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Research Article

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Research on evaluation algorithm of enterprise informatization maturity based on improved particle swarm optimization algorithm

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ABSTRACT

In order to evaluate enterprise informatization maturity accurately and effectively, an improved particle swarm optimization algorithm based on BP artificial neural network is developed. Based on analyzing the working principle of particle swarm optimization algorithm, the improved algorithm encodes its particles, formats its fitness function, and updates its particle speed and position, improves it though immunization information process mechanism; Then, paper integrates particle swarm optimization algorithm with BP neural network algorithm and redesigns the training steps for the improved algorithm. 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, BP neural network algorithm, performance evaluation, enterprise informatization maturity.

INTRODUCTION

In global informatization tide, 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. 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[1].

EXPERIMENTAL SECTION

Literature Review

At present, the evaluation methods of enterprises competitiveness at home and abroad are mainly the following four categories[2,3,4]. □ 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; □ 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. □ 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. □ 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; □. 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 with BP neural network algorithm to overcome the question of slow convergence. In so doing, not only the problem of convergence speed of BPNN has been solved, but also the simplicity of the model structure and the accuracy of the evaluation are ensured.

Mathematical Description of Particle Swarm Optimization

Suppose that in a D-dimensional target searching space, there is a group $T=\{X_1, X_2,..., X_N\}$ comprised of N particles representing potential problems, in which $X_i=(X_{i1}, X_{i2},..., X_{iD})$, $i=(1,2,...,N)$ represents a vector point of the i th particle in D-dimensional space. Substitute X_i into an objective function related to solving problem to obtain corresponding fitness value, and the merits and demerits of X_i can be measured according to fitness value. Record the best point (i.e. the obtained fitness value is the largest, which is P_i) searched by the i th particle up till now with $P_i=(p_{i1}, p_{i2},..., p_{iD})$, $i=(1,2,...,N)$. And in this group, there is at least one best particle, numbered as g, then $P_g=(p_{g1}, p_{g2},..., p_{gD})$ is the best value searched by the entire group, in which $g\in(1,2,...,N)$. And each particle has a speed variable; the speed of the i th particle can be expressed with $V_i=(v_{i1}, v_{i2},..., v_{iD})$, $i=(1,2,...,N)$. Particle swarm optimization generally adopts formula 1 and formula 2 to carry out operation on particles[5].

$$V_i^{k+1}=V_i^k+C1*r1*(P_i^k-X_i^k)+C2*r2*(P_g^k-X_i^k) \quad (1)$$

$$X_i^{k+1}=X_i^k+V_i^{k+1} \quad (2)$$

Evaluation Algorithm Design

This paper tries to put forward combination training algorithm combing PSO with BP algorithm to optimize BP neural network parameter and avoid the defects of network, i.e. PSOBPNN combination training algorithm. The basic concept is that first training BP network with PSO to find out a relatively optimal solution, then take the network parameter at this time as the initial parameter of BP algorithm to carry out the training, finally searching the optimal network parameter. Apply this combination training algorithm to nonlinear function approximation and stock price prediction with complex nonlinear dynamics features; the simulation experiment shows that the algorithm in this thesis avoids that the network falls into local minimum, having improved the generalization ability of network, and provides a brand new idea for the confirmation of BP neural network parameter, making BP neural network obtain favorable performance from a new perspective[6].

In consideration of the characteristics of PSO which is strong in global searching ability and poor in local searching ability and that of BP algorithm which is poor in global searching ability and strong in local searching ability, this thesis combines these two to form efficient combination training algorithm (PSOBPNN). The basic concept is that first training network with PSO to find out a relatively optimal solution, then take the network parameter as the initial parameter of network in BP algorithm to carry out the training, finally searching the optimal network parameter. Basic problems needing to be solved by combination training algorithm are encoding of particles, formation of fitness function, updating of particles speed and position, improvement on particle swarm optimization by using immunization information processing mechanism, combination of optimal particles and BP algorithm.

Encoding particles. Learning process of BP neural network is to carry out optimization study on such two continuous parameters of network as weight and threshold. As the initial value is difficult to be confirmed, this thesis adopts PSO to determine the initial parameter values of network, guaranteeing the scientificity of initial parameter values. In the encoding process of particles, if binary encoding is adopted on parameters, the encoding string will be too long, and shall be reverted to real numbers while decoding, thus influencing the learning accuracy of network and the running time of algorithm. Therefore, this paper adopts real number encoding form, i.e. code string form, as shown in formula 3, in which $V=(v_1,v_2,...,v_D)$, X represents the position of particles, V represents the speed of particles, D represents the total number of optimal network parameters; D can be obtained through formula 4[7].

$$X=(w_{n1},...,w_{n2},\theta_1,...,\theta_{n1},w_{m1},...,w_{mn1},\theta_1^{'},...,\theta_m^{'}) \tag{3}$$

$$D=n*n_1+n_1*m+n_1+m \tag{4}$$

Formatting fitness function. PSO algorithm basically makes no use of external information in the evolution searching, only taking fitness function as reference, making use of the fitness value of each individual in the group to carry out searching, judging the excellence of individuals with fitness value. Therefore, it is critical to choose fitness function, directly influencing the rate of convergence of PSO algorithm and whether able to find optimal solution. Generally, fitness function is transformed from objective function. This paper defines the network error as formula 5.Error function is also the objective function in this thesis. As the small the objective function value is, the larger the fitness value is, and the larger the objective function value is, the smaller the fitness value is, fitness function shall take the reciprocal of objective function, i.e. fitness function as shown in formula 6[8].

(5)

$$F(E_A)=1/E_A \tag{6}$$

$$E_A=\sum_{p=1}^{P}E^{(P)}=\frac{1}{2}\sum_{p=1}^{P}\sum_{k=0}^{m-1}(d_k^{(p)}-y_k^{(p)})^2$$

Updating particle speed and position. PSO algorithm first initializes a group of random particles, then find out optimal solution through iterations. During each iteration, particles update themselves through tracking two "extremum", i.e. individual extremum P_i and global extremum P_g . Suppose that the initialized group size is N , the position of the i th particle in the d th dimension is x_{id} , flying speed is v_{id} , the optimal position searched by it at present is p_{id} , the optimal position searched by the entire particle swarm at present is p_{gd} , then the algorithm formula for the updating of particles position and speed is formula 7[6].

$$\begin{cases} V_i^{k+1}=x(V_i^k+C1*r1*(P_i^k-X_i^k)+C2*r2*(P_g^k-X_i^k)) \\ X_i^{k+1}=X_i^k+V_i^{k+1} \\ w=w_{\max}-\dfrac{w_{\max}-w_{\min}}{num_{\max}}*num \end{cases} \tag{6}$$

In which $w_{\max}$ and $w_{\min}$ represent the maximum and minimum values of w respectively, $num_{\max}$ and num are largest iterations and current iteration respectively, $v_{id} \in [-v_{\max}, v_{\max}]$, x is constriction factor which can be obtained through formula 2. According to application experience, $x = 0.729$, $c1 = c2 = 2.05$, $r1$ and $r2$ are random numbers among $[0,1]$, $v_{\max}$ is constant which is set by users; termination condition of iteration, according to specific problems, is generally the largest iterations or that the optimal position searched by particle swarm up till now meeting the presupposed minimum threshold.

Improving Particle Swarm Optimization by Immunization Information Process Mechanism

Realizating immunological memory and regulation. Immunological memory means that immune system often saves the antibody intruding antigen reaction part as memory cells. While the antigens of the same kind re-intrude, memory cells will be activated and generate large quantity of antibodies. In IAPSO, this concept is used for saving excellent particles, viewing relatively excellent particles generated during the process of every iteration as memory cells. While new particles are tested to not conform to the requirements, it is considered that it is very low in fitness and shall be substituted by memory cells. Immunological regulation mechanism means that it will be promoted while the affinity of antibodies and antigens is large or low in concentration; while it will be restrained while the affinity of antibodies and antigens is small or high in concentration; different antibodies keep certain concentration all along. Such features are used for selecting new particles in PSO. □Substitute inferior particles. Test the newly-generated N particles; if the position of particles is infeasible solution, i.e. certain-dimensional component of X is not within the designated scope, substitute with memory particles; ② Randomly generate M new particles meeting requirements; ③Re-select N particles according to affinity and concentration of antibodies and antigens. While training BP network, the higher the fitness of particles (antibodies) is, the stronger the affinity is; the lower the fitness is, the poorer the affinity is; hence, affinity can be expressed with the reciprocal of fitness function, as shown in formula 8, selection probability determined by affinity as shown in formula 9, concentration of particles can be calculated with fitness, as shown in formula 10, selection probability determined by concentration as shown in formula 11, probability for particles to be selected can be obtained through formula 12, in which $i = 1,2,...,M + N$, α is a weight coefficient among $[0,1]$; $M + N$ particles can be ordered according to P_i, the first N particles with large P_i values will be selected.

$$Q_i = 1/F_i \tag{8}$$

$$P_{i1} = Q_i / \sum_{u=1}^{M+N} Q_u \tag{9}$$

$$D_i = 1/\sum_{u=1}^{M+N} |F_i - F_u| \tag{10}$$

$$P_{i2} = D^{-1}{}_i / \sum_{u=1}^{M+N} D^{-1}{}_u \tag{11}$$

$$P_i = \alpha P_{i1} + (1-\alpha) P_{i2} \tag{12}$$

Realizing accination and immunization selection. In immune system, vaccines are a kind of estimate on certain gene of optimal antibody, based on people's more or less priori knowledge on solving problems and extracting characteristic information. Vaccination is to alter certain components of antibodies according to vaccines. Immunization selection is used to check the performance of antibodies through vaccination. If the fitness is not as good as paternal generation after vaccination, the paternal generation shall be kept; if the fitness is better than paternal generation after vaccination, then choosing whether substitute its paternal generation through probability. In PSO, p_g generated in every iteration can be considered to be the most closed to the optimal solution, taking its certain component as vaccine to carry out vaccination and selection on particles. Methods are as follows. ①Vaccination. Randomly draw a particle from N new particles, then randomly draw a component in p_g and exchange with the drawn particle in corresponding position, finish one vaccination.② Immunization selection. Check whether the vaccinated particle meets the constraint conditions, abandon if not; carry out fitness calculation if yes. If the fitness is less than that before vaccination, then abandon; otherwise, carry out probability calculation. While calculating probability, randomly generate a number through $Rand()$ to compare with threshold p_g, selection the particle if it is larger, otherwise, abandon. ③Generate new-generation particles. After q times of looping execution (i.e. q times of vaccination) on the above vaccines and immunization selection, generate new-generation N particles, and carry out next iteration.

RESULTS AND DISCUSSION

Evaluation Indicators Analysis

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. 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 13 is adopted to carry out the normalization[3].

$$x' = \frac{0.8(x - x_{\min})}{(x_{\max} - x_{\min})} + 0.1 \tag{13}$$

Experimental Results

Limited to paper space, the evaluation of intermediate results is omitted here, only providing secondary evaluation results and final comprehensive evaluation results of three typical chains, see table 1.

Table 1 Part evaluation results

	Value chain perspective	Management perspective	Technical perspective	Final maturity
1	4.143	4.781	4.602	4.531
2	3.651	4.366	4.123	4.051
3	3.199	3.910	3.802	3.652

In order to illustrate the value of the presented algorithm and some other algorithms which are popular used for evaluating enterprise informatization maturity are realized with the same calculation platform in the paper. The indicators of the calculation platform can be listed as follows Intel i3 2120, 2GB DDR3, AMD Radeon HD 7450 and 3.3GHz CPU, and windows XP. Table 2 shows that the evaluation accuracy and time consuming of the different algorithms. Form the table we can see clearly that the algorithm in the paper has greater value than that's of ordinary BP neural network [4] and fuzzy evaluation algorithms[9] in evaluation accuracy or time consuming. In realization practice, the paper takes some obvious indicators as sample to calculate evaluation accuracy in order to make our comparison more believable.

Table 2 Calculation performance of different algorithms

	Algorithm in the paper	Ordinary BP model	Fuzzy evaluation model
Evaluation Accuracy	94.21%	84.66%	71.89%
Time Consuming (S)	12	641	10

CONCLUSION

It is shown through empirical research that the evaluation combination model presented in the paper is practicable, effective and feasible in performance evaluation of enterprise informatization maturity, and is able to effectively conquer some shortcomings of traditional evaluation models, as well as equipped with capabilities like self-learning, self-adaptation, strong fault tolerance and ability of expression, able to reduce some human subjective factors to the hilt, so as to improve the reliability of the performance evaluation of enterprise informatization maturity, making evaluation results more objective and accurate.

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