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Compensation Design of FDR Soil Humidity Node Based on BP Neural Network

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Abstract: Soil moisture sensors used in the actual farm monitoring have nonlinear errors. In order to improve measuring accuracy, BP neural network method was used to correct the nonlinear error of FDR soil moisture sensor nodes and least squares fitting method for comparative analysis. The experimental results show that the BP neural network method has strong search capability, high precision, the average error range can be reduced within 1.9%, better meet the needs of agricultural monitoring.

Key words: BP neural network, soil moisture, sensor, compensation

INTRODUCTION

Soil moisture measuring can effectively understanding soil humidity, is essential basis of agricultural irrigation and crop water requirement case studies (Sun *et al*., 2012). Soil moisture measurements consist of TDR (Time Domain Reflectometry) measurement method and FDR (Frequency Domain Reflectometry) measurement method (Jiang *et al*., 2013). FDR method is more simple and safe, accurate, save electricity, less calibration etc., and widely used. Most of the soil moisture sensor is nonlinear relationship between input and output, in order to improve the measurement precision of sensors, many correction methods at home and abroad are put forward. Software calibration method with look-up table method, artificial neural network, polynomial fitting, Support Vector Machine (SVM) and wavelet analysis methods such as (Zhou, 2002; Cai, 2004; Ni *et al*., 2008; Liu and Wang, 2011; Xie *et al*., 2007; Kizito *et al*., 2008). This article first analyzes the main factors influencing the moisture measurement and BP (back propagation) neural network method is used for the compensation for the actual use of SM series FDR soil moisture sensor, which are compared with the least squares fitting method. The results show that the BP neural network method can make error reduced to 1.9%, satisfy the requirements of farmland measurement.

SOIL MOISTURE SENSORS MEASURING PRINCIPLE

Measuring principle of FDR type soil moisture sensor: FDR (Frequency Domain Reflectometry) type sensor is mainly composed of parallel arrangement of metal bar as a capacitor. In which the soil acts as a dielectric, the capacitor and oscillator is composed of a high frequency tuning circuit. The electromagnetic wave through coaxial cable arrive the probe, the resonance frequency is detected by frequency sweep circuit. The dielectric constant of the soil can be measured, so that the soil water content is obtained. The dielectric constant of water is 80 F m^{-1} and the soil solid dielectric constant is 2~5 F m^{-1}, the dielectric constant of water is much bigger than soil's. Therefore, the dielectric constant of soil is mainly affected by soil moisture content. Moisture content increases, the soil dielectric constant will increases accordingly, the frequency of the electromagnetic wave propagation will change. The relationship between capacitance and apparent dielectric constant, resonance frequency and the capacitance, respectively (Lu *et al*., 2008) as follows:

$$C = \varepsilon g_{ar} \tag{1}$$

$$F = \frac{1}{\sqrt{2\pi LC}} \tag{2}$$

Here, g_{ar} is constant which is related to the distance between the electrodes and geometry shape of the electrode; ε is the apparent dielectric constant of soil.

Soil moisture sensors in different soil moisture content of the normalized frequency SF, such as Eq. 3:

$$SF = \frac{F_a - F_s}{F_a - F_w} \tag{3}$$

Frequency variation relationship with the soil volumetric water content such as shown in Eq. 4:

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$$SF = a\times\theta^b \tag{4}$$

Here, F_a is the frequency values for the probe measured in air, F_w is frequency values measured in water, F_s is frequency value in the soil. a and b is coefficient related to soil properties; θ for soil volumetric water content ($m^3\ m^{-3}$).

Main factors affecting soil moisture measurement: Sensor are greatly influenced by external factors in practical application, such as soil temperature, soil hardness, soil viscosity, conductivity and the voltage supply of the sensor itself. All these lead to the difference of measurement results:

- The node voltage supply has obvious influence on measurement data. Because the soil moisture sensor is a high integration level of capacitive transducer. Soil dielectric constant is related to capacitance and capacitance is determined by charging time, at the same time charging time is influenced by testing electrode geometry factor g, the resistance R and the voltage supply. Therefore, the change of the voltage supply, will naturally reflect changes in the soil dielectric constants, lead to sensor output voltage is different, affected the humidity measurement. Node voltage change around 1V, the maximum relative error of humidity sensor can reach more than 15% (Zhang *et al*., 2010)
- The FDR sensor had obvious temperature effect. The dielectric constant of the soil influenced by the amount of water, water temperature and the electrical conductivity of soil particles, when the temperature changes, the dielectric constant is bound to change. So the measurement result will affect. The practice shows that when the temperature in 5~60°C changes, FDR's humidity error within 6~9% (Gao *et al*., 2010)
- Different soil hardness may also affect humidity sensor measurement, experiments have shown that the increase of soil hardness results in increase of measuring humidity value (Sun *et al*., 2012)

ANALYSIS OF NONLINEAR COMPENSATION METHOD

Nonlinear compensation principle: Sensor's nonlinear relation between input and output as follows:

$$Y = f(x) \tag{5}$$

Here, x as the parameter to be measured; y for the sensor output.

To calibration of sensor nonlinear error, at the output end series a compensating link, as shown in Fig. 1.

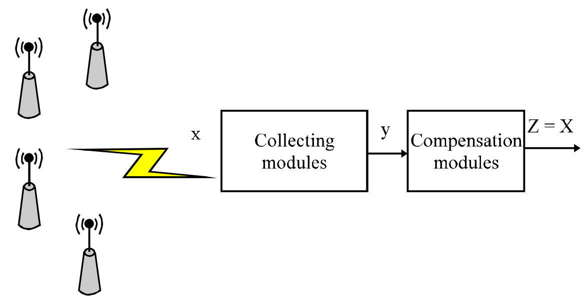

Fig. 1: Humidity sensor acquisition and compensation schemes

Least squares fitting method: According to the input and output data of the test, get a set of nonlinear curve v = f (θ), n times polynomial is used to approximate the nonlinear curve θ = f (v), by the least square principle to determine the polynomial coefficients.

Column write n times polynomial: Assuming that ntimes polynomial equation is:

$$\theta_i(v_i) = a_0+a_1v_i+a_2v_i^2+\cdots+a_nv_i^n \tag{6}$$

Considering the accuracy requirement of the actual farmland, n = 3, then the equation rewritten as:

$$\theta_i(v_i) = a_0+a_1v_i+a_2v_i^2+\cdots+a_3v_i^3 \tag{7}$$

Determine the coefficient of polynomial: According to the principle of the least squares, each θ_i (v_i) and standard humidity value θ_i with the corresponding minimum mean square error and a_0, a_1, a_2, a_3 can determined coefficient, namely:

$$\begin{aligned} F(a_0,\cdots,a_3) &= \sum_{i=1}^{w}[\theta_i(v_i)-\theta_i]^2 \\ &= \sum_{i=1}^{w}[(a_0+a_1v_i+a_2v_i^2+a_3v_i^3)-\theta_i]^2 = \min \end{aligned} \tag{8}$$

F (a_0, ···, a_3) function of four variables for partial derivatives, respectively and make it to zero, are:

$$\begin{cases} \sum_{i=1}^{w}[(a_0+a_1v_i+a_2v_i^2+a_3v_i^3)-\theta_i] = 0 \\ \sum_{i=1}^{w}[(a_0+a_1v_i+a_2v_i^2+a_3v_i^3)-\theta_i]v_i = 0 \\ \sum_{i=1}^{w}[(a_0+a_1v_i+a_2v_i^2+a_3v_i^3)-\theta_i]v_i^2 = 0 \\ \sum_{i=1}^{w}[(a_0+a_1v_i+a_2v_i^2+a_3v_i^3)-\theta_i]v_i^3 = 0 \end{cases} \tag{9}$$

Get relations function values and actual values: Through the Cramer's rule to calculate the equation, which can solve coefficients a_0, a_1, a_2, a_3 and the fitting equation is obtained.

BP neural network compensation algorithm: The BP (Back Propagation) neural network is a kind of efficient feed forward neural network, it can best approximation to arbitrary complex nonlinear system, simple structure, fast training speed (Longjun and Junyan, 2012). If the data in the input samples is sufficient and accurate, it doesn't need to know the internal mechanism. Through its self-learning and adaptive ability, the neural network can get very good output.

BP network usually consists of input layer, output layer and several hidden layers (Zhu *et al.*, 2012), this study used the BP network model with 1 m^{-1}. As shown in Fig. 2, one input layer, m implicit layers and one output layer. Input layer is collected by measured value of the sensor, output layer is a standard instrument value and the number of hidden layer node according to actual needs to be modified.

The learning process of BP neural network by the forward propagation and error back propagation process. Information from the input layer through the hidden layer to output layer. If the output layer didn't get the desired output values, error along the original path will return and modify the weights of neuron in each layer, so that the error can be reached the minimum. Ultimately achieve expected effect. The specific calculation process is as follows:

Forward propagation:

- **Input layer:** This layer for the neurons of the output is equal to the input x_i

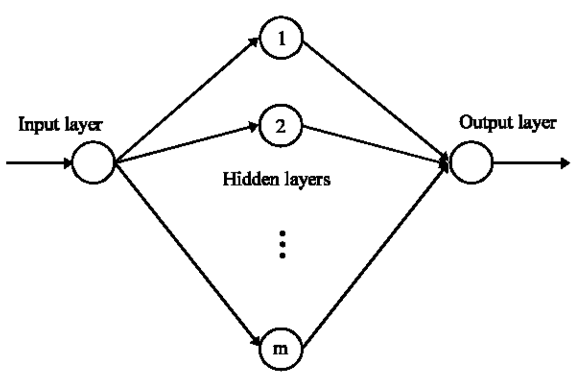

Fig. 2: Schematic diagram of back propagation neural network

- **Hidden layer:** Hidden layer neuron input value net_j is the weighted sum of first layer output value x_i:

$$net_j = \sum_i w_{ij} x_i + \theta_i \tag{10}$$

The output value as:

$$z_j = f(net_j) \tag{11}$$

Among them:

$$f(net_j) = \frac{1}{1 + \exp(-net_j)}$$

where, w_{ij} is the weights between input layer to hidden layer. θ_i is the threshold value of hidden layer.

- **Output layer:** Output layer adopts linear function, the output value of y_k is the weighted sum of the input value:

$$y_k = \sum_j w_{kj} z_j + a_k \tag{12}$$

Among them, v_{kj} is the weight between hidden layer to output layer. a_k is the threshold value of the output layer.

Back propagation process: Error function is defined as:

$$E = \frac{1}{2} \sum_j \sum_k (\hat{y}_k - y_k)^2 \tag{13}$$

Gradient descent method is used to adjust the output layer weights of the Δw_{ji}, output layer threshold Δw_{ji}, hidden layer weights of the Δw_{ij} and hidden layer threshold $\Delta\theta_k$.

$$\begin{aligned} \Delta w_{ji} &= -\eta \frac{\partial E}{\partial w_{ji}}; \Delta a_{ji} = -\eta \frac{\partial E}{\partial a_k}; \\ \Delta w_{ij} &= -\eta \frac{\partial E}{\partial w_{ij}}; \Delta \theta_i = -\eta \frac{\partial E}{\partial \theta_i} \end{aligned} \tag{14}$$

SOIL HUMIDITY SENSOR TEST RESULTS COMPENSATION ANALYSIS

Test samples: Take w = 30 kinds of different humidity of soil sample. The actual standard soil humidity value θ_i (i = 1, 2, ..., w) can be acquired by using Zhejiang TZS humidity sensor, the uncompensated measured value v_i be acquired by the FDR humidity sensor nodes, the measured relationship with v_i and θ_i as shown in Fig. 3.

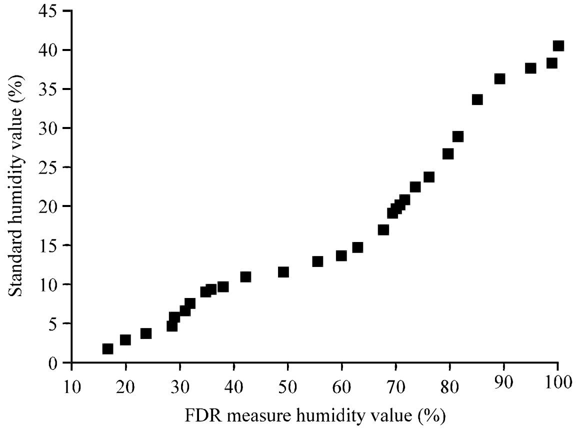

Fig. 3: Humidity relationship of soil sample real and measured values

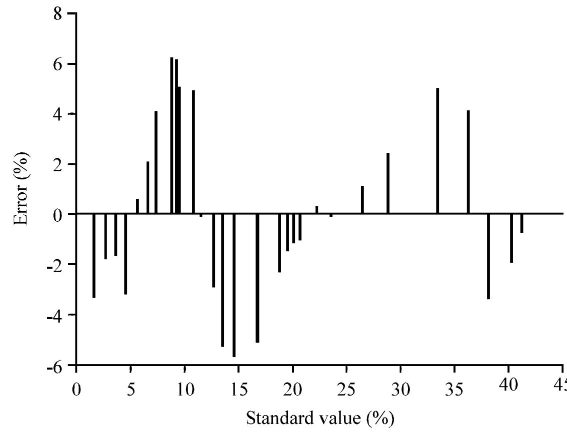

Fig. 5: Least squares humidity compensation error

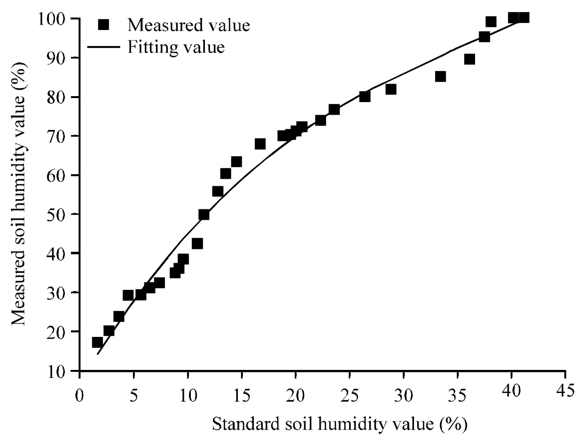

Fig. 4: Least squares fitting result of soil humidity

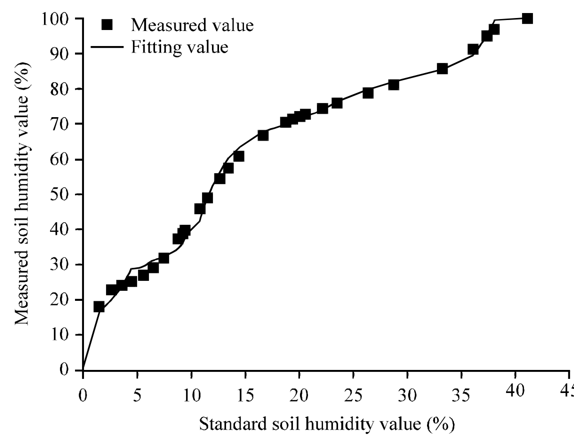

Fig. 6: Back Propagation neural network fitting result of soil humidity

Table 1: Soil sample humidity value for two types of sensor (v_i FDR humidity value; θ_i standard humidity value)

v_i (%)	θ_i (%)	v_i (%)	θ_i (%)	v_i (%)	θ_i (%)
17.0	1.7	42.3	10.9	72.6	22.3
20.2	2.8	49.4	11.6	76.2	23.6
23.8	3.7	55.6	12.8	79.7	26.5
28.9	4.6	60.1	13.6	81.7	28.8
29.3	5.7	63.1	14.6	85.1	33.4
31.1	6.6	67.8	16.8	89.3	36.2
32.2	7.5	69.6	18.9	94.9	37.5
34.8	8.9	70.2	19.6	99.0	38.1
36.1	9.3	78.3	20.1	100.0	40.2
38.2	9.6	70.9	20.7	100.0	41.2

The 30 samples of humidity value of FDR sensor and standards TZS sensor measuring as shown in Table 1.

RESULTS

Results of the least-square method

The least squares fitting coefficient: The coefficient is determined based on the least squares fitting equation:

$$\theta_i = 3.9027\times10^{-5}\text{-}0.0027v_i+0.3236\,v_i^2\text{-}2.3422v_i^3 \quad (15)$$

The being fitting the nonlinear curve as shown in Fig. 4. According to Eq. 15, the relationship between the measured values and standard values can be achieved through PC software programming.

Fitting error analysis: The relative error curve after correction of sensor is shown in Fig. 5. Error within +6.1% to -5.6% range, the mean error is 3.6%, basic meet the requirements of actual fields measuring.

Neural network analysis results: The above samples after neural network calibration curve as shown in Fig. 6, measurement error as shown in Fig. 7. Within ±2.8%, the average error is 1.9%

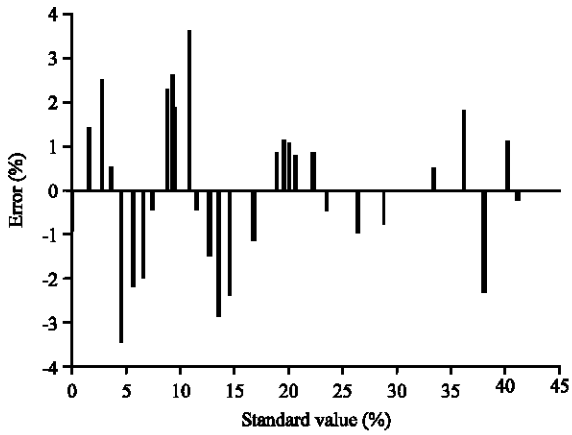

Fig. 7: Back Propagation neural network humidity compensation error

CONCLUSION

The sensor nonlinear phenomena appear in the condition of different workplace because of the influence of temperature and supply voltage etc. In this article, through analysis of factors affecting measurement, using the method of BP neural network for nonlinear correction, measurement of average error less than 1.9%, had a better fitting affect compared with the least square method. The BP neural network method improved the precision of soil moisture measurement, for intelligent agricultural irrigation and agricultural research provides a reliable guarantee.

REFERENCES

Cai, B., 2004. Some simple nonlinear compensation technique of sensor. J. Jianghan Pet. Inst., 1: 59-61.

Gao, L., B. Shi, C.S. Tang, B.J. Wang, K. Gu and Y.K. Gan, 2010. Experimental study of temperature effect on FDR measured soil volumetric water content. J. Glaciol. Geocryol., 32: 964-969.

Jiang, Z.H., C.J. Tan and X.Q. Zhi, 2013. Development of portable soil moisture detector based on principle of frequency domain reflectometry. Trans. Microsyst. Technol., 32: 79-82.

Kizito, F., C.S. Campbell, G.S. Campbell, D.R. Cobos, B.L. Teare, B. Carter and J.W. Hopmans, 2008. Frequency, electrical conductivity and temperature analysis of a low-cost capacitance soil moisture sensor. J. Hydrol., 352: 367-378.

Liu, T. and H. Wang, 2011. Nonlinear correction of sensor using genetic algorithm and support vector machine. J. Electron. Meas. Instrum., 25: 56-60.

Longjun, Z. and F. Junyan, 2012. The research of the pressure sensor error compensation algorithm based on BP neural network. China Instrum., 9: 32-36.

Lu, G.H., Z.Z. Li, B.X. Zhao, X.Y. Zhao and Z.G. Xiao, 2008. Calibration and verification of frequency domain reflectometry to measure soil water content. Agric. Res. Arid Areas, 26: 33-37.

Ni, X.Y., D.H. Wang and H.J. Zhang, 2008. Implement of nonlinearity correction for sensors based on SOPC. Transducer Microsyst. Technol., 27: 22-24.

Sun, D., W. Wang and S. Jiang, 2012. Measurement and modeling of soil moisture based on dual-sensor data fusion. Trans. Chin. Soc. Agric. Eng., 28: 60-64.

Xie, Y., S. Yang and X. Li, 2007. Nonlinear compensation of capacitance weighing transducer based on inverse fitting. Chin. J. Sci. Instrum., 28: 923-927.

Zhang, R., G. Yu, L. Zhang, L. Jun and Z. Yecheng, 2010. Voltage compensation method of WSN soil moisture acquisition nodes. Trans. Chinese Soc. Agric. Mach., 41: 178-182.

Zhou, S.H., 2002. Correction methods of sensor characteristic nonlinearity by hardwares. J. Transducer Technol., 5: 1-4.

Zhu, C., S. Tong and J. Hu, 2012. Application of nerve network on forecasting temperature in sunlight greenhouse. J. Agric. Mechanization Res., 7: 207-210.