Study on soft sensing method of plant growth water demand information based on RBF neural network

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Abstract. As one of the important factors in the process plant growth and development, water plays a very important role. Plant water potential is one of the important indexes to characterize plant water physiological characteristics. To obtain the accurate plant water potential, and then get the plant growth water demand information, can better guide the plant precision irrigation. Based on the soft sensing and artificial intelligence technology, the soft sensing model of plant growth water demand information based on RBF neural network is established and simulated. The simulation results show that the method has a high estimation accuracy and can measure and predict the water demand information of plant growth.

1. Introduction
In the study of plant water physiology, plant water potential can directly reflect the degree of plant water deficit and drought resistance, so it is one of the most commonly used physiological indicators of plant water demand information [1]. As the middle link of Soil-Plant Atmosphere-Continuum (SPAC), plant water potential will be affected by both air water potential and soil water potential at the same time [2]. In each part of the plant tissues and organs in water potential, Leaf water potential is the most sensitive physiological index to measure the water deficit state of plants. Under natural conditions, the water status of plants is determined by the soil water potential and the atmospheric water potential. In addition to the soil moisture, the weather factors such as temperature, light, relative temperature and humidity also affect the plant water potential [3].

In this paper, based on the inferential control theory of soft sensing technology [4], a hybrid intelligent soft sensing model is proposed, which can estimate the water potential of plants as a whole from the "micro environment information of plant growth", and then predict the water demand information in the process of plant growth. In this method, micro environment information factors (such as soil temperature and humidity, large temperature and humidity, plant canopy temperature and humidity, light intensity, CO₂ concentration, etc.) which are closely related to plant growth and water status are selected as auxiliary variables in the soft sensing method, and then RBF neural network [5] is selected to establish the soft sensing model of plant growth water demand information [6]. Through simulation and experimental verification, this method opens up a new method for obtaining water demand information of plant growth process.

2. Soft sensing principle of plant growth water demand information

2.1. Soft sensing technology of plant growth water demand information
Soft sensing technology is an advanced detection technology that selects a group of auxiliary variables that are closely related to the dominant variables and easy to measure, constructs a soft measurement model, and estimates the dominant variables by soft computing according to some optimal criteria.

Based on the plant growth mechanism and SPAC theory, a group of auxiliary variables which are closely related to and easy to measure the information value of water demand for plant growth are selected to construct a suitable soft sensing model, and the information of water demand for plant growth is estimated as a whole by soft computing. Soft sensing of plant growth water demand information is the application of soft sensing technology in precision irrigation, which is closely connected with plant growth state. Its principle is shown in Figure 1:

![Figure 1. Schematic diagram of soft sensing of plant growth water demand information.](image)

In the figure 1, \(U, \theta, D2\) respectively represent the measurable micro environment information (such as soil moisture content) that affects the water potential change of SPAC, the measurable micro environment information (such as canopy temperature) that reflects the water potential change of SPAC, and the measurable micro environment information (such as wind speed) that has a disturbance effect on the water potential of SPAC; \(D1\) represents various unmeasurable disturbance variables; \(\{\psi_s, \psi_c, \psi_a\}\) and \(\{\psi^*_s, \psi^*_c, \psi^*_a\}\) represent the plant respectively. The actual value and estimated value of water demand information for plant growth; \(\{\psi'_s, \psi'_c, \psi'_a\}\) represents the standard value (expected value) of water demand information for plant growth.

2.2. **Soft sensing model based on artificial neural networks**

ANN (artificial neural networks) has the advantages of non-linear, fault tolerance, learning, parallel computing and so on. It can be used to solve the modeling problems and model correction problems widely existing in all walks of life. To establish Ann soft measurement model is to take the auxiliary variable as the input (input layer) and the dominant variable as the output (output layer) of ANN, train ANN with a large number of effective data samples of the tested object, and use the trained ANN soft sensing model to estimate the current value of the dominant variable (model output) by the data which reflect the actual state of the auxiliary variable (model input).

3. **Soft sensing principle of plant growth water demand information**

3.1. **The structure of soft sensing model**

The establishment of accurate and reliable model is the key to realize the soft sensing of plant growth water demand information. Plant water potential is an important index of plant physiological state, which reflects the water condition in plant body. At the same time, it is closely related to the change of plant surrounding environment. The difference of environment will lead to the change of plant water potential.

According to the existing knowledge of the relationship between water potential and micro environment information, there is a quantitative relationship between atmospheric water potential and...
environmental temperature and humidity, so a pure mechanism model can be used. Because there is no quantitative relationship between soil water potential, plant leaf water potential and micro environment information, so the so-called "grey box" model, which combines mechanism and data drive, must be used. The complete soft sensing model of plant growth water demand information is layered structure, which is composed of air water potential soft sensing module, soil water potential soft sensing module and plant leaf water potential soft sensing module, as shown in Figure 2:

![Figure 2. The soft sensing model of plant growth water demand information.](image)

Plant leaf water potential is the most important for plant water stress. It is regarded as the final estimation result of plant growth water demand information soft measurement. Considering the water transfer relationship of SPAC, air water potential and soil water potential have a direct impact on plant leaf water potential, which should be regarded as the input variable of plant leaf water potential soft measurement model.

3.2. RBF neural network model
Radial basis function (RBF) neural network is a kind of neural network with radial basis function as activation function. It has the advantages of strong approximate simulation ability, strong classification ability and fast learning speed.

RBF neural network has three layers: input layer, hidden layer and output layer. The input layer is composed of signal source nodes, which can connect the network with the external environment. Hidden layer can realize nonlinear transformation from input space to hidden layer space. The output layer responds to the input mode, and the transformation from the hidden layer space to the output layer space is linear.

Generally, the basis function of RBF neural network is Gaussian function, and its expression is as follows:

$$\varphi_i(x) = \exp \left(-\frac{|x-c_i|^2}{2\sigma^2}\right)$$  \hspace{1cm} (1)

The training process of RBF network is divided into two steps: the first step is to learn without teachers and determine the weight W1 between the input layer and the hidden layer; the second step is to learn with teachers and determine the weight W2 between the hidden layer and the output layer. The weight W1 between the input layer and the hidden layer includes the center and radius of the RBF cell.

4. Modelling and Simulation of RBF network for soft sensing of plant growth water demand information

4.1. RBF network model for soft sensing of plant growth water demand information
The RBF neural network selected in this paper is mainly used for the realization of soil water potential model and plant leaf water potential model in the soft sensing method of plant growth water demand information. Since both models are implemented by RBF neural network, and only have different input parameters, the following only describes the soil water potential model in detail, as shown in Figure 3:

![Figure 3. The schematic diagram of soil water potential model.](image)

### 4.2. Modelling process

#### 4.2.1. Normalization of sample data.

Input layer vector includes canopy temperature, wind speed, illumination, leaf temperature, leaf humidity, CO$_2$ concentration, atmospheric water potential and soil water potential. These variables not only have different measurement scales, but also differ greatly in numerical value. If we directly use the original data for calculation, we will exaggerate the role of a large number of dimension data, reduce or even ignore other variables, which greatly increases the instability of calculation, and seriously leads to the unavailability of the model. Therefore, it is necessary to normalize the original data to improve the accuracy and stability of the algorithm.

The so-called normalization is to convert each component with different dimensions into a fixed interval in a certain way, so that each component of the sample has the same scale. The specific function of normalization is to induce the statistical distribution of unified samples. Neural network is trained (calculated) and predicted by the statistical probability of samples in the event. The normalization is the same statistical probability distribution between 0-1.

#### 4.2.2. Selection of hidden layer nodes.

In RBF network training, the determination of the number of neurons in the hidden layer is a crucial problem. The traditional method is to make the dimension of the hidden layer equal to that of the input vector. In this paper, we choose the MATLAB environment for simulation, the number of hidden layer nodes of RBF network can automatically get the best value in training, without giving it in advance. This reduces human subjectivity and makes the training result closer to the optimal value. At this time, the default maximum number of hidden layer nodes is the number of input and output sample pairs. You can also control the increase of the number of nodes by setting the training accuracy, or you can directly set a value less than the number of input and output sample pairs to limit.

#### 4.2.3. Selection of radial basis expansion coefficient.

The simulation part of this test is carried out in Matlab environment. One of the most important parameters in the RBF neural network model based on MATLAB is the radial basis expansion coefficient spread. The value should be large enough to make the radial basis neurons respond to the range covered by the input vector. Choosing appropriate expansion coefficient is a key technology. The general method is to select a relatively better spread value according to the results of trial calculation through multiple trial calculation. In this paper, the iterative search method is used for reference, which not only greatly improves the calculation speed, but also achieves good results in the experiment. In this paper, we first determine the interval $[a0, b0]$ of spread
based on experience, set a large step \( k \), search for the spread value with the smallest estimation error, then determine the neighborhood \([\text{spread} - \beta, \text{spread} + \beta]\) with \( \beta \) as the radius of spread, and set the neighborhood as a new search interval \([a_1, b_1]\), which reduces the step size by a certain multiple to \( k_1 \). Cycle like this until the error does not change much.

4.3. Model simulation
When using radial basis function neural network for simulation, firstly, determine the value range of spread as \([0,5]\), set the step as 0.1, and the curve of MSE with the change of spread is shown in Figure 4. At this time, when the spread is 1.7, the average relative error is the smallest, which is 0.0198. Select the most appropriate neighborhood \([1.7-0.1 \times 10, 1.7 + 0.1 \times 10]\), that is, the current search range becomes \([0.7, 2.7]\), the step size reduces 10 times to 0.01, and the research result is the most appropriate spread is 1.71, at this time, the minimum average relative error is 0.0191. The difference between the two search results is 0.0001, so the iteration can be terminated and the spread is 1.71. The simulation results of spread = 1.71 are shown in Figure 5. In Figure 5, "." represents the standard value of measured leaf water potential, and the straight line of point "," represents the estimated value of leaf water potential. At this time, the maximum absolute error value is 0.0394bar. From the above simulation results, it can be seen that RBF neural network can effectively predict the water potential of plant leaves with less noise interference.

![Figure 4. The mean square deviation curve.](image)

![Figure 5. Simulation results.](image)
It can be seen from the simulation results that the RBF neural network can estimate the plant leaf water potential well in the ideal environment.

The performance indexes of calculation model test are as follows:

Mean square error:

$$MSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^2} = 0.01199$$  \hspace{1cm} (2)

Average relative error:

$$AveRE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_{i} - y_{i}}{y_{i}} \right| = 0.021$$  \hspace{1cm} (3)

Maximum relative error:

$$MaxRE = \max \left( \frac{\hat{y}_{i} - y_{i}}{y_{i}} \right) = 0.026$$  \hspace{1cm} (4)

5. Conclusion

In this paper, a soft sensing method of plant growth water demand information based on RBF neural network is proposed, and the corresponding soft sensing model is established. The model takes the plant growth microenvironment factors (soil water potential, canopy temperature and humidity, light intensity, wind speed, CO₂ concentration, large temperature and humidity, etc.) which are easy to obtain as auxiliary variables, and RBF neural network as the model to realize the continuous soft estimation of plant leaf water potential. The simulation results show that the model has the advantages of small amount of calculation, high precision, simple and practical algorithm. It is a simple, reliable and low-cost online continuous measurement method for water demand information of plant growth, which is suitable for modern precision agricultural engineering.

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References

[1] Liu X 2015 Research and application review of plant water potential. J. Jilin Forest. Sci. Tech. 44: 35-44
[2] Kang S Z 1992 Theory and application of soil plant atmospheric continuum water transfer Beijing: China Water Power Press.
[3] Dai F Y, Lu S L and Pan Y M 2009 Soft-sensing for leaf water potential based on micro-environment factors of plant. United States Piscataway: IEEE Comp. Soc. 2:500-3
[4] Han D W and Zou Z Y 2005 Soft sensor and inferential control technology. J. Nanjing Uni. Sci. Tech. 29: 206-10
[5] Qi G Q, Liu Z W and Cui L F 2004 The soft measuring method based on RBF artificial neural network for municipal waste water treatment J. Food Sci. Tech. 22: 36-8
[6] Lu S L, Tian L G, Sun W J and Han Z J 2007 Soft-sensing of farmland water potential for precision irrigation J. Tianjin Uni. Tech. Edu. 17: 1-4