An Intelligent Pressure Sensor Using Neural Networks

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***Abstract*—In this paper, we propose a scheme of an intelligent capacitive pressure sensor (CPS) using an artificial neural network (ANN). A switched-capacitor circuit (SCC) converts the change in capacitance of the pressure-sensor into an equivalent voltage. The effect of change in environmental conditions on the CPS and subsequently upon the output of the SCC is nonlinear in nature. Especially, change in ambient temperature causes response characteristics of the CPS to become highly nonlinear, and complex signal processing may be required to obtain correct readout.**

The proposed ANN-based scheme incorporates intelligence into the sensor. It is revealed from the simulation studies that this CPS model can provide correct pressure readout within ±1% error (full scale) over a range of temperature variations from −20 °C to 70 °C. Two ANN schemes, direct modeling and inverse modeling of a CPS, are reported. The former modeling technique enables an estimate of the nonlinear sensor characteristics, whereas the latter technique estimates the applied pressure which is used for direct digital readout. When there is a change in ambient temperature, the ANN automatically compensates for this change based on the distributive information stored in its weights.

***Index Terms*—Artificial neural networks, automatic temperature compensation, intelligent sensor, multilayer perceptron, pressure-sensor modeling.**

I. INTRODUCTION

PRESSURE sensors have wide applicability in various systems including instrumentation, automobiles, bio-medical, and process control systems. The capacitive pressure sensor (CPS), in which the capacitance of a chamber changes with application of pressure finds extensive applications because of its low power consumption and high sensitivity [1]. However, its highly nonlinear response characteristics give rise to several difficulties including on-chip interface, direct digital readout and calibration.

To compensate for the difficulties faced due to the nonlinear response characteristics of the CPS, several techniques have been suggested. A switched-capacitor charge balancing technique [2], a ROM-based look-up table method and a nonlinear encoding scheme have been proposed [3]. The problem of nonlinear response characteristics of a CPS further aggravates the situation when there is change in environmental conditions. As the output of a CPS is dependent on applied pressure as well as temperature, when the ambient temperature changes frequently, the situation becomes very complicated. In this case the problem becomes two-dimensional (2-D), and complex signal processing techniques are required to make necessary corrections to obtain a correct digital readout. A scheme of microcomputer-based 2-D look-up table [4] and another approach based on an oversampling $\Delta - \Sigma$ demodulator and complex signal processing techniques for the sensor model have been reported [5] with some success.

For nonlinearity estimation and to obtain a direct digital readout of a CPS, an artifical neural network (ANN)-based modeling technique has been proposed with quite satisfactory performance [6]; however without any consideration of change in the ambient temperature. Recently, using two multilayer perceptrons (MLP's), auto-calibration and nonlinear compensation of a CPS, under variation of ambient temperature has been proposed [7]. The maximum error in estimation of pressure over a wide variation of temperature is reported as ±1% full scale (FS). An ANN-based smart CPS in a dynamic environment has been reported [8]. In practice, in a dynamic environment, the change in ambient temperature influences the sensor characteristics nonlinearly. This ANN model is capable of providing pressure readout with a maximum FS error of ±2% over a wide variation of ambient temperature.

In the present paper, we address the 2-D problem of a CPS using a multilayer ANN. A switched-capacitor circuit (SCC) converts the change in capacitance into an equivalent voltage. The intelligent behavior is implanted into the sensor by training the ANN to adapt to any temperature change. Two modeling techniques are proposed in this paper. In the direct modeling, the ANN is trained in a parallel mode to estimate the capacitance of the CPS. This model may be used for the purpose of on-line fault detection and quality control of the sensor during its production. In the inverse modeling, the ANN is trained in a series mode to estimate the applied pressure which is independent of ambient temperature. A plug-in module (PIM) is proposed to implement the scheme on-line. The effectiveness of both schemes has been verified by extensive computer simulation studies.

II. CAPACITIVE PRESSURE SENSOR MODEL

We have chosen a CPS in this study because of its wide applicability. The CPS has lower power dissipation and higher sensitivity than other types of pressure sensors. A CPS senses the applied pressure due to the elastic deflection of its diaphragm. In the case of a simple structure, this deflection is proportional to the applied pressure P, and the sensor capacitance $C(P)$ varies

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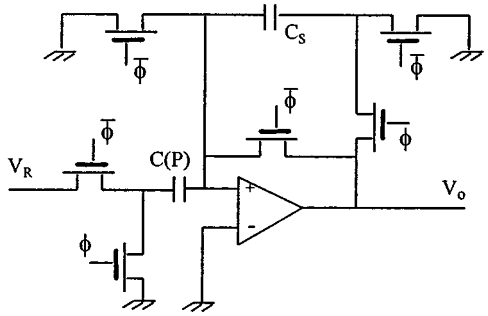

Fig. 1. Switched-capacitor interface circuit.

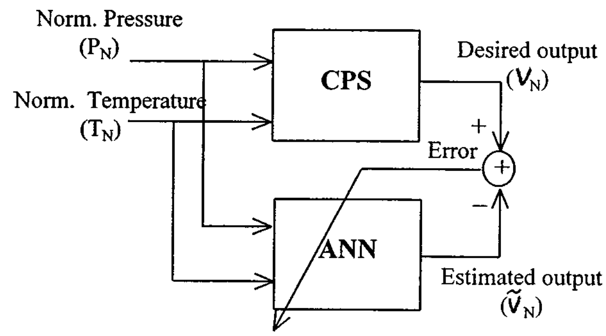

Fig. 2. Scheme of direct modeling of a CPS.

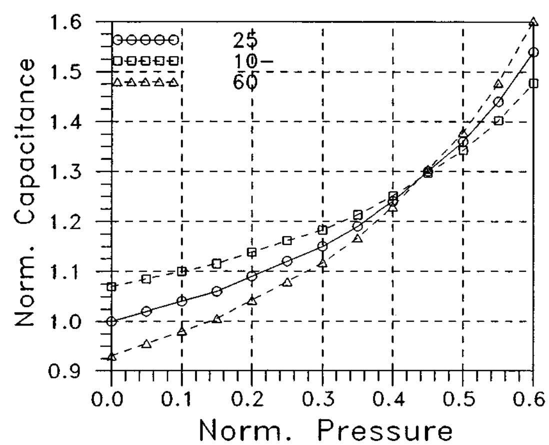

Fig. 3. Direct response characteristics of the CPS at -10 °C, 25 °C and 60 °C.

hyperbolically. Neglecting higher-order terms, $C(P)$ may be approximated by

$$C(P) = C_0 + \Delta C(P) = C_0(1+\gamma) \tag{1}$$

where C_0 is the sensor capacitance when $P = 0$; $\Delta C(P)$ is the change in capacitance due to applied pressure; $\gamma = P_N(1 - \alpha/(1-P_N)$; α is the sensitivity parameter which depends upon the geometrical structure of the sensor; P_N is the normalized applied pressure given by $P_N = P/P_{\max}$; and $P_{\max}$ is the maximum permissible input pressure.

In the 2-D problem discussed in this paper, the sensor capacitance is a function of the applied pressure and the ambient temperature T. Assuming that the change in capacitance due to change in temperature is linear and independent of the applied pressure, the CPS model may be expressed as

$$C(P,T) = C_0 f_1(T) + \Delta C(P,T_0) f_2(T) \tag{2}$$

where $\Delta C(P,T_0)$ represents the change in capacitance due to applied pressure at the reference temperature T_0 as given in (1). The functions $f_1(T)$ and $f_2(T)$ are given by

$$f_1(T) = 1 + \beta_1(T - T_0); \quad f_2(T) = 1 + \beta_2(T - T_0) \tag{3}$$

where the coefficients β_1 and β_2 may have different values depending on the CPS chosen. The normalized capacitance of the CPS, C_N is obtained by dividing (2) by C_0 and may be expressed as

$$C_N = C(P,T)/C_0 = f_1(T) + \gamma f_2(T). \tag{4}$$

A SCC for interfacing the CPS is shown in Fig. 1, where $C(P)$ represents the CPS. The circuit operation can be controlled by a reset signal Φ. When $\bar{\Phi} = 1$ (logic 1), $C(P)$ charges to the reference voltage V_R while the capacitor C_S is discharged to ground. Whereas, when $\Phi = 1$, the total charge $C(P)V_R$ stored in the $C(P)$ is transferred to C_S producing an output voltage given by $V_0 = K \cdot C(P)$, where $K = V_R/C_S$. It may be noted that if ambient temperature changes, then the SCC output also changes although the applied pressure remains the same. By choosing proper values of C_S and V_R, the normalized SCC output can be adjusted in such a way that $V_N = C_N$.

III. Direct Modeling of CPS

A scheme of direct modeling of a CPS is shown in Fig. 2. This scheme is analogous to that of the system identification problem in control engineering. The purpose of the direct modeling is to obtain an ANN model of the CPS in such a way that the outputs of the CPS and the ANN match closely. Once a model of the CPS is available, it may be used for fault detection of the sensor. An ANN based on the MLP is a feed-forward network with one or more layers of nodes between its input and output layers. The popular back-propagation (BP) algorithm, which is a generalization of the LMS algorithm, is used to train the MLP. The details of the BP algorithm may be seen in [9], [10].

Simulation studies were carried out to obtain a direct model of the CPS. The SCC output voltage V_N was obtained experimentally at the reference temperature of 25 °C for different values of normalized pressure chosen between 0.0 and 0.6 with an interval of 0.05. Thus, these 13 pairs of input-output data constitute a set of patterns at the reference temperature. Using (3), the functions $f_1(T)$ and $f_2(T)$ were generated by setting the values of β_1 and β_2 to -2.0×10^{-3} and 7.0×10^{-3}, respectively. From the available CPS pattern set at the reference temperature, i.e., $P_N \sim C_N$, and with the knowledge of functions $f_1(T)$ and $f_2(T)$, eight sets of patterns (each containing 13 pairs of input-output data) were obtained at an interval of 10 °C ranging from -10 °C to 60 °C. The CPS response characteristics for the chosen values of β_1 and β_2 at $T = -10$ °C, 25 °C, and 60 °C are plotted in Fig. 3.

A two-layer MLP with 3-5-1 structure was chosen for direct modeling of a CPS as shown in Fig. 2 (3, 5, and 1 denote the number of nodes including the bias units in the input layer, the first layer, i.e., the hidden layer and the output layer of the ANN,

TABLE I
FINAL WEIGHTS OF THE ANN USED IN THE DIRECT MODEL OF THE CPS

Node	First layer				
No.	0	1	2		
1	-0.0070	-0.0214	-0.4518		
2	3.1023	-0.5221	-3.3866		
3	-0.2722	0.6233	-0.5368		
4	-0.0432	0.1674	-0.0324		
	Second layer				
	0	1	2	3	4
1	1.8504	-0.1790	-1.3356	-0.2324	0.0112

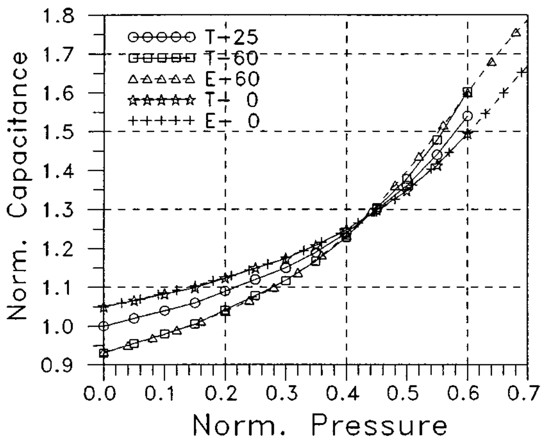

Fig. 4. True (T) and estimated (E) capacitances of the CPS at 0 °C and 60 °C (test set). The true characteristics at 25 °C are shown for reference.

respectively). Four sets of patterns corresponding to -10 °C, 10 °C, 30 °C, and 50 °C were chosen for training of the ANN. The BP algorithm in which both the learning rate and the momentum rate were chosen as 0.5, was used to adapt the weights of the ANN.

The normalized temperature (T_N) and the normalized applied pressure (P_N) were used as input pattern, and the SCC output $(V_N = C_N)$ was used as the desired pattern to the MLP. After application of each pattern, the ANN weights were updated using the BP algorithm. Completion of all patterns of all the training sets constitutes one iteration of training. To make the learning complete and effective, 10 000 iterations were made to train the ANN. Then, the weights of the MLP were frozen and stored in an EPROM. These weight values are shown in Table I.

During the testing phase, the frozen weights are loaded into the ANN model. Then the inputs, T_N and P_N from the test set were fed to this model. Next, the model output was computed and compared with the actual output (if known) to verify the effectiveness of the model. The normalized pressure values were chosen from 0.0 to 0.7 with an increment of 0.01 and applied to the ANN model along with normalized temperature. The estimated values $\tilde{V}_N$ and V_N at 0 °C and 60 °C (test set samples) are plotted in Fig. 4. From this figure it may be observed that the estimated values follow the true values very closely. Even for the P_N values from 0.6 to 0.7, for which true capacitance values are not known, the ANN model is capable of predicting

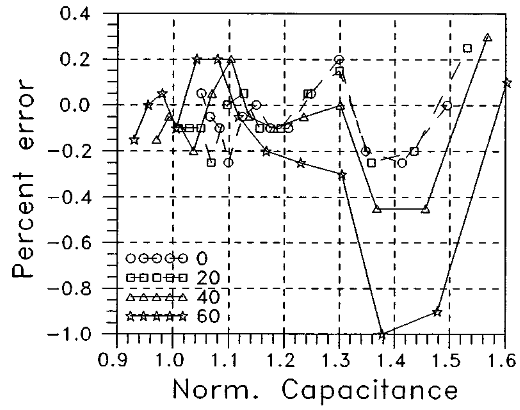

Fig. 5. Percentage of error (FS) between the true and estimated capacitances at 0 °C, 20 °C, 40 °C, and 60 °C.

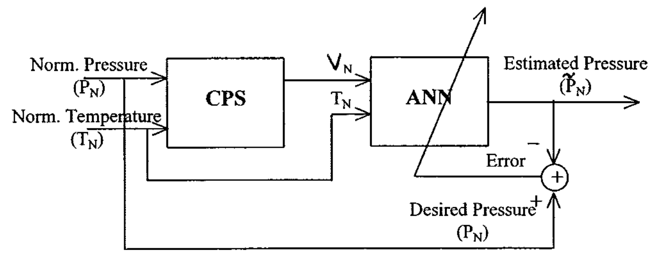

Fig. 6. Scheme of inverse modeling of a CPS.

the corresponding values correctly. Similar estimated characteristics close to actual one were observed for other temperatures.

The percentages of error (FS) between true and estimated capacitances at 0 °C, 20 °C, 40 °C, and 60 °C are shown in Fig. 5. It may be noted that, the MLP was not trained for the patterns at these temperature values. It may be seen from this figure that the estimation error remains within 1% (FS). From these studies the effectiveness of the ANN-based direct model is quite evident.

IV. INVERSE MODELING OF CPS

A scheme of inverse modeling of a CPS using an MLP for estimation of applied pressure is shown in Fig. 6. This is analogous to the channel equalization scheme used in a digital communication receiver to cancel the adverse effects of the channel on the data being transmitted. To obtain a direct digital readout of the applied pressure, an inverse model of the CPS may be used in cascade with it to compensate for the adverse effects on the CPS output due to the nonlinear response characteristics and the variations with ambient temperature. The generation of training-set and test-set patterns is similar to that of the direct modeling scheme. However, in the inverse modeling scheme, the normalized temperature T_N and the CSS output V_N are taken as input patterns, and the normalized input pressure P_N is taken as the desired output pattern in the ANN model. .

In the simulation study, the same MLP with 3-5-1 structure was chosen for inverse modeling of the CPS. The ANN was trained in a similar fashion as in the case of direct modeling. In this case also, all the 13 patterns corresponding to temperature values of -10 °C, 10 °C, 30 °C, and 50 °C were applied randomly during training. The learning rate and the momentum

TABLE II
FINAL WEIGHTS OF THE ANN USED IN THE INVERSE MODEL OF THE CPS

Node	First layer				
No.	0	1	2		
1	0.6934	0.0026	-1.1467		
2	2.7696	-1.0424	-7.0300		
3	1.4187	0.2697	-2.0573		
4	0.1405	0.0229	-0.2506		
	Second layer				
	0	1	2	3	4
1	-0.8835	-0.2683	-1.4867	-0.5091	-0.0590

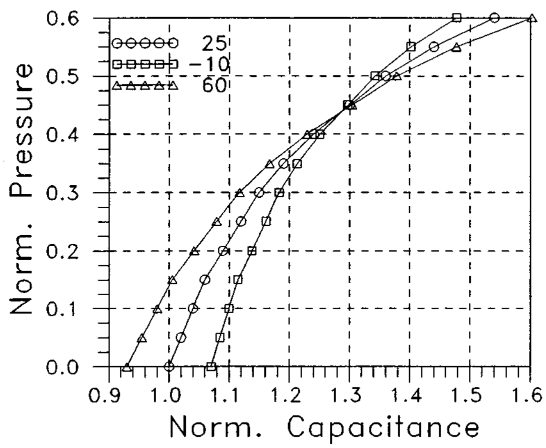

Fig. 7. Inverse response characteristics of the CPS at −10 °C, 25 °C, and 60 °C.

rate were chosen as 0.5 and 0.7, respectively. The MLP was trained for 10 000 iterations using the BP algorithm, the evolved weights were frozen, and stored in an EPROM. The final weight values of the MLP are listed in Table II.

The inverse response characteristics of the CPS for −10 °C and 60 °C are calculated using (4) and are plotted in Fig. 7. In the testing phase, the CSS output V_N was applied as input to the MLP with an increment of 0.001 in the range from 0.9 to 1.9 along with the normalized temperature T_N. Then, the estimated pressure $\tilde{P}_N$ was obtained from the output of the ANN model. The estimated pressure and the true pressure at 0 °C and 60 °C (test set) are plotted in Fig. 8. From this figure, a quite close resemblance between the estimated pressure and true pressure may be observed. Similar results were found for the full range of temperatures from −20 °C to 70 °C

The plots of normalized actual pressure versus estimated pressure (by the ANN model) at different ambient temperatures indicate a nearly linear relationship between the two. The variations of error in the estimation of pressure by the ANN model at 0 °C, 20 °C, 40 °C, and 60 °C are plotted in Fig. 9. From this plot it may be seen that the error between the actual and estimated pressure remains within ±1%(FS).

Extensive simulation studies were carried out with different MLP structures over a wide temperature range and tested for different temperature values. The 3-5-1 MLP structure was found to provide optimum performance. It may be noted that, although the MLP was trained with patterns corresponding to only four temperature values (−10 °C, 10 °C, 30 °C, and 50 °C), the

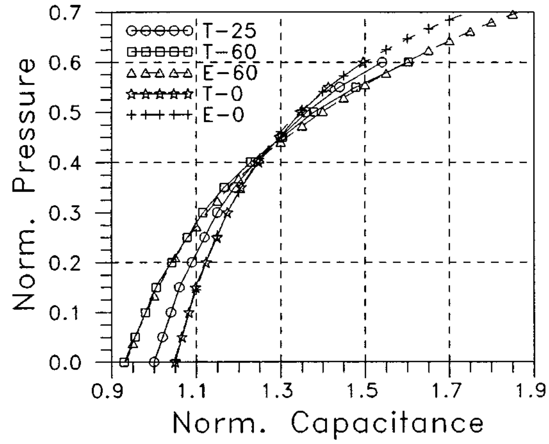

Fig. 8. True (T) and estimated (E) pressures at 0 °C and 60 °C (test set). The true characteristics at 25 °C are shown for reference.

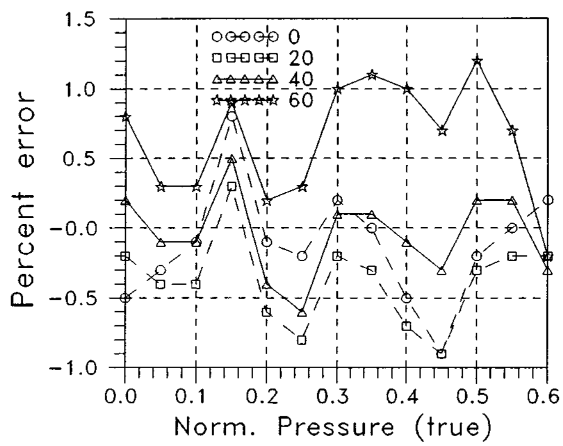

Fig. 9. Percentage of error (FS) between the true and estimated pressures at 0 °C, 20 °C, 40 °C, and 60 °C.

ANN model was found to be capable of accurately estimating the applied pressure at any ambient temperature from −20 ° C to 70 ° C. This fact is the novel characteristics of the proposed ANN model.

V. IMPLEMENTATION ISSUES

An implementation scheme of the inverse model for estimation of applied pressure is proposed here. The implementation scheme and details of the PIM are shown in Fig. 10. The output of the SCC passes through an ADC, and its digital output along with the temperature value are fed to the PIM. The output of the PIM is applied to the display unit for digital display of the applied pressure.

The training or learning phase of the ANN involves a considerable amount of computation and hence, it is carried out off-line. The 3-5-1 MLP structure, which is capable of modeling the CPS with quite satisfactory performance, is shown in the figure. Once the training is over, the frozen weights of the MLP are to be entered into shift registers of the PIM attached to the sensor to obtain direct digital readout of the applied pressure.

In the PIM, i_{11} and i_{12} refer to inputs, and u_{jk} refers to first-layer weights of the MLP. The outputs of the first-layer

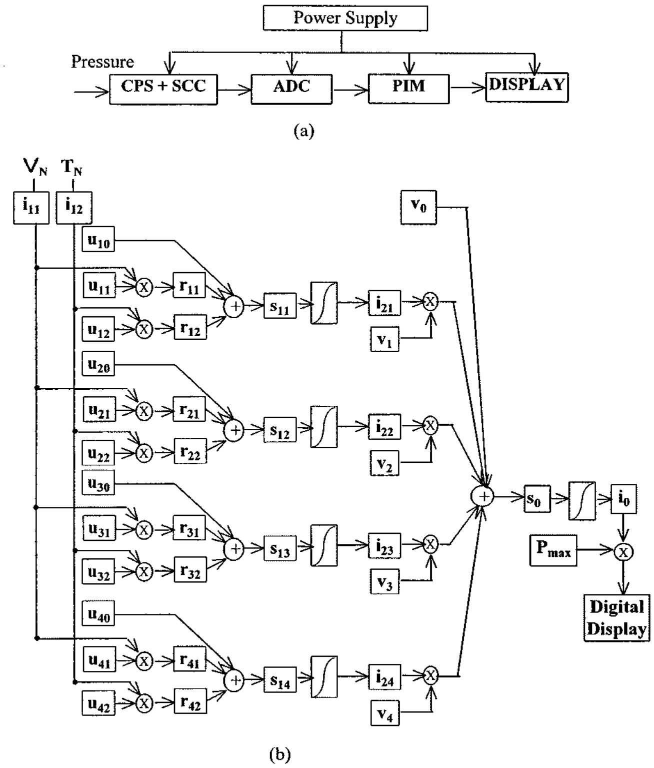

Fig. 10. (a) Implementation scheme for inverse modeling of the CPS. (b) Plug-in module.

nodes, which become input to the output node, are represented by i_{2k}. The weights of the second layer are denoted by v_k. The results of the multiplications in the first and second layers are denoted by r_{jk} and r_j, respectively. The results of the addition are represented by s_{jk} and s_0. The final output of the MLP is shown as i_0.

The temperature information after normalization is fed to the MLP manually. The normalization is made so as to keep the temperature value within ± 1.0. To dispense with manual feeding of the temperature information, a temperature sensor, such as a thermistor may be installed with suitable normalization of its output.

The PIM consists of several registers to store the weights of the ANN, the inputs, intermediate multiplication and addition results, and the final output of the ANN model. It also contains several multipliers, adders, and tanh circuits for carrying out required computations. All the registers are of 8-bit length, but the registers containing the results of a multiplication are of 16-bit length and are formed by cascading two 8-bit registers. For the 3-5-1 MLP structure implementation in the PIM, the hardware requirements are as follows. The number of shift registers, multipliers, adders, and tanh circuits needed for the implementation is 53, 12, 5, and 5, respectively. Finally, the output of the MLP model, i.e., i_0 is fed to the display unit for digital display of the applied pressure.

The implementation of the PIM may be carried out by using any available single-chip micro-controller unit (MCU). Presently, we have not shown the results of the proposed ANN model by an implementation scheme. We have demonstrated the effectiveness of the proposed model by simulation results only. However, we are confident that if this model using the PIM is implemented by a MCU, it will yield quite satisfactory result as deduced from the simulation studies.

VI. Conclusions

In this paper, we have proposed a scheme of ANN-based intelligent pressure sensor for the purpose of sensor fault detection, and for on-line direct digital readout of the applied pressure. Even though the sensor characteristics change with ambient temperature, the proposed model performs quite satisfactorily irrespective of any change in temperature from $-20\ ^\circ$C to $70\ ^\circ$C. This temperature range can be widened by training the MLP with sufficient number of pattern-sets covering the temperature range. In the direct modeling, the nonlinear response characteristics of the CPS are modeled by a two-layer MLP. From the simulation studies it is observed that the sensor characteristics and the model output match very closely. The direct modeling may be used for detection of sensor failure and quality control during its manufacturing process.

The proposed inverse model is for the purpose of estimation of applied pressure and used for direct digital readout. It is found to be capable of accurate estimation of unknown applied pressure, and is insensitive to the variation of sensor characteristics due to change in ambient temperature. It is revealed from the simulation studies that the estimation error remains within $\pm 1\%$ (FS) throughout the dynamic range of the sensor over a wide range of temperature. In the near future, we may be able to report our findings on the effectiveness of the proposed ANN-based intelligent CPS model implemented by using a MCU.

This technique incorporates intelligence into the CPS to make it temperature independent. Further, it provides flexibility and simplicity of operation. In the case of replacement of sensor due to aging, damage, or any other reasons (which may be detected by direct modeling), the inverse model is to be retrained, and the final weights of the ANN are to be reentered into the PIM for correct digital readout. The proposed ANN-based modeling technique may be extended to other types of sensors and devices to compensate the adverse effects due to change in environmental parameters on their performance.

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