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Thermocouples Data Linearization using Neural Network †

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Abstract – Thermocouples are usually used for measuring temperatures in steel industry, gas turbine, diesel engine and many industrial processes. Thermocouple usually have nonlinear Temperature-Voltage relationship ($mV=f(T^{\circ})$). However, on the monitoring side, it is required to have the inverse relationship [$T^{\circ}=f^{-1}(mV)$] to determined the actual temperature sensed by the thermocouple. In this work the neural network is fully utilized to represent the required inverse nonlinear relationship of different and most popular thermocouples (K, J, B) Types. Levenberg Marquardt is used as learning process to find these neural networks. It is found that each type of thermocouples under test can be represented by a single neural network structure. Moreover, the obtained results show the power of neural network in representing the inverse static relationship of each thermocouple that gives less than 1% of the actual measured temperature in the whole temperature range in comparison to polynomial fitting method.

Keywords – Thermocouple, Neural Network, Levenberg- Marquardt, polynomial fitting method.

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1. Introduction

Thermocouples are used to measure temperature since they are inexpensive, rugged, reliable, self powered and can be used for wide range of temperature. Thermocouples are available in various metal combinations, usually referred to by a letter e.g. J, K, B, etc [1]. The measured voltage from the thermocouple has to be converted into temperature. Several techniques are used to get the temperature such as piecewise linearization or polynomial fitting [2].

The piecewise linearization is a method of curve fitting using straight line equation. Linear interpolation on a set of data points (x0, y0), (x1, y1)... (xn, yn) is defined as the concatenation of linear interpolant between each pair of data points. This results in a continuous curve, with a discontinuous derivative [3]. The polynomial fitting is a generalization of linear interpolation. It replaces the interpolant by a polynomial of higher degree. For example, a polynomial equation used to convert thermocouple voltage to temperature (C°) over a wide range of temperatures. Equation (1) illustrates the polynomial equation:

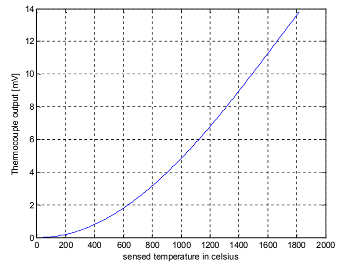
$$T = a_n V^n + a_{n-1} V^{n-1} + \cdots\cdots + a_0 \qquad (1)$$

Where V is voltage measured in mill volts and T is temperature measured in Celsius degree. The coefficients (a_n) are tabulated in many bandboxes [4].

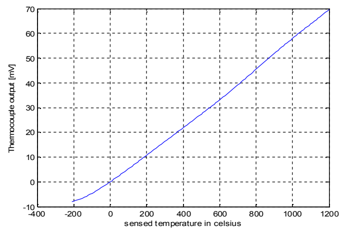
The obtained coefficients of the above techniques are stored in a conversion circuit (analog or digital) which has the measure voltage as an input and the measured temperature as an output. However, these techniques actually have an error between the actual and measured temperatures. The main reason of this error is the approximation of the nonlinear function that represents the inverse static relationship between the obtained voltage and calculated temperatures. In this work, the ability of the neural network in representing a nonlinear function is used to perform the conversion function.

2. Neuro data linearization

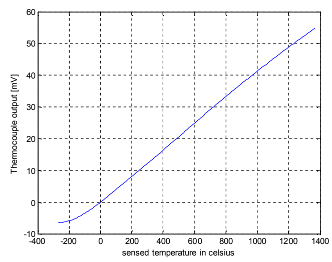
The sensed data of some popular thermocouples type B, J and K [5] are plotted as shown in Fig. 1.



(i)



(ii)



(iii)

Figure 1. Thermocouple relationship T=f(mV)
(i) B-Type (ii) J-Type (iii) K-Type

These data are used in a learning process of a [1: N: 1] neural network that represents the inverse relationship of the thermocouple as shown in the block diagram of Figure 2.

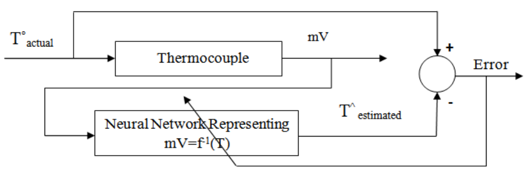


Figure. 2. Learning the thermocouple inverse relationship [T°=f -1(mV)]

Different trails are performed to determined N (the number of nodes in the hidden layer). It is found that suitable value of N for all types of thermocouple under test was N=5. This value gives minimum error between the actual temperature and estimated neural network temperature T. To find the weights of the selected neural network structure, Levenberg-Marquardt was chosen as a learning algorithm. The Levenberg-Marquardt is the standard of nonlinear least squares algorithms [6]. The structure of the Levenberg–Marquardt Neural Network is shown in Figure 3.

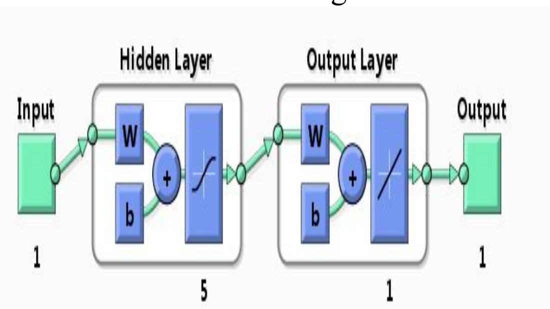


Figure 3. The structure of the Levenberg – Marquardt Neural Network

3. Experimental Results

As mentioned in section 2, three well-known and most popular industrial thermocouples were selected and their characteristics are summarized in Table (1) [7].

Using thermocouple, the measured voltage has to be converted to temperature. The temperature is usually expressed as a polynomial function of the measured voltage. Sometimes it is possible to get a decent linear approximation over a limited temperature range. The learned neural network which represents the inverse function [T=f-1(mV)] is simulated using MATLAB/SIMULINK as indicated in Figure (3) [8].

Table 1. The main characteristics of the selected thermocouples

Type	Temperature range °C - continuous	Temperature range °C (short term)	Tolerance class one (°C)	Tolerance class two (°C)
B	+200 to +1700	0 to +1820	Not Available	±0.0025×T between 600 °C and 1700 °C
J	0 to +750	−180 to +800	±1.5 between −40 °C and 375 °C ±0.004×T between 375 °C and 750 °C	±2.5 between −40 °C and 333 °C ±0.0075×T between 333 °C and 750 °C
K	0 to +1100	−180 to +1300	±1.5 between −40 °C and 375 °C ±0.004×T between 375 °C and 1000 °C	±2.5 between −40 °C and 333 °C ±0.0075×T between 333 °C and 1200 °C

For the B, J and K thermocouples, the trace of the mean square error (MSE) between the actual temperature and the neural network (estimated) temperature along the epoch number are illustrated in Figures 4, 5 and 6 for the three thermocouples, respectively.

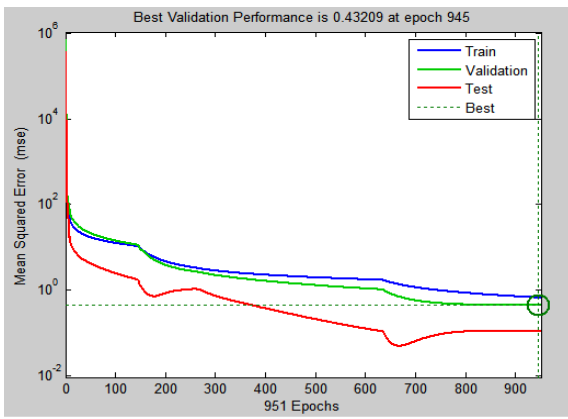


Figure 4. The trace of the MSE for the B-Type Thermocouple

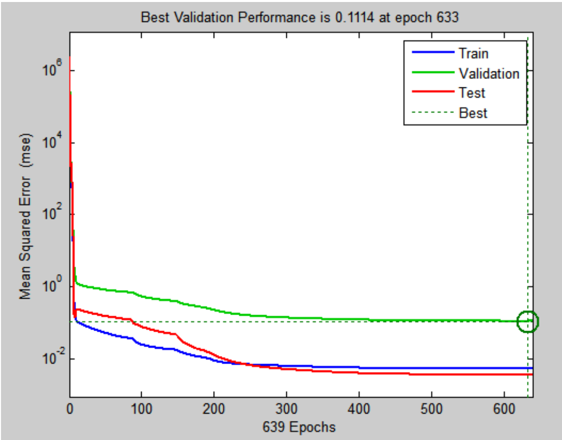


Figure 5. The trace of the MSE for the J-Type Thermocouple

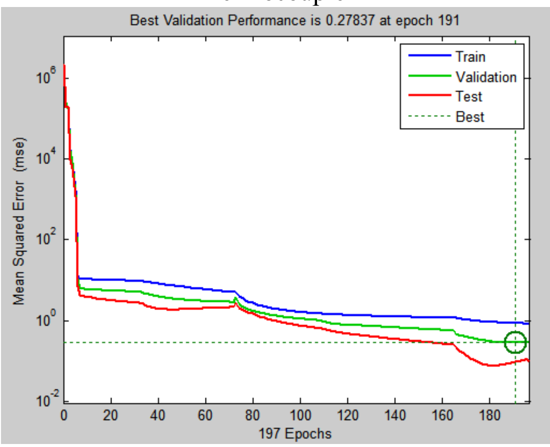


Figure 6. The trace of the MSE for the K-Type Thermocouple

The percentage error between the actual temperature and that obtained by the neural network is calculated as follows in 2 (as indicated in Figure (7)).

$$e_m = \frac{T_{actual} - T_{NN}}{T_{actual}} * 100 \qquad (1)$$

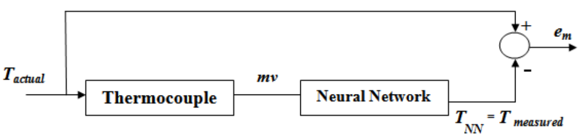


Figure 7. Validation test and error measurement

In order to show the validity of the learned neural network in representing the inverse relationship of each thermocouple, these percentage errors (Equation 2) are calculated for some points that are not used in neural network learning process as shown in Table (2).

Table 2. Validity test for B, J, K type thermocouples

Type	Thermoelectric Voltage (mV)	Actual Temperature	Measured Temperature by Neural Network	Error% (em)
B	0.04	107	106.4	0.560
	0.517	327	326.3	0.214
	3.254	813	813.1	0.012
	8.088	1322	1321.9	0.007
	12.921	1742	1741.98	0.001
J	-7.209	-173	-173.2	0.115
	-1.142	-23	-23.1	0.43
	8.120	152	152.004	0.003
	32.403	***588***	***588.026***	***0.0045***
	59.956	***1034***	***1034.026***	***0.0025***
K	***-5.097***	***-158***	***-158.8***	***-0.506***
	-3.911	***-112***	***-112.4***	***-0.357***
	-1.925	***-51***	***-51.05212***	***-0.102***
	5.410	***132***	***131.86537***	***0.101***
	46.809	***1145***	***1144.99763***	***0.0002***

Moreover, these percentage errors are plotted against the actual temperature for the B, J and K types of thermocouples as shown in Figures 8, 9 and 10 respectively.

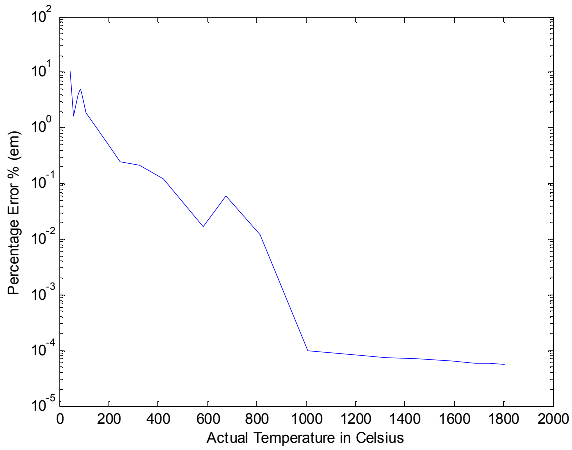


Figure 8. The percentage error verses actual temperature for the B-Type Thermocouple

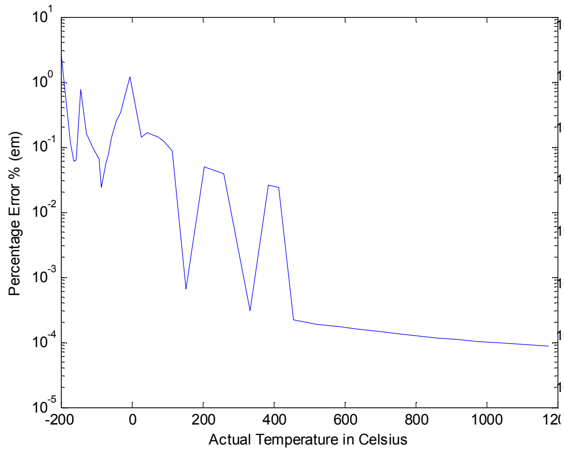


Figure 9. The percentage error verses actual temperature for the J-Type Thermocouple

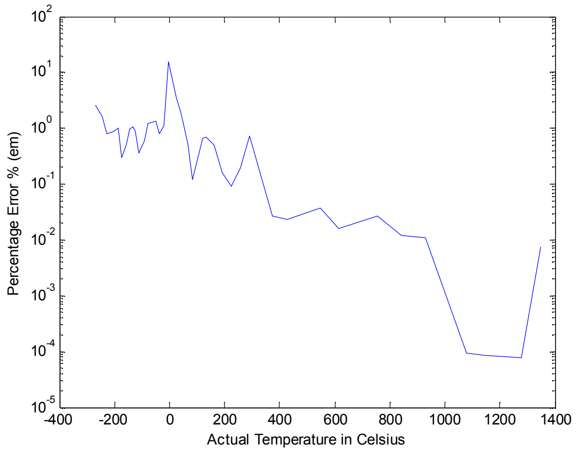


Figure 10. The percentage error verses actual temperature for the K-Type Thermocouple

For comparison purposes with the MATLAB polynomial fitting [9], the trace of error (the difference between the indicated temperature by either polynomial fitting or neural network with the actual temperature of the B, J and K types of thermocouples) are shown in Fig. 11, 12 and 13 respectively. In these figures, the polynomial order that is given in (1) is taken to be an=5 as it is found that this order gives minimum error over nearly the whole temperature range for the thermocouples under test. It is clear that the neural network gives less errors than those given by the polynomial fitting methods especially for the B-type thermocouple (see Figure 11) and along the most practical temperature range in industry(> 400 C0).

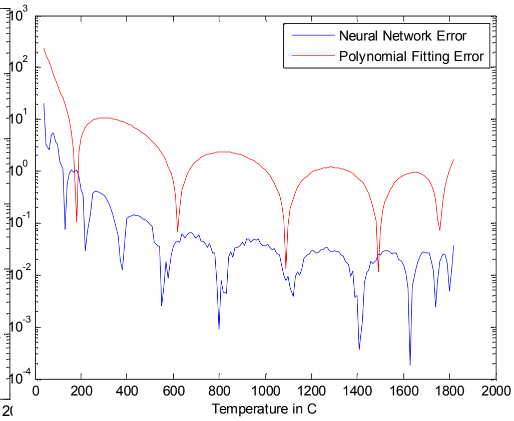


Figure 11. The trace of error obtained by neural network and polynomial fitting for the B-type thermocouple

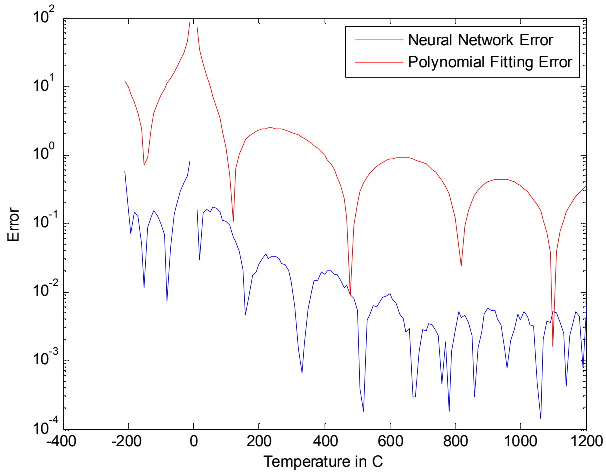


Figure 12. The trace of error obtained by neural network and polynomial fitting for the J-type thermocouple

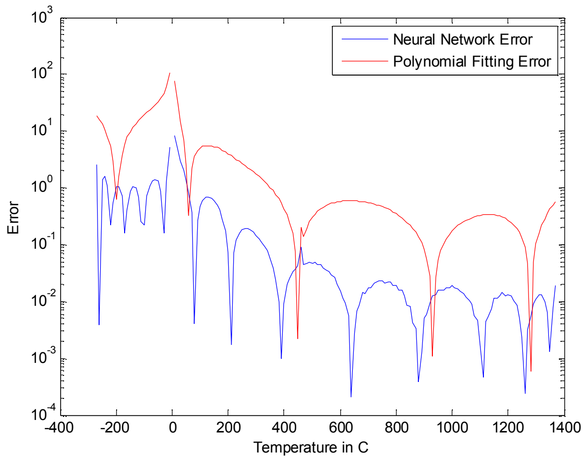


Figure 13. The trace of error obtained by neural network and polynomial fitting for the K-type thermocouple

4. Conclusion

In this work, the problem of extracting the measured temperature from the voltage readings of the thermocouple is solved using the neural network. It is found that the capability of the neural network in representing the nonlinear functions is fully exploited to map the required [T=f-1(V)] relationship for the three familiar types of thermocouples (B, J, and K types). Compression is made with polynomial fitting technique in representing the nonlinear [T=f-1(V)] relationship. It is noticed that the neural network is more powerful than the polynomial fitting since it gives less than 1% error between the actual temperature and that obtained by the neural network during nearly the whole temperature range. Different neural network structures of one or two hidden layers and different nodes within each layer were performed. These tests indicating that the structure of [1:5:1] is the most simple and suitable to represent the static inverse nonlinear relationship. Furthermore, the same neural network structure [1:5:1] can be used with the B, J and K types of thermocouples. This is important for on-line weight updating that can be achieved directly on the working site under operator request.

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