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Enhancing the Accuracy of Low-Cost Thermocouple Devices through Deep-wavelet Neural Network Calibration

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ABSTRACT (10 PT)

Data collection using thermocouple sensors on low-cost devices is susceptible to noise interference, leading to compromised data quality. Noise sources such as cold junction compensators, electromagnetic interference, and Johnson noise can significantly impact the reliability and accuracy of conventional measurements. This study aims to enhance the reading quality of thermocouple sensors on low-cost devices by employing a calibration method based on deep learning and a denoising process using wavelet transform. The proposed approach exhibits promising results, achieving a significant improvement in accuracy by 97.81% with a mean absolute error (MAE) of 0.2. Additionally, the denoising process effectively enhances the signal-to-noise ratio (SNR) quality, leading to an impressive increase of 97.67% with an SNR value of 105.29 dB. Performance analysis was carried out on National Instrument, and it was found that Deep-wavelet outperformed with an MAE value of 16.67% and 0.8% SNR. This research demonstrates that the integration of advanced techniques such as deep learning and wavelet transform-based denoising can significantly improve the accuracy and noise reduction capabilities of low-cost thermocouple devices. The findings provide a promising pathway for enhancing data quality in temperature measurements, allowing for reliable and cost-effective monitoring and analysis in various industries and applications.

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1. INTRODUCTION

Temperature is a fundamental parameter widely used in industry, manufacturing, and the environment for health. The wide use of these parameters has led to an increasing demand for accurate temperature measurement instruments. This is supported by data obtained from the global market, which estimates that the annual growth of temperature sensors will increase by 4.8% in 2027 [1], and it is estimated that the market of sensors will exceed 10 billion sensors/year in the next ten years [2]. The impact caused by the increased demand is the increase in the price of sensors with high accuracy resulting from the low availability of goods in the market. This has an impact on the increasing use of cheap sensors with low-quality accuracy.

The level of accuracy and reading range of the temperature sensor is influenced by the type of temperature sensor used, the use of thermocouple sensors is often used because of their high reading range capability and low price, rather than thermistors, which have low heat susceptibility and resistance temperature detectors (RTD) which have high prices [3]. The main problem found in thermocouple sensors is the presence of Johnson noise which is created due to thermal gradients at the reference junctions [4] caused by poor insulation, shielding, and temperature stabilization in thermocouple electronic devices, which causes thermal noise in the readings. In addition to the noise created on the thermocouple sensor, other noise created due to electromagnetic interference in electronic circuits and unstable input voltages due to ripple or poor grounding affects the quality of the readings produced [5].

In minimizing the presence of noise, several approaches have been taken, one of which is applying the Kalman filter algorithm to the denoising process [6], however, the process of implementing the Kalman filter is too dependent on the system dynamic model that is set at the beginning and is not effective on data that has high variation [7], an approach using a deep neural network has also been carried out to minimize the amount of noise contained in the thermocouple data and obtain a root mean squared error (RMSE) value of $1.19°C$ [8] but the presence of noise is still visible in the peak signal area. The use of Fast Fourier transform (FFT) in the denoising process is based on the observed frequency values [9], however, the denoising process using the Fourier transform has limitations in dealing with transient noise and frequency leakage, which are common in non-stationary signals such as sensor data readings. Moving average filter (MAF) is also used to minimize errors in thermocouple sensor readings to measure temperature in internal combustion engines with a maximum error value of 1.5% to 2% peak temperature [10], however, the MAF filtering process has limitations in multiresolution analysis because it treats all component frequencies in the signal evenly and does not respond well to non-stationary signals. The high fluctuation and noise generated by the thermocouple sensor cause conventional data acquisition techniques to be inaccurate and unusable.

In overcoming these problems, this research was conducted to improve the reading quality of the thermocouple sensor by using a deep neural network algorithm combined with the use of wavelet transform as a denoising signal reading method by providing a threshold based on the deviation value of the thermocouple sensor using a computer modeling program. By implementing these two techniques named Deep-wavelet, the identification of the mean absolute error (MAE) and signal-to-noise ratio (SNR) values will be used as basic metrics to determine the performance of the thermocouple sensor reading technique.

2. METHOD

Temperature measurements using thermocouple sensors often have low accuracy and precision as well as high noise caused by noise at the reference junction, poor shielding and insulation, unstable input voltage, and the effect of electromagnetic interference on the device module, which causes reliability and data quality using conventional methods has low accuracy and precision. The level of data reliability is inversely proportional to the noise level it has. The lower the deviation, the higher the level of data reliability.

This study aims to improve the quality and reliability of data using a wavelet transform to determine noise reduction and increase the SNR of the input signal using the ANN-based calibration method to obtain the lowest MAE value from the various methods used. Shown in Figure 1. The study began with a calibration process using a temperature-controlled water bath with an adjustable temperature to determine the value of the difference between the temperature readings from the measured sensor and the actual temperature, with repeated measurements made from 20°C to 73°C with a sampling frequency of 1 Hz, for five minutes. Data was collected using a 2-wire k-type thermocouple sensor with a probe length of 100mm and a diameter of 5mm made of stainless steel, which was connected to the 32-channel temperature Modbus module. The data is then calibrated using ANN by varying the activation function on the ANN architecture. The best activation function will be used as the activation function in ANN architecture, which will be continued for denoising using wavelet transform, with the research setup of the data collection process is shown in Figure 2.

Figure 1. Research setup

The study involves performance comparisons to assess accuracy, precision, errors, and data fluctuations across different module readings, including temperature measurements from low-cost devices and National Instrument-9213 (NI-9213) data. Specifically, the Deep-wavelet method's calibration and denoising capabilities were evaluated at temperatures ranging from 20℃ to 73℃ under steady-state conditions, considering each dataset's MAE, SNRdB, and uncertainty values. The Mean Absolute Error (MAE) was used to gauge accuracy and systematic errors, favoring lower MAE values to indicate superior calibration. Additionally, Signal-to-Noise Ratio in decibels (SNRdB) was employed to assess denoising performance, with higher values suggesting effective noise reduction. Evaluating uncertainty provided valuable insights into the technique's reliability and robustness for low-cost thermocouple measurements with Deep-wavelet. Ultimately, the comparison with NI-9213 and the application of Deep-wavelet showed significant implications for enhancing temperature measurements' accuracy and reliability, particularly when employing low-cost thermocouples. This research contributes to understanding calibration techniques, guiding informed decisions in selecting appropriate temperature measurement methods for real-world applications.

2.2. ANN

ANN is a computational model system created by mimicking the network pattern of the human brain so that it can recognize patterns and complex relationships in data [11], so the use of ANN in the calibration process using noisy data is suitable for use because of its ability to generalize and recognize outlier data [12]. ANN has an architecture consisting of layers of neurons with nodes connected. Interactions and relationships between each node in each layer have different weight and bias values that can function as regression or classification [13]. ANN performs learning through forward propagation to compute input values from data into initial node neurons to produce the expected output node output through a computational process of adding weight and bias to each neuron node through a specific activation function [14]. The performance test of the ANN uses the MAE shown in equation (1) as the accuracy test performance of the regression model, which is generally used because the model is due to intuitive interpretation of the model [15], the presence of this MAE represents the accuracy of the data.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|a_j^L - \hat{y}_i\right| \tag{1}$$

N : Number of samples in batch data

The accuracy performance of the ANN model is affected by the given activation function [16], in this calibration process, variations of the activation function are carried out by varying the activation function, namely rectified linear unit (ReLU), exponential linear unit (ELU), gaussian error linear unit (GELU), linear and leaky ReLU. The choice of the ReLU activation function is due to its ability to deal with vanishing gradients [17], ELU is used to prevent dying node neurons, and its robust ability to recognize noisy data [18], Linear is used to find out whether the simplification process can be used to ease model computation. Just like ELU, GELU is used to overcome dying node neurons with lighter computation than ELU, and the asymptotic behavior of GELU provides a more stable training process [19]. Equation simplification for computational process efficiency and prevention of dying node neurons is also found in LeakyReLU [20], stated in equation (2)-(6).

$$ReLU(z_j^L) = \begin{cases} 0 & for\ z_j^L < 0 \\ z_j^L & for\ z_j^L \geq 0 \end{cases} \tag{2}$$

$$ELU(z_j^L) = \begin{cases} \alpha \cdot (\exp(z_j^L) - 1), & for\ z_j^L < 0 \\ z_j^L \quad , & for\ z_j^L \geq 0 \end{cases} \tag{3}$$

$$GELU(z_j^L) = \frac{1}{2}\left(1 + erf\left(\frac{z_j^L}{\sqrt{2}}\right)\right) \tag{4}$$

$$Linear(z_j^L) = z_j^L \tag{5}$$

$$LeakyReLU(z_j^L) = \begin{cases} \alpha \cdot z_j^L, & for\ z_j^L < 0 \\ z_j^L \quad , & for\ z_j^L \geq 0 \end{cases} \tag{6}$$

Backward propagation is used to change the weight and bias values for each neuron node in all layers, which is obtained from the loss function error, the difference between the actual value and the predicted value.

[21], the mean squared error (MSE) function is used as the loss function in equation (9) instead of MAE because the error distribution of sensor readings has a gaussian distribution and not the Laplacian distribution [22].

2.3. Wavelet Transform

Wavelet transform is a mathematical technique for converting data from the time domain into the frequency domain in the form of the frequency domain, and the time domain makes it easier to perform multiresolution analysis than the Fourier transform, which only presents data in the form of the frequency domain [23]. Wavelet transform has more adaptability than Fourier transform in terms of noise suppression. This is because the threshold given to each coefficient is different at each level, which makes the use of Wavelet transform have various implementations [24]–[28].

Discrete Wavelet transform is a wavelet method that is more commonly used than continuous wavelet transform because it has lighter computations and makes it easier to do thresholding at each level [29]. The Haar wavelet transform is used because of its ability to perform noise suppression and light computation [30], which is shown in equations (6) and (7).

$$\varphi[n] = \begin{cases} 1, & if\ 0 \le n < \frac{N}{2} \\ -1, & if\ \frac{N}{2} \le n < N \\ 0, & otherwise \end{cases} \tag{6}$$

$$\phi[n] = \begin{cases} 1, & if\ 0 \le n < N \\ 0, & otherwise \end{cases} \tag{7}$$

N : Number of signal input
$\varphi[n]$: wavelet function at level-j and position-k
$\phi[n]$: wavelet scaling function at level-j and position-k

The thresholding calculation in equation (10) is used with VisuShrink based on the deviation value obtained in equations (8) and (9) by treating the global thresholding scheme by treating a single threshold for all wavelet coefficients, which is effective against additive noise that commonly occurs on the sensor [31].

$$M = J \times K \tag{8}$$

$$\hat{\sigma} = \frac{median\left(\left|cD_j\right|\right)}{0.6745} \tag{9}$$

$$T = \hat{\sigma}\sqrt{2\log M} \tag{10}$$

$\hat{\sigma}$: Signal deviation
K : Number of coefficient at level j
J : Number of level
T : Universal thresholding

The SNR equation measures the wavelet transform's denoising performance against the equation's actual value (12) and the uncertainty value is calculated using the mean deviation in equation (13) to find out the reliability data.

$$\mu = \frac{1}{N}\sum_{n=0}^{N-1} x[n] \tag{11}$$

$$SNR_{dB} = 10\log\left(\frac{\mu^2}{\sqrt{\frac{1}{N-1}\sum_{n=0}^{N-1}\left(x[n]-\mu\right)^2}}\right) \tag{12}$$

$$MAD = \frac{1}{N}\sum_{n=0}^{N-1}\left|x[n]-\left(\frac{1}{N}\sum_{n=0}^{N-1}x[n]\right)\right| \tag{13}$$

MAD : Mean absolute deviation
μ : Mean data

3. RESULTS AND DISCUSSION
3.1. Data calibration

The reading data of the thermocouple sensor connected to the module shows different offset variations to the actual temperature, as shown in Figure 2., and shows the presence of evenly distributed noise which shows the exact correlation as Nash et al. related to the presence of noise caused by sthe cold junction compensator in the amplifier contained in the thermocouple module [32], from the figure, it is kn own that the magnitude of the noise fluctuation is different at low temperature measurements with high temperatures, which is caused by the presence of Jonshon noise making the current flowing from the sensor to the thermocouple module fluctuate due to increased thermal energy and vibrations from the water as a reading environment [33].

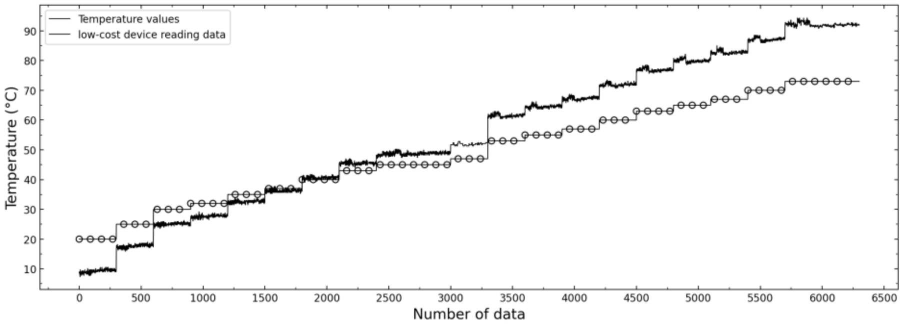

Figure 2. Research flowchart

Deep learning is used to reduce the presence of noise by varying the type of activation function in equations (4)-(8), with a two-layer architecture, eight neuron nodes in the first layer and one neuron node in the output layer with both layers having the same type of activation to be varied. The training process was carried out with an α value of 0.001 and i of 1000 iterations, shown in Figure 3. The ELU activation function has the lowest MAE value and GELU with a faster convergent time than the other four activation functions, showing the same results by Poulinakis et al [34] ELU, as an activation function, has high results when trained on data with high noise.

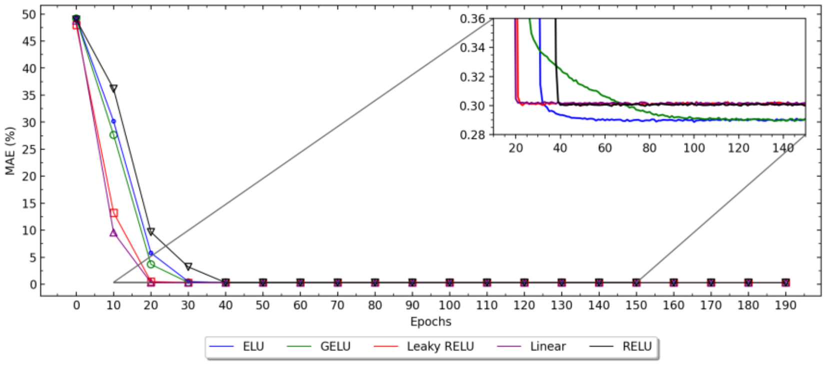

Figure 3. Activation functions MAE comparisons

3.2. Denoising signal

Data readings of thermocouple sensors that have been calibrated using deep learning are continued using wavelet transform as a denoising process with a J level value of 6 and a total N of 6300, with the decomposition results of the wavelet transform calculated using equations (2)- (6). The results of the wavelet decomposition process are shown in Figure 4., indicating that the value $cA_{6,k}$ shows the same trend as the input signal from Deep learning calibration, this is due to the value of $cA_{6,k}$ represents values at low frequencies. This is due to the sampling frequency in the data collection process, which is 1 Hz, which makes deep learning data emphasize the low-frequency trend in $cA_{6,k}$. In $cD_{5,k}$ high frequencies caused by fluctuations begin to appear. These fluctuations are caused by the presence of Johson noise and noise created from cold junction compensators on low-cost devices. The denoising process can be seen in each of the coefficients of $cA^{*}_{j,k}$ and $cD^{*}_{j,k}$ especially at high frequency, where the noise of the value of $cD^{*}_{6,k}$ can no longer be seen due to the influence of the denoising process.

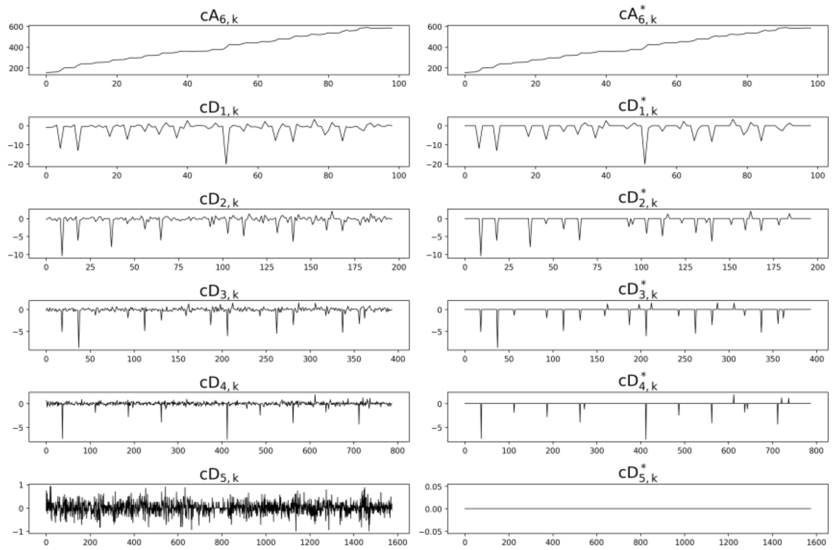

Figure 4. Deep-wavelet denoising process

Comparison of the initial measurements using the low-cost device, Deep-wavelet, and NI-9213 was carried out using the error plot graph shown in Figure 5., with the value of each point from Figure 5. The average value and deviation value of the total data collection in temperature varies from 20℃ to 73℃. Through this data, it is shown that the measurements made by the low-cost device have good measurements in the range of 37℃ to 40℃ with an offset value that gets bigger with every increase in temperature.

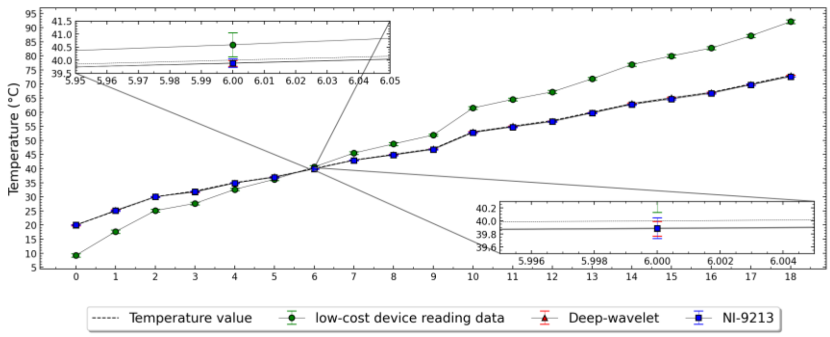

Figure 5. Deep-wavelet results

The calculation of MAE, SNR_{dB}, and uncertainty values is carried out at each temperature, and it is known that the performance of each measurement using the low-cost device, NI-9213, and measurements using Deep-wavelet is shown in Table 1. The average MAE value from the Deep -wavelet shows an advantage over other measurements of 0.2, as well as an increase of 97.61% from the initial measurement and 0.04 better than NI-9213, which indicates good calibration performance. The Deep-wavelet SNR_{dB} measurement is also superior to other measurements, which shows that the denoising process works well in increasing the reliability of the data with an increase of 97.67% and 6.73 dB better than NI-9213, but measurement uncertainty from NI-9213 0.02 is better than Deep-wavelet which informs that measurements using Deep-wavelet have high robustness and reliability even though they are perform through a low-cost thermocouple module device.

Table 1. Comparison of performances

Temperature value	**MAE**			**SNR_{dB}**			**Mean deviation**		
	Thermocouple Sensor reading	Deep-wavelet	NI-9213	Thermocouple Sensor reading	Deep-wavelet	NI9213	Thermocouple Sensor reading	Deep-wavelet	NI-9213
Average	8.59	**0.2**	0.24	40.07	**105.29**	104.45	0.4	0.16	**0.14**

4. CONCLUSION

This study investigated the quality of temperature measurements obtained from different devices, including low-cost thermocouple sensors, NI-9213, and measurements enhanced with a Deep-wavelet. The performance evaluation used Mean Absolute Error (MAE), Signal-to-Noise Ratio (SNRdB), and measurement uncertainty. The results demonstrated a significant advantage of the Deep-wavelet approach over other measurements, with an average MAE value of 0.2. This improvement marks an impressive 97.61% increase compared to the initial measurements and establishes Deep-wavelet as a superior calibration method for accurate temperature estimation. Moreover, the denoising process based on Deep-wavelet substantially enhanced the reliability of temperature data, leading to a remarkable 97.67% increase in SNRdB compared to the initial measurements.Additionally, Deep-wavelet outperformed NI-9213 by 6.73 dB, affirming its efficacy in noise reduction and data enhancement. While NI-9213 exhibited a slightly better measurement uncertainty by 0.02, deep-wavelet measurements' overall robustness and reliability on low-cost thermocouple devices were well-established. These findings underscore the potential of Deep-wavelet as a cost-effective and efficient solution for precise temperature sensing applications.

In conclusion, integrating deep learning calibration and wavelet-based denoising techniques presents a promising approach to improving temperature measurements on low-cost thermocouple devices. Deep-wavelet's significant enhancements in accuracy and noise reduction make it a valuable tool for enhancing data quality in temperature monitoring applications. As such, Deep-wavelet opens new possibilities for reliable temperature measurements in various industries and environments, providing valuable insights for research and real-world applications.

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