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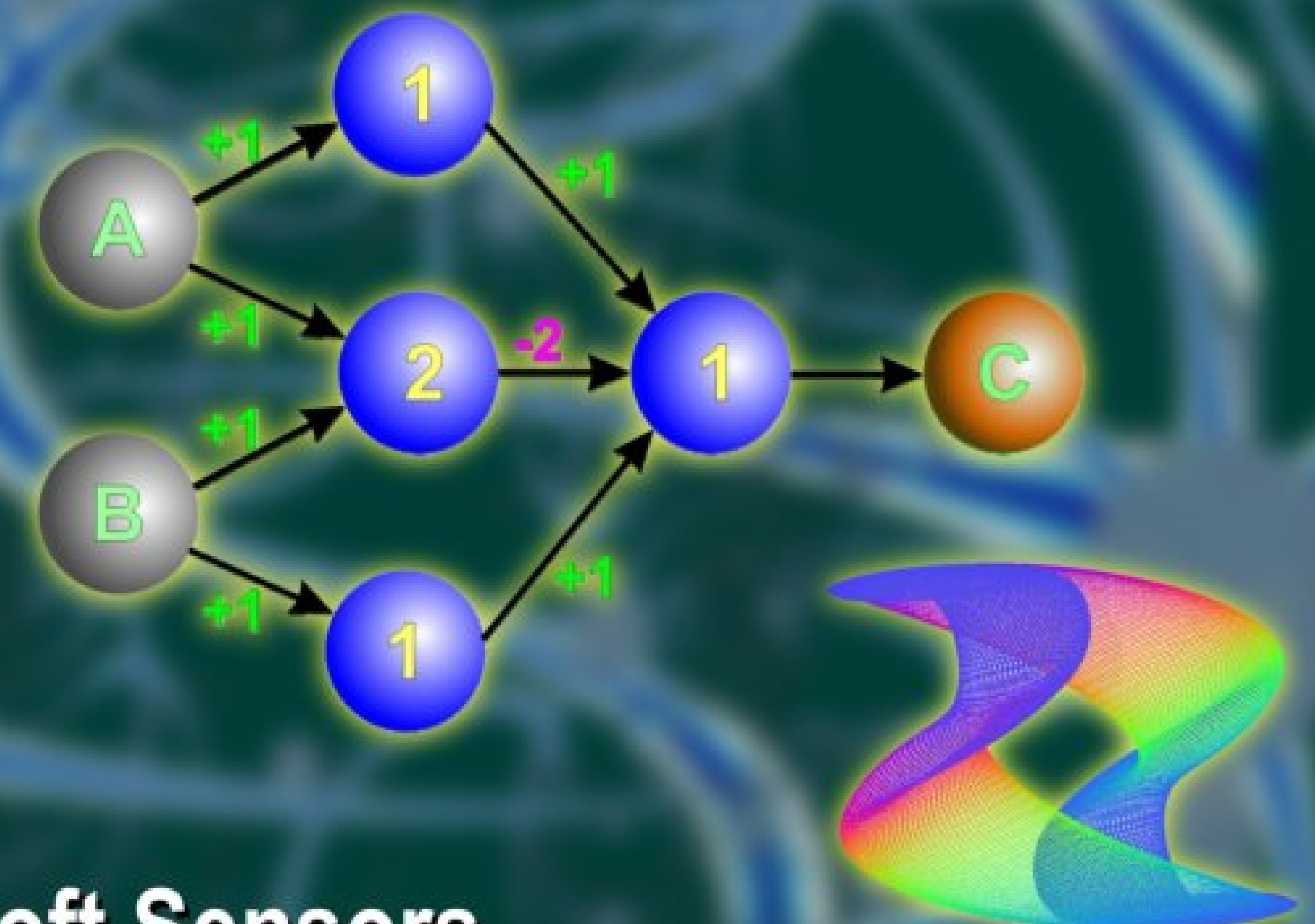

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Modeling of an Aged Porous Silicon Humidity Sensor Using ANN Technique

Tarikul ISLAM [2], Hiranmay SAHA[1*]

[1]IC Design and Fabrication Center, Dept. of E.T.C.E., Jadavpur University, Kolkata 700032, W.B., India, E-mail: juicc@vsnl.com, hsaha@vsnl.net, tel:913324146217, fax-913324146217,
[*]Corresponding author
[2]Electrical Engineering Department, Jamia Millia Islamia University, New Delhi, India, 110025,
E-mail: tariq940@rediffmail.com

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Abstract: Porous silicon (PS) sensor based on capacitive technique used for measuring relative humidity has the advantages of low cost, ease of fabrication with controlled structure and CMOS compatibility. But the response of the sensor is nonlinear function of humidity and suffers from errors due to aging and stability. One adaptive linear (ADALINE) ANN model has been developed to model the behavior of the sensor with a view to estimate these errors and compensate them. The response of the sensor is represented by third order polynomial basis function whose coefficients are determined by the ANN technique. The drift in sensor output due to aging of PS layer is also modeled by adapting the weights of the polynomial function. ANN based modeling is found to be more suitable than conventional physical modeling of PS humidity sensor in changing environment and drift due to aging. It helps online estimation of nonlinearity as well as monitoring of the fault of the PS humidity sensor using the coefficients of the model.

Keywords: Porous silicon; Humidity sensing; Aging; Drift due to aging; Modeling; ANN

1. Introduction

Humidity sensor finds wide applications in many systems like environment monitoring, weather forecasting, process control, medical and food processing industry. At present, it has been introduced in our day today life for human comfort [1]. Many useful properties of porous silicon (PS) such as very larger surface to volume ratio (typically >500 m^2 / cm^3), controllable structure through formation parameters and CMOS compatibility lead to develop humidity sensor using porous silicon with improvement in sensitivity, linearity, accuracy and reduced size [2-3]. With controllable pore morphology of the porous structure the response and recovery time can also be controlled [4]. However, the potentiality of the PS layer has not been exploited for developing commercial humidity sensor except some preliminary works because of some inherent problems of PS sensing layer [5-6]. One of the main problems of PS sensor is the long-term drift due to aging and stability. Gradual slow oxidation process of PS layer at room temperature leads to continuous changes in the structure and thus its physical parameters and the characteristics of the humidity sensor [3, 6].

Several works were reported to stabilize the PS layer to improve the stability and aging for humidity sensing, but such treatment could not stabilize the PS layer fully. A post oxidation of PS layer in H_2O_2 solution makes the PS layer oxidized in larger extent but fail to oxidize PS layer completely [7-8]. Modeling the behavior of the PS sensor both fresh and aged is very much essential for developing the signal-processing unit suitable for interfacing the sensor. It is also essential for developing the compensating algorithm for the non-ideal sensor characteristics if any and hardware design verification of the smart sensor chip [9-10]. Some research articles report the modeling of the sensor behavior of a PS humidity sensor without considering the drift behavior due to aging based on physical laws governing the relationship between the sensor input and output [1, 11]. Since the porous silicon suffers from stability, the modeling of the drift behavior due to aging is also very much essential in order to develop a compensating algorithm to minimize the effect of drift in the sensor output. Artificial neural networks (ANN) in the black box modeling approach are known to be excellent techniques to obtain approximate functional relationship between input and output of the sensor [12-13]. Among the features, which make ANN suitable are they can be trained to learn any function, provided that enough information is given during training process coupled with judiciously selected neural models, self-learning ability and fault tolerance capability due to structural parallelism of the ANN and adaptability due to change in environment. Another interest of ANN model is that the model parameters can be updated on line to accommodate changing operating conditions. These features on ANN technique have been exploited to model different type of sensors like humidity, pressure and temperature [14-15].

In this paper, we propose a technique to model the aged PS humidity sensor response characteristics by ANN with a view to develop a drift-compensating algorithm [10]. Conventional modeling based on physical laws which gives rise to complex mathematical model fails to accurately model the drift behavior of the PS sensor. Modeling based on parameter adaptation due to drift using ANN technique is found to be suitable for PS humidity sensor. For the full range of humidity, the sensor response curve obtained experimentally, then utilized to find the corresponding coefficients of the sensor polynomial function representing the relation between input and output. It is based on simple adaptive linear neural network (ADALINE) with linear activation function having single neuron with multiple inputs and single output. Firstly, the response curve of the fresh PS sensor without any drift was modeled by ADALINE and then drift of the sensor output was determined experimentally by using recalibration technique [16-17] and ultimately, for accurately modeling the drift nature of the humidity sensor, the weights were also updated to include the sensitivity change due to aging. Lastly the modeling technique has been utilized to estimate the nonlinearity by comparing the model output with desired linear output. In this paper section 2 is devoted to develop the basic polynomial model of the sensor. In section 3, sensor fabrication and testing results are reported. The detail modeling of the sensor using ADALINE and its simulation results are reported in section 4. Section 5 discusses the drift modeling of the PS sensor due to aging.

2. Modeling of the PS Sensor

A porous silicon capacitive humidity sensor can be equivalently represented by parallel combination of capacitance and resistance and at low measurement frequency, the sensitivity of the humidity sensor is predominantly capacitive and role of parasitic components are negligible [3]. Capacitance C_{ps}, of a porous silicon parallel-plate capacitor with membrane type contact structure having two rectangular contact pads is a nonlinear function of humidity and can be represented by the nth order polynomial function as

$$C_{ps} = \sum_{i=0}^{n+1} a_i RH^i \ , \tag{1}$$

where a_i is the coefficient of the sensor, RH is the relative humidity and n the order of polynomial. When the capacitance with the variation of humidity is converted into the voltage output by the phase detection circuit reported elsewhere [18], the voltage output of the humidity sensor can be given in power series form as

$$V = \sum_{i=0}^{n+1} b_i RH^i \ , \tag{2}$$

where V is the voltage output of detection circuit corresponding to humidity RH and b_i is the coefficient. The text should be typed single-spaced and justified.

3. Experimental

3.1. Fabrication of PS sensor

The porous silicon humidity sensor was fabricated on a polished silicon wafer, 2.5 cm × 2.5 cm × 0.5 mm, with <100> orientation having resistivity of 1-2 Ωcm by standard electrochemical etching in HF based electrolyte. A PC (personnel computer) interfaced special formation cell was utilized for the formation of the PS senor. The procedures of the porous formation were reported elsewhere [3, 5]. The anodization of the sample was done with formation parameters 10 mA / cm^2 current density, 48 % HF concentration and etching time of 7 min respectively. Current density and etching time are precisely controlled by the PC. The porosity of PS sample is measured by gravimetric technique and is approximately 60 %. The dimension of silicon nanocrystals are ~5-10 nm and the thickness of the PS film is around 3-7 μm. Metal contacts in interdigital form were fabricated by vacuum evaporation of aluminium on the top of the PS layer. The spacing between two contact electrodes is 1mm and dimension of each electrode is 5 × 0.5 mm. The aluminium contacts are thermally heated at 500°C for 40 sec in inert N_2 atmosphere [10]. The electrodes yield ohmic contacts showing approximately linear $I-V$ characteristics with applied biasing voltage as shown in Fig. 1. Fig. 2 shows the schematic of the PS humidity sensor.

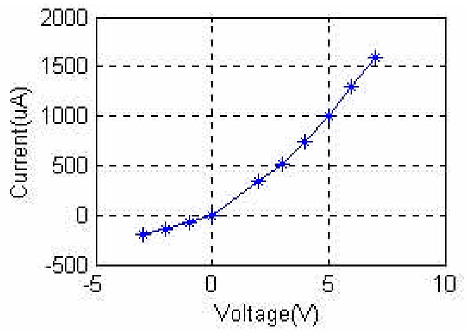


Fig. 1. I-V characteristics of porous silicon – silicon sandwich structure for 60 % porosity.

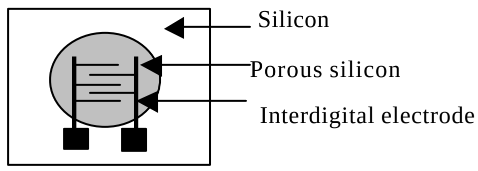


Fig. 2. Schematic of the PS humidity sensor.

3.2. Sensor testing

The PS sensor is tested in an in-house designed injection test rig for relative humidity. After anodization, the freshly prepared PS sample was post oxidized in H_2O_2 solution for 48 hours. For To determine the response of the sensor to the humidity, the relative humidity level in the airtight test chamber of 2000 cc volume was created by standard saturated salt solutions. Percentage relative humidity is monitored by standard humidity sensor (Honeywell) placed inside chamber. Initially the humidity level in the chamber was reduced to the lower base line value of 20 % RH using saturated salt solutions, the voltage output of the sensor for the change in capacitive impedance was measured by the detection electronics circuit, and then the concentration of water vapor was increased from 20 to 95 % RH gradually with the help of saturated salt solutions and the output of the sensor was measured. The output of the sensor was noted carefully allowing sufficient equilibrium time (24 h) in each measurement. The response of the sensor for the variation of humidity from 20 to 95 % is shown in Fig. 3. The results show that the response of the sensor is nonlinear function of RH. For the repeatability of the sensor, the vapor in the chamber was reduced to 20 % of its initial base line value and then suddenly the sensor was exposed to the humidity of 95 %, the experiments were repeated for several cycles of vapor in the range of 20 to 95 %. Fig. 4 shows the repeatability of the sensor output.

3.3. Drift due to aging

Electrochemical dissolution of silicon in HF solution leads to the formation of Si-Hx bonds, which are easily oxidized to replace Si-Hx bonds by Si-O bonds even at room temperature. The growth rate of oxidation depends on concentration of OH^- and higher concentration of hole in the valence band of the PS layer [10].

It is interesting to note that Si-Hx bond of as-anodized sample are hydrophobic in nature but Si-O bonds are hydrophilic in nature. Thus the sensor response is gradually increased till the layer is completely oxidized. A PS sample was post oxidized in H_2O_2 solution for 48 hours after etching to stabilize its performance [8-9]· However, by treating the sample with H_2O_2 solution it is not possible to fully oxidize the PS layer.

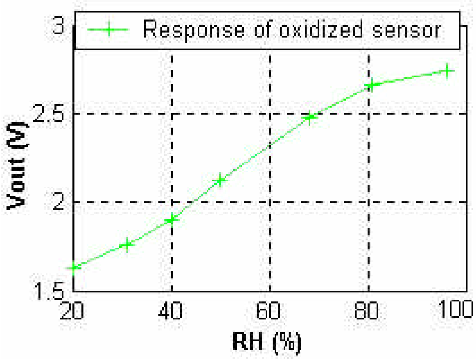


Fig. 3. Response of porous silicon humidity sensor with the variation of humidity (60 % porosity sample.

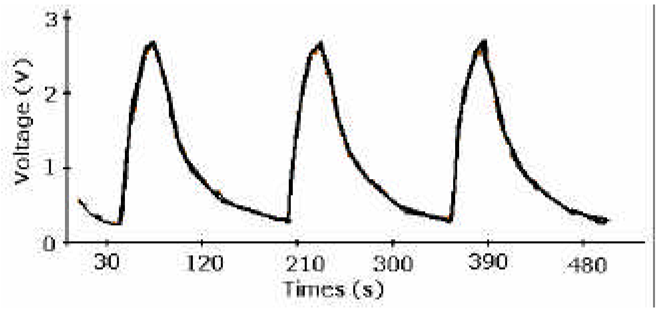
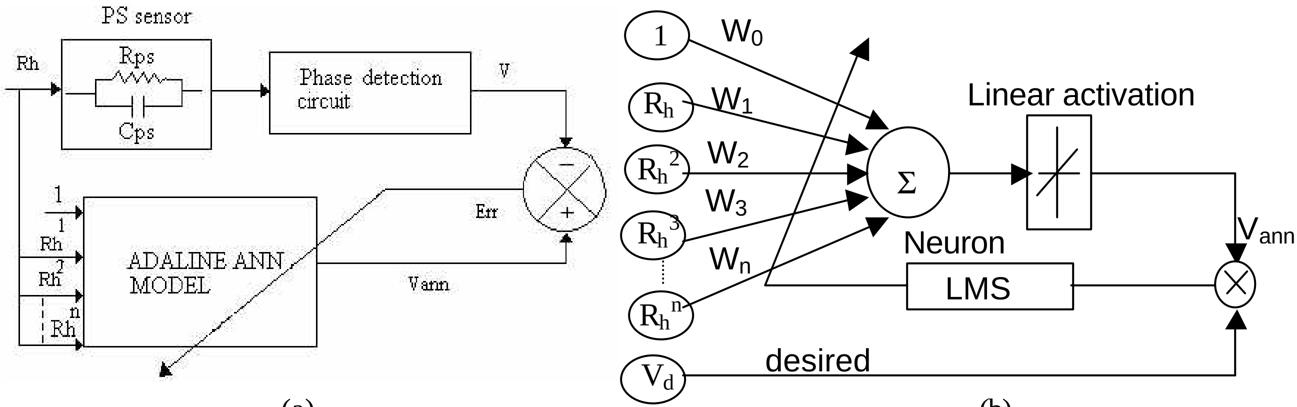


Fig. 4. Reproducibility of PS humidity sensor (frequency = 1 kHz).

An experiment was performed to obtain the long-term drift of the sensor for 15 days. The details of the experimental procedures for determining the long-term drift due to aging of the sensor were reported in [10]. The experimental results of the drift behavior of the PS humidity sensor on long-term basis as reported were found to be nonlinear but for short-term basis it is approximately linear [10, 16].

4. Modeling the Behavior of the PS Humidity Sensor Using ADALINE

Modeling of the PS sensor involves two steps. In the first step where structure identification is used, we need to apply priory knowledge about the sensor to assume an approximate mathematical function representing input and output relationship of the sensor as $V = f(U, B)$, where V is the model output, U is the input vector and B is the parameter vector. The determination of the function f is the problem dependent and based on designer experience, intuition and the laws of the nature governing the sensor. In the second step, the structure of the model is known and all we need to do is to apply optimization technique to determine the parameter vector $\hat{B} = B$ such that resulting sensor model $\hat{V} = f(U, \hat{B})$ can describe the sensor appropriately. The procedures are (i) specify and parameterize a mathematical model of the sensor, (ii) perform the parameter identification to chose the parameter that best fit the training data set, (iii) conduct validation test to see if the model developed responds correctly to an unseen data set, which is disjoint from training data set and called validation set, (iv) Terminate the procedure once the results of the validation test are satisfactory otherwise, another class of model is selected and steps (ii) through (iv) are repeated. The nonlinear response characteristics of the PS humidity sensor for the entire dynamic range of humidity measurement are modeled mathematically based on power series and is given in Equ. (2). The n^{th} order power series can be approximated with lower order polynomial function. A suitable ANN network can be utilized to determine the coefficients of the approximated polynomial function. An n^{th} order ADALINE neural network for sensor modeling is shown in Fig. 5 (a). In this model, the actual PS humidity sensor and ADALINE network is connected in parallel and the outputs of the ANN and the sensor are compared. Fig. 5 (b) shows structure of the network. It consists of single neuron with linear activation function network. For an n^{th} order model inputs are $[1, RH, RH^2, RH^3, ...RH^n]$ and the connecting weights to the neuron are $[W_0, W_1, W_2, ...W_n]$ respectively. The weighted sum of the inputs is the actual output of the network V_{ann}.



(a) (b)

Fig. 5. (a) Schematic diagram of the sensor model using ADALINE network (b) structure of the network.

The ANN weights are updated iteratively by least mean square (LMS) algorithm by comparing the network output with desired voltage output (sensor output voltage V) till the error goal is reached. Least –square method is powerful and well-developed mathematical tool that have been used in a variety of areas including adaptive control, signal processing, and statistics. The α-LMS algorithm was discussed in [14]. Once the network is trained, the weights can estimate the sensor output for the entire dynamic range of humidity. These weights of the model help to identify the faulty operation of PS humidity sensor in case sensor output deviates due to environmental conditions. Due to drift in sensor output, the current estimated sensor coefficients will differ from the initial estimated values. To estimate nonlinearity of the PS humidity sensor, the nonlinearity is defined as the maximum deviation of the actual sensor output from the straight-line relationship obtained joining two extreme points over the entire range [18]. For PS humidity sensor under consideration, the typical nonlinearity as shown in Fig. 3 is approximately 5 %. However, the nonlinearity in the sensor output is increased if we reduce the measurement range below20 % RH. To estimate the nonlinearity, the network output $V_{ann}(=V)$ is compared with the straight-line response curve obtained joining two extreme points of the response of the sensor. Thus, estimation of nonlinearity of the PS sensor response in fact involves the estimation of the function f , from a set of RH and $V_{ann} = f(RH)$ values from calibration data.

4.1. Determination of the coefficients of the network

To carry out the simulation works, the LMS algorithm was implemented by writing the MATLAB code. For modeling the sensor, the order of the polynomial basis function was chosen heuristically. The input which is the percentage humidity and the sensor output voltage obtained experimentally, the desired output of the network are normalized between 0 and 1 by dividing both input and output vector by their respective maximum values. The initial weights were generated randomly within 0 to 1. The total data points were divided into two groups training set and test data set. For a fixed iteration and fixed learning rate parameter [10,14], the network was trained by applying inputs nonlinearly and the root mean square error of the network was determined. The number of inputs of the network depends on the order of initial polynomial basis function. The root mean square error of the network can be written as

$$rms = (\sqrt{\frac{1}{N}\sum_{i=1}^{N}(V - V_{ann})^2}) \times 100\,, \tag{3}$$

where rms is the percentage root mean square error, V is the normalized desired output, V_{ann} is the normalized network output and N is the total data points. The final weights of the trained network were used to estimate the network rms for the entire data points including the test data points. The test data are those, which are unknown to the network. Simulation results show that the rms error for the third order basis function is sufficiently lower. However, by selecting higher order basis function, the rms error may be reduced further but the complexity of the network will also increase. Thus a third order polynomial function of the form given in Equ. (4) below has been selected finally for modeling the sensor. Using the actual input of sensor RH, a nonlinear set of data such as $[1, RH, RH^2, RH^3]$ is generated and output of the network is determined as

$$V_{ann} = W_0 + W_1 RH + W_2 RH^2 + W_3 RH^3, \tag{4}$$

where V_{ann} is the actual output of ANN, $[W_0, W_1, W_2, W_3]$ are the connecting weights and are equal to $[b_0, b_1, b_2, b_3]$ of Equ. (2).

4.2. Simulation results

During training, each set of normalized input vector was applied individually to update the weights. Completion of all training data points form one epoch of training. Training progresses and weights were updated till the rms error of the network reaches some preset minimum error goal. After training, the final weights were stored in the memory and used for evaluating the network performance and actual use of the sensor. Weights are shown in table I. Fig. 6 shows the simulation results for the full-scale data points, which include the data from validation set. It is seen in the results that network output closely follows the actual sensor output for the entire dynamic range of the humidity. The maximum rms error is reduced to only 1 %. Simulation studies were also carried on to understand the minimum requirements of the experimental data points to accurately model the sensor. In this case, the simulation was repeated with different data points for fixed epoch and learning rate and the rms error was calculated. The results are shown in table I. It is observed in the table that 8 data points are sufficient to model the sensor with sufficient accuracy. A sufficient equilibrium time for the sensor to stabilize at every reading should be given before measurement. Being able to calibrate quickly during operation of the sensor is necessary to reduce down time. Reducing the number of calibration points and then using the interpolation or LMS methods decreases the calibration time. The minimal set of calibration points depends on the nonlinearity of the sensor, the required accuracy and computational processing load.

Table 1. Network weights parameter for third order sensor model
(Training epoch = 45,000, learning rate = 0.2)

Training data pairs	**Weights fresh sample (Oxidized) [W_0 W_1 W_2 W_3]**	**Weights for 11 % drifted sensor output**	**Weights for 13.5 % drifted sensor output**	**Network rms error (%)**	**Estimated nonlinearity (%)**
11	[0.524, 0.09 1.068, - 0.667]	[0.580 0.122 1.148 - 0.721]	[0.594 0.119 1.186 - 0.745]	0.844	4
8	[0.520 0.14 0.95 - 0.59]	[0.575 0.170 1.024 - 0.631]	[0.59 0.168 1.057 - 0.652]	1.066	4

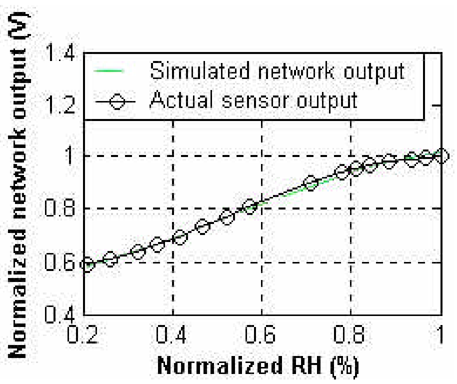


Fig 6. Simulated network output for third order model for the full-scale data points.

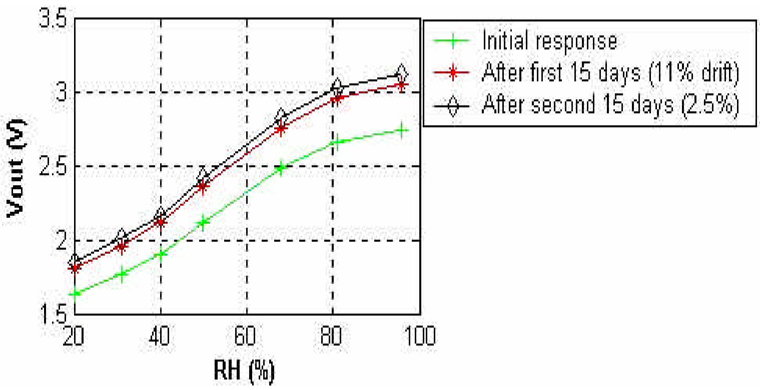
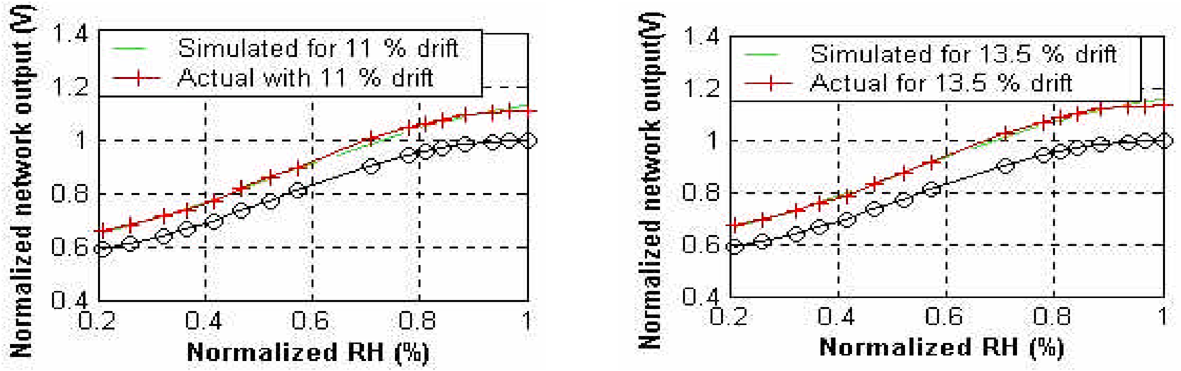


Fig. 7. Long-term drift in the sensor output due to aging.

5. Modeling the Sensitivity Drift Due to Aging

5.1. Modeling the drift behavior of the sensor

It is shown in the experimental results that the effect of aging leads to continuous change in the sensor output with time unless the PS layer is fully oxidized (stabilized). It is expected that on long-term basis the drift behavior is nonlinear in nature but for short-term basis, the sensor output drift with time can approximated as linear or the nonlinear long-term drift can be piece wisely linearized [18]. Assuming linear drift on short-term basis, the sensor output for humidity can be represented by two-dimensional equation. The drift behavior modeling of the PS humidity sensor due to aging was discussed in [10].



(a) (b)

Fig. 8. (a) Sensor output with humidity for 11 % sensitivity drift (b) Simulated network output for 11 % drift in sensitivity (c) Simulated network output for 13.5 % drift in sensitivity.

Fig. 7 shows the effect of drift on the overall response of the sensor output. Experimental results show that there was 11 % drift of sensor output for the first 15 days and 2.5 % drift for the next 15 days. To model the drift behavior due to aging, the weights of the ANN network modeling the behavior of the sensor, the weights were adapted by running the program for additional several thousands of epochs. The same ADALINE structure, where input to the model is remained unchanged (initial humidity) but the desired output of the network is changed according to drift due to aging (11.5 % drifted output). By running the program for additional epochs of few thousands the weight can accommodate the drift in sensor output. Table I shows the adapted weights for different percentage of sensor output drift. Fig. 8(a) shows the simulation results of the sensor model with 11.5 % drifted output while Fig. 8(b) shows the simulation results of additional 2.5 % drift. It is clear from the simulation that the sensor output drifts due to aging can be effectively adapted with this technique.

6. Conclusions

In this paper we have proposed a scheme based on simple adaptive linear neural network (ADALINE) for the purpose of simulation of the performance and fault detection of porous silicon capacitive relative humidity sensor. With simulation studies, it is found that a third order polynomial basis function is sufficient for accurately modeling the performance of the sensor. This modeling is useful for estimation of the faulty operation of the sensor due to drift in sensor output for environmental and aging effects. The coefficients of the model can be used to estimate the percentage nonlinearity of the sensor. The drift of sensor output due to aging is also adapted by adapting the weights of the model. It is also shown from the results that only 8 experimental data points are sufficient for sensor modeling. However, further accuracy may be improved by using multiplayer perceptron neural network with nonlinear activation function in the hidden layer. But the complexity of the network, computation as well as total weights may increase.

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