

# An integrated moisture and temperature sensor with model based temperature-dependent nonlinearity compensation

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**Abstract:** Moisture sensors have been widely implemented in agricultural and forestry applications, but they can not obtain satisfied sensing performance without calibration. This letter presents an integrated moisture and temperature sensor with a model based linearization for eliminating the temperature-dependent nonlinearity. The temperature related nonlinear model is built by analyzing the relationship between the real moistures and the pairs of measured moistures and temperatures. The least squares algorithm is applied to estimate the coefficients of the obtained nonlinear model. The proposed linearization system has the advantage of wide suitability and applicability, and its performance is validated by experimental results.

**Keywords:** moisture sensor, sensor calibration, nonlinearity compensation, temperature-dependent nonlinearity

**Classification:** Integrated circuits

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## 1 Introduction

Moisture is one of the most important parameter in agricultural applications. By applying the moisture sensor, the soil moisture is measured for improving water resources management. However, due to the fundamental principle of moisture sensor, the sensed values response nonlinear along with the true moisture increases [1, 2]. And also the nonlinearity changes violently with the variation of temperature conditions [3]. Thus, it’s difficult to calibrate the temperature dependent nonlinear characteristics of moisture sensor [4].

In the conventional moisture sensor, the calibrations are usually brought out by a large number of rigorous measurements. In each measurement, there have two inputs of the true moisture and the temperature, and one output of the sensed moisture. A so called Look-Up-Table (LUT) can be achieved by changing the values of the true moisture and the temperature. In the calibration process, the corresponding true moisture can be found in the LUT according to the two coordinates of the sensed moisture and temperature [5]. LUT based calibration is simple and effective, but is with a serious contradiction between accuracy and complexity [6]. To attain a high calibration accuracy, there requires a huge LUT which is too complicated to be implemented in a memory-limited microcontroller.

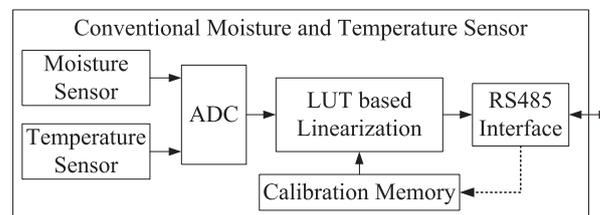
To overcome these shortcomings, mathematical models are constructed to describe the nonlinearity of moisture sensors [4, 5, 6]. For instance, a 3<sup>rd</sup> order mathematical formula is developed for representing the nonlinear relationship between the real volumetric soil moisture and the measured probe voltage of a commercial sensor [7]. However, the existing nonlinear models are independent

of the ambient temperature, which should effect on the measurement results drastically.

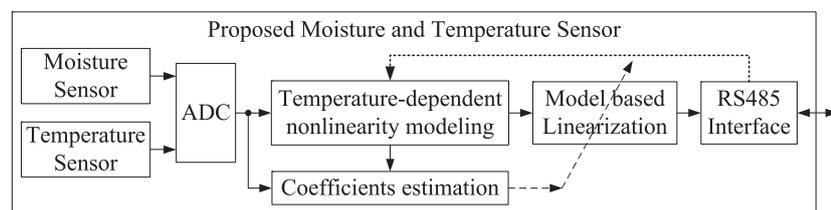
In this letter, we develop an integrated moisture and temperature sensor with model based temperature-dependent nonlinearity compensation technique. The nonlinearity compensation module concludes a temperature-dependent nonlinear model with corresponding coefficients estimation algorithm. The temperature-dependent nonlinear model is obtained by analyzing the measurement results of a commercial moisture sensor. The least squares (LS) algorithm is applied to estimate the nonlinear model's coefficients. The accuracy improvement of the integrated moisture and temperature sensor with nonlinearity compensation system is validated by experimental results.

## 2 System architecture

The conventional moisture and temperature sensor is shown in Fig. 1(a). The sensor IC integrates two sensor elements, *EC-5* from METER Group and *STLM20* from STMicroelectronics, for measuring moisture and temperature, respectively. After quantized by the analog to digital converter (ADC), the sensed signals are calibrated by a LUT based linearization module [8]. The calibration memory should be large enough to store a huge LUT for achieving high accuracy of moisture sensing. Otherwise, the LUT needs to be overwritten in case of the sensor's characteristic changes. Most sensors would never be re-calibrated, thus their sensitivities become lower and their lifecycles become shorter [9].



(a) System diagram of the conventional moisture and temperature sensor.



(b) Architecture of the proposed sensor with model based temperature-dependent nonlinearity compensation system.

**Fig. 1.** System architectures comparison.

As shown in Fig. 1(b), the proposed sensor takes temperature-dependent nonlinear model instead of LUT. Temperature-dependent nonlinearity modeling needs three sets of data including the internal sensed moisture, the internal sensed temperature, and the real moisture transmitted through RS485 interface from

outside. When the nonlinear model and its order are determined, LS algorithm is applied to estimate the model coefficients.

### 3 Nonlinear modelling and coefficients estimation

The nonlinear modelling and the coefficients estimation are brought out by the experimental data of moisture sensing as listed in Table I. All the experimental data were acquired in a sealed glass bowl with temperature and irrigation control system.

**Table I.** Experimental data of moisture sensing (in %)

Temp. $T$	5°C	10°C	15°C	20°C	25°C	30°C	35°C	40°C	Real Moisture $\theta_{real}(i)$
Test No. $i$	Measured Moisture $\theta_{meas}(i, T)$								
1	33.1	33.8	34.5	35.4	35.9	36.2	38.7	40.2	40.3
2	31.4	31.9	32.4	33.1	33.5	34.9	36.3	37.3	37.2
3	27.9	29.8	30.3	30.6	31.1	31.4	31.9	32.3	32.0
4	22.6	23.1	23.5	24.3	25.1	25.7	26.5	27.3	26.8
5	19.6	19.9	20.9	22.2	22.8	23.6	24.5	25.8	24.6
6	19.1	20.4	20.8	21.4	22.6	23.2	25.0	25.1	23.3
7	17.2	18.3	18.9	19.5	19.9	21.1	22.3	23.7	20.9
8	16.7	17.5	18.1	18.8	19.6	20.6	21.5	22.8	18.6
9	15.1	15.7	16.7	17.4	18.3	19.7	20.7	21.6	16.8
10	14.3	14.8	15.5	16.1	17.1	18.5	19.6	20.3	15.1
11	13.6	14.1	14.8	15.0	15.8	16.7	18.1	19.4	13.9
12	12.5	13.2	13.9	14.1	14.5	15.3	17.2	18.1	12.6

According to the Empirical Topps Equation [3, 10], the volumetric water content  $\theta$  can be nonlinearly described by the dielectric permittivity of water  $\varepsilon_b$  as the follows:

$$\theta = -5.3 \times 10^{-2} + 2.92 \times 10^{-2} \varepsilon_b - 5.5 \times 10^{-4} \varepsilon_b^2 + 4.3 \times 10^{-6} \varepsilon_b^3 \quad (1)$$

As shown in Table I, the measured moisture  $\theta_{meas}$  changes along with the temperature variation, and the relationship can be presented as the following formula:

$$\begin{aligned} \theta_{meas}(i, T) = & -5.3 \times 10^{-2} + 2.92 \times 10^{-2} \varepsilon_{b,meas}(i, T) \\ & - 5.5 \times 10^{-4} \varepsilon_{b,meas}^2(i, T) + 4.3 \times 10^{-6} \varepsilon_{b,meas}^3(i, T), \end{aligned} \quad (2)$$

where  $i = 1, 2, \dots, 12$ , and  $T = 5, 10, \dots, 40^\circ\text{C}$ .

In each test, the real moisture  $\theta_{real}$  is a fixed value. There needs to construct a temperature-related nonlinear model to compensate the influence of temperature. The dielectric permittivity of water decreases with increasing temperature [4, 11, 12], therefore the temperature-related nonlinearity can be assumed by

$$\begin{aligned} \theta_{real}(i) = & -5.3 \times 10^{-2} + 2.92 \times 10^{-2} \varepsilon_{b,real}(i) - 5.5 \times 10^{-4} \varepsilon_{b,real}(i)^2 \\ & + 4.3 \times 10^{-6} \varepsilon_{b,real}(i)^3 \end{aligned} \quad (3)$$

$$\varepsilon_{b,real}(i) = \varepsilon_{b,meas}(i, T) \cdot C(i, T) \quad (4)$$

$$C(i, T) = 1 - a_1(i) \times (T - 25) - a_2(i) \times (T - 25)^2 - a_3(i) \times (T - 25)^3, \quad (5)$$

where  $\theta_{real}(i)$  and is the real moisture of the  $i_{th}$  test.  $\varepsilon_{b,real}(i)$  is the real dielectric permittivity of water, while  $C(i, T)$  is temperature-related nonlinear factor, and  $a_m(i)$ ,  $m = 1, 2, 3$  are the nonlinear coefficients to be estimated.

Data in Table I are applied for coefficients estimation, the calculation procedure executes as bellow:

Step 1, calculate  $\varepsilon_{b,meas}(i, T)$  by solving Equation (2) with the measured moisture  $\theta_{meas}(i, T)$  in each row of Table I.

Step 2, acquire  $\varepsilon_{b,real}(i)$  by solving Equation (3) with the real moisture  $\theta_{real}(i)$  in each row of Table I.

Step 3, calculate  $C(i, T)$  by plugging  $\varepsilon_{b,meas}(i, T)$  and  $\varepsilon_{b,real}(i)$  into Equation (4).

Step 4, obtain  $a_m(i)$ ,  $m = 1, 2, 3$  by solving Equation (5) by LS algorithm.

In particular, the LS algorithm in Step 4 can be represented in matrix form as follows:

for the  $i$ th test, Equation (4) can be rewritten in the matrix form as

$$\mathbf{C}_i = \mathbf{ones}(8, 1) - \mathbf{T} \cdot \mathbf{a}_i, \quad (6)$$

where the matrixes are

$$\begin{aligned} \mathbf{C}_i &= [C(i, T = 5), C(i, T = 10), \dots, C(i, T = 40)]^T \\ \mathbf{ones}(8, 1) &= [1, 1, 1, 1, 1, 1, 1, 1]^T \\ \mathbf{T} &= [(T - 25)|_{T=5}, (T - 25)^2|_{T=5}, (T - 25)^3|_{T=5}; \\ &\quad (T - 25)|_{T=10}, (T - 25)^2|_{T=10}, (T - 25)^3|_{T=10}; \\ &\quad \vdots \\ &\quad (T - 25)|_{T=40}, (T - 25)^2|_{T=40}, (T - 25)^3|_{T=40}] \\ \mathbf{a}_i &= [a_1(i), a_2(i), a_3(i)]^T \end{aligned}$$

and  $(^T)$  denotes matrix transpose.

With the knowledge of  $\mathbf{C}_i$  and  $\mathbf{T}$ , the nonlinear coefficients  $\mathbf{a}_i$  can be estimated by the LS method. The objective function is

$$\arg \min_{\mathbf{a}_i} \|\mathbf{ones}(8, 1) - \mathbf{C}_i - \mathbf{T} \cdot \mathbf{a}_i\|^2 \quad (7)$$

The least squares solution to Equation (9) is

$$\hat{\mathbf{a}}_i = (\mathbf{T}^H \mathbf{T})^{-1} \mathbf{T}^H (\mathbf{ones}(8, 1) - \mathbf{C}_i), \quad (8)$$

where  $\hat{\mathbf{a}}_i$  is the estimated nonlinear coefficients matrix.

The nonlinear coefficients are estimated and listed in Table II.

#### 4 Experimental results and discussion

Estimated nonlinear coefficients in Table II are applied to validate the performance of the temperature-related nonlinearity compensation. Plugging  $\hat{a}_m(i)$ ,  $m = 1, 2, 3$  and  $\varepsilon_{b,meas}(i, T)$  into Equations (3~5), there obtains the estimation of the real

**Table II.** Estimated nonlinear coefficients

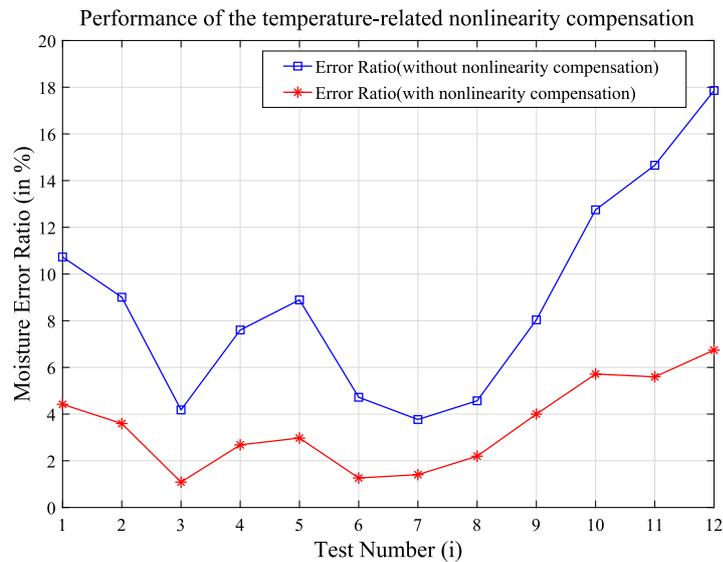
Test No. <i>i</i>	Estimated nonlinear coefficients		
	$\hat{a}_1(i)$	$\hat{a}_2(i)$	$\hat{a}_3(i)$
1	2.3059e-3	-0.1388e-3	-0.0048e-3
2	2.3831e-3	-0.1185e-3	-0.0052e-3
3	0.6369e-3	-0.0511e-3	0.0007e-3
4	2.3190e-3	-0.1013e-3	-0.0043e-3
5	3.0301e-3	-0.1183e-3	-0.0045e-3
6	2.5375e-3	-0.0515e-3	-0.0019e-3
7	2.2943e-3	-0.0170e-3	0.0004e-3
8	1.8741e-3	0.0943e-3	0.0035e-3
9	2.3390e-3	0.1327e-3	0.0040e-3
10	2.2872e-3	0.1928e-3	0.0050e-3
11	1.5311e-3	0.2383e-3	0.0081e-3
12	1.0382e-3	0.2828e-3	0.0109e-3

moisture  $\hat{\theta}_{real}(i)$ . For each test *i*, the moisture error ratios without and with nonlinearity compensation, expressed by  $R_{e,wo}(i)$  and  $R_{e,w}(i)$ , are respectively defined as

$$R_{e,wo}(i) = \sum_{T=5}^{T=40} \left| 1 - \frac{\theta_{i,meas}}{\theta_{i,nl}} \right| \times \frac{1}{8} \times 100\%$$

$$R_{e,w}(i) = \sum_{T=5}^{T=40} \left| 1 - \frac{\hat{\theta}_{i,nl}}{\theta_{i,nl}} \right| \times \frac{1}{8} \times 100\%$$

As shown in Fig. 2, the performance of the temperature-related nonlinearity compensation method is validated by the comparison of the moisture error ratios. It's obvious that the proposed nonlinearity compensation can significantly reduce the error of the moisture sensor.



**Fig. 2.** Performance validation of the temperature-related nonlinearity compensation.

## 5 Conclusion

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This letter presents an integrated moisture and temperature sensor with model based temperature-dependent nonlinearity compensation. A temperature-dependent nonlinear model with 3 coefficients are modified for modeling and compensating the nonlinearity. The nonlinear coefficients estimation algorithm is also provided. Experimental results indicate a significant reduction of the moisture sensing error. It's proven that the moisture sensor's nonlinearity can be excellently compensated by a mathematical model with only a few coefficients instead of a large-scale look-up-table.

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