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RESEARCH ARTICLE

An adaptive calibration technique for thermistor with varying temperature coefficient and reference resistance [version 1; peer review: 1 approved, 1 not approved]

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Abstract

Background: A thermistor is a nonlinear sensor requiring a precise calibration technique to achieve accurate temperature measurements. This paper attempts to design a calibration technique employing artificial neural network (ANN) algorithms. The present work fulfills the following objectives: (i) to cover 100% input range in the linearity range measurement; (ii) to make the measurement technique adaptive to variations in reference resistance and thermistor temperature coefficient using a calibration technique.

Methods: An ANN-based calibration circuit is cascaded to the data conversion circuit. Optimized ANN is trained with linear data independent of reference resistance and temperature coefficient effects on thermistor output. ANN optimization is performed by comparing various schemes, algorithms, and numbers of hidden layers to achieve a minimum mean square error and a regression close to 1.

Results: The proposed technique provides a linear relationship for the system over the entire input range and avoids the requirement of repeated calibrations each time the thermistor is replaced. Practical data are used to validate the proposed measurement technique.

Conclusions: The objectives and proposed technique have been demonstrated by results with a root mean square percentage error of 1.8%.

Keywords

Artificial neural network, Calibration, Optimization, Temperature, Thermistor

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1. Introduction

Temperature is an essential process measurement parameter. Temperature dependency is prevalent in practically all chemical processes and reactions. In chemical plants, temperature indicates the progress of a process. Incorrect temperature measurement may result in considerable loss of product in temperature-critical reactions. At times, failing to control temperature can result in catastrophic plant failure and loss of life. A thermistor is a commonly used temperature sensor because of its high sensitivity and low power dissipation.³⁸

The functionality of thermistors can be understood through a literature survey. In a proposed adaptive system,¹ complementary metal-oxide-semiconductor technology was used to design and integrate the system building blocks. The high-level models obtained after experimental characterization were verified for acceptable electronic behavior within a well-defined multilayer perceptron architecture. Enhanced sensing behavior observed in CaTiO_3 processed through high energy ball milling was much higher than that observed in CaTiO_3 processed through solid-state reaction method.² A 555 timer in the astable multivibrator mode has been used³ as a simple and economical signal conditioning circuit for negative temperature coefficient (NTC) thermistor temperature sensors. A substrate membrane has been fabricated to improve sensitivity using back etching technology,⁴ beneath the hot area. The performance of the microcalorimeter, transfer standard, and measuring system⁵ allowed Centro Nacional de Metrología to achieve efficiency measurement and uncertainties analogous to or even less than reported by other national metrology institutes. Analysis of changes in the thickness, growth rate, and temperature profile of ice was performed⁶ through data collected using an NTC thermistor.

A diamond thermistor was fabricated⁷ for high-temperature sensing with a high-pressure, high-temperature, and chemical vapor deposition technique. An NTC thermistor junction temperature estimation technique has been discussed⁸ for power metal-oxide-semiconductor field-effect transistors considering the temperature-sensitive electrical parameter as the ON-state voltage. For indoor and outdoor applications, the printing of disposable and degradable temperature sensors is possible using temperature-sensitive substrates incompatible with conventional inks, as proposed in.⁹ The fabrication of a liquid crystal thermistor was presented in.¹⁰ Based on the heat loss of self-heated NTC thick-film segmented thermistors and their operation, a novel heat loss flowmeter prototype has been proposed¹¹ that operates in the power-save regime. A linearization method in¹² demonstrated thermistor measurement results with a linearity error below $\pm 0.5\%$.

Based on a thermal tracer, a flow velocity measurement method has been reported in,¹³ temperature information is used to solve the problems in flow velocity monitoring due to the presence of sand in oil-water two phase flow. A proposed measurement system for a wide-range flow sensor was developed by¹⁴ to determine the thermal characteristics of the flow. The results can be used in developing and designing measurement systems for micro-electromechanical-system-based thermal gas flow sensors.

A fast and accurate method has been presented in¹⁵ to predict the junction temperature of insulated-gate bipolar transistor module chips with no additional temperature sensors. In,¹⁶ the authors simulated a thermistor's neural network-based signal conditioning circuit. Neural network algorithms have been used to design a linear compensation circuit for a resistance temperature detector.¹⁷ A support vector machine was used to develop a nonlinear compensation technique for a resistance temperature detector.¹⁸

Delay time of a negative temperature coefficient device has a significant reliance on the accuracy of the radiation measurement. An experiment consisting of double-thermistor structure for potassium tantalate niobate deflectors has been proposed in¹⁹ to suppress effect on delay time caused due to ambient temperature dependence. The results showed that the double-thermistor structure decreases the ambient temperature dependence by half compared with a conventional thermistor.

A temperature-compensated anemometer has been designed and tested based on an NTC thermistor couple in.²⁰ The fluid's temperature measured in this configuration is convenient for wind turbine testing. A new method has been presented in²¹ to fabricate a diamond-based thermistor that consists of ohmic contacts on sintered Si_3N_4 ceramics. The characteristic voltage-current curves display a linear variation over wide temperature and voltage ranges. A transient compensation method has been proposed in²² for thermistor-based sensors in a constant temperature configuration.

For temperatures in the 70–190°C range, a glass substrate with thin films of HCl-doped $\text{PO-Mn}_3\text{O}_4$ nanocomposites were fabricated in²³ and displayed flexibility, conformability, and fire resistance. Estimating the bulk physical parameters describing the behavior of thermo-electrical modules and their dependence on varying operating conditions was shown to be highly accurate²⁴ in employing the improved version of the unified method for transmission electron microscope based characterization. Apart from making the sensor smaller or more spherical and decreasing its radiation sensitivity, no improvements over the sensor in²⁴ were possible for the sensor in²⁵ using gold sputtering.

The drift of conductivity and temperature sensors fastened with the Ocean Moored Network for the northern Indian Ocean buoy system in the Arabian sea was investigated using pre- and post-deployment calibration.²⁶ During a heat tracing experiment in a groundwater flow simulator, fiber Bragg gratings, distributed temperature sensing, and continuous fiber Bragg gratings based temperature measuring techniques were compared, and it was reported that distributed temperature sensing produces more accurate results over the other type.²⁷ A novel circuit solution has been proposed in²⁸ for temperature measurement. The temperature of a pick tip was obtained in a coal rock cutting experiment along with the circuit design and calibration, showing that the wear rate of the polycrystalline diamond compact bit increases at a critical temperature of 700°C. Nanomaterials and conductive polymer-based flexible temperature sensors have been evaluated in²⁹ with the temperature response, sensitivity, and production methods. Calibration of NTC thermistors using the residual compensation method was discussed in.³⁰

In,³¹ four-wire measurements were used to eliminate errors and maximize resolution and current consistent with the thermistor's input voltage range and self-heating. Results showed that the number of parameters could considerably influence the interpolation error. A thermistor was developed by³² with a guard heater to minimize heat loss for accurately measuring the surface temperature of a material. The results show good performance and accuracy. Thermal conditions for the small-sized, long-stroke, low-speed stages of piston compressors have been investigated in.³³ The reading stability of the thermistor was studied for 120 hours at 90°C. The impact of different thermistor linearization techniques on the temperature uncertainty is presented in³⁴ for the temperature history characterization of phase-change materials. A method was proposed by³⁵ to minimize the resolution per analog-to-digital converter step for a specified temperature range using the thermistor resistance and its derivative at the boundary.

From the reported literature, it is clear that most studies discuss the linearity of sensors over a certain range rather than full scale, and the calibration process must be repeated every time a thermistor is replaced. These calibrations are time-consuming and may require a change in hardware, increasing the overall cost of the instrument. This paper overcomes these problems by proposing a method using the artificial neural network (ANN) concept. The ANN model is cascaded to the buffer circuit and trained to achieve a linear output independent of physical parameters like the temperature coefficient (β) and reference temperature resistance (R_0). An optimized ANN is developed using diverse algorithms and schemes and comparing their mean square error (MSE) and regression (R). The optimized ANN model provides the lowest MSE and a R close to one. The proposed technique is validated in this extended version by subjecting it to practical data implemented on the embedded platform for online temperature measurement.

The organization of the remainder of this paper is as follows. A brief description of the challenges faced in using thermistors for temperature monitoring is provided in Section 2. Section 3 describes the proposed solution, followed by results and discussion in Section 4. Finally, the conclusions of the study are provided in Section 5.

2. Problem statement

Thermistors are temperature-sensitive resistors, having either a negative or positive resistance-temperature coefficient. A decaying exponential function best describes an NTC thermistor's resistance-temperature (R-T) characteristics, and interpolation can be performed using different equations.³⁶⁻³⁹ The Steinhart-Hart equation, shown in Equation (1), is considered here:

$$R_T = R_0 e^{\frac{-\beta(T-T_0)}{T T_0}} \Omega \quad (1)$$

where

R_T : Thermistor's resistance at temperature T

R_0 : Reference resistance at a specified reference temperature T_0 ($T_0 = 25^\circ\text{C}$)

β : Temperature coefficient

This work uses a 5 k Ω thermistor (Sowparnika Thermistors and Hybrids Pvt Ltd, make) with a temperature coefficient of 4000 K. Output resistance obtained for the change in temperature from 20 to 200°C derived from equation 1 is shown in Figure 1. A signal conversion circuit in the form of a voltage divider and amplifier is used to convert the resistance obtained from the thermistor to a voltage, as shown in Figure 2. Mathematical equations for the voltage divider are given in Equations (2) and (3). The outputs obtained from the voltage divider and amplifier are shown in Figure 3a and b, respectively.³⁵

Figure 1. Simulated response of 5 kΩ thermistor.

Figure 2. Signal conversion circuit used for testing thermistors with different temperature coefficients.

$$V_1 = V \left(\frac{R_T}{R - R_T} \right) \text{ V} \quad (2)$$

$$V_{out} = V_1 \left(1 + \frac{R_2}{R_1} \right) \text{ V} \quad (3)$$

where: R is the fixed resistance of 6.7 kΩ

V is the source voltage of 5 V

R₁ and R₂: amplifier resistance of 470 Ω and 1 kΩ potentiometer

Figure 3. (a) Output obtained from voltage divider circuit; (b) Output obtained from amplifier circuit.

Several types of thermistors are available commercially. These thermistors are classified based on their reference resistance (R_0) and temperature coefficient (β) values. The most commonly available thermistors have 5, 10, and 20 k Ω reference resistances. Thermistors are also available,^{37–39} with varying temperature coefficients. Characteristics of various thermistors are included in this section and are tested to understand the difficulties involved in available measurement techniques. For this purpose, measurement is carried out with three different thermistors with reference resistances (R_0) of 5, 10, and 20 k Ω and a temperature coefficient of 4000 K. Results obtained for variation with temperature are shown in Figure 4.

Tests were also conducted using thermistors with different temperature coefficient values of $\beta = 4000, 8000$, and 12000 K, and a reference resistance (R_0) of 5 k Ω . The output obtained for temperature measurements is shown in Figure 5. All the available thermistors were tested with the signal conversion circuit shown in Figure 2.

The output obtained from the amplifier for varying temperatures for different thermistors is shown in Figures 4 and 5. From these graphs, it is clear that the amplifier output has a nonlinear relation with temperature. The output varies with changing reference resistance and temperature coefficient. Because of the high nonlinearity of the thermistor, it is only used over 10%–60% of its full-scale range in practice. Users must perform repeated calibrations whenever a thermistor with a different reference resistance (R_0) or temperature coefficient (β) is used. These conventional techniques are time-consuming because they must be calibrated every time a thermistor is changed in the system.

Figure 4. Measured output voltages as a function of temperature for different thermistors with a temperature coefficient of 4000 K and varying reference resistances (R_0) measured in Ω .

Figure 5. Measured output voltages as a function of temperature for different thermistors with a reference resistance (R_0) of 5 k Ω and varying temperature coefficients (β) measured in K.

Objectives: With an arrangement for temperature measurement in a system consisting of a thermistor in cascade with a signal converter circuit, as shown in Figure 2, design an intelligent temperature measurement technique using an optimized neural network model and with the following properties:

- Adaptive to variation in R_0 .
- Adaptive to variation in β .
- Output should have a linear relation with the input temperature.
- Measurement of full-scale input range should be possible.

3. Methods

The objectives defined in section 2 are achieved by cascading a neural network model with a data converter unit by switching the conventional calibration circuit, as shown in Figure 6. The practical setup of the implemented calibration technique is shown in Figure 7. The experimentation setup consists of a muffle furnace (BML instruments Ltd make) to heat the sensor. The sensor output is connected to the signal conditioning circuit designed on Elvis board. The Elvis board is interfaced to the computer. For computation MATLAB⁴⁰ (RRID:SCR_001622), LabVIEW tools⁴⁰ (RRID:SCR_01325) are used to develop neural network model and interface with the system. Alternatively, an open-source alternative SCILAB model has also been developed and archived in.⁵¹ The measurement technique is implemented in the LabVIEW program,⁴⁰ with the front panel window shown in Figure 8.

The front panel window consists of two numerical controls to feed the neural network with the R_0 and β values. Two numerical indicators display the temperature of the system calculated using the conventional method and calibrated using the ANN. Two graphical indicators display the temperatures, display titled “Uncalibrated” will display the output from

Figure 6. Block diagram of the proposed technique. Reference resistance - R_0 and temperature coefficient - β .

Figure 7. Experimental setup.

Figure 8. Front panel window of the proposed LabVIEW program.

conventional technique and display titled “Calibrate” display’s the output of ANN-calibrated techniques. A block diagram of the proposed technique is shown in [Figure 9](#).

The block diagram window consists of the data acquisition (DAQ) assistant to acquire real-time data from the buffer output and feed it to the LabVIEW MATLAB script window, which is programmed with the trained ANN model using the net function. The ANN is trained on the MATLAB platform, and the executed net function is used to calculate the output value for varying input temperatures with various R_0 and β . The computed output using the ANN is displayed using numerical and graphical indicators. The values computed using the conventional method are also displayed for reference.

Training is the process of obtaining the weights to achieve the desired output. Consideration of different algorithms with varying hidden layers results in an optimized ANN. The average of the squared difference between outputs and targets gives the MSE. Lower MSE values are better, with a zero MSE meaning no error. The correlation between output and target is measured by R. A close relationship is when R is one, and a random relationship is zero.

Different schemes and algorithms have been used to find the optimized ANN. These are back propagation trained with particle swarm optimization (AL1), radial basis function trained by ant colony optimization (AL2), radial basis function trained by artificial bee colony (AL3), radial basis function trained by genetic algorithm (AL4), radial basis function trained by particle swarm optimization (AL5), and radial basis function trained by firefly algorithm (AL6).^{41–50}

ANN training is done first by assuming only one hidden layer, and the resulting MSE and R values are recorded. Training is then repeated by increasing the number of hidden layers to two, and this process is repeated up to four hidden layers. MSE and R are recorded in all cases, these results are provided in [Table 1](#). A mesh plot of MSE and R values corresponding to different algorithms and numbers of hidden layers are shown in [Figures 10–11](#). From [Table 1](#), [Table 2](#), [Figure 10](#), and [Figure 11](#), it is evident that back propagation trained by ant ACO results in the most optimized

Figure 9. Block diagram window of the proposed LabVIEW program.

Table 1. Variation of mean square error (MSE) and regression (R) for different layers and algorithms (AL). AL1 - back propagation trained with particle swarm optimization, AL2 - radial basis function trained by ant colony optimization, AL3 - radial basis function trained by artificial bee colony, AL4 - radial basis function trained by genetic algorithm, AL5 - radial basis function trained by particle swarm optimization, AL6 - radial basis function trained by firefly algorithm.

Layers		AL1	AL2	AL3	AL4	AL5	AL6
1	MSE	4.62E-3	5.17E-3	4.25E-3	2.71E-3	1.04E-3	8.17E-4
	R	0.836	0.799	0.855	0.878	0.898	0.913
2	MSE	7.35E-6	8.99E-6	7.61E-6	5.66E-6	4.27E-6	1.20E-6
	R	0.963	0.934	0.949	0.972	0.981	0.991
3	MSE	8.15E-7	9.94E-7	8.47E-7	8.01E-7	5.33E-7	2.32E-7
	R	0.996	0.994	0.995	0.9968	0.9973	0.9987
4	MSE	1.88E-8	5.02E-8	3.87E-8	3.67E-8	2.17E-8	9.55E-9
	R	0.9990	0.9986	0.9988	0.9989	0.99899	0.9992
5	MSE	3.25E-10	6.11E-10	4.87E-10	5.01E-10	3.01E-10	1.21E-10
	R	0.9996	0.9993	0.9995	0.9994	0.9998	0.9999

Figure 10. Variation of Mean square error (MSE) with the number of hidden layers and algorithm (AL). AL1 - back propagation trained with particle swarm optimization, AL2 - radial basis function trained by ant colony optimization, AL3 - radial basis function trained by artificial bee colony, AL4 - radial basis function trained by genetic algorithm, AL5 - radial basis function trained by particle swarm optimization, AL6 - radial basis function trained by firefly algorithm.

network when taking MSE as the threshold. back propagation trained by and colony optimization with two hidden layers is considered the most optimized ANN for the desired accuracy. Details of the optimized ANN are summarized in Table 3.

4. Results and analysis

The optimized ANN is trained, validated, and tested with simulated data using equation 1, 2 and 3. It is subjected to various test inputs corresponding to thermistors with different reference resistances and temperature coefficients, all within the specified range. The temperatures measured by a practical set up along with the output of the data conversion unit are recorded for (i) $R_0 = 800 \, \Omega$ and $\beta = 5000 \, \text{K}$ and (ii) $R_0 = 5000 \, \Omega$ and $\beta = 5000 \, \text{K}$, and (iii) $R_0 = 10000 \, \Omega$ and $\beta = 8000 \, \text{K}$. These data are listed in columns 1 and 2 of Table 4.⁵¹

Figure 11. Variation of regression (R) with the number of hidden layers and algorithm (AL). AL1 - back propagation trained with particle swarm optimization, AL2 - radial basis function trained by ant colony optimization, AL3 - radial basis function trained by artificial bee colony, AL4 - radial basis function trained by genetic algorithm, AL5 - radial basis function trained by particle swarm optimization, AL6 - radial basis function trained by firefly algorithm.

Table 2. Variation of mean square error (MSE) and regression (R) for different layers and algorithms.

Serial. No	Transfer function	MSE
1.	Tanh	7.91E-4
2.	Sigmoid	7.80E-4
3.	Linear Tanh	7.46E-4
4.	Linear sigmoid	7.19E-4
5.	Softmax	6.51E-4
6.	Bias	7.33E-4
7.	Linear	8.17E-4
8.	Axon	7.62E-4
9.	Tansig	6.98E-4
10.	Logsig	6.72E-4

Table 3. Optimized parameters of the neural network model.

Database	Training base	100
	Validation base	33
	Test base	33
Number of neurons in	1 st layer	8
	2 nd layer	6
Transfer function of	1 st layer	Softmax
	2 nd layer	Softmax
	Output layer	linear

Table 4. Output obtained from the proposed technique for real-life testing.

Actual temperature in °C	Output of data conversion unit	Temperature in °C by proposed technique	% Error
Case 1: Reference resistance (R_0) = 800 Ω and temperature coefficient (β) = 5000 K			
20	2.4358	20.00	0.00
30	2.0195	29.92	0.27
40	1.6529	39.97	0.08
50	1.3424	50.87	-1.74
60	1.0867	60.71	-1.18
70	0.8798	69.10	1.29
80	0.7143	79.60	0.50
90	0.5826	89.40	0.67
100	0.4779	101.80	-1.80
110	0.3945	111.17	-1.06
120	0.3279	121.23	-1.03
130	0.2744	130.31	-0.24
140	0.2313	139.70	0.21
150	0.1962	148.36	1.09
160	0.1675	159.10	0.56
170	0.144	169.70	0.18
180	0.1245	178.90	0.61
190	0.1083	189.80	0.11
200	0.0947	199.70	0.15
Case 2: R_0 = 5000 Ω and β = 5000 K			
20	3.6409	19.93	0.35
30	2.4645	29.88	0.40
40	1.3671	39.91	0.23
50	0.6691	48.99	2.02
60	0.3136	60.12	-0.20
70	0.1477	71.01	-1.44
80	0.0713	80.56	-0.70
90	0.0356	91.02	-1.13
100	0.0184	100.87	-0.87
110	0.0098	111.15	-1.05
120	0.0054	121.34	-1.12
130	0.0031	129.66	0.26
140	0.0018	141.44	-1.03
150	0.0011	152.01	-1.34
160	0.0007	162.00	-1.25
170	0.0004	171.58	-0.93
180	0.0003	181.03	-0.57
190	0.0003	188.72	0.67
200	0.0003	199.10	0.45

Table 4. *Continued*

Actual temperature in °C	Output of data conversion unit	Temperature in °C by proposed technique	% Error
Case 3: $R_0 = 10000 \Omega$ and $\beta = 8000 \text{ K}$			
20	7.356	20.08	-0.40
30	4.887	29.87	0.43
40	2.465	39.85	0.37
50	1.176	50.76	-1.52
60	0.743	60.89	-1.48
70	0.477	69.76	0.34
80	0.266	79.55	0.56
90	0.118	89.01	1.10
100	0.057	99.66	0.34
110	0.048	110.23	-0.21
120	0.027	120.51	-0.43
130	0.016	129.04	0.74
140	0.009	139.12	0.63
150	0.005	148.87	0.75
160	0.003	158.8	0.75
170	0.001	171.2	-0.71
180	0.0007	180.9	-0.50
190	0.0006	188.6	0.74
200	0.0005	199.6	0.20

Figure 12. Output characteristics of proposed calibration technique with different thermistors.

Figure 13. Error variation for testing of different thermistors.

The output of the data conversion unit, and R_0 and β , are used as inputs to the trained, optimized ANN. The corresponding ANN outputs and the temperature measured by the proposed technique are noted in columns 3 and 4 of Table 4. The results shown in Table 4 suggest that the proposed system has measured the temperature with very high accuracy. It is evident from Table 4 that the proposed measurement technique has gained intelligence and increased the linearity range.

Next, the output is made to adapt to variations in reference resistance and temperature coefficient. The calibration process need not be repeated if the thermistor is changed to another with different R_0 and β . The signals are fed online to the proposed system through LabVIEW DAQ Assistant, and the output corresponding to various inputs is provided in Table 4. Figure 12 is a picture of the experimental setup used to carry out the proposed work.

Figure 12 plots the input–output characteristics obtained by the proposed calibration technique. It is seen that the output obtained is linear and is adaptive to different thermistors. The output value does not vary with thermistor type. Figure 13 shows a plot of the measurement errors. The proposed measurement technique can achieve an accuracy of 1.8% and a maximum 2°C temperature deviation in monitoring even when using different sensors.

5. Conclusions

Thermistors are the most widely used temperature sensors because of their economic feasibility and higher sensitivity, although they are highly nonlinear and have longer response times. Several calibration techniques were studied, and a broad literature survey indicated around 30 reported works in the last decade on thermistor-based temperature sensing. Existing works^{1–32} have investigated various techniques for temperature measurement calibration using thermistors. A few have also reported on sensor design to obtain better characteristics.

However, the literature has not discussed systems adaptive to reference resistance and temperature coefficient variations. Hence, any change in reference resistance and temperature coefficient of a thermistor requires repeated calibration. Furthermore, most reported works have not utilized the full-scale measurement range. In all the above-referenced literature, neural networks were selected without any justification when used.

In contrast to the existing literature,^{1–32} linear input output characteristics for the entire input temperature range have been achieved with the measurement technique proposed in this study. These objectives have been fulfilled using an optimized

ANN. Training, validation, and testing were conducted employing different schemes and algorithms. The desired MSE and R (near one) with two hidden layers were attained using the radial basis function trained by the firefly algorithm, in contrast to arbitrary ANNs used in most reported studies. The neural network model data are further validated with practical data online in a real-time environment. The results show that the proposed technique can be used to design an adaptive calibration technique.

Data availability

Underlying data

Open Science Framework: Extended data for ‘Can an adaptive calibration technique be implemented for a thermistor?’ <https://doi.org/10.17605/OSF.IO/4KE9U>⁵¹

This project contains the following extended data:

- Store.xlsx (Data related to simulation, training and testing of thermistor)

Extended Data

Open Science Framework: Extended data for ‘Can an adaptive calibration technique be implemented for a thermistor?’ <https://doi.org/10.17605/OSF.IO/4KE9U>⁵¹

This project contains the following extended data:

- code.sce (Code that can be used with SCILAB to achieve desired results)

Data are available under the terms of the [Creative Commons Zero “No rights reserved” data waiver](#) (CC0 1.0 Public domain dedication).

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Atasi Dan

Virginia Tech India Centre for Research and Innovation, Chennai, India

The manuscript reports on an approach to calibrating negative temperature coefficient thermistors (NTC) having different thermal constants and reference resistance by implementing artificial neural network (ANN) algorithms. An optimized method using different algorithms, and transfer functions have been proposed to improve the accuracy of the predicted output with minimized error. While the work is interesting, I would encourage the authors to present the data more systematically and explain them with appropriate reasoning. Moreover, the methods, results and analysis sections require significant attention to better describe the work. I recommend addressing the following comments and incorporating them in the revised manuscript to make the manuscript useful for a broader audience.

1. The abstract needs to be written to provide a better picture of the investigation
2. In the Introduction section, the authors have described mostly the functionality of the different types of thermistors used in various systems. However, the manuscript is mainly focused on the calibration technique of thermistors using ANN. Therefore, there is a requirement to refer to the previous literature, investigating thermistors by ANN for appropriate contextualization. This is missing in the present form of the manuscript. Please find the references. (Dongale et al. Modelling of NTC thermistor using an artificial neural network for non-linearity compensation. Inf. Eng. Int. J 1, 15–20, 2013¹; Dey et al. Simulation studies on a new intelligent scheme for relative humidity and temperature measurement using thermistors in 555 timer circuit. Int. J. smart Sens. Intell. Syst. 3, 217–229; 2010²). Authors should emphasize how their work is different compared to the reported literature.
3. Prior to explaining the results with ANN, it will be a good idea to write about the ANN model used in the current study. Also, it will be relevant for a broad audience if, in the method section, the authors write an introductory short paragraph about the ANN-based prediction modeling methodology for the thermistors used in their work, the training network, clear indication of input and output parameters, the calculation procedure of MSE and R which are very important performance indices to correlate the results. These references may be helpful (M. Hemmat Esfe et al. *International Communications in Heat and Mass Transfer* 66

(2015) 246–249³, L. Yun et al. *Journal of Cleaner Production* 218 (2019) 763–771⁴). A structure diagram including input, output, and hidden layers will provide better clarity. Also, some background information related to transfer functions needs to be highlighted in the Method section before directly putting them in Table 2.

4. While providing data in Table 1, the authors can explain the effect of the hidden layers on the prediction in the text. Although authors have performed testing up to 6th layer, optimized parameters of the neural network only contain 2 layers (Table 3). Please indicate the reason in detail. Also, the authors can mention why the number of neurons was kept 6/8 in 2 layers.
5. It is not clear from the manuscript about the subdivision of the data set (in %) between network training and testing.
6. The authors show different transfer functions in Table 2. But, in the manuscript text, there is no mention of which transfer function was suitable for the data prediction. It seems from Table 3 that a linear function was used. The authors can give some comments on why the linear function was implemented. Also, the caption of table 2 is confusing. There is no information about the algorithm, number of layers, and R values in the content of the Table, although it is written in the caption.
7. Table 3 shows that 100 training database was used. Authors can write in the “method” section how the large data set was made using the thermistors. Also, indicate the database boundaries.
8. Table 4 indicates the prediction accuracy of ANN model. It will be interesting to know how prediction accuracy can be varied depending on the size of data sets.
9. I notice that author mentioned ant colony optimization exhibited the optimized conditions (last paragraph, Page 9, of the pdf). But, in conclusion, the authors mentioned that “the desired MSE and R (near one) with two hidden layers were attained using the radial basis function trained by the firefly algorithm.”
10. The conclusion can be written concisely, and the authors should emphasize the important outcome of the study.
11. Was the thermistor material the same for three cases with varying R_0 and β values? If the NTC thermistor is replaced by a different material, how effectively the developed ANN model will be able to predict the output? Authors may consider commenting on that in the manuscript for using the ANN model to predict the performance of other thermistors in the future.
12. The temperature coefficient of resistance or TCR (%/°K) and thermal constant, β (K) is different parameters (*Ceramics International* 38 (2012) 6481–6486⁵). However, in this manuscript, β values (4000, 8000, 12000 K) are represented as temperature coefficients which may confuse readers.
13. Please find the following observations

- Y axis label is missing in Figure 4
- Page 3, first paragraph - "A thermistor is a commonly used temperature sensor because of its high sensitivity and low power dissipation³⁸." The first reference starts from 38.
- Page 3, 3rd paragraph: "....the printing of disposable and degradable temperature sensors is possible using temperature sensitive substrates **incompatible** with conventional inks,...."
- Please indicate individual variables like V_1 , R , R_T in the schematic (Figure 2).
- In this manuscript, R has been referred to as resistance as well as correlation coefficient for regression. So, I suggest giving two different symbols for these parameters. Here, R has been mentioned here as regression. In general, it is called the correlation coefficient
- "From Table 1, Table 2, Figure 10, and Figure 11, it is evident that back propagation trained by ant ACO results in the most optimized." Please write the full form of ACO (Ant colony optimization).
- Both X and Y axis labels show "temperature in degree Celsius". Please put different names as they are different variables.
- Different components can be pointed out in the Experimental setup (Figure 7).
- Suggestion: Figure 8 and Figure 9 can be kept together as they are from LabView program.
- Suggestion: Fig. 10 and Fig. 11 can be kept as Fig. 10 (a) and (b) to visualize the variation of MSE and R simultaneously.
- In the first paragraph of the results and analysis, indicate Case 1, Case 2, and Case 3 instead of writing (i), (ii), and (iii).
- The authors have to check the content of the manuscript carefully to avoid several typographical errors.

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Is the work clearly and accurately presented and does it cite the current literature?

No

Is the study design appropriate and is the work technically sound?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?

No

If applicable, is the statistical analysis and its interpretation appropriate?

Partly

Are all the source data underlying the results available to ensure full reproducibility?

Partly

Are the conclusions drawn adequately supported by the results?

Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Thin film thermal sensors, thermo-electrical properties, evaluation of temperature coefficient of resistance, spectral selectivity, optical properties of materials, infrared reflectors, fabrication of metals, oxide, oxynitrides using physical vapour deposition, magnetron sputtering, radiative cooling, stability of materials at high temperature

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

Reviewer Report 05 September 2022

<https://doi.org/10.5256/f1000research.121006.r147799>

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Oleg Vasyliovych Zaporozhets

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This article proposes a thermistor calibration technique using a neural network model. It should

be noted that the use of artificial neural networks for the calibration of nonlinear sensors is not a completely new approach. However, in my opinion, the authors have significantly improved the existing results of solving this problem.

The introduction provides an analysis of a significant amount of literature dedicated to the research of various techniques for temperature measurement using thermistors. The main problem is the nonlinearity of the thermistor, which prevents the use of the full-scale measurement range. The calibration method proposed in the article is quite interesting and promising. Its main advantage is the use of the values of the reference resistance R_0 and the temperature coefficient β of the thermistor when training the ANN. This eliminates the need for recalibration when replacing the thermistor, which reduces the cost of metrological regulation. Another positive aspect of the work is the optimization of the structure and learning algorithm of the ANN using mean square error (MSE) and regression (R).

However, there are some questions. It is not entirely clear what data was used for training the ANN: the characteristics of the three thermistors presented for validation or some others?

As a metrologist, I would like to see how the inaccuracy (uncertainty) of the R_0 and β values affects the measurement error. But this is rather a problem for future research. By the way, the measurement error will be affected by the instability of the resistance R of the voltage divider and resistances R_1 , R_2 of the amplifier.

Minor comments:

- in equation (2), which describes the voltage divider, the minus sign must be changed to a plus sign;
- The sentence "The corresponding ANN outputs and the temperature measured by the proposed technique are noted in columns 3 and 4 of Table 4." (Section 4) should be amended to "The temperature measured by the proposed technique and measurement error are noted in columns 3 and 4 of Table 4.";
- The sentence "Figure 12 is a picture of the experimental setup used to carry out the proposed work." (Section 4) should be amended to "Figure 7 is a picture of the experimental setup used to carry out the proposed work."

Is the work clearly and accurately presented and does it cite the current literature?

Yes

Is the study design appropriate and is the work technically sound?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?

Yes

If applicable, is the statistical analysis and its interpretation appropriate?

Yes

Are all the source data underlying the results available to ensure full reproducibility?

Yes

Are the conclusions drawn adequately supported by the results?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Adaptive information and measurement systems

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

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