微粒群优化神经网络及其在环境评价中的运用

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摘要：农业项目环境影响综合评价是目前新的研究领域，随着农业项目的增加，其环境影响的研究愈来愈重要。以某农业项目为例，运用 PSO-BP 进行农业项目环境评价；仿真和实验表明：微粒群优化神经网络，能够克服神经网络收敛速度慢，陷入局部最小的缺点；微粒群优化算法涉及的参数不多，但是微粒群优化结果是比较理想的。

关键词：环境评价；微粒群优化；神经网络；仿真
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The enviromental quality assessment of neural network algorithm trained by particle swarm optimization

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Abstract: The environmental effect evaluation of agricultural projects is current a new research field. With the increase of projects, the study of environmental effect appears more and more important. We applied PSO-BP to evaluate the environmental effect of an agricultural project. Emulation and experiment show that the method of neural network algorithm trained by particle swarm optimization has overcome its disadvantage of slow convergent speed and shortcoming of local optimum. Particle swarm optimization needs only a few parameters and is a simple, while the result is pretty good.

Key Words: environmental evaluation; particle swarm optimization; Neural network; emulation

1 Introduction

Neural network is an intelligent algorithm, which has been widely used in automatic control, artificial intelligence, prediction science, intelligent control, etc. There are a lot of training methods of neural network. But they have a few defects, like overfit phenomenon. It looks like that the results of learning is pretty good, but in fact the generalization is rather bad. When the neural network is been training, a lot of parameters need to drafted, such as the input layer and the latent layer of nodes counts, times of the maximum training, efficiency of learning, parameter of momentum, etc. But the methods of drafting these parameters need to be well characterized. Usually

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the input layer and the latent layer of nodes are fixed by consulting some empirical formulae. The learning efficiency and momentum parameter are generally determined by training repeatedly using the "the law try by mistake" method in order to drawing relatively ideal value. But these methods could be very uncertain, and it's impossible to get the optimal solution, which will influence the result of training[1,2].

Traditional optimization strategies are mostly based on the gradient calculation, which need relatively higher requirement for the continuity of the function, existence of derivative. This limits their further development and application. Furthermore, the strategies based on gradient calculation are often sensitive to initial value. A good initial value is easy to make the algorithm to converge quickly to maximal optimization; otherwise it will slow the convergent speed and is not able to guarantee the algorithm to maximal optimization. For example, back propagation network (BP network) is one of the most widely used neural networks. BP network is designed based of gradient method. Standard BP network is a kind of multi-layer back propagation neuron network. It contains three layers: the first layer is called input layer, the last layer is called output layer and the layers between are hidden layers. Because it can adjust the weight through learning algorithm of back propagation, so it was called BP network. The BP algorithm is made up of two parts: the before propagation of information and the back propagation of error. Each sample for network training includes: the input value X, the desired output t, and the deviation between output value Y and desired output t. The information inputted is calculated step by step from the input layer and propagate for output layer. If we haven't get the ideal result in the output layer, the network will calculate the variation of error and then propagate back. This process applies again and again until error signal reaches the expectation target. As one of the neural network models, BP model, which is a simple and effective algorithm, has been applied widely. It has already extensively applied in pattern-recognition, knowledge engineering, trend analysis, ect. The BP network application in agriculture project includes: (1) Modeling and simulation of post-evaluation based on rough set-neural network. (2) Application of rough neural network in agricultural engineering project evaluation. (3) Appraise a model of agricultural high sci-tech agriculture projects base on BP. But the BP network also has disadvantages such as it is slow to disappear, apt to fall into the local minimum, etc[3-5].

Particle swarm optimization (PSO) is a kind of new evolution algorithm developed in recent years. Like genetic algorithms, PSO is initialized with a population of random solutions and calculates the fitness values for each subject. And then population duplicates according to the fitness value, searches for the optimum solution by updating generations. Compared with genetic algorithms, information sharing mechanism of PSO is different. In genetic algorithms, whole population moves to the optimum area evenly. However, only the best position (pbest or gbest) provides the information for other ones in PSO, and this is what called a one-way information flows. The whole process of searching and renewing follows present optimum solution course. In most cases, all particles converge to optimum solution more quickly in PSO than in genetic algorithms. PSO leaves no heredity operation such as crossover and mutation. But it seeks the entire optimum through following the present searched optimal value[6].

In order to avoid the disadvantage of traditional BP algorithm, which is to trap into the local minimum. Herein we utilize a new learning algorithm of BP network — particle swarm learning algorithm (PSO). The PSO algorithm, proposed by Kennedy and Eberhart, adopts parallel technology to quicken the speed and has proved to be very effective in solving global optimization for multi-dimensional problems in noisy and continuously changing environments. PSO characterized with easy description and implementation with few parameters, relatively smaller scale population, less function number for convergent evaluation, and quick convergent speed. Moreover, PSO does not need gradient information of the goal function, only depends on the function value. It has been proved to be the effective method to figure out a lot of the overall situation about the optimum problem. PSO is considered a useful algorithm to develop neural network, follow the dynamic systems, control the fuzzy systems, solve multiple goals optimization, minimize and maximize problems, integrate planning problem. In addition, PSO is also applied to a lot of industrial fields, such as the energy and voltage control reflection, mixed composition optimization, workshop homework deployment, robot real-time route plan, automatic goals detection and frequent analyzation[7,8], etc.

As the combination of neural network and particle calculation has good expectancy in theory and great potentiality in practical application, we will use this strategy to evaluate agricultural projects. This will not only greatly accelerate the development and application of PSO algorithm, but also increase the calculation performance of the neural network.

2 Methods

2.1 Mathematical models of PSO algorithm

PSO is an evolutionary algorithm, which based on the components of the population. Every individual is known as the particle in the population. Particle flies by a certain speed in a searching space and will dynamically adjust itself according to the flying status of itself and its companions. The particle will update its own velocity and position according to following formulas:

$$v_{id}^{n+1} = wv_{id}^{n} + c_1 r_1^n (p_{id}^n - x_{id}^n) + c_2 r_2^n (p_{gd}^n - x_{id}^n) \quad (1)$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \quad (2)$$

where v_{id}^{n+1} is the velocity of the particle; x_{id}^{n+1} is the position of the particle; P_{gd} is the best position of all particles occupied; W is the inertial weight, which is able to adjust the abilities of overall and local search; c_1, c_2 are called the study factors and usually taken as two; and r_1^n, r_2^n are the random data between 0 and 1.

The right side of the formula consist of three parts. The first part is initial particle velocity and inertia, and the next two parts reflect the updated particle velocity and inertia. The first part of v_{id}^{n+1}, offers an essential momentum for particle, which determine its inertia ability according to it's own velocity. The inertia weight has the equilibrious ability to maintain particle's overall and local search. But because the particles move at random and lack remembrance ability, they have the tendency to expand the search space to a new area. Thus it has the ability of the overall optimization. The second parts of the right formula define the remembrance ability of particles by recognizing the present optimal situation of particle grouping the population, which makes the particle get near to the most optimal position during the process of flying. It can be described as the "cognition" behavior of the particle, which means that particles itself have thinking ability. The third part can be described as "society" behavior of the particle, showing that the particles can communicate and cooperated each other[9–11].

2.2 PSO algorithm procedures

Neural network is a kind of parallel running network that summarized, simplified and refined from the characteristics of biological neuron and neural network. It has fast modeling ability to the non-linear data. It has already become an important method to dig the data. But the neural network has its limitation. For instance, it is slow to disappear, apt to fall into local optimum. When the neural network is been training, a lot of parameters need to drafted, such as the input layer and the latent layer of nodes counts, times of the maximum training, efficiency of learning, parameter of momentum, etc. But the quality of these parameters influences the convergent velocity and the precision of prediction directly. These methods of drafting parameters have very great uncertainty, and this will influences the result of training. Training the neural network by PSO mainly includes three respects: the connection weights, the neural network structure and the transmitting function, the studying algorithms. Each particle includes all parameters of the neural network, and reach the goal of training through changing and substituting these optimal parameters. Compared with traditional back propagation network, the advantage of using PSO to train the neural network lies in not only using gradient information, but also using some transmitting functions those can't be differential. The result of PSO training is superior to that of BP algorithm in most situations. The flow chart is described in Fig. 1.

PSO algorithm procedures are as follows(Fig. 1):

(1) Initialize position and velocity of each particle in PSO. The initial position and velocity of the particles usually are produced at random in the permitting range. Consider i as the particle in the total swarm. The best previous position of the ith particle is stored and represented as *pbest*. The best value among all *pbest* is represented as *gbest*.

(2) Calculate the desired fitness function values for current each particle.

(3) Update *pbest* and *gbest*. To each particle, compare the evaluated fitness value of each particle with its *pbest*. If current value is better than *pbest*, then set the current location as the *pbest* location. Furthermore, Compare each individual's evaluation value with its *pbest*. The best evaluation value among the *pbest*'s is denoted as *gbest*.

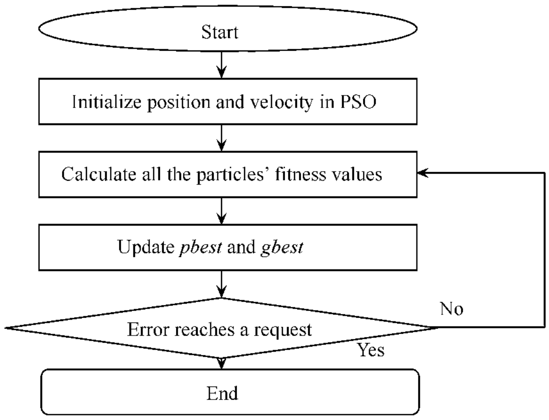


Fig. 1　The flow of PSO -BP algorithm

(4) According to formulas (1), (2), update the location and flying velocity of each particle.

(5) If the stopping criteria are met, the positions of particles represented by *gbest* are the optimal solution. Otherwise, stop and return to step 2[12-14].

When the parameters of BP network were optimized with PSO algorithm, the elements of location vectors of PSO were defined as the inputting layer of nodes counts, the latent layer of nodes counts, learning efficiency, the momentum parameter, etc. First, initialize the position vector and velocity vector, then search for the optimum position with PSO algorithm, make the minimum error requirement.

3　Artifical experiments

3.1　Establish index system of an environmental assessment of agricultural project

In this paper, we use an agricultural project as an example; utilize PSO-BP to evaluate environmental-quality assessment. There are several principles when selecting the environmental evaluation index of agricultural project:

(1) Comprehensiveness. The index can completely express the situation of agricultural project.

(2) Comparability. The standard of selected index should remain unchanged.

(3) Representation. The selection of index can reflect the main characteristics of the project.

(4) Operability. The relevant data should be easy to count, quantify and interpret. The evaluation results can provide a theoretical basis of the ecological environmental planning of the agricultural development.

The index we select here is mainly according to the technical guidelines for environmental impact assessment of State Environmental Protection Administration of China. Based on the principles of the evaluation index and the availability of data, we can determine evaluation index system, which mainly reflect environmental benefits, environmental pollution and ecological degradation. The index of environmental benefits mainly includes the rate of lawn area and seedlings area. The index of environmental pollution mainly includes water pollution, soil contaminates and agricultural product pollution. The index of ecological degradation mainly includes the loss of soil and water area, the amounts chemical fertilizer, the lessening rate of vegetation coverage and so on (Fig .2).

3.2　The environmental quality assessment of agricultural developing project by PSO-BP

The measured and forecast data for the environmental quality assessment were shown in table 1. According to

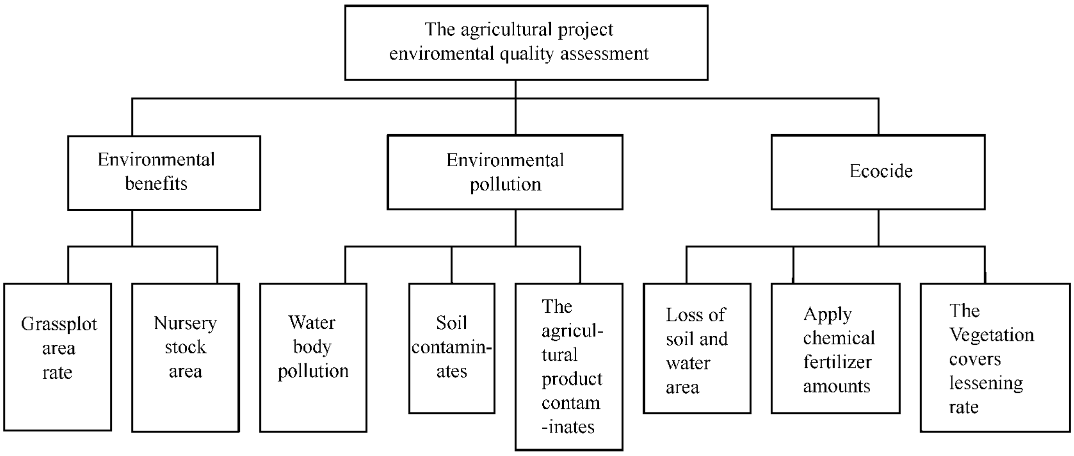
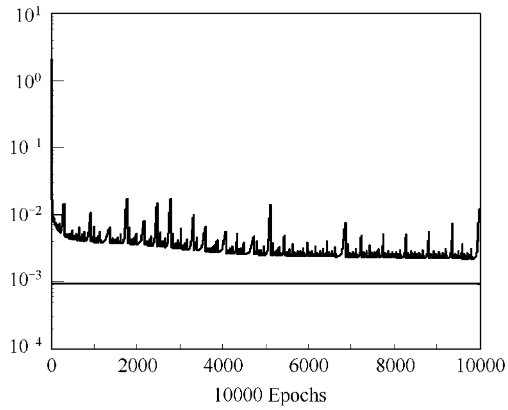


Fig. 2 Index system of an environmental assessment of agricultural project

table1, we can see that the ideal value and the actual value are very similar, which shows that the optimal result is reliable. We are able to get the best process parameters by the optimization. Then we use these parameters and measure the environmental quality assessment with BP and PSO-BP algorithm. The results at Fig. 3 showed that the plot of convergence of the best solution obtained by the BP network and the PSO-BP network . In the standard back-prapagation network: net. trainParam. epochs = 10000; SSE = sumsqr$(t-Y)$, t is ideal value; Y is value that reality appraises SSE is equivalent to 1. 6061. In the neural network algorithm trained by Particle swarm optimization: net. trainParam. epochs = 5000; SSE is equivalent to 0. 3016; The results proved that the proposed algorithm of the PSO-BP network has better quality of solution than the BP methods[15—17].

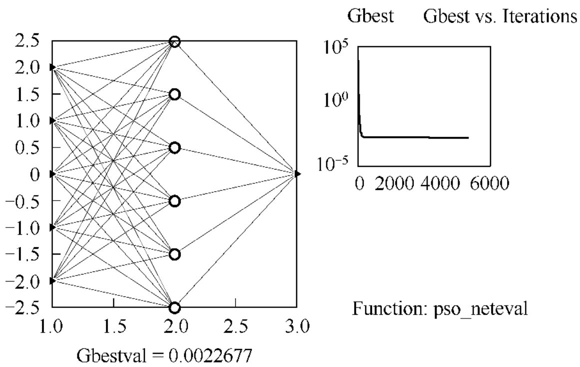
Table 1 Results of *y* of optimization

Actual value	Ideal value	Actual value	Ideal value	Actual value	Ideal value	Actual value	Ideal value	Actual value	Ideal value	Actual value	Ideal value
0.3620	0.2	0.4115	0.4	0.4115	0.4	0.4115	0.4	0.4115	0.4	0.4159	0.4
0.5983	0.6	0.6714	0.6	0.7241	0.6	0.7241	0.6	0.7854	0.8	0.7855	0.8
0.4159	0.4	0.4158	0.4	0.3620	0.4	0.3620	0.4	0.4521	0.4	0.5640	0.6
0.8350	0.8	0.8350	0.8	0.7855	0.8	0.7855	0.8	0.7855	0.8	0.7855	0.8
0.3964	0.4	0.4115	0.4	0.4115	0.4	0.4115	0.4	0.3638	0.4	0.4158	0.4
0.6374	0.6	0.6736	0.6	0.7855	0.8	0.7855	0.8	0.7855	0.8	0.7855	0.8
0.3620	0.4	0.3620	0.4	0.3620	0.4	0.3893	0.4	0.5238	0.4	0.5221	0.6
0.6374	0.6	0.6374	0.6	0.6377	0.6	0.7491	0.8	0.7855	0.8	0.7855	0.8
0.3982	0.4	0.4115	0.4	0.3982	0.4	0.5101	0.4	0.4116	0.6	0.5596	0.6
0.7203	0.8	0.7241	0.8	0.7241	0.8	0.7241	0.8	0.7855	0.8	0.4115	0.4
0.4115	0.4	0.3620	0.4	0.4739	0.4	0.5709	0.6	0.5716	0.6	0.5716	0.6
0.7855	0.8	0.7855	0.8	0.7855	0.8	0.7855	0.8	0.4115	0.4	0.4115	0.4
0.5016	0.6	0.5622	0.6	0.5716	0.6	0.5998	0.6	0.6330	0.6	0.8350	0.8
0.4007	0.4	0.3620	0.4	0.4115	0.4	0.4115	0.6	0.7775	0.8	0.7855	0.8
0.7855	0.8	0.7855	0.8	0.7855	0.8	0.4159	0.4	0.8002	0.8	0.8190	0.8
0.5640	0.6	0.6702	0.6	0.6703	0.6	0.7855	0.8	0.5221	0.6	0.5835	0.6
0.8350	0.8	0.7855	0.8	0.3622	0.2	0.3620	0.4	0.4115	0.4	0.4115	0.4
0.5716	0.4	0.5716	0.6	0.5221	0.6	0.6374	0.6	0.5640	0.6	0.6135	0.6
0.7855	0.8	0.3620	0.4	0.3620	0.4	0.3620	0.4	0.4115	0.4	0.4115	0.4
0.7811	0.8	0.7946	0.8	0.7855	0.8	0.5835	0.6	0.6374	0.6	0.4115	0.4
0.4115	0.4	0.4115	0.4	0.4115	0.4	0.4115	0.4	0.3996	0.4	0.7855	0.8
0.7969	0.8	0.8350	0.8	0.7855	0.8	0.6114	0.6	0.7241	0.8	0.4115	0.4



TRAINGDA, Epoch 0/10000, MSE 2.12339/0.00095238, Gradient 4.13589/1e-006
TRAINGDA, Epoch 25/10000, MSE 0.0161011/0.00095238, Gradient 0.0404656/1e-006
TRAINGDA, Epoch 9900/10000, MSE 0.00227707/0.00095238, Gradient 0.0272965/1e-006
TRAINGDA, Epoch 9925/10000, MSE 0.00254853/0.00095238, Gradient 0.0577897/1e-006
TRAINGDA, Epoch 9950/10000, MSE 0.0036832/0.00095238, Gradient 0.11871/1e-006
TRAINGDA, Epoch 9975/10000, MSE 0.00730752/0.00095238, Gradient 0.220285/1e-006
TRAINGDA, Epoch 10000/10000, MSE 0.0120761/0.00095238, Gradient 0.303738/1e-006
SSE = 1.6061

Training by the stand BP network



PSO: 1/5000 iterations, GBest =7504.3095444928504.
PSO: 100/5000 iterations, GBest = 0.033576215062861854.
PSO: 200/5000 iterations, GBest = 0.0031122359211243349.
PSO: 4300/5000 iterations, GBest = 0.0022684604294561017.
PSO: 4400/5000 iterations, GBest = 0.0022683633684786792.
PSO: 4500/5000 iterations, GBest = 0.0022682365550045487.
PSO: 4600/5000 iterations, GBest = 0.0022679525036250195.
PSO: 4700/5000 iterations, GBest = 0.0022678767629683546.
PSO: 4800/5000 iterations, GBest = 0.0022678109328905446.
PSO: 4900/5000 iterations, GBest = 0.0022677589327473003.
PSO: 5000/5000 iterations, GBest = 0.002267663819278916.
SSE = 0.3016

Training by the PSO- BP network

Fig. 3　Results of optimization with PSO

4　Discussions

From the result of PSO operation of a agriculture project, we find that there is obvious advantage of PSO trained algorithm neural network comparing with standard BP net network. Although only few parameters are required, they are important for the optimization efficiency of Particle swarm optimization . During calculation process, numerous trials are required to confirm the parameters in PSO, especially for complicated optimization questions. So many parameters will seriously influence the convergent property when there are improper parameters.

The strategy of combination of PSO and BP algorithm to learn and train the neural network has overcome the disadvantage of slow convergent velocity, easy falling into the smooth platform of BP algorithm, and it makes the neural network learn with fast disappearance and the high precision. PSO algorithm is a quite simple algorithm, only needing few codes and parameters, but it has a very useful algorithm in the application of asking and solving various questions. It has great advantage of than the traditional method especially in optimizing overall situation performance.

But the study and application of PSO algorithms is still at the primary stage. The method it used need to be practice and performance test and without powerful theory support. So its application field and the theory about PSO still need exploring.

Recently, two global random and optimal algorithms: genetic algorithms (GA) and simulated annealing (SA) have been widely applied. Genetic algorithm adopts the idea of the biological evolution and has a powerful quality of global search. GA are versatile evolutionary computational techniques that are largely based on the principle of survival of the fittest. However, GA have shortcomings of premature convergence, less diversity control, time consuming, weak efficiency of fine-tuning and poor solution quality and thus has a weak ability for local searching and a lower computing efficiency, especially in the later process of GA. ANN training by GA also exists fall short: complicated genetic algorithms, too much CPU time, too early convergence, and slow convergence.

SA originates from the method of the statistical physics and first employed by Kirkpatric to solve the optimization problem, on the other hand, has more powerful local search ability, but it depends more on parameter. However, because the algorithm has no knowledge about the global objective space that has been detected, it is hard to figure out which area contains optimal results more likely, resulting lower computing efficiency. The disadvantage of SA is that it cannot directly enter into the most expected search area and hence it runs very slowly. ANN combined SA exist certain limitation: (1) The training time of ANN combined SA is usually too long . (2) It is hard to operate and has low efficiency[18–21].

PSO can generate high-quality solutions within shorter calculation time and have more stable convergence characteristics than other stochastic methods. It has the characteristics of seeking excellent from overall situation and disappears fast. The combination of neural network and PSO make BP network excellent to seek further, improving the precision and disappearing pace. The results of this paper confirmed that the reliability of the PSO algorithm is more powerful in the aspects of solution quality and computation efficiency.

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