal point, thus fasting converging in the optimal point, which is very favorable in the late phase of algorithm evolution search, but unfavorable for the early phase of algorithm evolution, as the diversity of particles will be decreased under such circumstance. Hence, the value of w is contradictory with respect to convergence and finding optimal value. The mostly used method currently is to increasing the decrease of w with the times of iteration, i.e. adopting larger value of w in the early phase of algorithm evolution, and adopting smaller value of w in the late phase of evolution, which meets the requirement of early search ability of particles as well as demand of convergence in late phase. However, there are also shortcomings. If the global best position is found in the early phase of algorithm search, such best position may be skipped due to too large inertia weight, not searching next to optimal point, so as to reduce the search ability for optimal position[7].

While in the process of obtaining solution by using PSO algorithm, we need to final global best solution at last. Each iteration shall lay emphasis on the search next to global best particle $gBest$, as it is more likely to have truly global best position next to the optimal particle. Two dynamic adjustment strategies of non-linear inertia weight are put forward based on the above analysis. In order to conquer the shortcoming of linearly decreased inertia weight, based on Formula 5, control factor m is introduced to control the evenness between w and t changing curve, i.e. inertia weight with non-linear dynamic adjustment is shown in Formula 7[8].

$$w = (w_{\max} - w_{\min}) * ((iter_{\max} - iter) \wedge (m-1) / iter_{\max} \wedge m) + w_{\min} \quad (7)$$

Redesigning calculation flows

From the above analysis, we can find that PSO algorithm is a global optimization algorithm, the calculation flows of the new algorithms are as follows. (1). Initialize population. Giving the initial value of each parameter, and initializing the speed and position of each particle in the population within the scope the designated optimization; initialing acceleration C_1 and C_2 as well as inertia weight w parameter. Setting the personal best value of each particle as $pBest_i$, and setting the global best value of population as $gBest$. (2). Evaluating particles. According to target function, calculating the fitness value of each particle. (3). Updating optimal value. ① If the fitness value of the updated particle is better than the original value, taking new fitness value as the fitness value of the particle, and new particle position being the $pBest_i$ of the particle[5]. ② If the fitness value of the updated particle is better than the original global best, taking the position of the particle as new global best $gBest$. (4). Updating the speed and position of each particle according to Formula 1 and Formula 2. (5). Returning to Step 2 until not meeting the conditions for cycling (generally reaching designated largest time of iteration or obtaining optimal solution good enough).

RESULT AND DISSCUSS

Evaluation indicator system analysis and construction

On the basis of referring to references, experts consultation and practice survey, this paper designs a set of evaluation indicator system of enterprise informatization maturity according to value chain perspective, management perspective and technical perspective, which includes 3 first-class indicators, 10 second-class indicators, 42 third-class indicators[9]. The system is really complicated and here is only the example for the evaluation algorithm confirmation, so only the simplest first-class indicators (technical perspective) is given as follows. Technical perspective includes three second-class indicators, that are the IT level of employee (including 2 third-class indicators, that are the IT level of technical specialist and the IT level of user), technological innovation (including 2 third-class indicators, that are new technology penetration and new technology diffusion capacity) and Infrastructure construction (including 3 third-class indicators, that are network connectivity, informatization security, operation and maintenance system).

Data collection and preprocessing

Choose 10 typical enterprise informatization, make use of statistical data to compute the values of 42 indicators of each informatization maturity of different enterprises, and compute corresponding overall evaluation score of each enterprise with 42 indicator weights through determination and normalization processing of experts, so as to obtain 10 training mode pairs, training the model of this paper with such 10 training mode pairs. Subsequently, model in this paper can be applied to the performance evaluation of enterprise informatization maturity. Every time when inputting 42 third-class evaluation indicators of enterprise informatization maturity to be evaluated, we can obtain the informatization maturity of different enterprise.

The questionnaires of all the evaluation indicators were made and surveyed to the enterprises and consumers related to get the score of each indicator for different supply chains of fresh agricultural products. The original data acquired by the survey are pre-processed to the scope of [0, 5]. Due to the feature of S -type function in BP neural network, the characteristic values shall be normalized, and the normalized values shall be limited within [0.1,0.9]; so formula 8 is adopted to carry out the normalization[3].

$$x' = \frac{0.8(x - x_{\min})}{(x_{\max} - x_{\min})} + 0.1 \quad (8)$$

Experimental results

In order to save paper space, here omits the evaluation of intermediate results, only are the secondary evaluation results and final comprehensive evaluation results of three typical chains listed in TABLE 1.

TABLE 1 : Part evaluation results of the presented algorithm

	Value chain perspective	Management perspective	Technical perspective	Final maturity
1	4.152	4.792	4.618	4.652
2	3.831	4.499	4.321	4.215
3	3.371	4.043	3.981	3.843

In order to show the superior performance of the improved PSO algorithm, the paper also realizes ordinary BP neural network[4] and fuzzy evaluation algorithms[9], the two algorithms are wildly used for enterprise informatization maturity evaluation in the same calculation environment. The calculation environment of the calculation platform can be listed as follows: Intel i7 4510U, 4GB（4GB×1） DDR, AMD Radeon R5 M230 and 2GHz CPU, and windows 8.164. The TABLE 2 shows us clearly that the improved PSO algorithm in the paper has greater value than that's of in evaluation accuracy or time consuming. In actual calculation, some obvious indicators are taken as sample to illustrate the evaluation accuracy in order to make our comparison more believable in the paper.

TABLE 2 Calculation performance of different algorithms

	Algorithm in the paper	**Ordinary BP model**	**Fuzzy evaluation model**
Evaluation Accuracy	95.68%	83.72%	72.34%
Time Consuming (S)	12	689	11

CONCLUSIONS

The empirical research of the paper shows that the improved evaluation algorithm based on particle optimization algorithm presented in the paper is feasible, effective and practicable when used in enterprise informatization maturity evaluation, and the new algorithm is able to effectively overcome some defects of original PSO algorithm, and has some superior performances, such as strong fault tolerance and ability of expression, self-adaptation, self-learning, able to reduce some human subjective factors to the hilt, so the new algorithm can improve the reliability of the performance evaluation of enterprise informatization maturity, making evaluation results more objective and accurate.

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