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Design of a Smart Pressure Transmitter and Its Temperature Compensation Using Artificial Neural Network

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Abstract

This paper presents a smart pressure transmitter using bellow as primary sensor. The deflection of bellow is converted into electrical output using hall probe sensor as secondary sensor. The output Hall voltage is affected by change in input parameters like temperature. So firstly the effect of temperature on Hall voltage is derived mathematically and then experimentally analyzed. This effect of temperature on output Hall voltage is then compensated using artificial neural network. The compensated output Hall voltage is then converted into (4–20) mA current signal using signal conditioning circuit. The proposed design, experimental and testing results are reported in this paper.

Keywords Artificial neural network (ANN) · Pressure measurement · Bellows · Temperature compensation

1 Introduction

In any process industry, mainly the liquids and gases are contained in closed vessel. The accurate measurement and control of pressure variable is important because various key operations like flow, chemical reaction rate, vapor–liquid equilibrium and safety are affected by process variable like pressure. A pressure measurement system consists of a primary sensor like bellows, bourdon tube, diaphragm, which senses the pressure and converts it into corresponding displacement, and this output of primary sensor is converted into electrical signal through a secondary sensor. The output of secondary sensor is then amplified, and through a constructive signal conditioning circuit it is prepared for remote indication and control (Bentley 1995; Gurney 1997; Liptak 1999). The conventional pressure transmitter suffers from various drawbacks, and limitations and researchers are working for improving the performance of existing methods.

Beeby et al. (2000) have designed a low-cost pressure sensor based on the principle of capacitive pressure sensor using MEMS (micro-electro-mechanical systems) technology. The fabricated pressure sensor produces a capacitance change in about 100 Pf for applied pressure of 8 bars. The microcontrollers used also calibrate the device, and no extra circuitry is required for linearization. Bera et al. (2011) have proposed a pressure transmitter in which the bourdon tube movement is converted into 4–20 mA current signal using an improved inductance bridge network. The error due to stray capacitance and stray electromagnetic interference is reduced in this measurement technique. Chattopadhyay and Sarkar (2012) and Chattopadhyay et al. (2013) have designed and developed a low-cost reluctance type pressure transmitter using C-type bourdon tube. In this work, one ferromagnetic core is attached to C-type bourdon tube while the position of other ferromagnetic core is fixed. With change in pressure, the air gap between both the ferromagnetic core decreases, due to which magnetic reluctance of the circuit decreases. This change in magnetic reluctance changes the output AC voltage. In industries, accurate pressure measurement is an important requirement. Rajita et al. (2015) have proposed a non-contact type measurement technique using bellows with Hall probe sensor. Bellow is mainly used as a local indicating instrument, and for remote indication and control a secondary transducer is required. When pressure is applied on bellow then displacement is produced. So for remote control, this displacement has to be converted into some electrical signal for which Hall probe sensor is used as secondary transducer. This Hall voltage is amplified and then through signal conditioning circuit it is converted into (4–20) mA current signal. These pressure sensors output are affected by various environmental conditions like change in temperature and if

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accuracy of the output is significant then monitoring of system errors with respect to temperature change is important since the output changes with small change in temperature variation. Zhou et al. (2017) have proposed a measurement technique based on ultrasonics in which fusion of information occurs for multiple measuring waves. The proposed model increases the accuracy of the measurement system without any requirement of temperature measurement. Dong et al. (2018) have proposed a measurement system which can measure both pressure and temperature simultaneously using optical fiber sensor. The system consists of Fabry–Perot interferometer (FPI) in integration with fiber Bragg grating method. The compactness of the proposed sensor makes it useful for biomedical and nano system application. Rogers et al. (2018) have designed wireless pressure sensor which can operate in harsh environments. The diaphragm and the body structure of sensor are made of sapphire, while the capacitive plate is made of platinum. The designed pressure sensor can work in high temperature of up to 1000 °C.

Many researchers used ANN technique to compensate the effect of temperature on the measurement system. Patra (1997), Patra and Panda (1998), Patra and Van den Bos (1999, 2000), and Patra et al. (2011) have also proposed the smart techniques for compensating the effect of temperature, linearizing the output in noisy environment using ANN. Massicotte et al. (1998) have constructed a static calibration technique using multilayered neural network-based technique for calibrating high-pressure multi-sensor-based measurement system with respect to change in temperature. Rath et al. (2000) have proposed an intelligent capacitive pressure sensor using ANN which linearizes and compensates the sensor output. Hooshmand and Joorabian (2006) have calibrated electromagnetic flowmeter using artificial neural network. The output of electromagnetic flowmeter is affected by various input parameters like liquid level and conductivity coefficient. Using back propagation of artificial neural network, the effect of these input parameters on output is compensated. For auto calibration and compensation of nonlinearity and external environmental factors, intelligent signal processing techniques are required. Patra et al. (2008) have proposed a novel and efficient Chebyshev neural network (CNN) model which forms an automated measurement system which do the auto compensation and auto calibration function. The proposed model is less complex since it consists of a single layer. Huang et al. (2010) have developed a non-intrusive pressure measurement technique using capacitive based method which can be used for hydraulic system. The accuracy of the system is increased by using reverse modeling technique using functional link ANN. Vaegae et al. (2016) have implemented a pressure transmitter using bellows with inductive pick up as primary measuring element, and the nonlinear output from the signal conditioning circuit inductance to voltage conversion circuit (ITVCC) was linearized using Radial basis function of ANN. Kumar and Narayana (2016) have developed an ANN-based pressure transducer. They used bellows with inductive pick up as primary sensing element and calibrated nonlinear output from op-amp inductive signal conditioning circuit (OISCC) using Levenberg–Marquardt (LM) algorithm of ANN. Sinha and Mandal (2017) have compensated the effect of temperature on modified rotameter using ANN.

Apart from ANN, there are various other ways through which temperature can be compensated. Chen et al. (2006) have designed temperature compensation technique using MAX1452, and the curve fitting is done using B-spline curve. This can work in temperature range of −40 to 125 °C. Reverter Cubarsí et al. (2009) have proposed an economic temperature compensation technique for piezoresistive pressure sensor. In this work, the equivalent resistance of one arm of formed Wheatstone bridge circuit is dependent on temperature change and it is free from pressure variation. The temperature and pressure are measured by the same sensor. For temperature compensation, microcontroller-based interface is used. The operating pressure range is 0–103 kPa, and operating temperature range is −40 to 85 °C. Yao et al. (2016) have also compensated temperature for piezoresistive pressure sensor using a passive resistor which is assumed temperature independent. Its pressure range 2 MPa and temperature range is 20–220 °C. These methods make the system more complex, and also the whole measurement system becomes costly. These methods rely on hardware circuitry whose maintenance is a difficult task, and these are more prone to environmental influences. So for making a measurement system economic, smart and simple calibration using ANN is a better alternative.

Pressure measurement is important for running any process industry. Bellows are among the simple techniques for measuring pressure because they are durable, have robust construction, have wide range and are easy to fabricate. But various factors affect the measurement using bellows which includes corrosion, sensitivity to fluctuating pressures and its less capability to perform in dynamic environment. These drawbacks can be removed by proper calibration of the measurement technique. Zenere and Zorzi (2018) have proposed Kalman filter-based robust model predictive control (MPC) controller. The conventional MPC controller output was affected by uncertainities and environmental noise. The use of Kalman filter enhanced the properties of MPC controller without increasing cost and complexity of the conventional MPC controller. In case of bellows, at constant pressure as the temperature increases the elasticity of bellows increases resulting in increased displacement of bellows and the Hall voltage is directly proportional to displacement. So increased displacement results in increased Hall voltage and hence increased pressure. This results in error. So, to overcome this drawback a Hall probe-based smart pressure transmitter is implemented using ANN, in which the mechanical displacement of bellows corresponding to applied pressure is converted into an efficient electrical output voltage signal and finally to current signal. This electrical signal can be further transmitted through a wire, optical fiber or electromagnetic waves as per industrial requirement for remote monitoring and control of the process variable. The design of the measurement system is simple and cost-effective as the hardware parts of the measurement system are less costly. The proposed method is a non-contact type smart pressure transmitter which increases the lifetime of sensing portion.

The outline of the present paper can be given as follows. Section 2 is divided into two parts. Firstly, pressure transmitter is analyzed mathematically to show the effect of varying temperature on output Hall voltage. Then, the pressure transmitter is calibrated using ANN to compensate the effect of varying temperature on output Hall voltage. In Sect. 3, the experimental and simulation results are shown. In Sect. 4, the proposed method is concluded with a comparative study with other techniques.

2 Theory

2.1 Analysis of Pressure Transmitter

The block diagram of proposed ANN-based pressure measurement system is shown in Fig. 1. The input pressure is converted into corresponding Hall voltage using bellows with hall probe sensor, but the output pressure is dependent on change in input temperature which results in error and hence inaccurate measurement. So by calibrating the pressure transmitter using multilayer perceptron of ANN, the effect of temperature is compensated at the output. The reference temperature for desired output is taken as 27 °C. During training process, the ANN compares the Hall voltage at some varying temperature value with respect to the Hall voltage at reference temperature and calculates the error. This error is minimized or nullified by using back propagation algorithm of ANN, and the corrected Hall voltage is obtained at the output of ANN. The corrected output voltage is then converted into (4–20) mA current signal using signal conditioning circuit.

2.2 Bellows with Hall Probe Sensor

Let the applied pressure on bellow is P; thus, pressure applied, P, is given by

$$P \propto Ex \tag{1}$$

$$P = KEx \tag{2}$$

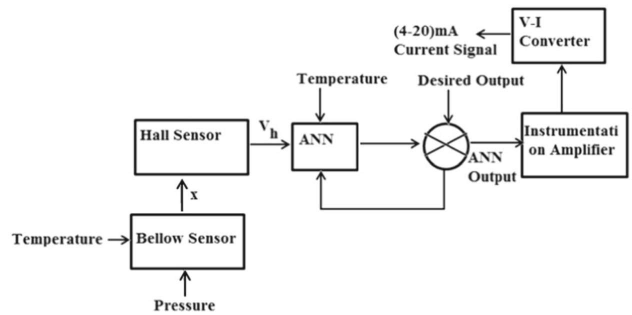

Fig. 1 Block diagram of proposed pressure transmitter

where K is a constant, E is modulus of elasticity and x is displacement. At no applied pressure, the magnet and the Hall probe sensor is having distance H and at some bellows displacement the distance between the magnet and the Hall probe, h, becomes $h = H – x$. In this experiment circular magnet is used. Now the magnetic field intensity, B_h, of Hall probe sensor can be written as

$$B_\mathrm{h} = \frac{K'h}{(h^2 + a^2)^{3/2}} \tag{3}$$

where K' is constant and a is radius of circular magnet. Since $h \gg a$, so Eq. (3) can be written as

$$B_h \approx \frac{K'}{h^2} \tag{4}$$

When constant current passes through sensor then output Hall voltage V_h becomes proportional to magnetic field given by

$$V_\mathrm{h} = K'' B_\mathrm{h} \tag{5}$$

where K'' is a constant. Substituting the value of magnetic field from Eq. (4) in Eq. (5), we get

$$V_h \approx \frac{K'K''}{(H - x)^2} \tag{6}$$

Since height, H, is very large than displacement x. So on further simplification, Eq. (6) becomes

$$V_\mathrm{h} = \frac{K_1 K_2}{H^2}\left(1 + \frac{2x}{H}\right) \tag{7}$$

where K_1 and K_2 are constants and H is the distance between the magnet and the Hall probe sensor at zero gauge pressure. Now, on substituting the value of displacement, x, from Eq. (2) in Eq. (3) we get

$$V_\mathrm{h} = \frac{K_1 K_2}{H^2}\left(1 + \frac{2P}{HKE}\right) \tag{8}$$

Let $K_3 = \frac{K_1 K_2}{H^2}$ and $K_4 = \frac{2K_1 K_2}{K H^3}$

$$\text{Therefore} \quad V_\mathrm{h} = K_3 + K_4\left(\frac{P}{E}\right) \tag{9}$$

where K_3 and K_4 are constants.

We know that Young's modulus of elasticity is property of material which depends on nature of bonds and atomic bonding strength. If the bonding strength increases, then the stiffness of the material (young's modulus of elasticity) also increases. Also as the temperature increases there is decrease in bonding strength. So mostly modulus of elasticity, $E(T)$, decreases as temperature, T, increases as given by

$$E(T) = E(0\,\mathrm{K})\left\{1 - C\left(\frac{T}{T_\mathrm{m}}\right)\right\} \tag{10}$$

Putting the value of modulus of elasticity, $E(T)$, Eq. (10) in Eq. (9), we get the dependency of Hall voltage, $V_\mathrm{h}\,(T)$, due to varying temperature, T, as follows

$$V_\mathrm{h}(T) = K_3 + \frac{K_4 P}{E(0\,\mathrm{K})}\left(1 \middle/ 1 - \frac{CT}{T_\mathrm{m}}\right) \tag{11}$$

where K_3, K_4 and C are constants. $E(0\ \mathrm{K})$ is modulus of elasticity at zero kelvin. T_m is melting point. Equation (11) shows the relationship between the output Hall voltage and temperature.

2.3 Calibration of Pressure Transmitter Using Artificial Neural Network

While selecting a rubber bellow for a particular application, there are various factors which have to be considered during the selection process. These factors include temperature, pressure, whether the system is static or dynamic, the process media, aesthetics, cost and many more. Among these, temperature is one of the important parameter for consideration. The maximum temperature limit of the rubber bellows is determined by their chemical stability while at low temperature they behaves like a glass where with the change in temperature their properties transit between hardness, stiffness and brittleness. So the property of rubber bellows is dependent on its glass transition state, T_g, when it is above its T_g then it is elastic and below its T_g it becomes hard and brittle. When a pressure is applied to a hydraulic or gaseous system then the value of T_g increases by 10 °C per 5.2 MPa or 1.80 F Per 750 psi. So if a rubber bellow has a low temperature limit of − 40 °C, then by applying a pressure of 103 MPa (15,000 Psi) its temperature limit becomes − 20 °C. These analyses show that as the pressure increases the variation in temperature becomes large which can result in large errors in the output of measurement system. The calibration of pressure transmitter using ANN is shown in Fig. 2 in form of

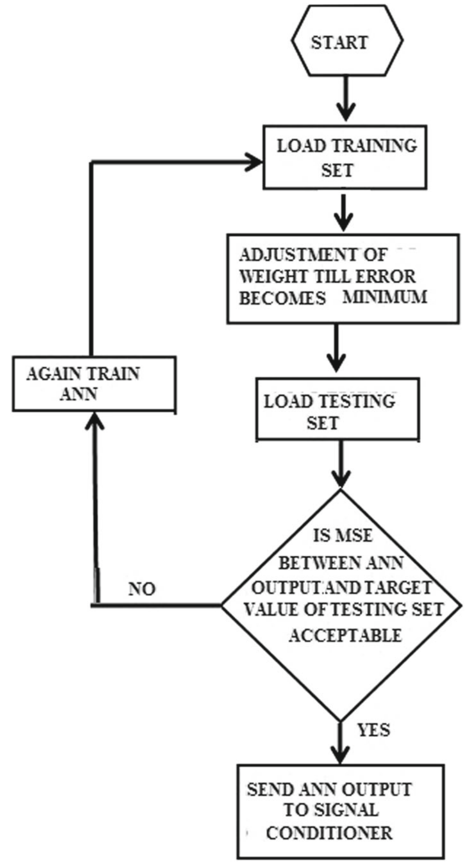

Fig. 2 Flowchart of proposed calibration technique using ANN

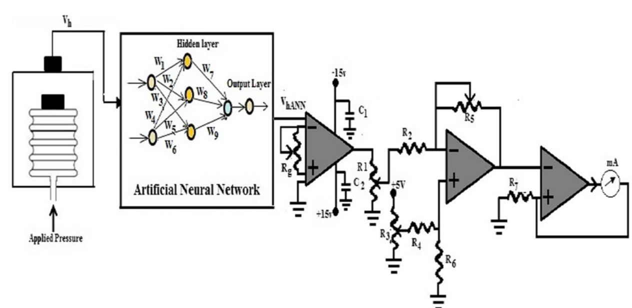

Fig. 3 Graphical abstract of pressure transmitter

flowchart. The MSE (mean squared error) of Fig. 2 is a performance function of neural network according to the mean of squared errors.

The graphical abstract of the proposed measurement system can be represented in Fig. 3.

The ANN-based calibration of pressure transmitter includes back propagation algorithm as shown in Figs. 4 and 5 (Gurney 1997; Yegnanarayana 2005). The inputs to the neural network are the Hall voltage from hall sensor and varying temperature, and the ANN output is corrected output Hall voltage. Tan sigmoidal and linear transfer functions are used in the hidden and the outer layers, respectively.

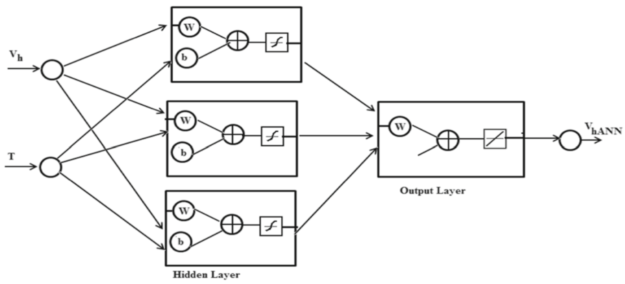

Fig. 4 ANN model

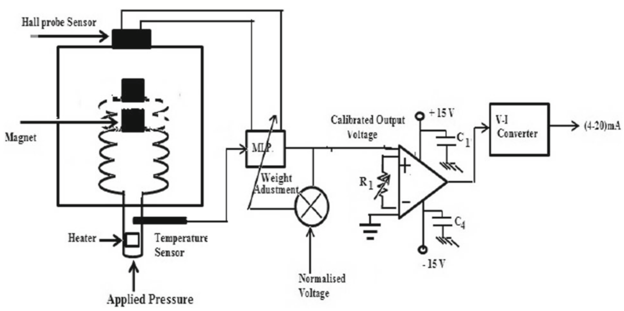

Fig. 5 The experimental model

Table 1 ANN training parameters

Method	Back propagation algorithm
No. of neurons	Input neurons—2 Hidden neurons—3 Output neurons—1
Activation function	Tan sigmoidal for hidden neurons Linear function for output neurons
Value of weights in different layers	$W_1 = 5.74$, $W_2 = -2.62$, $W_3 = -3.64$, $W_4 = 0.86$, $W_5 = 1.94$, $W_6 = 0.91$, $W_7 = -7.42$, $W_8 = 0.92$, $W_9 = 1.28$

The weights (W) generated during training process as given in Table 1 are stored in erasable programmable read only memory. These stored weights are loaded during testing process. If the test result and desired output are closely related, then it shows that the ANN has learnt the characteristics of measurement system.

With the weights, a bias value (b) is there in every layer except output layer. In this work, the bias value is 1 and threshold value is 0.001. By assigning the appropriate value of bias, the neural network can effectively map all the combinations of input to their output.

After training, the system is tested at different temperatures for various pressures. In this work, the range of pressure used is 10–60 Psi as shown in Fig. 4.

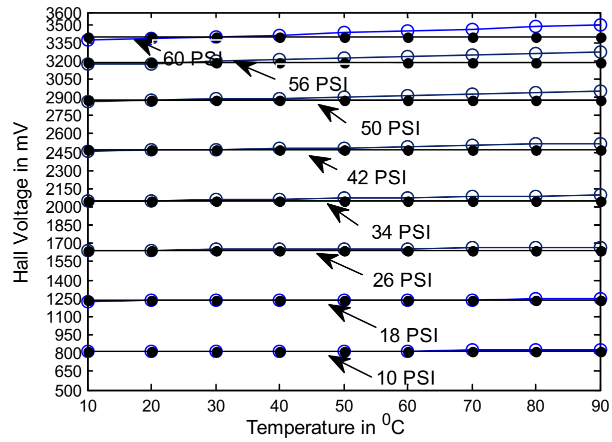

Fig. 6 Variation of Hall voltage with Temperature at different constant pressure (-o-) before and (-●-) after calibration

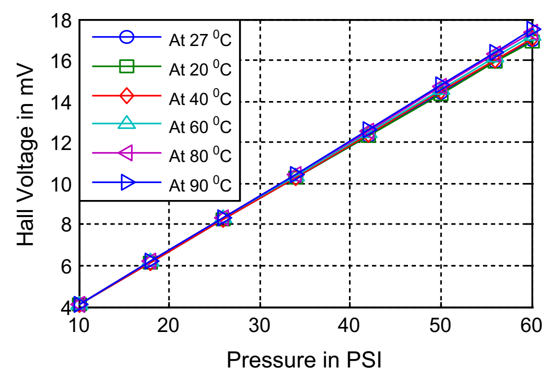

Fig. 7 Variation of Hall voltage with respect to desired Hall voltage

3 Results and Simulations

3.1 Experimental Results

The experiment is done in three steps. The experimental model of the proposed method is shown in Fig. 5. In the first step, the variation of Hall voltage with temperature is analyzed by performing experiment at fixed pressure and varying temperature. The Hall sensor used in this work is SS490, and it has a positive temperature coefficient of +0.02%/°C.

The experimental results show that with the change in temperature the Hall voltage also varies, also the range of variation increases as the pressure is increased as shown in Fig. 6. It can be seen from Fig. 6 that at constant pressure the output Hall voltage varies with change in temperature and as the temperature and pressure increases the variation from actual data increases. It also shows that after calibrating the measurement system using ANN, the output Hall voltage does not change with the varying temperature and the desired output Hall voltage is obtained. It can be seen from Fig. 7 that for low pressure and low temperature, the variation in output Hall voltage is less but for high temperature and high

Table 2 Testing results

Pressure (Psi)	Temperature (°C)	Hall voltage (mV) before calibration	Hall voltage (mV) after calibration	Desired output hall voltage (mV) at room temperature (27 °C)	Percentage deviation from desired value (at 27 °C) before Calibration
10	20	4.09	4.09	4.09	− 0.34
	40	4.09	4.09	4.09	− 0.25
	60	4.10	4.09	4.09	0.03
	80	4.11	4.09	4.09	0.23
	90	4.11	4.09	4.09	0.33
18	20	6.15	6.16	6.16	− 0.62
	40	6.17	6.16	6.16	− 0.31
	60	6.19	6.16	6.16	0.01
	80	6.21	6.16	6.16	0.37
	90	6.22	6.16	6.16	0.55
26	20	8.23	8.24	8.24	− 0.85
	40	8.26	8.24	8.24	− 0.46
	60	8.30	8.24	8.24	0.02
	80	8.34	8.24	8.24	0.52
	90	8.36	8.24	8.24	0.77
34	20	10.26	10.28	10.28	− 1.08
	40	10.33	10.28	10.28	− 0.55
	60	10.37	10.28	10.28	0.02
	80	10.44	10.28	10.28	0.65
	90	10.47	10.28	10.28	0.97
42	20	12.32	12.34	12.34	− 1.29
	40	12.40	12.34	12.34	− 0.66
	60	12.48	12.34	12.34	0.02
	80	12.58	12.34	12.34	0.77
	90	12.62	12.34	12.34	1.16
50	20	14.37	14.40	14.40	− 1.49
	40	14.48	14.40	14.40	− 0.74
	60	14.59	14.40	14.40	0.02
	80	14.71	14.40	14.40	0.88
	90	14.78	14.40	14.40	1.34
56	20	15.90	15.95	15.95	− 1.64
	40	16.09	15.95	15.95	− 0.82
	60	16.17	15.95	15.95	0.04
	80	16.32	15.95	15.95	0.97
	90	16.39	15.95	15.95	1.46
60	20	16.93	16.98	16.98	− 1.72
	40	17.07	16.98	16.98	− 0.87
	60	17.23	16.98	16.98	0.05
	80	17.39	16.98	16.98	1.02
	90	17.48	16.98	16.98	1.52

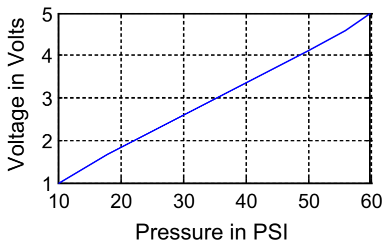

Fig. 8 Output voltage after signal conditioning

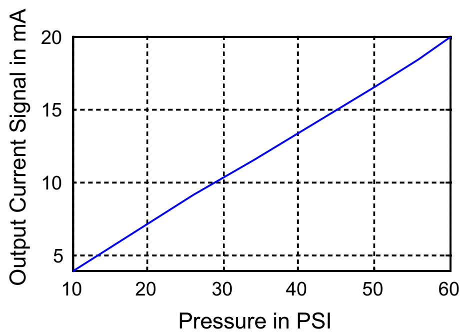

Fig. 9 Output in form of current signal

pressure the variation in Hall voltage is markable and also it is not negligible. The output Hall voltage before training and after training is shown in Fig. 6.

During the training process, the ANN learns about characteristics of the measurement system. In this work, the system trained for temperature range from 10 to 90 °C since the environmental temperature mostly varies in this range, but since the system has learned the output characteristics so even if environmental temperature varies beyond this range then the output can be obtained with minimum error.

After training the measurement system using ANN, the system is tested at different temperatures keeping the pressure constant. The output Hall voltage before calibration and after calibration is summarized in Table 2.

3.2 Simulation Testing Results

In third step, the obtained Hall voltage from ANN is amplified using an instrumentation amplifier and then it is converted into (1–5) volts and finally it is converted into (4–20) mA current signal distant transmission using signal conditioning circuit. The output voltage and current signal obtained after signal conditioning are shown in Figs. 8 and 9, respectively.

4 Conclusion

The proposed pressure transmitter does not need to be recalibrated with the change in temperature. In this work, auto compensation of temperature occurs so no extra shielding or casing is required in the pressure sensor for avoiding temperature variation. The proposed ANN-based pressure transmitter can be implemented using low-cost microcontroller units. This leads to development of smart pressure transmitter which can do auto calibration and optimization of undesired input parameters which affect the output. In process plants, it is not always possible to maintain various environmental factors like temperature, humidity, etc., constant. So in that case measurement system can be calibrated using ANN for maintaining the accuracy of the system. The main objective of proposed work is to make the measurement system smarter and simpler as compared to other temperature compensation techniques. Temperature can also be compensated with other techniques (Beeby et al. 2000; Hooshmand and Joorabian 2006; Rajita et al. 2015) such as with the help of IC'S and other components like resistors and capacitors, but all these methods make the system more complex as an extra hardware need to be connected to the system but by calibrating the system using ANN no extra circuitry is required. In the proposed work, the variation in Hall voltage with change in temperature at different constant pressure is analyzed. It is observed from Fig. 6 that the hall voltage varies linearly with temperature. It can be also be observed from Table 2 that as the pressure is increased the variation of Hall voltage with change in temperature increases. So due to change in temperature, obtained Hall voltage differs from the true value. This effect of temperature on Hall voltage is compensated using ANN, and recalibration is not required. The testing results show that after calibration the obtained hall voltage and corresponding (4–20) mA current output is equal to the desired value. The proposed method can operate in pressure range up to 413 kPa and can operate in temperature range from − 40 to 150 °C since various components used measurement process like bellows; Hall probe operate in this temperature range. This calibration technique can be used for dynamic measurements, and accuracy of the system is increased to a greater extent. A comparative study on calibration of various pressure transducers can be presented in Table 3.

Table 3 Comparative study of calibration of various pressure transducers using ANN

S. no.	Technique	Range	Nonlinearity/ sensitivity	Notable feature
1	Chen et al. 2006	0–0.6 Mpa		Temperature compensation for silicon piezoresistance pressure sensor using MAX1452 as a compensation unit
2	Reverter Cubarsí et al. 2009	0–103 Kpa	214 µV/Kpa	Temperature compensation for piezoresistive pressure sensor using microcontroller-based interface circuit
3	Huang et al. 2010	0–15 Mpa		CPS with FLANN-based inverse modeling
4	Patra et al. 2011	0–0.6 normalized pressure	± 1%	Linearization and compensation of environmental factors on CPS using LaNN
5	Kumar and Narayana 2016	0–70 psig	± 0.6%	ANN-based pressure transmitter with bellows and inductive pick up coil. ITVCC is used for signal conditioning
6	Yao et al. 2016	100–2 Mpa	210 Mv/100 Kpa	Temperature compensation for high-temperature piezoresistive pressure sensors using passive resistor
4	Proposed method	0–60 psig	± 0.03	Hall probe-based pressure transmitter calibrated using ANN

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