

## MODELLING OF SMART CAPACITIVE HUMIDITY SENSOR USING ANN

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## ABSTRACT

This paper basically presents a modelling of smart capacitive humidity sensor in order to correct the non linear characteristics of capacitive humidity sensor (CHS). For surveillance in supply chain smart capacitive humidity sensor are integrated with RFID tag. Change in ambient temperature leads to non liner characteristics of capacitive humidity sensor. Under such condition to obtain correct humidity readout, several techniques have been proposed. To provide compensation and self-calibration artificial neural network (ANN) is proposed. A microcontroller unit based hardware experimental set up has been implemented and experimentally measured data has been used to train ANN. In this paper simulation results have shown. This model can estimate the humidity over temperature variation from 20 C to 50 C with maximum full scale error  $\pm 1\%$ .

KEYWORDS: Smart Capacitive Humidity Sensor, Artificial Neural Network (ANN), RFID

## **INTRODUCTION**

Humidity sensor is widely used for much application area such as food storage, agriculture, domestic appliances and climate control. Humidity sensor should have linear response, low hysteresis and high sensitivity to fulfil the requirement of such appliances. Power consumption, response time, low cost, and high stability are some important parameter of smart humidity sensor that must be listed. RFID integrated with smart sensors (including PH, relative humidity, temperature etc) opens up much new attractive application. An RFID tag equipped with smart capacitive humidity sensor used for instant monitoring and for food quality training.

Capacitive technique is most widely used for humidity sensor, where the RH change is detected by humidity –induced dielectric constant change of thin film, where the most widely used material as humidity sensitive dielectric are polyimide film as they provide high sensitivity, low response time and low power consumption [1]. However on comparison with offset capacitance there is small Capacitance change of the CHS (Capacitive humidity sensor). Due to its nonlinear response characteristics and temperature dependence, difficulties arise in online calibration and digital interface for readout [2]. ANN can successfully tackle complex non linear modelling. Neural modelling is much faster than physics/electromechanical model and has higher accuracy than analytical and empirical model.

In this paper, humidity readout is carried out with two MLPs. The first MLP provides calibrated response characteristics due to change in ambient temperature. The second MLP provides accurate humidity readout.

### **CAPACITIVE HUMIDITY SENSOR**

A block diagram of capacitive humidity sensor is shown in figure 1. There is two capacitive sensors (1) reference

(1)

capacitance and (2) sensor capacitance. The reference capacitance is generally not exposed to environment where as sensor capacitance is mainly exposed to environment. To do measure the reference capacitance must be known. For example, if we have a sensor that has to variate from 60 to 100 pF, the reference capacitance value should be approximately 80 PF [3]. The oscillator is to relate the change in capacitance to a voltage. A low pass filter removes the oscillation frequency leaving the voltage response and gain amplifies the signal to the desired Vout range [4]. As 5 volt  $V_{dc}$  is used. From equation (1) voltage can be measured.



Figure 1: Block Diagram of Capacitive Humidity Sensor

$$V_{0ut} = V_{dc} * (0.00474 * \% RH * 0.2354)$$

**Behaviour of Capacitance Sensor:** When the water vapour blows over the surface; it is adsorbed on the surface. The adsorbed molecule diffuse in the polymer inducing a variation of its permittivity [5]. The variation in permittivity causes variation in capacitance.

$$C = \in_0 \in_r \frac{A}{a}$$

Where  $\in_0$  is the dielectric constant for vacuum,  $\in_r$  is relative dielectric constant for the polyster, a is thickness of active layer and A is conductive area.

### **EXPERIMENTAL SET UP**



Figure 2: Overall System Architecture

Figure 2 shows the overall system. A microcontroller unit based hardware experimental set up has been implemented and experimentally measured data has been used to train ANN. Simulation result show that this model can estimate the humidity over a wide variation of temperature 20 to 50 degree. This system measure the humidity and provides an analogue signal that is converted into digital with ADC(Analog-to-digital converter). This signal is given to microcontroller which perform the necessary processing and display results on the LCD.

### **DESIGNING OF ANN MODEL**

In general designing ANN model follows these steps: Data collecting, Data pre-processing, Building network, Training network, Testing network.

### **Data Collection**

In designing ANN model preparing and collecting data is the first step. The experimental set up results was used for database arrangement as (H, C, T, and V) where H is humidity is capacitance, T is temperature and V is voltage.

#### **Data Pre-Processing**

Data Pre processing refers to transforming and analyzing the input and output variables to highlight important relationships. The input and output variables are fed into the networks.

#### **Building the Network**

At this stage, the numbers of neurons in each layers, training function, and transfer function in each layer is specified. In this work feed forward MLP is used.

#### **Training Network**

Training set is the largest set used by the neural network to learn the pattern present in the data. In MLP-1 393 and in MLP-2 262 data has been used.

### **Testing Network**

The performance of the developed model is test by this step. The comparison between initial database and that obtained after training, using the test base, indicates that our model express accurate response of the capacitive humidity sensor (CHS) [6].



Figure 3: Flow Chart of ANN Designing

## THE MLP-BASED CHS MODEL

The proposed ANN model basically consists of two MLP. The first MLP is used to transfer the characteristics to the estimated characteristics. The second MLP used to compensate the non linearity's in sensor characteristics and to estimate the humidity readout.

#### **MLP-1: Transfer of Sensor Characteristics**

The scheme of Transfer of sensor characteristics to normalized estimated response characteristics is sown in figure 6. The input to MLP-1 is temperature and voltage. The desired output for MLP is estimated capacitance.

### **MLP-2: Estimation of Humidity**

The scheme of estimation of humidity is shown in figure 7. Here input to MLP-2 is estimated capacitance and desired (target) output is humidity.

#### SIMULATION STUDIES

To evaluate the performance of MLP -based CHS model, extensive simulation studies have been carried out.

### **Training and Testing of MLP-1**

To transfer the sensor characteristics to estimated response characteristics an MLP with {2-5-1} architecture is considered. During training BP (Back Propagation) data was used and 393 training base data were chosen randomly. For testing purpose 114 databases was chosen randomly the voltage was simulated within the range from (2.24 to 3.24) and then applied to MLP with temperature information.



Figure 4: Training Errors versus Number of Epochs in MLP-1



Figure 5: MLP-1 Model for Transferring the CHS Response



Figure 6: MLP-2 Model for Estimation of Humidity

Detahasa	Training base		393
Database	Test base		114
Number of	Input layer		2
Number of	Hidden layer		5
ineurons	Output layer		1
Transfer	Hidden layer		Log-sig
Function	Output layer		Linear
Input		Voltage	Temp
	Max	3.475	30
	Min	2.125	20
Output	Capacitance		
	Max	7626	
	Min	3586	
Architecture	2-5-1		
<b>Training Rule</b>	Backpropogation		

Table 1: Optim	ized Parameter	for	MLP-1
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Figure 7: Neural Network Response for MLP-1

### **Training and Testing of MLP-2**

To estimate the humidity a MLP with {1-4-1} architecture was chosen for MLP-1. The input to MLP-1 is estimated capacitance and target output is humidity. The training is done using BP (Back propagation) algorithm and training 148 were randomly chosen. For testing purpose 76 data base were selected. In testing the comparison between initial database and that obtained after training, using the test base, indicates that our model express accurate response variation of the CHS [6]. This model provides the estimated humidity readout accurately that is independent on temperature and non linear response characteristics.



Figure 8: Training Error versus Number of Epochs in MLP-2



Figure 9: ANN Model Performances at 30 Degree

Detabase	Training base		262
Database	Test base		76
Number of Neurons	Input layer		1
	Hidden layer		4
	Output layer		1
Transfer	Hidden layer		Log-sig
Function	Output layer		Linear
Input	Capacitance (nf)		
	Max	7626	
	Min	3586	
Output	<b>Relative Humidity (%RH)</b>		
	Kelativ	e nume	ILY (70KII)
	Max	e numu	97
	Max Min	e nunne	97 40
Architecture	Max Min	1-4-1	97 40

**Table 2: Optimized Parameter of MLP-2** 

### **RESULTS AND DISCUSSIONS**

Experimental data has been measured at different temperature using a microcontroller based hardware experimental set up. Due to non linear responses a neural network has been trained, as described before. In the end, results of the neural network application to the sensors response are presented. Figure 4 shows the training error versus the number of epochs in MLP-1. For each of the 393 randomly generated data set, we first trained the network with the training data up to 12 epochs. The best validation performance is 0.21965 at epoch 6. Figure 7 shows the estimated (via ANN) and the measured (via sensor) capacitance value versus voltage for MLP-1.

Figure 8 shows the training error versus the number of epochs in MLP-2. For each of the 262 randomly generated data set, we first trained the network with the training data up to 13 epochs and the best validation performance is 0.38978 at epoch 7. As the number of training iteration (epochs) increased, the performance for predicting the training humidity continues to be improved. Figure 9 shows the shows the ANN model performance at 30 degree.

### CONCLUSIONS

To obtain auto-compensation and auto-calibration of the non linear characteristics, an intelligent modal for CHS using two MLP is proposed. The first MLP is used to provide the estimated response characteristics at any temperature. The second MLP provides the accurate humidity readout and compensate the nonlinearity in sensor characteristics. The proposed model estimates the humidity over wide range of temperature. With this low power, linear response and low cost devices can be developed. Hence, linear response, low cost and low power are the main requirements for RFID sensors and their applications such as medical supplies and traceability of food products.

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