Prediction of soil humidity based on random weight Particle Swarm Optimized Extreme Learning Machine

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Abstract: The prediction of high quality soil moisture is of great significance to agricultural production and scientific research. In order to solve the problem that the prediction results of (ELM) regression model of limit learning machine are affected by input parameters, the stochastic weight particle swarm optimization algorithm (RandWPSO) is applied to ELM regression model. In this paper, a soil moisture prediction method of particle swarm optimization limit learning machine based on random inertia weight is proposed. In this method, the data of soil temperature and light intensity measured by sensor are used to preprocess the data, the training sample set is constructed, and the ELM regression model is established. The input weight and threshold in ELM are optimized by using random weight particle swarm optimization algorithm to avoid falling into local optimization, thus the prediction model of soil moisture based on RandWPSO-ELM is established. The soil moisture of sugar beet in Hulan area was studied. The experimental results show that the method has high accuracy and stability, and can provide an effective reference for the growth of sugar beet in greenhouse.

1. Introduction
Soil moisture is closely related to agriculture. Soil moisture determines the water supply of crops. If soil moisture is too low, it is easy to form soil drought and affect plant photosynthesis. Excessive soil moisture will worsen soil aeration and affect crop respiration and normal growth [1]. Soil moisture is greatly affected by climate factors, such as light intensity, air temperature, rainfall and other factors [2]. Therefore, the study of soil moisture has important theoretical and practical significance. At present, many scholars at home and abroad have done research on soil moisture prediction, and most of them use artificial neural network and support vector machine to predict soil moisture, but few use limit learning machine to simulate and predict soil moisture in greenhouses. Yang Xiaoxia et al. [3] used the improved BP neural network model to predict soil moisture in the grain barn test area. Although the initial BP threshold was solved, the measured error was large due to the slow learning speed of BP itself. Xue Xiaoping, Wang Xin, Zhang Lijuan et al. [4] established a soil moisture prediction model with high prediction accuracy by using the support vector machine method, but ignored the hysteresis of soil moisture change to the response of various meteorological factors, and the parameter selection was based on the traditional trial calculation method, which made it difficult to find the optimal parameter and the operation efficiency was low. Mei Yi, Song Peiyi et al. [5] put forward GA-ELM model to predict the vibration of manipulator. Although the prediction fitting is good, it ignores the genetic algorithm, which is easy to fall into local optimization.

Based on the above on the basis of predecessors research, this article mainly USES the improved
Extreme Learning Machine (Extreme Learning Machine, ELM) to forecast soil moisture, the algorithm is randomly generated between the input layer and hidden layer connection weights and threshold of hidden neurons, and no adjustment in the process of training, only need to set the number of neurons in hidden layer, can obtain the optimal solution. Compared with the traditional training method, this method has fast learning speed and good generalization performance. However, as the initial input weight and threshold of ELM are randomly determined, the training effect will be affected by the initial value, while the elementary particle swarm is easy to fall into local optimization. Therefore, Random Weights Particle Swarm Optimization (RandWPSO) was combined with ELM in this paper. In this way, the improved PSO can optimize the input weight and threshold of ELM, improve the accuracy and stability of the traditional prediction model, and provide a new method for predicting soil moisture.

2. Basic theory

2.1 ELM algorithm

ELM is a single hidden layer feedforward neural network [6]. Due to its fast learning speed and good generalization, ELM is widely used in crop yield prediction, construction and bridge construction prediction, etc. In this paper, it is applied to soil moisture prediction. In this algorithm, the connection weights between the input layer and the hidden layer and the threshold of the hidden layer neuron are generated randomly, and the unique optimal solution can be obtained by setting the number of hidden layer neurons without any adjustment in the training process.

The typical feedforward neural network structure of single hidden layer is shown in Figure 1. The unknown quantity in the figure is expressed as follows: \( x_q = \left[ x_{q1}, x_{q2}, \ldots, x_{qN} \right]^T \), \( q = 1,2,3,\ldots,n \) as the input vectors; \( g(x) \) as hidden layer excitation function; \( \{ w_{ij} \}_{n \times l} \) and \( \{ \beta_{jk} \}_{l \times m} \) are the weight matrix from the input layer to the hidden layer and the weight matrix from the hidden layer to the output layer respectively; \( \{ b_j \}_{l \times 1} \) as the hidden layer node threshold. Where, \( m \) and \( n \) represent the node number of ELM input layer and output layer respectively; \( l \) is the number of hidden layer nodes. The corresponding output for \( m \) inputs of ELM is \( Y_q = \left[ y_{q1}, y_{q2}, \ldots, y_{qm} \right]^T \). It can be expressed as Equation (1):

\[
y_q' = \sum_{j=1}^{l} \beta_j g(\sum_{i=1}^{n} w_{ij} x_{i\cdot k} + b_j)
\]

In the formula, \( q' = 1,2,3,\ldots,m \); \( k = 1,2,3,\ldots,m' \); \( k = 1,2,3,\ldots,n \)

![Figure 1. Structure diagram of feed-forward neural network with single implicit layer.](image)

Set \( T_q' = \left[ t_{q1}', t_{q2}', \ldots, t_{qm}' \right]^T \) as the output of the extreme learning machine. When ELM can be approximated with \( Y_q \) the error of 0, then:
\[ \sum_{q'=1}^{m} \left\| T_q' - Y_q' \right\| = 0 \]  \hspace{1cm} (2)

Equations (2) and (3) are simultaneous, then:

\[ \sum_{j=1}^{l} \beta_{jq} G( \sum_{i=1}^{n} \alpha_{ij} x_{ik} + b_j ) = t_q k' \]  \hspace{1cm} (3)

In the formula, \( q'=1,2,3,\ldots,m \) : \( k'=1,2,3,\ldots,m' \) : \( k=1,2,3,\ldots,n \).

If the output matrix of the hidden layer is \( H \), then Equation (3) can be rewritten as:

\[ H \beta = T \]  \hspace{1cm} (4)

When the weights and thresholds of the hidden layer are generated randomly, the output matrix of the hidden layer is determined accordingly. The least squares solution can be obtained through Equation (4), and the weights of the output layer can be obtained:

\[ \beta = (H^+)^T \]  \hspace{1cm} (5)

Where, \( H^+ \) is the Moore - Penrose generalized inverse of the hidden layer output matrix \( H \).

2.2 Stochastic weighted particle swarm optimization algorithm

In 1995, the American scholar Kennedy and Eberhart [7] particle swarm optimization algorithm is proposed PSO [8], it is an imitation of birds foraging behavior, will every bird abstract as a massless particles without volume, a candidate solution is used to indicate, at the same time, the dimension of the particles is also the target space dimension, particle in each dimension has a speed and position of two component. The particle swarm optimization algorithm first makes a comprehensive analysis of the flight experience of individuals and groups, and dynamically adjusts the speed and position of individual particles according to the analysis results. At the same time, search is conducted in the solution space to find the i optimal solution iteratively, and the velocity and position of particles are constantly updated according to the optimal solution \( \text{pbest} \) found by the particle itself and the optimal solution \( \text{gbest} \) found by the whole population.

Assuming that the number of particles in a target space with a dimension of \( d \) is \( n \), the velocity and position of the particle in the particle swarm can be expressed by a \( d \)-dimensional vector, as shown in Equations (6) and (7):

\[ V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) , i = 1,2,3,\ldots,n \]  \hspace{1cm} (6)

\[ X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) , i = 1,2,3,\ldots,n \]  \hspace{1cm} (7)

The optimal position searched so far for the \( i \) particle is called individual extremum and is denoted as \( \text{pbest} \), as shown in Equation (8):

\[ \text{pbest}_i = (p_{i1}, p_{i2}, \ldots, p_{id}) , i = 1,2,3,\ldots,n \]  \hspace{1cm} (8)

The optimal position searched so far by the whole particle swarm is the global extreme value, denoted as \( \text{gbest} \), as shown in Equation (9):

\[ \text{gbest} = (g_1, g_2, \ldots, g_d) \]  \hspace{1cm} (9)

When the two optimal values are found, the particle updates the individual velocity and position according to Equations (10), (11) and (12):

\[ v_{ij}(t+1) = w v_{ij}(t) + c_1 r_1 (p_{ij}(t) - x_{ij}(t)) + c_2 r_2 (p_{gj}(t) - x_{ij}(t)) \]  \hspace{1cm} (10)

\[ w = \mu + \sigma \times N(0,1) \]  \hspace{1cm} (11)

\[ \mu = \mu_{\text{min}} + (\mu_{\text{max}} - \mu_{\text{min}}) \times \text{rand}(0,1) \]

\[ x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \]  \hspace{1cm} (12)

In the formula, \( i = 1,2,3,\ldots,n \) , \( j = 1,2,3,\ldots,d \).

Equations (10), (11) and (12) constitute the improved particle swarm optimization algorithm, where: \( n \) represents the number of particles in the particle swarm, \( d \) represents the dimension of the particles.
the target space. $c_1$ and $c_2$ represents the learning factor. Usually set $c_1 = c_2 = 2$; $w$ represents the inertia weight coefficient, $N(0,1)$ Represents the random number of the standard normal distribution, $rand(0,1)$ Represents a random number between 0 and 1; $r_1$ and $r_2$ are uniform random number and independent of each other, and the value range is $[0,1]$; $v_{ij}$ is the velocity of the particle, $v_{ij} \in [-v_{\text{max}}, v_{\text{max}}]$. The magnitude of the velocity is determined by the nature of the target function.

3. Random Weight PSO optimize ELM based soil moisture prediction model

3.1 RandWPSO-ELM prediction model

As mentioned above, the initial input weight and threshold of ELM are randomly determined, and the training effect will be affected by the initial value. Therefore, the improved PSO is adopted to optimize the input weight and threshold of ELM, so as to avoid blind training of ELM model. In the steps of optimizing ELM with the improved PSO algorithm, PSO parameters are firstly initialized. Including the size of the particle swarm, spatial dimension $d$ iterations $n$ and maximum speed $v_{\text{max}}$, inertia weight $w$ generated randomly based on the sample data, choose the best learning factor $c_1$ and $c_2$. RandWPSO-ELM prediction model is to substitute the input weight and threshold corresponding to each particle into the ELM prediction model, and take the Mean Squared Error (MSE) of the ELM learning sample output and the actual output as the fitness of the improved PSO. To the particle's current fitness and optimal fitness do contrast, if the current fitness is smaller than the optimal fitness, is the current input weights and threshold of the ELM model to forecast the smaller mean square error, the current fitness can be updated to the best fitness, will update the current position for individual extreme value $p_{\text{best}}$, otherwise the optimal fitness stays the same. Similarly, fitness and global fitness were compared, and all extreme values $g_{\text{best}}$ were updated. When the number of iterations reaches the maximum or the fitness reaches the set value, the algorithm is stopped. After the improved PSO optimization obtained the optimal input weight $w$ and threshold $b$, it was substituted into the ELM model for prediction. RandWPSO-ELM algorithm flow chart is shown in Figure 2.
start
Initialize the PSO parameter
Randomly generated weight
ELM training output mean square error as PSO fitness
Individual extremum and global extremum initialization
Update individual particle position and velocity
Calculate the particle fitness
Update individual and global extrema
Whether the end condition is satisfied
end
Input training data
Data preprocessing
Initialize ELM input weight w and threshold b
Output weight W
MSE is calculated
Obtain the optimal input weight w and threshold b of ELM
Predict with pso-elm algorithm
Input test data

Figure 2. Flow chart of RandWPSO-ELM algorithm.

3.2 Evaluation index
In order to verify the prediction effect of this model, Absolute Error and Relative Error were used to calculate the test group, and Mean Square Error (MSE) was used to evaluate the prediction effect of the model.

The absolute error is denoted as $E_{AE}$, as shown in Equation (13):

$$E_{AE} = |y_i - x_i|$$  \hspace{1cm} (13)

Where, $x_i$ represents the predicted value of soil moisture, and $y_i$ represents the actual measured value of soil moisture.

The relative error is denoted as $E_{RE}$, as shown in Equation (14):

$$E_{RE} = \frac{|y_i - x_i|}{x_i}$$  \hspace{1cm} (14)

Mean square error is denoted as $E_{MSE}$, as shown in Equation (15):

$$E_{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2$$  \hspace{1cm} (15)

Where, $E_{AE}$ is absolute error and $E_{AE} = |y_i - x_i| ; n$ is the number of data of the test group.

4. Experimental simulation analysis
4.1 Parameter setting
Running in MATLAB R2018a platform, the parameters of RandWPSO-ELM model are set as follows:
the number of nodes in the input layer is 2; The number of nodes in the hidden layer is 10; The number of nodes in the output layer is 1; The activation function selects the Sig function by default. The iteration number of particle swarm is 100, and the inertia factor w is generated randomly in 0.4-0.8 during the iteration. The learning factor is closely related to the training effect of this model. In this experiment, four PSO learning factors X1, X2, X3, X4 and RandWPSO learning factor c parameters are selected, as shown in Table 1.

Table 1. PSO learning factor parameter table.

| Learning factor | X1 | X2 | X3 | X4 |
|-----------------|----|----|----|----|
| c1              | 3.0| 2.3| 2.4| 2.2|
| c2              | 3.0| 2.5| 1.8| 1.6|

According to the data in the above table, the iteration diagram of MATLAB simulation adaptive value change is shown in Figure 3:

As shown in Figure 3, when c1=2.3 and c2=2.5, the mean square error is relatively large. When c1=3.0, c2=3.0, c1=2.4 and c2=1.8, the convergence speed was slow and the mean square deviation could not reach the minimum, while when c1=2.2 and c2=1.6, the convergence speed was fast and reached the minimum. In conclusion, the fourth learning factor parameter was selected to establish the RandWPSO-ELM model.

4.2 Experimental simulation
RandWPSO-ELM and ELM models were established by training 20 sets of soil temperature and light intensity data of beet greenhouses in Hulan area. The same test sets were used to predict soil humidity respectively and compared with the real value. The prediction results of test data were shown in Figure 4:
Figure 4. Test data forecast result diagram.

Directly by the graph 4.2.1 shows: with no optimization ELM algorithm for soil moisture forecast, forecast value and real value of the difference is very big, but with random weight PSO algorithm to optimize ELM later to predict soil moisture, the curve of the forecast value and real value almost overlap, this shows fully convincingly that: ELM input initial weights and threshold is randomly determined, its training effect will be influenced by the initial value, which greatly reduces the prediction precision. RandWPSO algorithm can optimize the input weight and threshold of ELM to avoid falling into local optimization, which greatly improves the accuracy and stability of the traditional prediction model.

In order to evaluate the prediction effect of RandWPSO-ELM model more directly, the absolute and relative errors of each group of data were calculated to compare the prediction errors of the two models. The absolute error and relative error of test set prediction are shown in Figure 5(a), (b):

Figure 5. (a) Absolute error of test set prediction. (b) Relative error of test set prediction.

It can be clearly and directly seen from Figure 6 that the absolute error and relative error in predicting soil moisture after optimizing ELM with RandWPSO are extremely small and almost zero, while the error in predicting soil moisture with ELM model is extremely large, with large fluctuation and poor stability.

The target value, absolute error and relative error of the above two models are combined into a table. The prediction results of the improved ELM network algorithm are shown in Table 2:
Table 2. Improved ELM network algorithm forecast results.

| Test sample | Predict output | ELM target output | Absolute error | Relative error | RandWPSO-ELM target | Absolute error | Relative error |
|-------------|----------------|-------------------|----------------|---------------|---------------------|----------------|---------------|
| 1           | 45.1           | 40.3417           | 4.7583         | 0.1055        | 45.1                | 1.9114e-12     | 4.238e-14     |
| 2           | 46.7           | 42.6517           | 4.0483         | 0.086687      | 46.7                | 1.6911e-12     | 3.6212e-14    |
| 3           | 48.5           | 39.5349           | 8.9651         | 0.18485       | 48.5                | 1.7764e-12     | 3.6626e-14    |
| 4           | 46.2           | 39.6365           | 6.5635         | 0.14207       | 46.2                | 1.4424e-12     | 3.1221e-14    |
| 5           | 28.6           | 31.7903           | 3.1903         | 0.11155       | 28.6                | 5.1514e-13     | 1.8012e-14    |
| 6           | 37.1           | 38.7205           | 1.6205         | 0.043678      | 37.1                | 5.258e-13      | 1.4173e-14    |
| 7           | 36.4           | 35.7608           | 0.63923        | 0.017561      | 36.4                | 9.6634e-13     | 2.6548e-14    |
| 8           | 28.2           | 30.3869           | 2.1869         | 0.077551      | 28.2                | 5.9686e-13     | 2.1165e-14    |
| 9           | 37.2           | 36.8997           | 0.30025        | 0.0080712     | 37.2                | 1.0303e-12     | 2.7696e-14    |
| 10          | 49.9           | 42.6273           | 7.2727         | 0.14575       | 49.9                | 1.8545e-12     | 3.7165e-14    |

5. Conclusions

This paper studies the basic ELM algorithm and improves it on the basis of ELM algorithm. Since the initial input weight and threshold of ELM are randomly determined, the training effect will be affected by the initial value, reducing the prediction accuracy. In order to improve this shortcoming, RandWPSO algorithm is boldly combined with ELM, and RandWPSO algorithm is used to determine the input weight and threshold of ELM, which is conducive to improving the prediction accuracy. In this experiment, 20 sets of meteorological factors data of beet greenhouses in Hulan area were trained and 10 sets of data were tested. The experiment shows that the RandWPSO-ELM model established in this paper is better than the ELM model in predicting soil moisture.

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