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Research Paper

A Piezoresistive Pressure Sensor Modeling by Artificial Neural Networks

Behzad Hadi[1], Farzin Shama[2*], Hamid Sherafat Vaziri[2], Mohsen Eghbalkhah[3]

[1]Mechanical Engineering Department, Faculty of Engineering, Razi University, Kermanshah, Iran
[2]Electrical Engineering Department, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran E-mail: f.shama@aut.ac.ir
[3]Electrical Engineering Department, Faculty of Engineering, Razi University, Kermanshah, Iran

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Abstract

An efficient artificial neural network (ANN) model for a pressure sensor is presented in this paper. This pressure sensor has a piezoresistive structure and its experimental data is used in this work to train and test the proposed ANN model. The selected network is a multi-layer perceptions ANN type, which has one hidden layer with five neurons inside. The proposed MLP modelled system has been trained to recognize the output of the pressure sensor, which is a generated voltage in millivolts, according to the temperature and pressure levels. The obtained mean square relative error (MSRE) error of this method is only 0.137 for test data set.

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***Corresponding author:** Farzin Shama

Address: Electrical Engineering Department, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran E-mail: f.shama@aut.ac.ir
Tell: 00989183363650 **Email:** f.shama@aut.ac.ir

1. INTRODUCTION

There is a lot of electronic-based sensors for various purposes [1-20]. MEMS (micro-electromechanical system) pressure sensors are one the most important devices because of their wide application in industry, and so many studies have been done in order to improve their performance. Also, many structures such as piezoresistive, capacitive and optical pressure sensor have been proposed [1]. Modeling the MEMS structures is an efficient method to study their behavior which can be useful in optimization of their performance and also predicting their responses. Piezorsistive pressure sensors are the most common pressure sensors because of their desirable performance and ease of fabrication. In [2], a novel piezoresistive pressure sensor is presented. In the proposed paper, a shield layer is used to help improving the stability of the sensor. Fig.1 shows the pressure sensor presented in [2]. There are a lot of modeling methods including artificial neural network modeling [3-12] and other mathematical or physical modeling methods [13-14].

Artificial neural network (ANN) modeling is one of the popular tools to recognize and investigate the nonlinear and complex systems and devices. In fact, an ANN is a big-data/information processor, which inspires from human cognition and neural biology as a mathematical abstraction form. There are two common architectures for ANNs, the feedforward ones and feedback ones. There are also many learning algorithms types for each ANN [3-4]. A multi-layer perceptron (MLP) is a feedforward ANN, which is widely used in modeling and prediction [5-7] problems.

Pressure sensors (transducers) are fundamental components in control systems due to their extensive utility in detecting mechanical parameters like pressure and flow. As a result, various configurations have been explored and suggested over the years to create a pressure transducer with optimal characteristics including high sensitivity, excellent linearity, cost-effectiveness, and simplicity in manufacturing. Piezoresistive pressure sensors are the predominant structures among MEMS pressure transducers, having been pioneered in 1962. The fundamental concept involves converting mechanical stress into an electrical signal through a Wheatstone bridge integrated onto a thin square diaphragm that bends under applied pressure. This principle can also be extended to other MEMS devices such as accelerometers. The benefits of Piezoresistive pressure transducers include compact dimensions, straightforward and economical fabrication processes typically utilizing bulk micromachining methods, superior sensitivity, and a direct current output [15-17].

In this paper, using the experimental results in [2], an efficient MLP type ANN model is proposed, which is a predictable model for output voltage of the sensor in some temperatures and any variable pressures. The applied learning algorithm is Levenberg Marquaret (LM) that is a good learning method using in MLP networks, due to fast and stable convergence [7]. The Levenberg-Marquardt algorithm is an estimation of the Hessian matrix commonly encountered in Newton's optimization method. This feature enables the algorithm to significantly decrease complexity, presenting a substantial advantage [7].

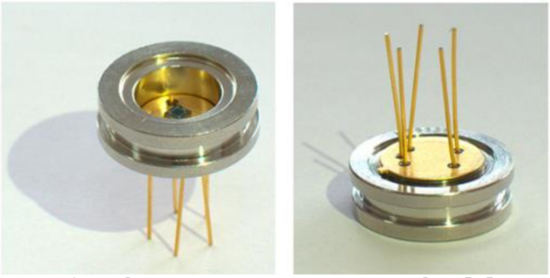


Fig.1 the pressure sensor presented in [2]

Fig.2 shows the output signal of the sensor (in mV) for different value of input pressure and the temperature.

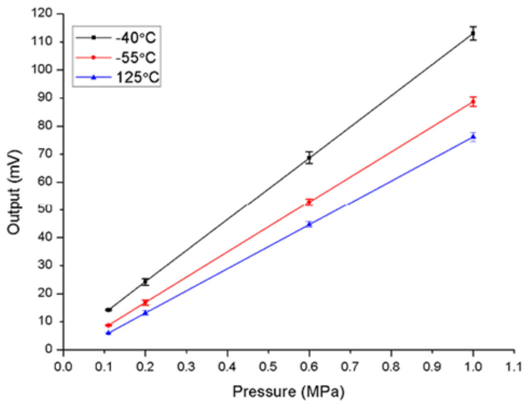


Fig2. characteristics of the pressure sensor

2. ANN Model

Multi-layer perceptions (MLPs) are the most frequently used ANN network architectures in modeling and prediction issues. MLPs include calculation systems including simple processing components called neuron which, has been ran in parallel at multiple layers [3]. The feed forward network has been used just with minimum three layers. Processing units of Each layer are independent and each unit has been completely interconnected with weighted connections to units in the next layer [4]. The offered model in this work has been shown in Figure 3. The used input variables in this network are sensor temperature (in °C) and input pressure of the sensor (in MPa); the output is sensor output as a DC voltage (in mV). The input to the node l at the only hidden layer is obtained as below [5]:

$$\eta_l = \sum_{u=1}^{4} (X_u w_{ul}) + \theta_l \qquad l=1, 2, \ldots, 10 \qquad (1)$$

Where variables are defined as: x as the input, b as the bias parameter, w as the weighting parameter and η as the neuron activation function, which are applied at the hidden layer. The j^{th} output neuron will be:

$$Y_j = \sum_{u=1}^{9}(\eta_l w_{uj}) + b_j \quad j=1, 2, \ldots, 2 \tag{2}$$

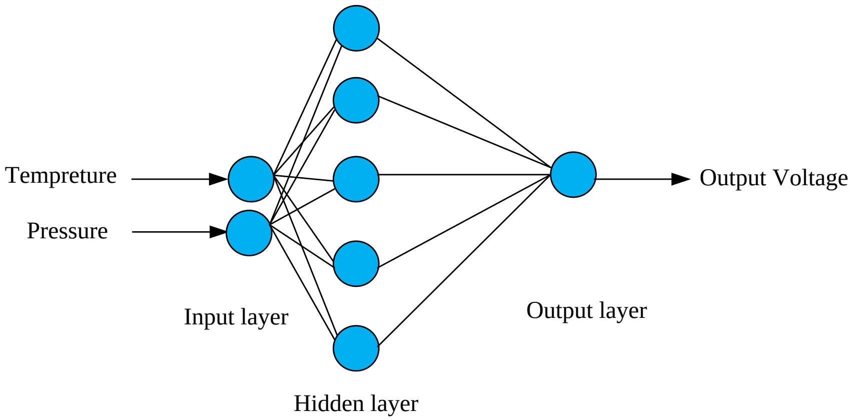


Fig. 3. The designed MLP model

The acquired values for training the obtained ANN is achieved using the validated actual data in [2]. To obtain an accurate model and validate the results, there are two set experimental data: 70% as training data-set and 30% as testing data-set. MATLAB 7.0.4 program has been employed for training the MLP modeled system. The details of the designed network have been shown in Table 1.

Table 1. Specifications of the network

Neural network type	MultiLayer Perceptron
Neurons deposed at the input layer	2
Neurons deposed at the first hidden layer	5
Neurons deposed at the output layer	1
Epochs repetition	300
Neuron activation function	Tangent sigmoid

3.Results

The calculated errors for the designed MLP modeled system have been illustrated in Table 2. In this table, mean absolute error percentage (MAE %), the mean relative error percentage (MRE %) and the roots mean square error (RMSE), of the model are defined as [6-12]:

$$\mathbf{MAE\,\%} = 100 \times \frac{1}{N}\sum_{i=1}^{Z}\left|X_i(\mathrm{Exp}) - X_i(\mathrm{Pred})\right| \tag{3}$$

$$\mathbf{MRE\,\%} = 100 \times \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i(\mathrm{Exp}) - X_i(\mathrm{Pred})}{X_i(\mathrm{Exp})}\right| \tag{4}$$

$$\mathbf{RMSE} = \left[\frac{\sum_{i=1}^{N}(X_i(\mathrm{Exp}) - X_i(\mathrm{Pred}))^2}{N}\right]^{0.5} \tag{5}$$

Where N is the number of features and ‘X (Exp)’ and ‘X (Pred)’ consider as real and predicted (ANN) values, respectively.

The ANN design and learning process flowchart in MATLAB software has been illustrated in Fig.4.

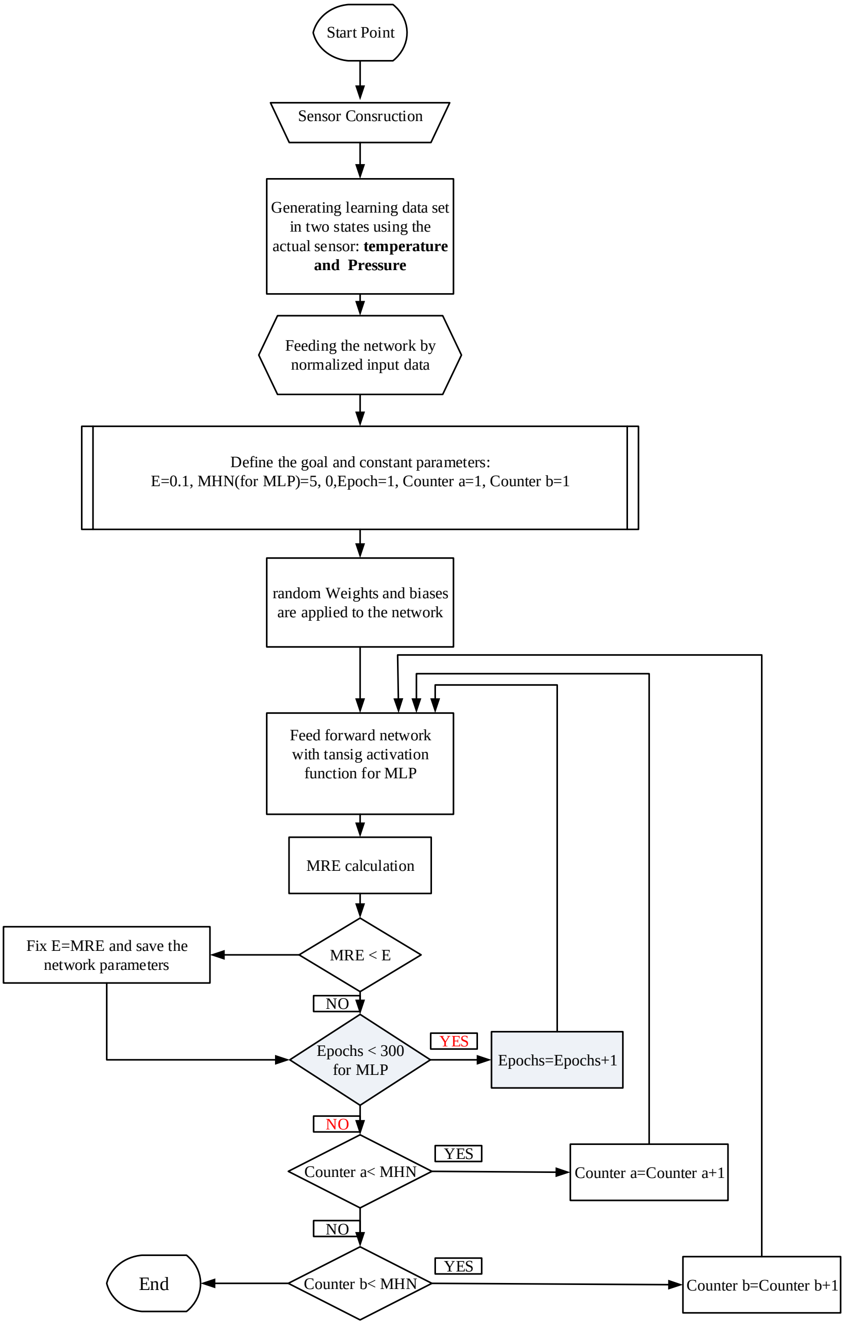


Fig. 4. The ANN design and learning process flowchart in MATLAB

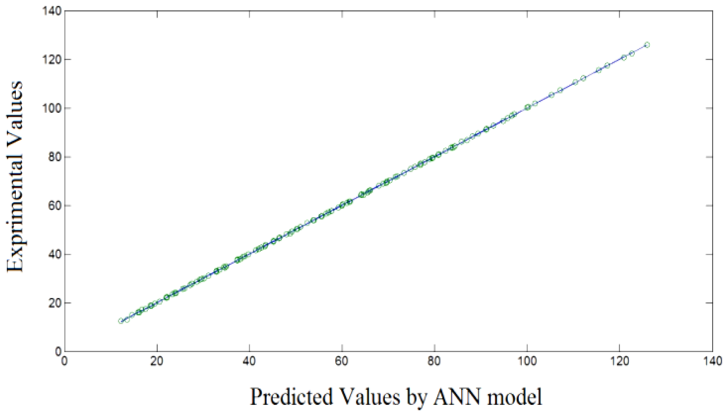
As seen in Table. 2, the MAE%, MRE% and RMSE of the MLP modeled system for train and test data have very dispensable values. The RMSE is only 0.13700 for test data and can validate the efficiency of this model.

Table 2. Calculated Errors

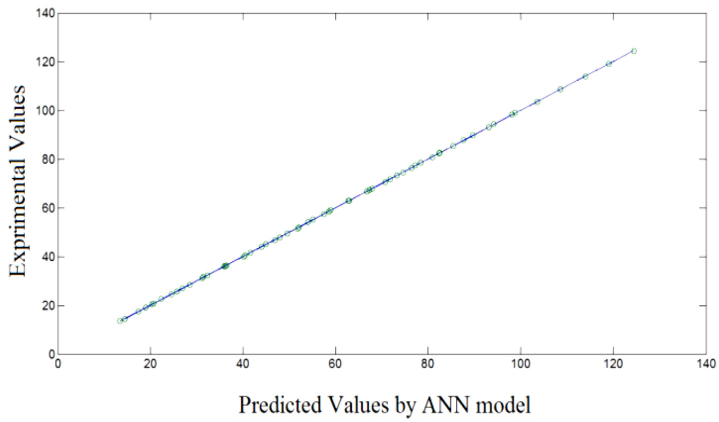
Error type	For train	For test
MAE %	0.11231	0.11110
MRE %	0.00065	0.02910
RMSE	0.14410	0.13700

The regression diagram of the MLP modeled network are illustrated in Figs. 5 for trained and tested results. As can be seen from Table 2 and Fig.5, it is obviously the predicted voltage by the proposed network is near to the experiential results, which proves the strength of the MLP ANN as a precise and accurate model for the prediction of sensor output voltage as a function of other temperatures and any input pressures.

Some predicted output voltage in new temperatures at the previous pressures has been indicted in Table 3.



(a)



(b)

Fig 5. Regression diagrams of real and predicted results (a) trained data (b) tested

Table 3. Predicted Sensor output (mV) using ANN model.

Desired Pressure (MPa)	**Variable Temperatures (C)°C)**	**Sensor output (mV)**
2	125	166.0733
1.8	125	150.7200
1.5	125	125.9944
1.2	125	100.5504
2	-40	218.9349
1.8	-40	206.2966

1.5	-40	181.1562
1.2	-40	149.4540
2	-55	187.5937
1.8	-55	169.0529
1.5	-55	138.8035
1.2	-55	124.2340

4 Conclusion

The output of a pressure sensor in voltage depends on pressure (in Pa) and temperature. This tomography system only measures the output voltage of the sensors at 3 temperature points. The measurement accuracy one of the main challenge in the industry. In this work, easy and powerful method of artificial intelligence has been used to prediction problems, the sensor has been modeled. In this study, we select pressure and temperature as the input of the MLP modeled system. Then, the output voltage is used as the output of the MLP modeled system. The outcomes of proposed ANNs proof that the presented MLP modeled system would be used to predict the unknown desired points.

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