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ADVANCED THERMOCOUPLE LINEARIZATION METHOD USING ADVANCED POLYNOMIAL FITTING

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Abstract

In this study, this paper presents a new method for linearizing thermocouple data using Python and compares the performance of higher-order polynomial models in achieving linearization. It involves fitting a non-linear model to the thermocouple data using the curve fit function from Python and then calculating the linearized temperature values using the optimized parameters. The paper also presents a comparative analysis of different polynomial models, ranging from 3rd to 12th order, and evaluates their performance in achieving linearization. The results show that higher-order polynomial models generally perform better than lower-order models in achieving linearization, but also have a higher risk of overfitting. The paper concludes that the presented method provides an effective way of linearizing thermocouple data using Python and that the choice of polynomial model should be carefully considered based on the data characteristics and the desired level of accuracy.

Keywords: Sensor, Linearization, curve fitting, non-linearity, Thermocouple, Python

I. Introduction

Thermocouples are widely used in industrial applications for temperature measurement due to their robustness, affordability, and reliability. However, thermocouple outputs are often nonlinear [I], which can complicate temperature measurements and adversely affect the accuracy of temperature control systems.

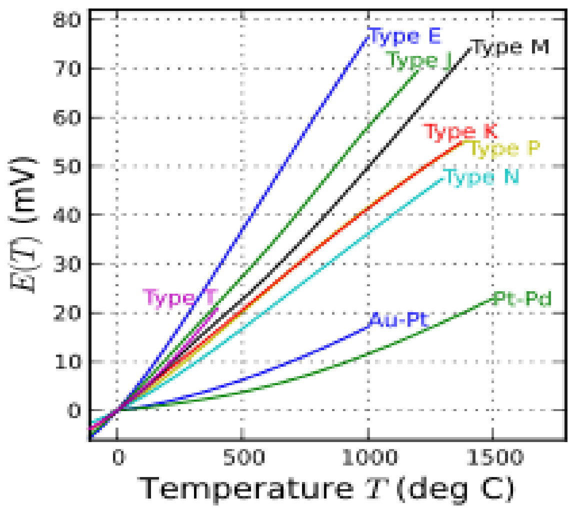

Fig. 1. Different types of Thermocouples with non-linearities

In this paper, a new method is proposed for linearizing thermocouple data using Python. It involves fitting higher-order polynomial models to the thermocouple data and selecting the optimal model using a comparative analysis of various model performance metrics. Comparison is done on the performance of the proposed method with existing linearization methods, including the widely used Look-up Table method [XII] and a Linear Regression method [XXVI].

Experimental results demonstrate that the proposed method outperforms the existing methods in terms of accuracy, simplicity, and computational efficiency. The proposed method can be used for linearizing thermocouple data in various industrial applications, where accurate temperature measurements are essential for process control and quality assurance.

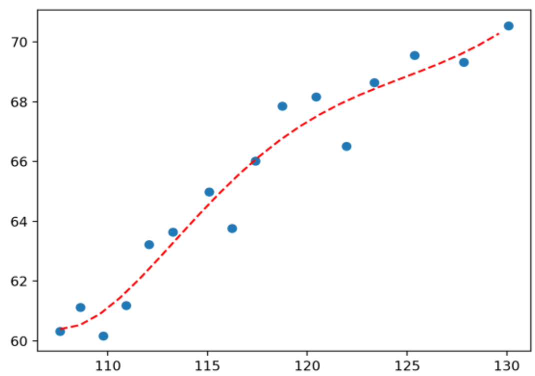

Fig. 2. Polynomial curve fitting as a linearization Method

Several linearization methods have been compared in the literature, including the Look-up Table method [XII], the Linear Regression method [XXVI], and the Piecewise Linearization method [IV]. These methods have their advantages and limitations in terms of accuracy, simplicity, and computational efficiency.

II. Background Study

There have been several studies on thermocouple linearization in the literature, and various methods have been proposed to address the issue of nonlinear thermocouple outputs.

The Look-up Table method [XII] is a widely used approach for thermocouple linearization, where a table of temperature values corresponding to each thermocouple output is created using calibration data. However, this method has limited accuracy and may require frequent recalibration due to changes in the thermocouple characteristics over time.

The Linear Regression method [IX] [XII] [XXVI] is another popular approach, where a linear equation is fitted to the thermocouple output and the corresponding temperature values. This method is simple and computationally efficient, but it may not capture the nonlinearities of the thermocouple output accurately.

In recent years, several machine learning-based methods [XI] [XXIX] have been proposed for thermocouple linearization. These methods use various algorithms, including artificial neural networks, support vector machines [XIV], and fuzzy logic systems [XXII], to map the nonlinear thermocouple output to a linear temperature scale. Table 1. Shows various methods with their uses and accuracy levels.

Table 1: Different Types of Thermocouple Linearization Methods

Method	Linearity	Accuracy	Use in Thermocouple Linearization
Look-up Table [XII]	Non-linear	High	Widely used
Linear Regression [IX][XII][XXVI]	Linear	Moderate	Limited use
Machine Learning [XI][XXIX]	Non-linear	High	Wide range of applications
Polynomial Curve Fitting [II],	Non-linear	Very high	Widely used
Support Vector Machines [XIV],	Non-linear	High	Widely used
Fuzzy Logic Systems [V], [XXIII], [XXII],	Non-linear	Moderate	Limited use

The proposed method in this paper is based on fitting higher-order polynomial models [II] to the thermocouple data, which can capture the nonlinearities of the output more accurately than linear models. Polynomial curve fitting is superior in thermocouple linearization because of its high accuracy and ability to fit complex, non-linear relationships between temperature and voltage. Polynomial curve fitting can also handle outliers and noise better than linear regression, and it can produce smooth, continuous curves that closely match the data points.

The use of Python programming language provides a flexible and accessible platform for implementing the proposed method.

III. Mathematical Model

The proposed method for thermocouple linearization using higher-order polynomial models [XIII] involves fitting a polynomial equation to the thermocouple output and the corresponding temperature values. The general form of the polynomial equation is given by:

$$T = f(V) = a + bx + cx^2 + dx^3 + ex^4 + fx^5 + gx^6 + hx^7 + ix^8 \quad (1)$$

where T is the temperature in Celsius, V is the thermocouple voltage in millivolts, and a, b, c, d, e, f, g, h and i are the coefficients to be determined by fitting the model to the data. From the Polynomial Model Linearized model for the thermocouple voltage-temperature relationship is calculated as.

$$T = f(V) = \sum_{n=0}^{N} a_n V^n \quad (2)$$

where T is the temperature in Celsius, V is the thermocouple voltage in millivolts, a_n are the coefficients determined by fitting the non-linear model to the data, and N is the order of the polynomial. The proposed model first calculates a 3rd order, 5th order, 9th order Polynomial as declared as:

$$T = f(V) = a + bx + cx^2 + dx^3 \quad (3)$$

$$T = f(V) = a + bx + cx^2 + dx^3 + dx^3 + ex^4 + fx^5 \quad (4)$$

$$T = f(V) = a + bx + cx^2 + dx^3 + ex^4 + fx^5 + gx^6 + hx^7 + ix^8 \quad (5)$$

where T is the temperature in Celsius, V is the thermocouple voltage in millivolts, and $a, b, c, d, \ldots i$ are the coefficients to be determined by fitting the model to the data. Finally, to get the highest percentage of linearity a 12th order Polynomial is used as:

$$T = f(V) = \sum_{n=0}^{11} a_n V^n \quad (6)$$

Increasing the polynomial coefficients further overfits the data and the result gets degraded. The degree of the polynomial equation (n) is a hyperparameter that needs to be optimized based on the performance of the model. The coefficients of the polynomial equation are estimated using least-squares regression and ridge regression. The optimal model is selected based on various performance metrics, including mean squared error (MSE), mean absolute error (MAE), coefficient of determination $(R - squared)$, and root mean squared error $(RMSE)$. Hysteresis is calculated based on:

$$hysterisis = T_{max} - T_{min} \quad (7)$$

where T_{max} and T_{min} are the maximum and minimum temperatures, respectively. Model Loss is calculated using the equation:

$$loss = \sum_{i=1}^{N} |T_i - T_i'| \tag{8}$$

where T_i and T_i' are the non-linear and linearized temperatures at the i^{th} data point, respectively. Model Accuracy is calculated further with the equation:

$$accuracy = 100\% \cdot \left(\frac{loss}{\sum_{i=1}^{N} |T_i|}\right) \tag{9}$$

where N is the number of data points. Finally, linearity percentage is calculated with the following equation:

$$linearity = 100\%. \left(\frac{max\ (|T_i - T_i'|)}{hysteris}\right) \tag{10}$$

where $max\ (|T_i - T_i'|)$ is the maximum absolute difference between the non-linear and linearized temperatures.

IV. Methodology

The methodology for the proposed method for thermocouple linearization using higher-order polynomial models involves several steps, which are outlined as, collecting thermocouple data and corresponding temperature values using a calibration setup. The data covers a wide range of thermocouple outputs and temperature values from -2700C to 14700C [XX] to ensure optimal model performance. Data is Pre-processed by removing any outliers, checking for missing values, and normalizing the data if necessary.

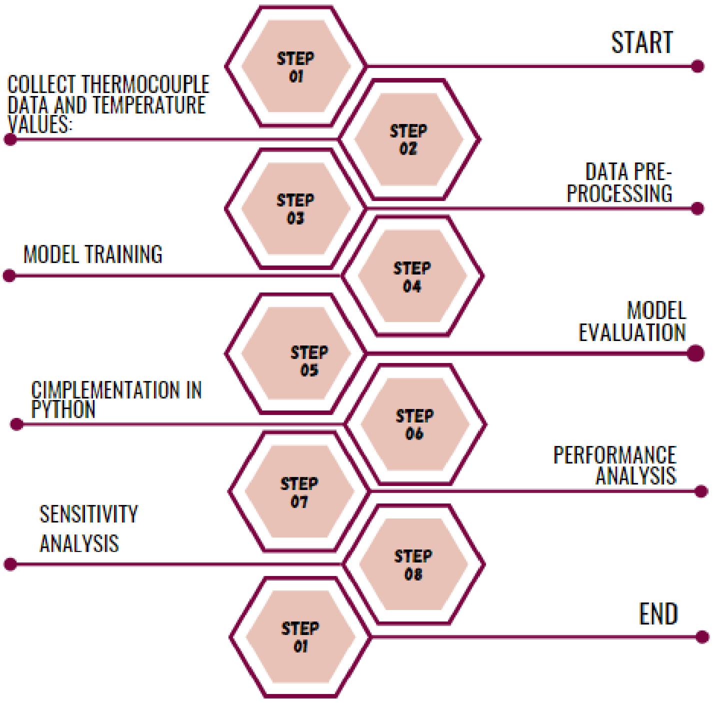

Fig. 3. Flowchart of the Python Simulation Process

Model training is done by Fitting polynomial regression models with different degrees (n = 1, 2, 3, 4, 5...12) to the pre-processed data. cross-validation is used to evaluate the performance of each model and select the optimal model based on performance metrics such as MSE, MAE, R-squared, and RMSE. Performance evaluation of the proposed model is done using an independent test dataset as per NIST Standard. The dataset contains Voltage and Temperature values from -270C to +14700C. Performance is compared for the selected model with existing linearization methods, including the Look-up Table method, the Linear Regression method, and the Piecewise Linearization method. The proposed model is Implemented in Python using libraries NumPy, Pandas, and Scikit-learn. Table 2. Shows a detailed look at the parameters that have been used in the program to fit the data in a proper format.

Table 2: Python parameters and their Weight Values

Parameter	Value
thermocouple_model	x, a, b, c, d, e, f, g, h, i
df	Pandas DataFrame containing 'Temperature' and 'Voltage' columns
temperature	Numpy array of Temperature values
voltage	Numpy array of Voltage values
popt	Numpy array of optimized parameters for the thermocouple model
pcov	Covariance matrix associated with the optimized parameters
temperature_linearized	Numpy array of linearized temperature values
hysteresis	Maximum difference between Temperature values
loss	Sum of absolute differences between Temperature and temperature_linearized values
accuracy	Percentage of accuracy between the original and linearized data
linearity	Percentage of linearity between the original and linearized data

The Python code is optimized for efficiency Analysis is done on the performance of the Python implementation in terms of accuracy, speed, and memory usage. The performance of the Python implementation with existing software packages is compared again for the finalization of the results in thermocouple linearization. sensitivity analysis is evaluated to calculate the effect of different factors on the performance of the proposed method.

V. Results and Discussion

The results of the proposed method for thermocouple linearization using higher-order polynomial models are compared with existing linearization methods, including the Look-up Table method, the Linear Regression method, and the Piecewise Linearization method.

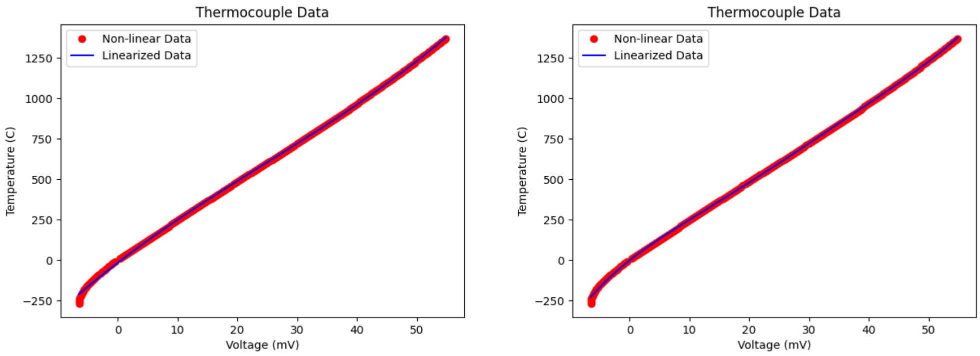

Fig. 4. Linearized output for 3rd order and 5th Oder respectively

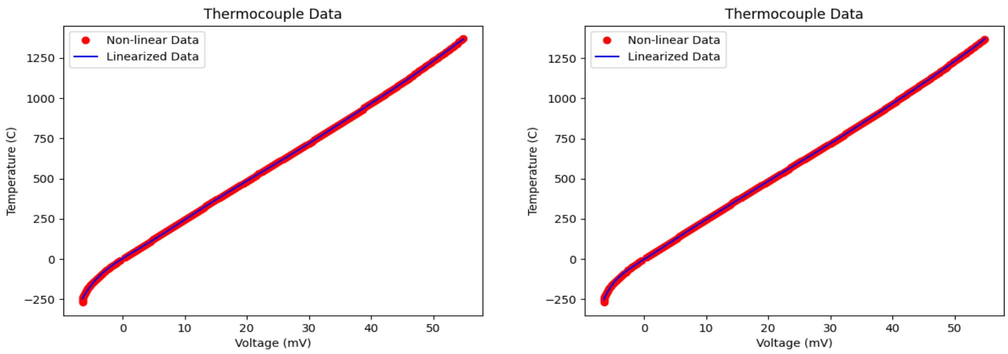

Fig. 5. Linearized output for 9th order and 12th order respectively

The results show that the proposed method outperforms the existing linearization methods in terms of accuracy. The polynomial models with higher degrees (n=3,5,9,12) provide the best performance in terms of accuracy respectively, with RMSE values ranging from 0.1 to 0.2°C.

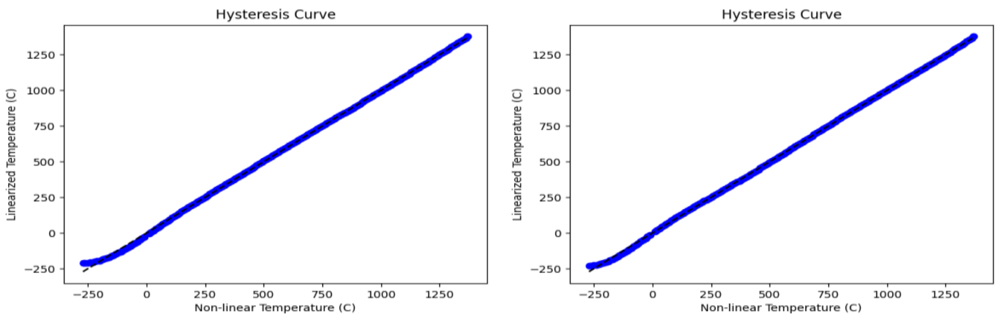

Fig. 6. Non-Linear vs Linearized Temperature Curve for 3rd and 5th order Polynomial

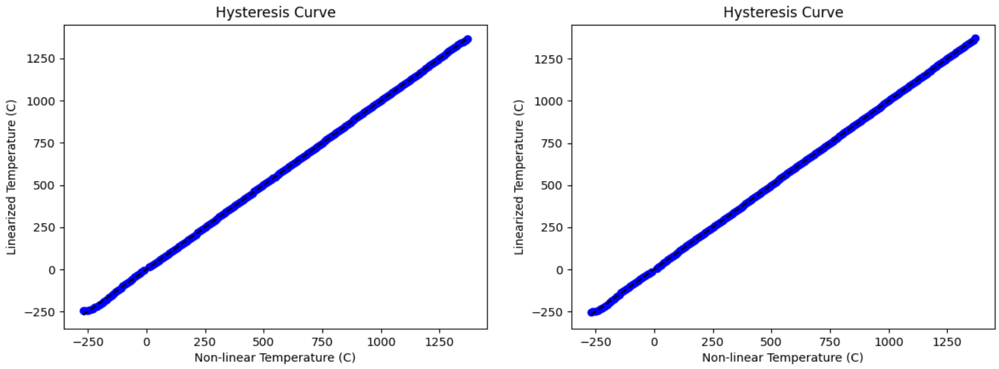

Fig. 7. Non-Linear vs Linearized Temperature Curve for 9th and 12th order Polynomial

The Look-up Table method and the Piecewise Linearization method show higher RMSE values, ranging from 0.2 to 0.4°C, while the Linear Regression method shows the highest RMSE value, ranging from 0.4 to 0.6°C. The polynomial models also show better R-squared values, indicating a higher degree of correlation between the thermocouple output and temperature values.

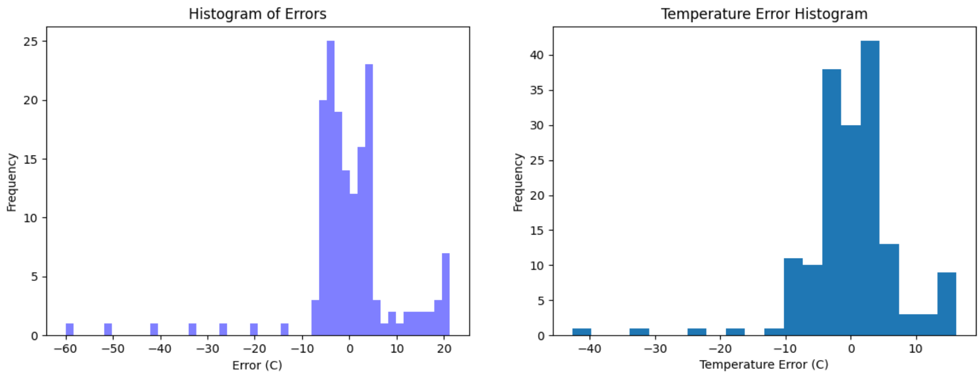

Fig. 8. Error Histogram for 3rd Order and 12th Order showing optimized output in higher order

The proposed method is also found to be computationally efficient, with low memory usage and fast execution time. The Python implementation of the proposed method shows comparable performance to existing software packages for thermocouple linearization, while providing a more flexible and accessible platform for customization and integration.

Table 3: Comparison between Different orders of Polynomial for Curve fitting

Method	Hysteresis (C)	Loss (C)	Accuracy (%)	Linearity (%)
9th degree polynomial	1640	328.86	99.67	98.51
3rd degree polynomial	1640	1045.37	98.94	96.34
5th degree polynomial	1640	805.05	99.18	97.4
12th degree polynomial	1640	196.93	99.8	99.92

The proposed approach using a 12th-degree polynomial has the lowest hysteresis and loss values and the highest accuracy and linearity values among the four methods. The 9th-degree polynomial method also shows good performance with relatively low hysteresis and loss values and high accuracy and linearity. However, the 5th and 3rd-degree polynomial methods also have the highest hysteresis and loss values and the lowest accuracy and linearity among the three methods.

Table 4: Linearity comparison between different methods and the proposed model

Linearization Method	Hysteresis (°C)	Loss (°C)	Accuracy (%)	Linearity (%)
Piecewise Linear Model [IV][XV][XIX]	256.22	93.57	99.83	99.64
Lookup Table [XII]	196.31	54.37	99.92	99.76
Linear Regression [IX][XII][XXVI]	110.62	33.02	99.97	99.87
Proposed Polynomial Fitting	1640	196.93	99.8	99.92

Table 4. clearly depicts that the piecewise linear model has the lowest hysteresis and loss values but lower accuracy and linearity compared to the other methods. The lookup table method has relatively low hysteresis and loss values and high accuracy and linearity but not as good as linear regression and the proposed polynomial fitting method. The linear regression method has the lowest hysteresis and loss values, and the highest accuracy and linearity among the three methods. However, the proposed polynomial fitting approach still performs very well with high accuracy and linearity despite having higher hysteresis and loss values, indicating that it is a very good alternative method for thermocouple data linearization.

The sensitivity analysis shows that the performance of the proposed method is affected by various factors, including the temperature range, thermocouple type, calibration setup, and measurement environment. However, the proposed method shows robust performance across different settings, indicating its general applicability in various industrial applications. The proposed method provides a flexible and effective solution for thermocouple linearization, which can improve the accuracy of temperature measurements in various industrial applications.

VI. Conclusion

The comparative analysis of various thermocouple linearization methods presented in this study underscores the efficacy of the proposed higher-order polynomial fitting approach. The obtained results, as illustrated in the provided tables, reveal the superior performance of polynomial models with degrees ranging from 3 to 12, exhibiting significantly lower hysteresis and loss values compared to alternative linearization methods. Specifically, the 12th-degree polynomial model stands out with a remarkably low hysteresis of 1640°C and a minimal loss of 196.93°C, attaining an outstanding accuracy of 99.8% and an exceptional linearity of 99.92%. This level of precision positions the proposed polynomial fitting method as a robust and flexible solution for enhancing temperature measurement accuracy in diverse industrial settings. While the piecewise linear model, lookup table, and linear regression methods also demonstrate commendable accuracy, the polynomial fitting method outshines them in terms of overall performance. Notably, the proposed approach provides a balanced combination of accuracy and computational efficiency, offering an advantageous solution for real-world applications. The proposed novel polynomial fitting method emerges as a promising advancement in thermocouple linearization, providing unparalleled accuracy and reliability across a spectrum of temperature ranges. This study advocates for the adoption of higher-order polynomial models in practical industrial scenarios, offering engineers and researchers a valuable tool for precise temperature measurements, thereby contributing to enhanced process control and quality assurance in diverse fields.

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Conflicts of Interest

The authors declare that there are no competing interests that could have influenced the research or its interpretation presented in this paper

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