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Auto-compensation of nonlinear influence of environmental parameters on the sensor characteristics using neural networks

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Abstract

Usually the environmental parameters influence the sensor characteristics in a nonlinear manner. Therefore obtaining correct readout from a sensor under varying environmental conditions is a complex problem. In this paper we propose a neural network (NN)-based interface framework to automatically compensate for the nonlinear influence of the environmental temperature and the nonlinear-response characteristics of a capacitive pressure sensor (CPS) to provide correct readout. With extensive simulation studies we have shown that the NN-based inverse model of the CPS can estimate the applied pressure with a maximum error of $\pm 1.0\%$ for a wide temperature variation from 0 to 250 °C. A microcontroller unit-based implementation scheme is also proposed.

Keywords: Smart sensor; Self-correction; Nonlinear dependencies

1. Introduction

Sensors are widely used in many practical systems, for example, avionics, robotics, missile guidance, oil drilling, industrial measurement, and control systems. The sensors attached to a system may operate in harsh environments, such as, extreme ambient temperature, pressure, humidity, gravitational force, magnetic field, etc. In such situations, depending on the material and technology used in manufacturing of the sensor, its response depends not only on the measurand but also on the environmental parameters in a nonlinear manner. An exact mathematical model of a sensor showing a relationship between the measurand and its response, and its dependencies on the environmental parameters is, usually, not available. Besides, as most of the sensors exhibit some amount

of nonlinear-response characteristics, the problem of obtaining an accurate readout becomes quite complex.

Some of the desirable properties of a sensor include linear-response characteristics, auto-correction due to adverse effects of nonlinear environmental parameters, high sensitivity and accuracy, and low power consumption. However, in practical situations, it is not easy to achieve ideal sensor characteristics, especially when the sensor is operating in a harsh environment. In order to compensate for the nonlinear-response characteristics and to obtain accurate readout, in the past, several digital and analog interface circuits have been proposed [1–4]. These techniques include both iterative and noniterative algorithms, and involve complex signal processing to model the sensor characteristics. Under the assumption that the range of variation of environmental parameters is small and the influence of the environmental parameters on the sensor characteristics is linear, these algorithms provide a limited solution to the complex problem.

The artificial neural networks (NNs) have emerged as a powerful learning technique to perform complex tasks in dynamic environments. These networks are endowed with certain unique characteristics: the capability of universal approximation, the ability to learn from and to adapt to their environment, and the ability to cope with weak assumptions about the underlying physical phenomenon responsible for generation of input data. Another important property of the NNs is their fault tolerance capability, because of which graceful degradation of performance takes place if the network is partially damaged. Because of these characteristics, there have been numerous successful applications of NNs in various fields of science, engineering, and industry [5] including instrumentation and measurement [6,7].

Dias Pereira *et al.* [8] have reported the performance of the NN model for fitting transducer characteristics to measured data. They compared the performance of the NN model with other classical methods, such as Newton, Lagrange polynomial and spline interpolations, and polynomial least-mean-square regression, and concluded that the artificial NN interpolation is more accurate than other methods, especially when multivariable extrapolation, or nonlinear characteristics, are under analysis. Application of NNs with superior performance in magnetic field measurement [9] and in ultrasonic distance measurement [10] have been reported. Recently, an NN-based technique to compensate for the nonlinear interference of structural and geometrical parameters in a differential eddy-current displacement transducer has been reported [11]. In our earlier works, we have shown the effectiveness of NNs in modeling and compensation of environmental dependencies and nonlinearities of sensor characteristics in pressure sensors [12,13]. However in these works, the temperature dependency on the sensor characteristics was assumed to be linear. The present work is an extension and improvement of our earlier works.

Some of the major contributions of the present paper with respect to our earlier paper [13] are highlighted here. In Ref. [13] two multilayer perceptrons (MLPs) were used in different configurations to provide calibrated response characteristics and to obtain correct pressure readout for a CPS. The first MLP was used to transfer the nonlinear characteristics at any temperature to the calibrated response characteristics. The second MLP was used to compensate for the nonlinear-response characteristics and to provide

accurate pressure readout. In the present paper we have used only one MLP to compensate for the nonlinear-response characteristics and to provide accurate pressure readout. Most importantly, we have considered the effect of nonlinear influence of ambient temperature on the sensor characteristics, whereas in Ref. [13] only the linear influence of ambient temperature was considered a variable learning.

In this paper we demonstrate the potential of NNs in development of smart sensors capable of mitigating adverse nonlinear influence of environmental parameters on the response characteristics of any type of sensor. For this purpose we propose a multilayer perceptron (MLP)-based scheme for a capacitive pressure sensor (CPS) operating in a harsh environment with a wide temperature variation (from 0 to 250 °C). This model provides a linear-response characteristics with accurate pressure readout and compensates for the nonlinear temperature dependency. An inverse model of the CPS is obtained by training the MLP using popular backpropagation (BP) learning algorithm. For efficient learning, during training of the MLP, we adopted a variable learning rate to improve the accuracy of the model. Considering three forms of nonlinear dependency functions, we showed the effectiveness of the NN model in mitigating adverse nonlinear influence of the ambient temperature on the sensor characteristics.

2. Mathematical modeling of a CPS and the switched capacitor interface

When pressure is applied to a CPS, it is sensed by the elastic deflection of its diaphragm. The elastic deflection causes the capacitance of the CPS to change. The capacitance of a CPS due to the applied pressure P at the ambient temperature T is given by

$$C(P, T) = C_0(T) + \Delta C(P, T), \quad (1)$$

where $\Delta C(P, T)$ is the change in capacitance and $C_0(T)$ is the offset capacitance, i.e., the zero-pressure capacitance, both at the ambient temperature T . The above capacitance may be expressed in terms of capacitances at the reference temperature T_0 as

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

where C_0 is the offset capacitance and $\Delta C(P, T_0)$ is the change in capacitance, both at the reference temperature T_0 . The nonlinear functions $f_1(T)$ and $f_2(T)$ determine the effect of the ambient temperature on the sensor characteristics. This model provides sufficient accuracy in determining the influence of temperature on the sensor response characteristics [1].

When pressure is applied to the CPS, its change in capacitance at the reference temperature T_0 is given by

$$\Delta C(P, T_0) = C_0 P_N \frac{1 - \tau}{1 - P_N}, \quad (3)$$

where τ is the desensitivity parameter, P_N is the normalized applied pressure given by $P_N = P/P_{\max}$, and $P_{\max}$ is the maximum permissible applied pressure. The parameters τ and

$P_{\max}$ depend on the geometrical structure and physical dimensions of the CPS. Since $\Delta C(P, T_0)$ becomes very large as P_N approaches 1, in practice, the value of P_N is normally kept within about 0.9.

In this study, in conformance with practical conditions, we have considered that the ambient temperature influences the CPS characteristics nonlinearly. The nonlinear functions involved are given by

$$f_i(T) = 1 + g_i(T), \quad (4)$$

$$g_i(T) = \kappa_{i1}T_n + \kappa_{i2}T_n^2 + \kappa_{i3}T_n^3, \quad (5)$$

where $T_n = (T - T_0)/T_{\max}$. The coefficients, κ_{ij} , $i = 1, 2$, $j = 1, 2, 3$, determine the extent of nonlinear influence of the temperature on the sensor characteristics. Note that when $\kappa_{ij} = 0$ for $j = 2$ and 3 , the influence of the temperature on the CPS response characteristics is linear. Let the normalized temperature T_N be given by $T_N = T/T_{\max}$, where the maximum permissible temperature at which the sensor may be operated is denoted by $T_{\max}$. The normalized capacitance C_N may be expressed as

$$C_N = C(P, T)/C_0. \quad (6)$$

Using Eqs. [2] and [3], this may be rewritten as

$$C_N = f_1(T) + \gamma f_2(T), \quad (7)$$

where $\gamma = P_N(1 - \tau)/(1 - P_N)$. Because of the requirement of the NN modeling, C_N in Eq. (7) is divided by a scale factor of 2, so as to keep its maximum value within 1.

A switched capacitor interface (SCI) circuit for the CPS is shown in Fig. 1, where the CPS is represented by $C(P)$. The SCI output provides a voltage signal proportional to the capacitance change in the CPS due to the applied pressure. The SCI operation can be controlled by a reset signal θ . When $\bar{\theta} = 1$ (logic 1), $C(P)$ charges to the reference voltage V_R while the capacitor C_S is discharged to ground. On the other hand, when $\theta = 1$, the total charge $C(P)V_R$ stored in $C(P)$ is transferred to C_S producing an output voltage given by

$$V_O = K \cdot C(P), \quad (8)$$

where $K = V_R/C_S$. It may be noted that if the ambient temperature changes, then the SCI output also changes, although the applied pressure remains the same. By choosing proper values of C_S and V_R , the SCI output V_O may be set to an appropriate level.

3. NN model of the CPS

The proposed scheme of the NN-based CPS model for estimation of the applied pressure is shown in Fig. 2. 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 [5]. To obtain direct digital readout of the applied pressure, an inverse

model of the CPS is used to compensate for the adverse effects of the nonlinear characteristics, and its variations due to the influence of the ambient temperature.

In this NN-based CPS model all the signals used for training and testing are normalized by dividing the signal by appropriate scale factors (SFs) so as to keep their values between 0 and 1.0. The normalized applied pressure, estimated pressure, ambient temperature, the CPS capacitance, and SCI output are denoted by P_N , $\hat{P}_N$, T_N , C_N , and V_N , respectively. The model operates in two phases: the training phase and the test phase. In the training phase, the NN is trained to learn the sensor characteristics and its dependency on the ambient temperature.

Several data sets are needed to train the NN. An input pattern and its corresponding desired, or target, pattern constitute one pair of data in the data set. The available data sets are segregated into two parts. The first part, called the training set, is used for training of the NNs, and the other part, called the test set, is used to verify the effectiveness of the model.

3.1. Training-phase of the MLP

A multilayer perceptron is used to learn the CPS response characteristics. The scheme for this is shown in Fig. 2(a). In this case, the two inputs to the NN are T_N and V_N , and the desired output is the normalized applied pressure P_N . It is assumed that the ambient temperature is available from some other source, for example, from another temperature sensor. One data set for a specific temperature is obtained by recording the SCI output (V_N) for different values of applied pressure, covering the operating range of the sensor at that temperature. Next, at different temperature values, covering the full operating range, data sets are generated. The NN is trained by taking the patterns from the training set, and its weights are updated using the BP algorithm. To improve the learning performance, we have used a variable learning parameter during training of the MLP. After training, the weights of the NN are frozen and stored in an electrically erasable and programmable ROM (EEPROM). In what follows, the final weights are denoted by W_p .

3.2. Test-phase of the MLP

The complete scheme of the MLP-based model is shown in Fig. 2(b). This model output provides an estimate of the applied pressure accurately. The model output is not affected by any variation in ambient temperature and is independent of any nonlinear influence of temperature on the CPS characteristics. During the test phase, and actual use, the weights W_p , stored in the EEPROM are loaded into the NN. The NN has learned the inverse characteristics of the CPS at different values of temperature, and this knowledge has been stored in its weights in a distributive manner.

Next, the input patterns from the test set are applied, and the model output ($\hat{P}_N$) is computed. If the model output matches closely with the actual applied pressure (P_N), then it may be said that the NN has learned the CPS characteristics correctly. The mean-square error (MSE) between the true and the estimated pressure (by the NN model) is used to measure the performance of the NN model. Thereafter, the NN model can be used in practice to estimate the pressure and to obtain its readout. Fig. 2(c) shows the nonlinear-

response characteristics of the CPS, the inverse response characteristics learned by the NN model and the combined linearized response.

There are various types of neural networks with different architectures and learning algorithms. Besides the popular MLP, examples of other supervised NNs are radial basis function networks and vector support machines [5]. These networks have been successfully applied for pattern classification, recognition, functional approximation, prediction of time-series data, etc. In the case of MLP the popular learning algorithms are the BP [5], conjugate gradient [5], and the Marquardt [14] algorithms. With a large number of hidden layer nodes, an MLP can be a universal approximator [15]. In a modeling problem using MLPs, the parameters to be selected are the number of layers, the number of nodes in each layer, and the learning algorithm. For the BP algorithm, the learning parameter and the momentum factors are to be properly selected for optimum performance in terms of MSE between the desired output and the actual output of the MLP. The parameters of the MLP and the BP algorithm, as in the case of any learning network, are usually selected after conducting several experiments. The final architecture of the MLP and the parameters chosen for the sensor modeling are provided in the next section.

4. Simulation studies

We carried out extensive simulation studies to evaluate performance of the proposed NN-based CPS model. In the following we describe the details of the simulation study.

4.1. Preparation of data sets

It is shown in Ref. [1] that the mathematical CPS model [refer to Eqs. (1)–(7)] represents the CPS characteristics with sufficient accuracy. Therefore we have generated the data sets needed for training and testing through simulation using this sensor model. All the parameters of the CPS, such as ambient temperature, applied pressure, and the SCI output voltage, used in the simulation study were suitably normalized so as to keep their values between 0 and 1.0. Appropriate scale factors (SFs) were chosen for this purpose. For example, the SF for T_N is selected as $T_{\max}$ (it represents the maximum ambient temperature under consideration, i.e., $T_{\max} = 250$).

The goal is to obtain the values of the pressure at any temperature level (between 0 and 250 °C) from the MLP model trained with data taken from only few temperature settings. Several data sets are needed for training as well as for testing of the NN model. These data sets were generated as follows. First, at the reference temperature ($T_0 = 25$ °C), the SCI output voltage (V_0) was recorded [refer to Eq. (8)] for 13 known values of normalized pressure (P_N) (from 0.0 to 0.6 with an increment of 0.05). These 13 pairs of data (P_N vs V_N) constitute one data set at the reference temperature T_0 .

To study the influence of temperature on the CPS characteristics, we have considered three forms of nonlinearities [refer to Eq. (4)] denoted by NL1, NL2, and NL3, and a linear form denoted by NL0. These are simulated by choosing proper values of κ_{ij} in Eq. (5). The corresponding values of κ_{ij} are tabulated in Table 1.

The data sets for 26 temperature levels (from 0 to 250 °C at increments of 10 °C) for a specific NL form were obtained using the data set at T_0 and corresponding values of κ_{ij} [refer to Eq. (7)]. Each data set consists of 13 data points (P_N vs V_N). This results in a total of $26 \times 13 = 338$ data points for each of the NL forms. Next, these data sets were divided into two groups: the training set and the test set. The training set, used for training of the NN, consists of only five data sets corresponding to the temperature levels 0, 60, 120, 180, and 250 °C, and the remaining 21 data sets constitute the test set. The data set of the reference temperature T_0 was not used for training or testing purposes.

The response characteristics of the CPS for different values of temperature are shown in Fig. 3. It may be observed from this figure that wide variation in the sensor characteristics occurs when the ambient temperature changes from 0 to 250 °C. Further, the response characteristics change drastically for different forms of nonlinear influence of the ambient temperature.

4.2. Training and testing of the NN model

In this modeling problem [see Fig. 2(a)] we selected a two-layer MLP with 2-4-1 architecture. This architecture implies that the MLP has one input layer, one hidden layer, and one output layer containing 2, 4, and 1 nodes (excluding the bias unit), respectively. Every node in the hidden and the output layers contains a $\tanh(\)$ nonlinear activation function. Initially, the weights of the NN were set to some random values within ± 1.0 .

During training, the five data sets were chosen randomly and the individual patterns of each set were also selected in a random manner. For example, say that the five temperature values were randomly ordered as 60, 250, 0, 180, and 120 °C. Then the 13 data values for each temperature were randomly ordered. During training of the NN, first, the data values for temperature 60 °C were presented in their random order; second, the data values for temperature 250 °C; third, the data values for temperature 0 °C, and so on. The above was repeated for each iteration.

The initial values of the learning parameter α and the momentum factor β were selected as 0.3 and 0.55, respectively. After carrying out several experiments, we arrived at this particular NN architecture and the values of the learning parameter and the momentum factor in order to achieve the best performance.

One iteration of training corresponds to completion of weight adaptation for the 13 data pairs of all the five training data sets. For effective learning, 100 000 iterations were made to train the MLP model. At the end, the final weights (W_p) of the NN were stored for later use. This procedure was repeated for the linear (NL0) as well as three chosen nonlinear forms of temperature dependencies (NL1–NL3). The MLP and the BP algorithm were implemented using C++. Using a Pentium 4, 2.8-GHz MHz machine, it took only 14 sec to train the MLP with 100 000 iterations. algorithm. During training, the learning parameter at the i th iteration was computed from the $(i-1)$ th value as

$$\alpha_i = \alpha_{i-1} \left(1 - \frac{i}{N_{itr}} \right), \quad (9)$$

where N_{itr} is the total number of iterations and α_0 is the initial learning parameter (we set $N_{itr}=100\ 000$ and $\alpha_0 = 0.3$). The final weights W_P of the MLP model for the linear (NL0) and nonlinear forms of influences (NL1–NL3) are shown in Table 2.

The MSE in dB between the true and the estimated pressure is defined as

$$\text{MSE} = 10 \log_{10} \left(\frac{1}{N_{set} N_{pat}} \sum_{i=1}^{N_{set}} \sum_{j=1}^{N_{pat}} (P_{ij} - \hat{P}_{ij})^2 \right), \quad (10)$$

where N_{set} and N_{pat} denote the number of training sets ($= 5$) and the number of data patterns in each set ($= 13$), respectively. The true pressure and estimated pressure for the j th pattern of the i th set is denoted by P_{ij} and $\hat{P}_{ij}$, respectively. The MSE for the four forms of temperature dependencies NL0, NL1, NL2, and NL4 was found to be -51.3 , -49.6 , -50.1 , and -49.7 dB, respectively.

Here w_{ij} ($i = 1, 2, 3, 4$ and $j = 0, 1, 2$) represents the weight of the i th node of the hidden layer to the j th node of the input layer. The weight of the output node connected to the j th node of the hidden layer is denoted by v_j ($j = 0, 1, \dots, 4$). One set of weights was obtained for each of the linear and nonlinear forms of dependencies by training the MLP separately.

The performance evaluation of the model was carried out by loading the final stored weights (W_P) into the MLP. It may be noted that, during testing and actual use of the CPS model, updating of the weights does not take place. When inputs are applied to the model, the NN estimates the applied pressure from the knowledge of the stored weights loaded into it. For testing purpose, the normalized SCI output voltage (V_N) was simulated with a range from 0.35 to 0.90 with increments of 0.001, and then applied to the model along with the temperature information (T_N). To evaluate the effectiveness of the model, the NN output ($\hat{P}_N$) was computed and then compared with the true values of applied pressure (P_N).

5. Results and discussions

Fig. 4 shows the true pressure and the pressure estimated by the MLP model at different values of temperature taken from the test set for the linear (NL0) and the three nonlinear forms (NL1–NL3). Here, the dotted lines denote the estimated pressure and the symbols represent true normalized pressure. It may be noted that the NN has not seen the sensor characteristics for the values of temperature taken from the test set. From this figure it is observed that the MLP is capable of estimating the applied pressure quite accurately for the full range of applied pressure from 0.0 to 0.6. Even, it is capable of estimating the applied pressure for the range beyond 0.6, although the MLP was not trained for this.

The plots between the true and the estimated pressures at different values of temperature for NL0 and NL1–NL3 are shown in Fig. 5. The linearity of estimation is found to be quite good.

The full-scale (FS) percent error is defined as $100 (P_N - \hat{P}_N)$. The FS error at specific values of temperature is plotted in Fig. 6. For the whole range of applied pressure from 0.0 to 0.6, the maximum FS error for NL0 remains within $\pm 0.5\%$, but in the nonlinear forms of dependencies, the maximum FS error remains within $\pm 1.0\%$. Fig. 7 shows the FS error for the whole temperature range from 0 to 250 °C at specific values of applied pressure (i.e., $P_N = 0.1, 0.4$, and 0.6) for NL0 and NL1–NL3. It may be seen that for the whole range of temperature variation, the maximum FS error in the case of the linear and the three nonlinear forms of influences, remains within $\pm 0.5\%$ and $\pm 1.0\%$, respectively.

From the above findings, it may be concluded that the performance of the MLP model for estimation of pressure is excellent in the linear form of interaction and it is satisfactory for the three forms of nonlinear influence of the ambient temperature on the CPS characteristics. It may be noted that for a similar application, an MLP with 43 hidden layer nodes was used and a maximum error of $\pm 2.4\%$ was obtained [11]. In the present study we could achieve a maximum error of only $\pm 1.0\%$ with a MLP of 2-4-1 architecture (having only 17 weights) after careful training of the MLP. The novelty of the proposed scheme is that, although the MLP was trained with patterns taking from only five temperature values (0, 60, 120, 180, and 250 °C), the MLP model is capable of estimating the applied pressure accurately when the ambient temperature varies from 0 to 250 °C by nullifying the nonlinear influence of the temperature on the CPS characteristics.

To demonstrate the effectiveness of the NN model to compensate for the nonlinear dependency of the ambient temperature on the sensor characteristics we have selected three forms of nonlinearities (NL1–NL3). Considering the linear and the three NL forms, the final set of weights for each are shown in Table 2. But, in practice, depending on the environmental conditions, there will be only one set of weights and this set of weights is to be used in practice as is discussed in the next section.

In this study, we have generated the data sets at different temperature levels using the mathematical sensor model from the measured data at the reference temperature ($T_0 = 25$ °C). But, in practice, the training data set should be generated from the physical sensor at different temperature settings. The measured data from the physical sensor may be embedded with noise and drifts. In the current study we have not considered these issues. We believe that if a sufficient amount of noisy data are available, then the NN can be effectively trained to learn the sensor characteristics. We intend to carry out a future study considering these aspects either through simulation or through experimental setup in the near future.

6. MCU-based implementation scheme

The microcontroller units (MCUs) have been found quite suitable for use in various intelligent embedded systems due to the decrease in unit cost and the fast increase in on-chip capabilities. Currently available MCUs can be configured with all the required RAM/ROM/EEPROM as well as serial interface and multiple channel analog-to-digital converter (ADC) support chips. A scheme of implementation of the MLP-based CPS model using a MCU is depicted in Fig. 8. The SCI converts the change in capacitance of the CPS due to applied pressure into an equivalent voltage level. This analog SCI voltage

is passed through an ADC. The digital temperature information is similarly obtained from a separate source.

During the training phase, the CPS is operated under a controlled temperature and the data pairs so collected can be stored in the memories of the MCU. These training data can be fed to a PC connected to the MCU during training of the MLP-based model. After completion of training, the weights of the MLP are stored in the EEPROM of the MCU. With the available hardware, such as adders and multipliers of the MCU, the MLP-based model can be implemented and the digital readout of the applied pressure can be displayed.

7. Conclusions

Smart sensors with the capability of accurate readout and auto-compensation of the nonlinear influence of the environmental parameter on the sensor characteristics are needed in many practical applications. For this purpose we have proposed a novel and effective neural-network-based technique for modeling a capacitive pressure sensor operated in a harsh environment in which the temperature can vary from 0 to 250 °C. The effectiveness of the model in different forms of nonlinear influence of the ambient temperature on the pressure sensor characteristics is demonstrated with computer simulated experiments.

The training of NNs may be carried out off-line and the final NN weights can be stored in an EEPROM of the microcontroller unit. After completion of training, the MLP model is capable of estimating the applied pressure accurately irrespective of nonlinear characteristics of the CPS and its nonlinear dependence on ambient temperature. Appropriate logic and control circuits may be implemented along with a MCU to carry out the measurement cycle. The accuracy of the NN model for estimation of pressure remains within $\pm 1\%$ (FS) for the three chosen forms of nonlinear dependencies over a temperature from 0 to 250 °C. Such NN-based models may be applied to other types of sensors to incorporate intelligence in terms of mitigating nonlinear influence of environmental parameters on their response characteristics.

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References

- [1] Yamada, M. and Watanabe, K., A capacitive pressure sensor interface using oversampling $\Delta - \Sigma$ demodulation techniques. *IEEE Trans. Instrum. Meas.* **46**(1), 3–7 (1997).
- [2] Hille, P., Hohler, R., and Strack, H., A linearization and compensation method for integrated sensors. *Sens. Actuators B* **44**, 95–102 (1994).
- [3] Lyahou, K. F., van der Horn, G., and Huijsing, J. H., A noniterative polynomial 2-D calibration method implemented in a microcontroller. *IEEE Trans. Instrum. Meas.* **46**(4), 752–757 (1997).
- [4] Li, X., Meijer, G. C., and de Jong, G. W., A microcontroller-based self-calibration technique for a smart capacitance angular-position sensor. *IEEE Trans. Instrum. Meas.* **46**(4), 888–892 (1997).
- [5] Haykin, S., *Neural Networks*. Maxwell MacMillan, Ontario, Canada, 1994.
- [6] Pau, L. F. and Johansen, F. S., Neural network signal understanding for instrumentation. *IEEE Trans. Instrum. Meas.* **39**(4), 558–564 (1990).
- [7] Daponte, P. and Grimaldi, D., Artificial neural networks in measurements. *Measurement* **23**, 93–115 (1998).
- [8] Dias Pereira, J. M., Silva Girao, P. M. B., and Postolache, O., Fitting transducer characteristics to measured data. *IEEE Instrum. Meas. Mag.* **4**(4), 26–39 (2001).
- [9] Dias Pereira, J. M., Postolache, O., and Silva Girao, P. M. B., A temperature compensated system for magnetic field measurements based on artificial neural networks. *IEEE Trans. Instrum. Meas.* **47**(2), 494–498 (1998).
- [10] Carullo, A., Ferraris, F., Graziani, S., Grimaldi, U., and Parvis, M., Ultrasonic distance sensor improvement using a two-level neural networks. *IEEE Trans. Instrum. Meas.* **45**(2), 677–682 (1996).
- [11] Arpaia, P., Daponte, P., Grimaldi, D., and Michaeli, L., NN-based error reduction for experimentally modeled sensors. *IEEE Trans. Instrum. Meas.* **51**(1), 23–30 (2002).
- [12] Patra, J. C., Kot, A. C., and Panda, G., An intelligent pressure sensor using neural networks. *IEEE Trans. Instrum. Meas.* **49**(4), 829–834 (2000).
- [13] Patra, J. C. and van den Bos, A., Auto-calibration and -compensation of a capacitive pressure sensor using multilayer perceptrons. *ISA Trans.* **39**, 175–190 (2000).
- [14] Hagan, M. T. and Menhaj, M. B., Training feedforward networks with the Marquardt algorithm. *IEEE Trans. Neural Netw.* **5**(6), 989–993 (1994).

- [15] Hornik, K., Stinchombe, M., and White, H., Multilayer feedforward networks are universal approximators. *Neural Networks* **2**(5), 359–366 (1989).

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List of Tables

Table 1 The values of κ_{ij} for linear and nonlinear temperature dependencies.

Table 2 Final weights W_P of the NN model (2-4-1 architecture).

List of Figures

- Fig. 1. A switched capacitor interface circuit.
- Fig. 2. The scheme of NN-based modeling of a capacitive pressure sensor: (a) training phase; (b) test phase.
- Fig. 3. The response characteristics of the capacitive pressure sensor operating at different values of temperature with linear and nonlinear dependencies: (a) NL0; (b) NL1; (c) NL2; (d) NL3.
- Fig. 4. True CPS response characteristics and the estimated pressure by the NN model for the CPS operating at different temperature levels with linear and nonlinear dependencies: (a) NL0; (b) NL1; (c) NL2; (d) NL3.
- Fig. 5. Plots of the true pressure and the pressure estimated by the NN model at different values of temperature with linear and nonlinear dependencies: (a) NL0; (b) NL1; (c) NL2; (d) NL3.
- Fig. 6. Full-scale percent error between the true and estimated pressures at specific temperature levels (0, 80, 150, and 250 °C) with linear and nonlinear dependencies: (a) NL0; (b) NL1; (c) NL2; (d) NL3.
- Fig. 7. Full-scale percent error between the true and estimated pressures at specific normalized pressures ($P_N = 0.1, 0.4, \text{ and } 0.6$) with linear and nonlinear dependencies: (a) NL0; (b) NL1; (c) NL2; (d) NL3.
- Fig. 8. A scheme of a microcontroller unit-based implementation of the pressure sensor NN model.

NL form	κ_{11}	κ_{12}	κ_{13}	κ_{21}	κ_{22}	κ_{23}
NL0	-0.20	0.00	0.00	0.70	0.00	0.00
NL1	-0.20	0.20	-0.10	0.70	-0.30	0.40
NL2	-0.20	0.05	-0.20	0.70	-0.10	-0.50
NL3	-0.20	-0.10	-0.07	0.70	0.10	-0.30

Table 1

Weights	NL0	NL1	NL2	NL3
w_{10}	1.125	0.194	0.195	0.478
w_{11}	0.630	0.363	0.730	1.356
w_{12}	-0.995	-3.625	-0.892	-0.890
w_{20}	-1.949	-1.908	-2.073	-1.992
w_{21}	1.026	1.093	1.033	1.197
w_{22}	6.112	5.727	5.823	5.691
w_{30}	1.185	1.354	2.036	1.010
w_{31}	-0.563	-0.650	-1.729	-0.891
w_{32}	-1.555	-1.571	-0.190	-0.828
w_{40}	0.240	0.054	1.147	0.624
w_{41}	0.201	0.880	-0.485	0.754
w_{42}	-1.955	-0.504	-1.550	-2.466
v_0	-1.572	-2.111	-0.654	-0.839
v_1	-0.587	-0.911	-0.672	-0.504
v_2	2.081	1.773	1.503	1.548
v_3	-0.345	-0.530	-0.472	-0.670
v_4	-0.484	-0.562	-0.402	-0.194

Table 2

Fig. 1

Fig. 2

Fig. 3

Fig. 4

Fig. 5

Fig. 6

Fig. 7

Fig. 8