Pulse Train Modulation And ANN Based Temperature Sensor With Semi-automatic Calibration

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***Abstract*—The paper presents a temperature measurement system involving thermocouples. An NTC thermistor, as an inexpensive electronic component, plays dual role in the experimental setup. Firstly, it keeps track of temperature at cold junction of the thermocouple. Secondly, it modulates the ON and OFF time of pulses generated from a 555 timer based astable multivibrator. The thermocouple signal feeds the control input of the 555 timer. The multivibrator output is fed to a pre-trained ANN embedded in a personal computer (PC), to complete the measurement. The scheme has an arrangement for calibration involving a multitude of knots, resulting in very effective training of ANN. The semi-automatic calibration arrangement facilitates ANN to be trained with more data. The system is capable of measuring any unknown temperature, irrespective of the cold junction temperature. The experimental validation of the proposed scheme employs a type-T thermocouple. A measurement error of approximately ±0.38°C is obtained over temperature range from 55°C to 138°C. The proposed measurement system outperforms all the thermocouple-based temperature measurement techniques proposed in recent literature, in terms of accuracy, reliability, cost, and potential for embedded system application.**

***Keywords*—Artificial Neural Network, Multivibrator, IC555, Linearization, Temperature Sensor, Semi-automatic Calibration.**

I. Introduction

Ever since the discovery of the Seebeck effect in 1822, thermocouples fascinated many scientists and engineers, which culminated in their use as one of the most popular commercial temperature sensors. The century-old acceptability of the thermocouple temperature transducers is due to their ability to be used over wide temperature ranges, their ruggedness, relatively lower cost than platinum resistance temperature detectors (RTD), and also because of their sustainability at diverse environmental surroundings – both oxidizing and reducing. Two important issues that require attention when

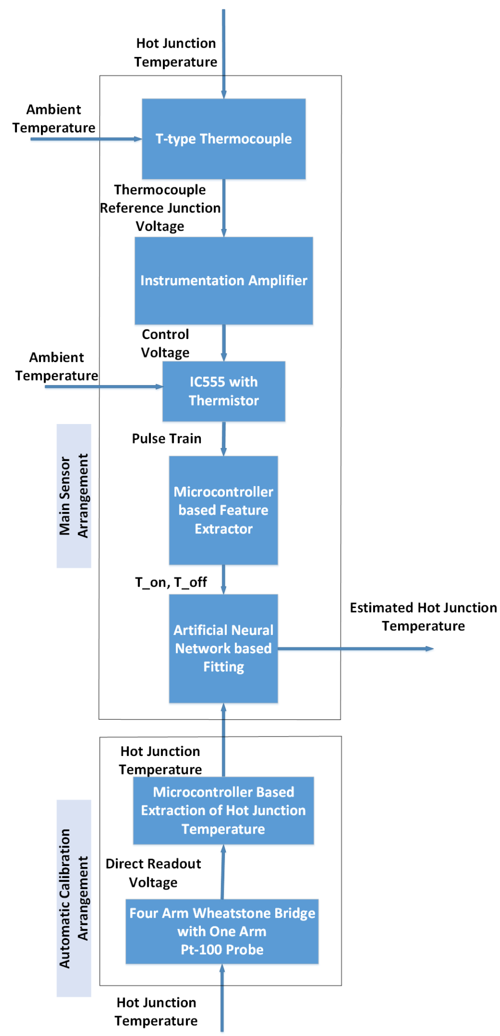

Fig. 1. Block Diagram of Proposed Sensor Arrangement

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developing such thermometers are reference junction compensation and linearization. While linearization is a general requirement for all types of sensors, the problem of reference junction compensation is unique to the thermocouples. It is not astonishing that the conditioning/ processing arrangements for thermocouple signals have gone through a sea change over the century. Over the years, quite a few circuits and arrangements have been developed to accomplish the task of reference junction compensation of thermocouple temperature sensors. The intrinsic philosophy of all these schemes is to utilize the well-known 'law of intermediate temperatures', to introduce an additive voltage to the thermocouple voltage difference between it's hot and cold junctions. This additive voltage equals the thermo-emf corresponding to temperature difference between reference junction temperature and 0ºC. Thus, such schemes mandatorily deploy an extra temperature sensor for tracking the cold junction temperature [1]–[4]. Early linearizing arrangements involved vortex thermometers equipped with resistance wire sensors [5], which were subsequently replaced by bridge circuits [6]. Diode-based piecewise linear function approximation circuits were also utilized [3]. With the ushering of the digital era, particularly with giant strides made in the advancement of systems containing powerful processors, task of conditioning thermocouple output signals was vastly facilitated [3], [7]–[10]. Soon to follow were those who use soft-computing based tools for sensing [11]–[15]. This abundance of powerful processor based systems could not, however, eclipse the use and therefore the urge of research and development (R&D) personnel to come up with newer hardwired arrangements for conditioning thermocouple signals. Such schemes find applications in stand-alone low-cost temperature monitoring systems, where very high accuracy might not be of prime concern. Another application area of them is for interfacing processor-based systems, where the interface itself serves as the first-stage linearizer, while the linearity of the static transfer characteristic may be furthered by appropriate software residing in a microcontroller or personal computer (PC). However, very few analog circuits have been reported in recent times [16], [17], although some of the circuits developed for other sensors may be effectively used for thermocouples as well [18]. Multivibrators and voltage-controlled oscillator (VCO) circuits with trains of rectangular pulses as output have served as important signal conditioning circuits for transducers [19], [20]. The quasi-digital output of these circuits can be taken to digital signal processing systems without digitization. As it is the time-period/ frequency of the signal that carries information of the physical variable (here temperature) being monitored, any distortion and attenuation of the pulse train do not result in a loss of intelligence. Thus, the signal can be transmitted over a long distance. Additionally, if a resistive sensor acts as a timing resistor, it experiences a pulsating voltage, and therefore has a much less self-heating than in the case of dc excitation. Very recently, two of the authors of this paper also co-authored a paper that reported about a voltage-to-frequency converter (VFC) for thermocouple signals [21]. That arrangement deploys the LM331 VCO IC, and an NTC thermistor monitoring the reference junction temperature serves as a timing resistor for the VFC. One important aspect that is most often ignored or not reported by many researchers is the necessity of not only automated measurement but also automated calibration of the transducer. In such a case, the system can operate with minimal intervention by any human operator. In the work reported here, a 555 timer is configured to work in the free-running multivibrator mode. The cold junction temperature is tracked by an NTC thermistor. The themistor also serves as timing resistor of the multivibrator. The cold junction of the thermocouple is exposed to the ambient temperature. The output voltage coming from thermocouple is fed to control input of the IC555. The multivibrator outputs rectangular quasi-digital pulse train, which can be directly fed to any processor-based system. Thus, the requirement of a separate analog-to-digital converter (ADC) is annulled. Lastly, no previous work profoundly addresses the problem of manually calibrating the sensor repeatedly, which is unavoidable as the environmental conditions change and aging of the sensor components happen. Also, while using ANN based sensors, more amount of experimental data facilitates use of large networks and better training of the networks. But, this is not possible when human intervention, while reading the data, is involved.

II. Proposed Methodology

The block diagram representation of the methodology proposed in this paper is given in Fig. 1. It encapsulates the significance of both hardware and software in the two types of arrangements, i.e., Main Sensor Arrangement and Semi-automatic Calibration Arrangement.

A. Main Sensor Arrangement

The signal conditioning circuit, for main sensor arrangement, proposed by the authors is shown in Fig. 2. The circuit consists of a 555 timer configured to work as an astable multivibrator. The reference junction temperature of the thermocouple transducer under consideration is measured using a thermistor with a negative temperature coefficient (NTC), which serves as one of the timing resistors of the multivibrator. The output of the thermocouple, after buffering and amplification by a three-opamp instrumentation amplifier, is fed to the control pin (5) of the 555 timer IC. Thus, this signal e_o = v_m modulates the frequency, pulse width of train of pulses v_{out}. Assuming that v_m has a constant value, the output periodic pulse train v_{out} of multivibrator is shown in Fig. 3.

Let timing capacitor (C_o) of multivibrator is initially under discharged condition. This gets charged from the supply V_{cc} along the path with charging resistance R_o+R_T. Then, when

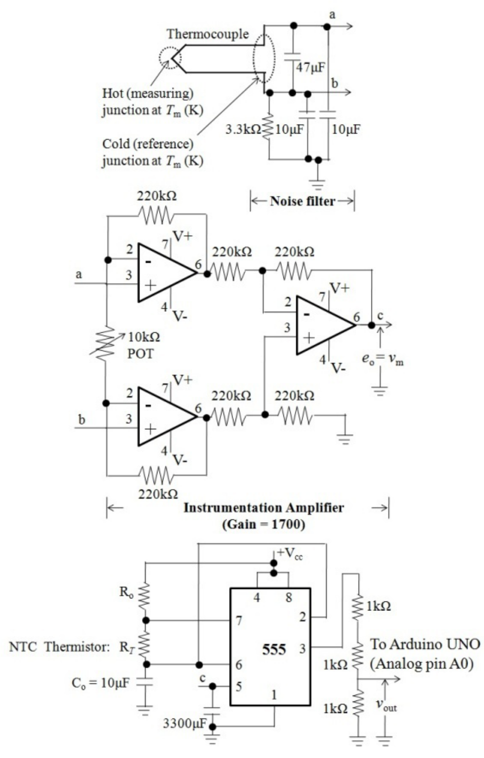

Fig. 2. The signal conditioning circuit

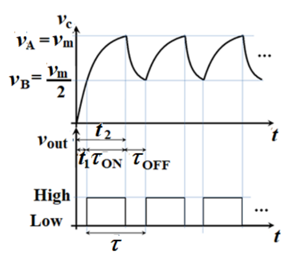

Fig. 3. Capacitor voltage and output voltage waveforms of the multivibrator

the capacitor reaches V_c, it discharges with discharging resistance R_T [2], [22]. Therefore, the duration τ_{off} of the low level of multivibrator output depends on R_T and hence, on the ambient temperature T_{ref}. On the other hand, the duration τ_{on} of the high level depends on V_c and R_T, i.e., on the measured T_m and the ambient T_{ref} as well. In both cases, the relation is nonlinear as given in Eq. 1.

$$\{\tau_{on}, \tau_{off}\} = \left\{C_o(R_o + R_T)\ln\frac{1 - \frac{V_c}{2V_{cc}}}{1 - \frac{V_c}{V_{cc}}}, C_o R_T \ln 2\right\} \quad (1)$$

The output signal v_{out} is taken to an Arduino Uno microcontroller via its analog input pin A0. The microcontroller calculates τ_{on} and τ_{off} and feds them to a pre-trained ANN in the PC, which, based on every set of measured values of τ_{on} and τ_{off}, performs the task of nonlinear function approximation to determine the unknown temperature T_m to which the measuring junction of the thermocouple is exposed. With the inclusion of τ_{off} as one of the inputs to the ANN, any variation in the ambient temperature T_{ref} is taken into account.

1) ANN Configuration and Training: The architecture of the ANN has one hidden layer. The input layer, hidden layer and output layer consist of two, ten and one neurons respectively. Increasing the number of layers will increase the computational burden and may introduce a lag between input and output. Therefore, number of hidden layers was restricted to one. For this experiment, MATLAB's Neural Fitting [23] app was used, for ANN training.

The ANN is a simple feed-forward neural network. The activation function used in the hidden layer is sigmoid and in the output layer is linear.

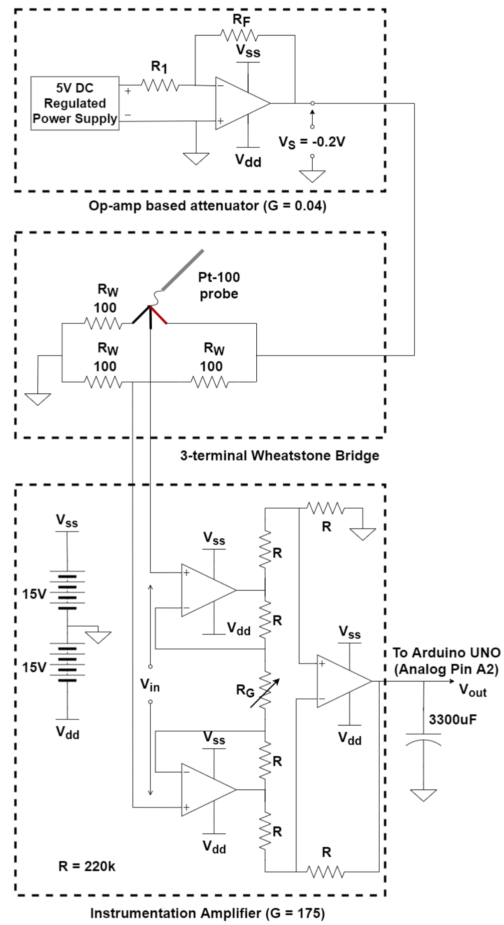

Fig. 4. Wheatstone bridge based automatic calibration arrangement

$$\mathbf{h} = sigmoid(W_h\mathbf{X} + b_h) \quad (2)$$

$$\mathbf{Y} = W_o\mathbf{h} + b_o \quad (3)$$

Eqn. 2 and Eqn. 3 represents the forward propagation equations. W_h and W_o are weight matrices of hidden layer and output layer respectively. b_h and b_o are weight matrices of hidden layer and output layer respectively. **X** and **Y** are input and output of neural network respectively. To achieve good generalization, the network training uses Bayesian Regularization algorithm for backpropagation, which computes weighted sum of squared error and weights. Although the algorithm is time-consuming, it can result in good generalization, which may give robust performance on difficult, small, or noisy datasets. For training the network and evaluating the output, the data available at hand was split into 5:2:3 for training, validation, and testing respectively. The ratio was so chosen because the sample size was small (5 features and less than 1000 samples). It is worth mentioning that the number of nodes in hidden layer was decided after multiple iterations of training the network.

B. Semi-automatic Calibration Arrangement

In the calibration circuit, as shown in Fig. 4, a Pt-100 temperature standard (with an accuracy of ±0.03°C), constitutes one arm of Wheatstone bridge arrangement. The output of the bridge circuit has a simple relation with the Pt-100 resistance, involving the other three bridge arm resistances and the bridge supply voltage. The RTD is exposed to the thermocouple measuring junction temperature T_m, i.e. the measured oven temperature. When sensor is put in calibration mode, the time spans τ_{on} and τ_{off} of the pulse train are measured by the microcontroller for different pre-decided values of the oven temperature setting (T_m) at regular intervals. From the measured output voltage of Wheatstone bridge, the RTD resistance is calculated by the microcontroller, and subsequently, the exact value of temperature T_m is obtained using the well-known resistance-temperature expression for the Pt-100 standard [2]. In this way, good amount of calibration data is collected automatically. The values of τ_{on} and τ_{off} are used to train the ANN, with T_m (read by the Pt-100) as the target. The training is done on the MATLAB platform on a PC. The trained ANN is now ready to measure an unknown value of T_m. Hence this scheme is aptly described as quasi-smart.

In the measurement phase, corresponding to every unknown combination of T_m and T_{ref}, the microcontroller measures the values of τ_{on} and τ_{off} and uses the pre-trained ANN to determine the unknown temperature. A preliminary simulation study of the proposed system has been studied using manufacturers' data for a T-type thermocouple and an NTC thermistor has been recently reported by the authors in a conference [24]. This paper reports few improvements and additional works over [24], namely, implementation of experimental setup of the model, successful validation of the hypothesis and development of semi-automatic calibration.

III. EXPERIMENTAL RESULTS

A temperature controlled oven, containing Pt-100 probe and hot junction of T-type thermocouple, serves as main experimental setup for the study. The cold junction of the thermocouple is exposed at ambient temperature. By what has been mentioned earlier, a thermistor with a declared nominal resistance of 5 $k\Omega$±5% at 25°C monitors this ambient temperature. The β(25°C/85°C) value for the thermistor is 3977K and power rating at 55°C is 100mW. For both the calibration phase and test phase of the setup, experimental studies have been carried out for the thermocouple's hot junction temperature varying over 55°C to 138°C. However, no attempt was made to maintain the cold junction temperature at specific values, but it was allowed to wander with the natural variation of the ambient (room) temperature. However, it was found that during the experimentation, the cold junction temperature of the thermocouple varied approximately from 28°C to 35°C. Hence the measurement is completely automated with the option of calibration as and when required. The arrangement, therefore, is free from any requirement of human observers for noting data. The ANN deployed, a feed-forward network has ten neurons in the single hidden layer. Five runs of the experiment were performed with five different temperature intervals, namely, 0.1°C, 0.2°C, 0.25°C, 0.5°C and 1°C. The actual sets of temperature values considered during calibration and during testing were mutually exclusive. For every hot junction temperature T_{act} indicated by the Pt-100 standard, the full-scale percent error in the temperature T_{meas} measured by the thermocouple was obtained.

$$\epsilon(\%) = \frac{T_{mes} - T_{act}}{FullscaleT_{act}} \times 100 \tag{4}$$

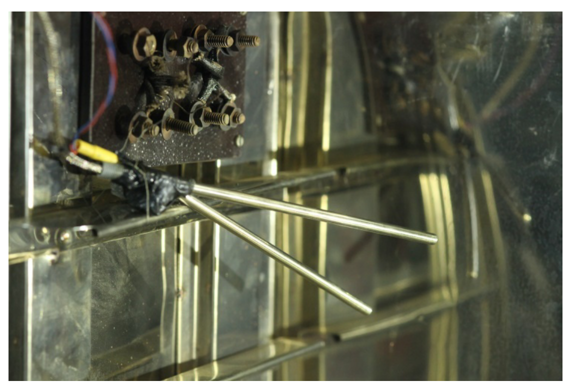

Fig. 5. Interior of the temperature controlled oven with Pt-100 and thermocouple sensors

where, the full-scale temperature is 138°C. This error has been plotted against the actual temperature T_{act}, in Fig. 6, for five different values of temperature resolution considered for calibration as well as testing.

It is observed that for temperature resolutions of 0.1°C, 0.2°C, 0.25°C, 0.5°C, and 1°C, the measurement error of temperature by the thermocouple, lies in the range of ±0.39%, ±0.25%, ±0.29%, ±0.28% and ±0.28% of full scale respectively. These percentage errors in measurement translate to a pessimistic estimate of at most ±0.5°C error in measurement over the temperature span covered. It can be well appreciated that calibration at temperature intervals less than 1°C is too stringent a condition to be practiced. Hence, the error obtained with a resolution of 1°C may be considered as the actual performance metric of the arrangement.

Now, it may not seem obvious from the experiment, that this process auto-calibrates the thermocouple sensor and is independent of the reference junction temperature. To test our hypothesis, we train a feed-forward neural network N, mapping **X** to **Y**. We now compute **Y'**, taking **X'** as the input. We find that the deviation **Y'**(=N(**X'**)) - **Y**(=N(**X**)) is negligible (order of 10^{-5}°C), where,

$$\mathbf{X} = [T_{on}, T_{off}, \mathbf{0}] \quad (5)$$

$$\mathbf{X'} = [T_{on}, T_{off}, T_{ref}] \quad (6)$$

$$\mathbf{Y} = T_m \quad (7)$$

Hence, we conclude that the accuracy of the predicted hot junction temperature T_{meas}, is independent of the reference junction temperature T_{ref}.

Table-1 compares the performance of the proposed system with respect to existing systems in the literature, vis-à-vis accuracy, temperature range covered, simplicity of hardware, etc. It can

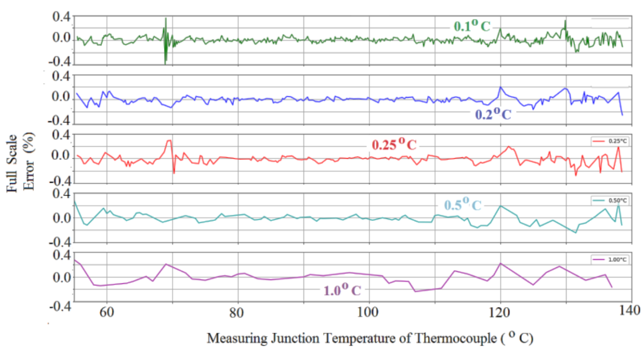

Fig. 6. Percentage Error in Measurement versus Temperature (ºC) for five different values of temperature resolution

be seen that some of the studies reported in recent times do not report anything about the range of temperature, that the cold junction is subjected to, during the experiment. One of the developed systems [8] utilizes a comparatively expensive AD590M sensor for sensing cold junction temperature. Apart from that, it involves sophisticated circuit components, for example, multiplexers, A to D converter, standard resistors etc. Also, no study reports the temperature standard used as ground truth, for computing the measurement error. The study, reported here, addresses these shortcomings. In addition to that, it reports exorbitant accuracy, with respect to Pt-100 temperature standard as ground truth. Lastly, as the calibration scheme is automated, the sensor can swiftly be re-calibrated for different ranges of temperature.

TABLE I
COMPARISON WITH EXISTING LITERATURE

Setup Details	**Temperature Range**	**Error/ Type of Thermo-couple**	**Comments**
Proposed approach	40ºC to 138ºC in step of 1ºC	±0.28%, i.e., ±0.38ºC for Type-T	Extremely good accuracy. Compact hardware. Low cost thermistor sensor for cold junction compensation. Automated arrangement permits calibration with fine resolution.
Processing by VFC and subsequent processing by a continued-fraction algorithm [21].	45ºC to 100ºC	±1.4ºC for Type-T	Simple hardware. Thermistor sensor for reference junction temperature. quasi-digital pulses output. Processor based software implementation. Good accuracy.
Employs inverse transfer LUT [10].	–100ºC to +1372ºC	±1ºC for Type-K	Hardware is highly complicated. Thus, very low reliability. Uses AD590M as reference temperature sensor.
Employs Radial Basis Function (RBF) based neural network [15].	0ºC to 1370ºC	–0.015ºC to +0.035ºC for Type-J and –0.2 ºC to +1.1 ºC for Type-K	Uses MATLAB and Labview. Uses inverse transfer to compute error.
Computation utilizing non-linearity characteristics in thermo-couples for reference junction compensation [9].	0ºC to 100ºC	±1 ºC for J, K and T type thermocouples	Acceptable accuracy. No reporting on cold junction compensation. Nothing has been stated about standard temperature transducers used.

IV. CONCLUSION

The proposed temperature sensing scheme is a low-cost system, consisting of T-type thermocouple lying at the heart of it. The system is very compact, making it suitable for embedded system applications. For processing the thermocouple signal, it uses IC555 based frequency converter circuit, whose quasi-digital output can be directly interfaced with a processor.

Few important properties of the system are,

(a) The system employs T-type thermocouple with a thermistor, for temperature sensing.

(b) The output of the multivibrator being quasi-digital pulses, it can be directly interfaced with a processor, without requirement of an ADC.
(c) The simplicity of the setup ensures its reliability and cost-effectiveness. In this connection, it is worthy to note that the cost of a thermistor is ten-fold less than the AD590 module usually employed for reference junction temperature sensing.
(d) The ON and OFF duration of the multivibrator output pulse train, and not the amplitude, contain information about both hot and cold junction temperatures. Thus, any attenuation or distortion of the pulse shape during communication does not affect the information.
(e) The measuring junction of the thermocouple can be exposed to a high temperature and then subjected to a natural fall in the temperature. The microcontroller can be programmed to take note of T_m, τ_{on}, and τ_{off} at regular time intervals. Thus manual intervention in setting the measuring junction temperature can be dispensed with, and the training data becomes ready automatically.
(f) The effect of aging of the circuit components can be mitigated by just performing the proposed automated calibration process.
(g) An extremely good accuracy of ±0.38°C has been achieved, and that too, over a reasonably wide range of temperature spanning from 55°C to 138 °C. Thus the measurement system becomes a candidate for use in vending machines for hot beverages, household water heaters, steam sterilizers for most commonly used medical devices (autoclaves) [25], [26], to cite a few.
(h) Whenever any major component/ parameter, e.g., the 555 IC is used, the system should be recalibrated, only if high accuracy is required. The merits of the presented scheme outweigh its demerit. Thus the presented quasi-smart temperature transducer outshines all other methods reported in recent times.

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