Thermocouple Signal Conditioning Using Augmented Device Tables and Table Look-Up Neural Networks, with Validation in J-Thermocouples

1st Moses L. Maseko
Department of Electrical, Electronic & Computer Engineering
University of Kwa-Zulu Natal
Durban, South Africa
mosesk394@gmail.com

2nd John T. Agee
Department of Electrical, Electronic & Computer Engineering
University of Kwa-Zulu Natal
Durban, South Africa
ageej@ukzn.ac.za

3rd Innocent Davidson
Department of Electrical & Electronic Engineering
Durban University of Technology
Durban, South Africa
Innocentd@dut.ac.za

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Abstract— **The relatively high accuracy, large measurement range, and durability of thermocouple devices make these devices to probably be the most-widely used temperature measuring devices in industrial applications. The ability of thermocouples to sense temperature is derived from the generation of thermoelectric voltages arising due to temperature differences between the hot and cold junctions of the thermocouple. Thermocouple temperature measurement processes suffer from inaccuracies arising from both the unwanted or undetected variations in the cold junction temperature of the thermocouple, and nonlinearities in the generated thermoelectric voltage. This paper presents an enhancement of thermocouple temperature measurement using a combination of augmented thermocouple tables generated from thermocouple polynomial functions, look-up MLP neural networks trained to accept the thermocouple output voltage, and the cold or reference junction temperature measurements: to produce improved hot-junction temperature outputs. Experimental validation of the current approach for a J thermocouple, using data from augmented device tables, reproduced the measured temperature values with a worst-case error of 0.0094%.**

Keywords— Artificial neural networks, thermocouple, nonlinear, multilayer perceptron

I. INTRODUCTION

Most processes in biological tissues, chemistry, power generation and manufacturing, etc., involve energy exchange of one sort or the other [1,2]. Such energy exchanges are often accompanied by temperature changes. Consequently, temperature is one of the most widely measured quantities. Thermocouple devices are the most ubiquitous of sensors for temperature measurement. Despite the high utility of these class of temperature sensors, the thermoelectric voltage generated by them suffers from nonlinearities; and is also affected by unwanted variations in the temperature of the reference junction. Both factors affect the accuracy of temperature measurements with thermocouples. Thermocouple devices generate a small dc voltage (electromotive force) in the millivolts and microvolts range that can be represented in the form;

$$V = a_0 + a_1(T_H - T_{ref}) + a_2(T_H^2 - T_{ref}^2) + \cdots + a_n(T_H^n - T_{ref}^n) \quad (1)$$

Where $a_0, a_1, \dots, a_n$ thermocouple constant of type K, J, B, R or S. T_H is hot/measuring junction temperature (°C) and T_{ref} the reference/cold junction temperature (°C).

The cold and hot junction of the thermocouple contribute to the generated thermoelectric voltage, as such the cold junction variation must be monitored or controlled. There exist many methods for dealing with the effects of cold junction disturbances on thermocouple output voltage. One such method involves keeping the reference junction at 0°C in an ice bath [3,4]. This approach is not always economic, in terms of cost and space utilization. Moreover, this method cannot be applied where an ice bath is not available. Another physical approach to correcting the effect of variations in the cold junction temperature is effected by measuring the variations in the reference junction temperature or voltage, and then subtracting the measurements from the measured thermocouple voltage [5], as such thermocouple equation is then reduced to:

$$V_{meas} = V_H(T_H) - V_{ref}(T_{ref}) \quad (2)$$

Where V_{meas} , $V_H(T_H)$, $V_{ref}(T_{ref})$ are the measured thermocouple output voltage, hot junction voltage, and the cold junction voltage.

Two other methods for cold junction compensation, are classified as: hardware compensation and software compensation. With hardware compensation, a variable voltage source is inserted into the circuit to cancel the contribution of the reference junction in the measured voltage. This variable voltage source generates a compensation voltage according to the ambient temperature, thus adding the correct voltage to cancel the reference junction voltage. The resulting voltage measured at the output is used to compute thermocouple temperature using the ITS-90 tables [5]. The major disadvantage of hardware compensation is that it is expensive. Each thermocouple type must have a separate compensation circuit that would add correct compensation voltages, as each thermocouple type has different characteristics.

Software cold compensation has better accuracy than hardware compensation [6]. It requires a direct reading sensor to measure the reference junction temperature; after that, the software can add the correct compensation voltage to the measured voltage of the thermocouple.

The above methods generally lack flexibility at implementation, or a computationally intense and only suitable for low speed temperature measurement application. The main reason the ITS-90 tables are limited is the fact that, they are only useful if the reference temperature is 0°C. However, using the thermocouple polynomial function, an augmented thermocouple table could be generated, which would provide thermocouple output for random values of both the reference junction and hot-junction temperatures. In the approach used in this paper, the augmented table of a given thermocouple was programmed into a microcontroller. Then, random values of the cold and hot junction temperatures were used with the thermocouple polynomial to generate data for training a look-up multi-layer perceptron neural network that uses cold-junction temperature values and the thermocouple output voltages to look up or compute the corresponding hot junction temperatures. The neural network is also programmed into the microcontroller.

The overall thermocouple conditioning technique is summarized in Fig. 1.

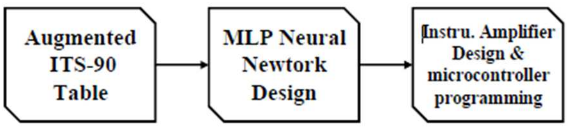

Fig. 1. Thermocouple signal conditioning using NN

Fig. 1, shows the proposed technique for temperature measurement accuracy enhancement with thermocouples. First thermocouple polynomial equation is used to generate a new ITS-90 (International Temperature Standard of 1990) table for J-type thermocouple. The new ITS-90 table referred to as Augmented ITS-90 table provides training data for the MLP neural network. For practical validation, instrumentation amplifier (amplify thermoelectric voltage), temperature-voltage sensor and microcontroller are used.

The rest of this paper is organized as follows. The generation of augmented ITS-90 is presented in section II of this paper. The MLP neural network design and validation are discussed in section III. Conclusions are presented in section IV. A list of references and an appendix conclude the paper.

II. AUGMENTED IST-90 TABLE GENERATION

Data available from the National Institute of Standards and Technology (NIST) on thermocouple ITS-90 tables is limited, the fact that the International Temperature Scale of 1990 (ITS-90) tables were calibrated only for reference junction temperature of 0°C. For the approach used in this research, where the thermocouple reference junction temperature is assumed variable beyond the 0°C value, augmented ITS-90 thermocouple tables are required. From generalized thermocouple equation for output thermoelectric voltage relating to the hot and cold junction temperatures given in equation (1), the reference junction temperature was varied between -10°C to 30°C, assuming average room/open-space temperature and application-specific temperatures. Then using MATLAB, thermocouple coefficient and equation (1), several values of the thermocouple output voltage V, using randomly generated values of T_H and T_{ref} (within pre-defined ranges) to form new, expanded table for J-type thermocouple with varying reference junction temperatures were generated.

For accuracy validation, readings from the augmented table for the J-thermocouple with zero reference junction temperature was compared with standard ITS-90 Table. The results showed that the maximum error was within 5x10-4 millivolt, as observable from the error plot below.

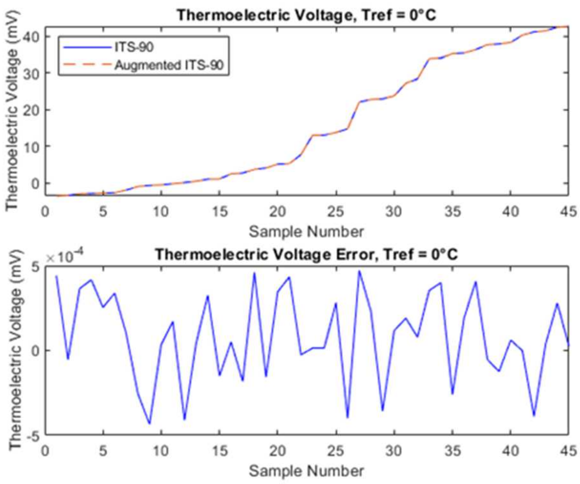

Fig. 2. Augmented ITS-90 table for J-thermocouple validation results

III. NEURAL NETWORK DESIGN

An artificial neural network is composed of a large number of interconnected units called neurons that have a certain natural tendency for learning information from the outside world. Neural networks are best at estimating or approximation of functions that may depend on many variables [7-11], nonlinear function approximators. Thermocouples are nonlinear temperature measuring devices; therefore, neural networks will be used to linearize thermocouples in this study.

A. Multilayer Perceptron Neural Network

The proposed study of thermocouple signal conditioning using neural networks involves the design and training of a neural network for type-J thermocouples using the MATLAB neural network toolbox. The selection of the particular neural network structure for use in linearization and cold junction compensation for the J-type thermocouple was decided after comparing the generalization capability and structure the neural network when trained to compensate and linearize the J-type thermocouple. The most interesting property of artificial neural networks is the ability to learn, collect information by a process called training [13, 14]. Training is when a neural network collects information using example data by applying an algorithm whose purpose is to reduce some error function. The error function employed in this study is the sigmoid function represented by;

$$f(net_i) = \frac{1}{1+e^{-net_i}} \quad (3)$$

The figure below depicts a typical MLP neural network structure with an activation function with two hidden layers.

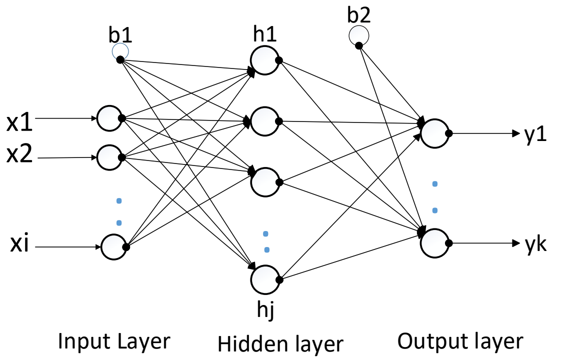

Fig. 3. MLP neural network Structure

B. MLP Neural Network Design and Training

A neural network with sufficient nodes can approximate any function, either linear or nonlinear [4], this property of NN was used in this study to design a neural network that predicts the measured temperature given reference temperature and measured thermoelectric voltage. The results from the comparison showed that the MLP neural network is better than the other models. The selection of an MLP was based on its ability to predict future variables given an input vector containing earlier observations [10]. The next step involved finding the smallest MLP architecture that had sufficient generalization capability without a significant loss of accuracy of generalization. Such pruning of the MLP neural network is required to reduce the requisite computational efforts during the microcontroller implementation of the conditioning system. The architecture of the MLP can be assessed by changing the ANN parameters (weights and biases) by using the pruning methods presented in [7]. Through pruning the size of the neural network, a neural network with excellent generalization capability was found. Below is the final neural network structure designed for approximating thermocouples characteristics.

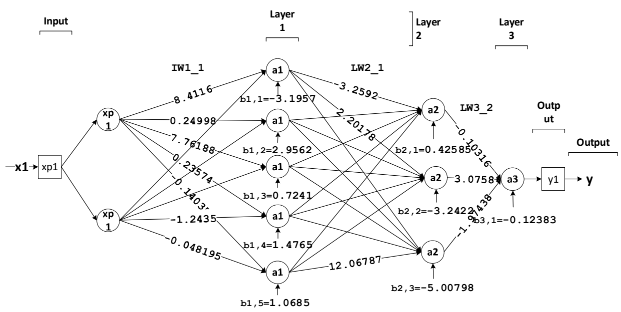

Fig. 4. Type J thermocouple neural network structure

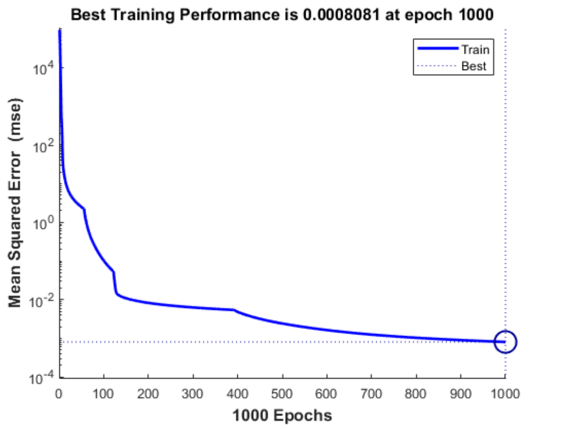

Fig. 5. Type J thermocouple training error for network

Fig. 5 shows training error for the Type J thermocouple neural network. The training of these neural network continued until the best training performance was reached. Careful consideration was taken not to over fit the neural networks that can give rise to the low generalization capability of the network.

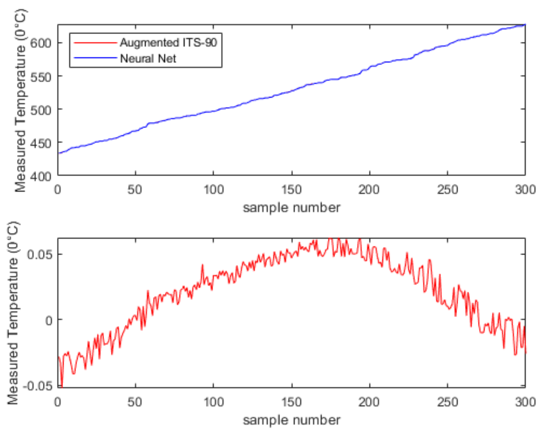

Fig. 6. Type J thermocouple neural network generalization test

The J thermocouple neural network was designed and the performance of the MLP neural network was tested with unknown input vectors. Fig. 6 show the generalization error plots for the J-type thermocouple for the performance of the neural networks in predicting the measured temperature of a thermocouple with an input vector of reference junction temperature and thermoelectric voltage. As it can be seen from Fig. 6, the neural networks produced acceptable accuracy with the worst-case error within 0.0094%.

IV. CONCLUSION

It can first be concluded that, thermocouple polynomial equation can be used to expend the standard ITS-90 thermocouple tables. As the augmented ITS-90 generated in this study produced an error within $5x10^{-4}$ millivolt when compared with the ITS-90 table for the J-thermocouple. The J thermocouple signal conditioning neural network showed measurement accuracy error within 0.0094% during the experimental validation. This performance of cold junction

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compensation showed an improved performance from other cold junction compensation methods, and there is a potential to improve this performance by increasing the parameters of the neural network, such as the number of hidden layers and neurons. The results achieved in this study leads to the conclusion that this design was a success, and it will be implemented in the laboratory to confirm the theoretical results that were found here.

Future recommendation is for practical validation of the results by implementing a signal conditioning system using microcontroller, a high accuracy instrumentation amplifier to improve the accuracy of thermocouple thermoelectric voltage readings by the microcontroller, and with a temperature-voltage sensor with improved accuracy. Thermocouple temperature measurement accuracy of within 0.0094% can be achieved.

V. APPENDIX I: MATLAB BASED GENERATION OF AUGMENTED TABLE FOR THE TYPE J THERMOCOUPLE.

```
%--=========-Type J Thermocouples Coefficients in mV--------------
%------------- Type J -210 to 760
C=[0.15631725697E-22 -0.12538395336E-18 0.20948090697E-15 -0.17052958337E-12...
0.13228195295E-9 -0.8568106572E-7 0.3047583693E-4 0.50381187815E-1 0 ];
% %--------------Type J 760 to 1200--------------
%C=[-0.306913690560E-12 0.157208190040E-8 -0.318476867010E5...
%     0.317871039240E-2 -0.149761277860E1 0.296456256810E3];

Th=randi([-210 760],[1 1500]);
Tc=randi([-10 30],[1 1500]);
% Th=randi([760 1200],[1 500]);
% Tc=randi([-10 30],[1 500]);

Vm= polyval(C,Th)- polyval(C,Tc);
C_Set=C';
Data_set=[Vm',Tc',Th'];
```

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