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Application of Particle Swarm Optimization BP Algorithm in Air Humidity of Greenhouse Crops

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Abstract: The advancement of artificial intelligence, the synonym of precision agriculture has approached the public's vision, and the different requirements for air humidity in different growth periods of crops are proposed. The BP neural network optimized by particle swarm optimization algorithm is proposed to predict the air humidity of crops. Algorithm, this paper chooses BP algorithm network topology structure is 2-5-1, improves the inertia weight of PSO

algorithm, proposes nonlinear inertia weight reduction strategy $w = w_s - (w_s - w_e) \left| f_1 \sqrt{\frac{t}{T}} \right|$,

trains BP algorithm with improved PSO algorithm, has no gradient information, jumps out local pole Value, reduce the number of iterations of the algorithm, and speed up the training speed of the neural network. According to the experimental results of MATLAB simulation, the air humidity prediction model of particle swarm optimization neural network is constructed, which proves the effectiveness of the improved particle swarm neural network prediction system. It can be shown that the proposed algorithm has a relative error of at least 0.0134 compared with other algorithms.

Key words: intelligent agriculture; air humidity; BP neural network; particle swarm optimization

1. Introduction

This paper proposes to combine the improved particle swarm optimization algorithm with BP neural network and apply it to the prediction of air humidity required by crops. In 1986, Rumelhart et al. [1] proposed the BP neural network algorithm, which solved the problem of hidden unit connection weight in multi-layer neural networks and has been widely used. However, BP algorithm based on gradient descent is easy to fall into local poles. Inadequate defects such as value and slow convergence rate. In 1995, the particle swarm optimization algorithm PSO proposed by American scholars Eberhart and Kennedy [2] introduced them into the training of neural networks and received wide attention. Song Xiaomeng et al [3] introduced the Internet of Things technology and fuzzy PID control to In the greenhouse environmental monitoring system, from the aspects of low cost, precise control and easy operation, the intelligent monitoring of strawberry greenhouses is realized. Wang Yaodong [4] proposed to construct a seismic prediction model based on improved particle swarm neural network, using inertia. Weights and learning factors dynamically adjust the strategy balance algorithm, and get a lower average error rate; Zhang Ermei [5] based on the characteristics of



ammunition storage reliability, established a prediction model combining particle swarm and neural network, which added the momentum term. And variable learning rate parameters, to achieve the function of ammunition storage reliability assessment and prediction.

In this paper, the inertia weights in the PSO algorithm are improved, and combined with the BP algorithm in the prediction of crop air humidity, the purpose is to control the air humidity demand of different growth periods of crops through the effective prediction of intelligent algorithms. Bakker [6] Studies have shown that changes in humidity in the greenhouse can affect the yield of growing crops. In the case of high humidity, crops are easily corroded by fungal diseases, directly affecting the quality and yield of crops. On the contrary, when the humidity is too low, It will cause serious water loss of crops and lead to poor growth or even death of crops. Therefore, effective control of air humidity is necessary, and the air temperature and humidity in the greenhouse have a certain coupling relationship. We can stabilize the air temperature. Apply BP intelligent algorithms to air humidity.

2. Improved particle swarm optimization algorithm

The PSO particle swarm optimization algorithm has a fast calculation speed and the algorithm itself has few parameters and strong global search ability. In order to improve the convergence speed and accuracy of the algorithm, a nonlinear weight decrement strategy is proposed in this paper. The experimental results show that the effect is the best [7].

In order to balance the algorithm's global search and local search ability, and to solve the shortcomings of the algorithm's low convergence and falling into local extremum, in 1998, YHShi et al. introduced the inertia weight into the PSO algorithm, and improved the particle swarm algorithm. To ensure a good convergence effect, the evolution process is shown in equations (1) and (2):

$$V_{ij}(t+1) = wV_{ij}(t) + c_1r_1[V_{ij}(t) - X_{ij}(t)] + c_2r_2[P_{gj}(t) - X_{ij}(t)] \quad (1)$$

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \quad (2)$$

Where $i=1, 2\dots n$, $j=1, 2\dots d$, n represents the number of particles in the particle group, and d represents the dimension of the target space. c_1 and c_2 represent learning factors, r_1 and r_2 are random numbers, the value range is $[0,1]$, and w represents inertia weight.

The standard particle swarm optimization algorithm is commonly used in Y.H.Shi[8] to propose a linear decrement weight strategy expression as shown in (3):

$$w = w_s - (w_s - w_e) \frac{t}{T_{\max}} \quad (3)$$

The search process is a nonlinear and complex process, so this paper improves the linear decreasing weight strategy into a nonlinear decreasing weight strategy to enhance the local and global search ability. The formula is shown in (4):

$$w = w_s - (w_s - w_e) \left| f_1 \sqrt{\frac{t}{T_{\max}}} \right| \quad (4)$$

Where T_{\max} represents the maximum evolution algebra; w_s represents the initial inertia weight value, w_e represents the inertia weight that evolved to the maximum allowed number of iterations, t represents the current number of iterations, f_1 is the control factor, and $w_s = 0.95$, $w_e = 0.4$. When $t = 0$, the function value is equal to the initial weight w_s . When $t = T_{\max}$, different values of f_1 will get different decreasing effects. When f_1 is larger, it will decrease to close in the early stage of the algorithm. Forcing the algorithm to fall into the local search

early; when the value is small, it will make w more than we when $t = T_{\max}$. When the experimental test f_1 takes the value of 0.9, the experimental effect is the best, so the value of f_1 in this paper is 0.9. The result shows that the improved strategy can better maintain the balance between global search and local search.

3. Particle Swarm Optimization of BP Neural Network

The particle swarm optimization algorithm optimizes the initial weight and threshold of the BP neural network, and sets the position in the particle swarm as the set of weights and threshold values in the current iteration in the BP network, ie $p_g = \{W_1 B_1 W_2 B_2\}$, where W_1 is the hidden layer weight

$$\text{matrix, } W_1 = \begin{bmatrix} w_{31} & w_{32} \\ w_{41} & w_{42} \\ w_{51} & w_{52} \\ w_{61} & w_{62} \\ w_{71} & w_{72} \end{bmatrix}, W_2 \text{ For the output layer weight matrix, } W_2 = [w_{83} \quad w_{84} \quad w_{85} \quad w_{86} \quad w_{87}]^T,$$

B_1 is the hidden layer threshold matrix, $B_1 = [\theta_3 \quad \theta_4 \quad \theta_5 \quad \theta_6 \quad \theta_7]^T$, B_2 is the output layer threshold matrix, and the dimension of the $B_2 = [\theta_8]$ particle is mapped to the number of weights and the number of thresholds that are connected, through the optimal position The optimization process obtains the initial weight and threshold of the optimal BP neural network, making full use of the global search ability of the PSO algorithm and the local search ability of the BP neural network.

3.1 Particle Swarm Optimization Algorithm for BP Neural Network Optimization

(1) Initialization parameters: such as BP neural network topology, particle number $n = 30$, particle dimension $d = 21$, maximum iteration number $T_{\max} = 1000$, learning factor $c_1 = c_2 = 2$, inertia weight $w_s = 0.95$, $w_e = 0.4$, learning rate $lr = 0.05$, target error $goal = 0.0001$, maximum particle velocity $v_{\max} = 1$ and minimum speed $v_{\min} = -1$ and other parameters;

(2) Calculating the fitness value of the particle, that is, the neural network output error, determining the individual extremum and the global extremum of the particle: for each particle i , the fitness value p_i is compared with the individual optimal value p_i' , if $p_i < p_i'$, Then $p_i' = p_i$, and record the position of the current best particle; for each particle i , compare the fitness value p_i with the global optimal value p_g , if $p_i < p_g$, then $p_g = p_i$, and record the position of the current best particle;

(3) Updating the velocity and position of each particle according to formulas (1) and (2), and judging whether the speed and position of the updated particle are within a limited range;

(4) Checking the iterative stop condition of the algorithm. If the result is ideal, stop the iterative output of the BP neural network weight or threshold, so that the BP network can better reduce the error, otherwise go to step (2).

3.2 Particle Swarm Optimization Algorithm and Neural Network Simulation Analysis

In this experiment, the cultivation of strawberries in greenhouses in Suihua City, Heilongjiang Province was taken as an example to study the air humidity requirements of strawberries in different growth periods in greenhouses. Strawberry humidity control requirements in greenhouse: The relative air relative humidity required for strawberry flowering is 40%; the initial temperature of strawberry is to prevent strawberry from entering dormancy period, and the required temperature is relatively high. At this time, the relative humidity of air is controlled at 85%-90%; The flowering period of strawberry is stricter to the air humidity. If the humidity is too small or too small, the pollination will be poor. At

this time, the relative humidity of the air is controlled at about 40%; the fruit of the strawberry is swollen and mature, and the strawberry is affected by the temperature at this time. The humidity can be controlled between 60% and 70%.

According to these control requirements, this paper uses an optimized intelligent algorithm to control and construct a 3-layer BP neural network applied to the prediction of greenhouse air humidity, in which there are 2 input layer nodes and 5 hidden layer nodes, hidden layer. The activation function is 'tansig', the output layer node is one, and the output layer activation function is 'logsig'. In the application, the two parameters of sun light and air temperature in the shed are taken as input variables, and the optimum air humidity required by strawberry is used as the output variable for simulation test. This simulation experiment selects 30 data of winter strawberry, the first 20 data. For the training data, the last 10 data are the detection data. In order to better reflect the excellent value of the result, we compare the results of BP network algorithm, linear PSO-BP network algorithm and nonlinear PSO-BP network algorithm. The simulation results are as follows: The Figure shows:

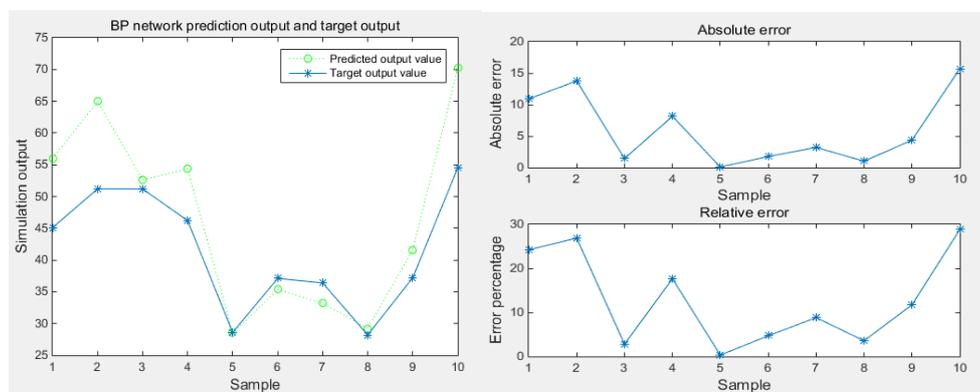


Figure 1. BP network prediction output and target output and associated error map

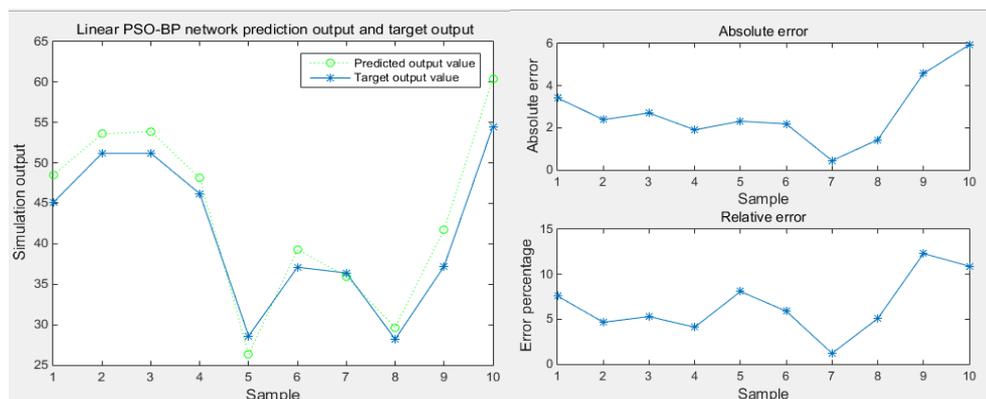


Figure 2. Linear PSO-BP network prediction output and target output and associated error map

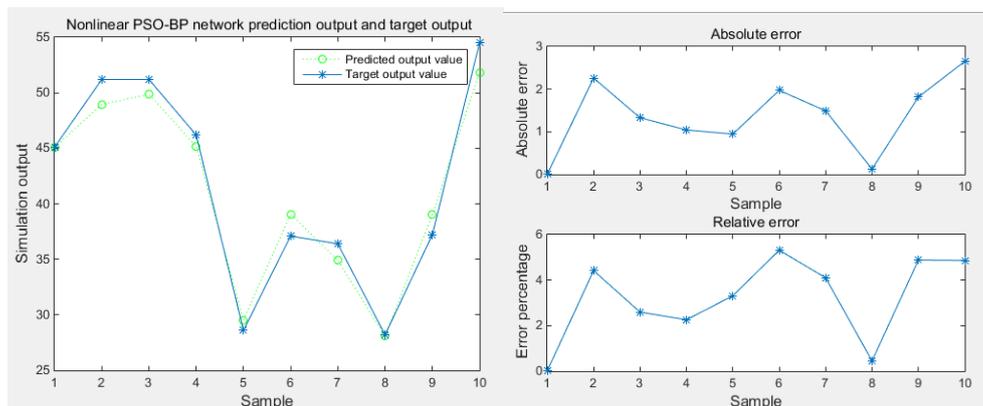


Figure 3. Nonlinear PSO-BP network prediction output and target output and associated error map

Table 1. Comparison of average error rates of the three algorithms

Algorithm selection	Relative error										Average error rate
	21	22	23	24	25	26	27	28	29	30	
BP	24.1901	26.8582	2.7993	17.6296	0.3141	4.7043	8.8011	3.5698	11.7018	28.7990	12.9367
LinearPSO-BP	7.5760	4.6593	5.2843	4.1138	8.0835	1.5592	1.2038	5.0751	12.3016	10.8968	6.0753
NonlinearPSO-BP	0.0134	4.4126	2.5937	2.2553	3.3092	5.3133	4.0995	0.4464	4.8785	4.8665	3.2188

Result analysis:

It can be seen from the above simulation results that the BP neural network optimized by nonlinear PSO is much smaller than the other two algorithms in training error. Especially for the traditional BP network algorithm, the training effect is much better than the traditional BP network. The linear PSO-BP algorithm has strong learning ability and generalization ability. It can be seen from Figure. 1 that the traditional BP is easy to fall into the extreme value, especially the target output value of the sample 22 reaches 64.9, far exceeding the predicted output value, and the error. The rate is also the highest of the three algorithms; from Figure. 2 and Figure 3, the linear PSO-BP network and the nonlinear PSO-BP network have similar training effects, but the nonlinear PSO-BP network has a linear error rate. Smaller, the absolute error of the nonlinear PSO-BP network is less than 3, and the error is minimum at 0.0060 when the sample is 21, which shows the best training effect. Finally, the nonlinear PSO-BP network can be seen from Table 1. The relative error is the smallest, the accuracy is the highest, and the global search ability is also good. In summary, the optimization scheme proposed in this paper is feasible.

4. Conclusion

Aiming at the prediction of air humidity in agricultural planting, this paper proposes an intelligent optimization algorithm based on particle swarm optimization PSO to optimize BP neural network. The algorithm combines the idea of population activity mechanism and back propagation neural network, which improves the global algorithm to some extent. Search ability, convergence accuracy and speed, so as to quickly control the demand for air humidity in different growth periods of crops, so that crops have a better growing environment.

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