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Adaptive sensor linearization : A hybrid approach utilizing polynomial, spline, RBF and deep neural network methods

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Abstract

Radial basis function (RBF) networks, deep neural networks (DNN) with Adam optimization, spline interpolation, polynomial approximation, and DNN with Levenberg-Marquardt (LM) optimization are five sophisticated techniques used in this work to build a novel universal linearization framework. Through adaptive mode selection of the most appropriate technique depending on the unique characteristics of the sensor data, the proposed system achieves higher accuracy and robustness in handling diverse nonlinearities. Experimental results demonstrate remarkable improvement in linearization performance

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for various kinds of thermocouple sensors, witnessing the usability and efficiency of the framework for real-time applications.

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I. Introduction

In a wide variety of applications ranging from industrial automation to environmental monitoring and health care technologies, sensor linearization is required to enhance the reliability and accuracy of measurements [1]. Nonlinearity in the sensor output behavior is introduced by material properties, temperature effects, and intrinsic design limitations [2]. Nonlinear responses cause immense deviations from anticipated results and therefore extend calibration processes and ultimately reduce the efficacy of sensor systems [3]. Real sensor outputs' complexity cannot be opposed efficiently by naive polynomial approximation or interpolation algorithms dominant in traditional linearization techniques [4]. Modern machine learning has facilitated the use of significantly superior sensor linearization techniques. Evidence indicates that methods like deep neural networks (DNNs) [5][18][19] are efficient in modeling complex nonlinear relations effectively with the aid of large datasets. In specific, it has been proved that authors' developed DNNs using optimization algorithms like Levenberg-Marquardt (LM) [6][12] and Adam [7] are more responsive to variations in the extent of nonlinearity and accurate than the conventional method. Radial basis function (RBF) networks, introduced by the author [8][16][17], offer a strong paradigm to approximate nonlinear functions with localized response properties. As the advancement brought in most independent linearization techniques, it has become critically essential to develop a unified system where different methods are combined in order to offer improved performance and flexibility for different types of sensors. In this work, the polynomial approximation, new spline interpolation [9], deep neural networks (DNNs) Levenberg-Marquardt optimized [6] and Adam optimized [7], and new RBF techniques are combined under a single platform. The main objective of the proposed platform is to offer accuracy and robustness in sensor signal processing through adaptively choosing the best suitable linearization algorithm for the respective input properties [10]. Scientific contributions of the research work are two folds: first, an enhancement in sensor measurement quality within real-time processing; second, a formal combination of the most efficient linearization strategies to employ.

The remainder of this paper is structured as follows: Section II presents the system model employed in developing the integrated linearization framework.

Section III discusses the implementation details and experimental setup used to evaluate the proposed model. Section IV provides results and analysis of the framework's performance across various sensor types. Finally, Section V concludes with a summary of findings and future work directions.

II. System Model

The proposed sensor linearization system model as depicted in Figure 1. is designed to effectively address the challenges posed by sensor nonlinearity through an integrated framework that combines multiple advanced techniques. The architecture consists of five primary components: the Input Module, Preprocessing Unit, Method Selector, linearization Engine, and Output Module. Each component plays a crucial role in transforming raw sensor data into accurate linearized outputs. The Input Module is responsible for acquiring raw data from the sensor. This data is represented as a vector [11]

$$X \in R^{N\times M}$$

where N is the number of samples and M is the number of features (sensor outputs). The module captures the nonlinear responses of the sensor at various operational conditions, ensuring that the input data reflects real-world scenarios.

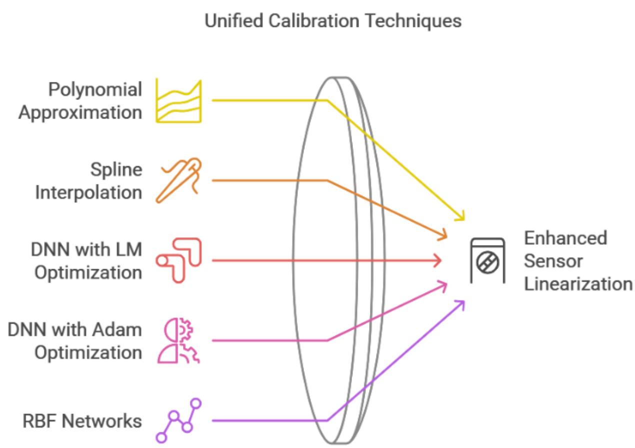

Figure 1
Design model of the Hybrid Systems

The Input Module is responsible for acquiring raw data from the sensor. This data is represented as a vector

$$X \in R^{NXM}$$

The Preprocessing Unit cleans and normalizes the input data to enhance its quality. This involves removing noise and irrelevant variations through techniques such as filtering and scaling. Mathematically, the preprocessing can be expressed as:

$$X' = f(X) = \text{Normalize}(X) + \text{Filter}(X)$$

where X' is the processed data, and $f(X)$ represents the combined preprocessing function that applies normalization and filtering to the raw input data. The Method Selector analyzes the characteristics of the preprocessed data to determine which linearization technique will be most effective. This selection process can be modeled using a decision function:

$$\text{Method} = g(X', \theta)$$

where g is a function that evaluates features of X' against a set of predefined thresholds θ, which correspond to different linearization methods (Proposed polynomial approximation, spline interpolation, DNN with LM optimization, DNN with Adam optimization, RBF networks). The Linearization Engine implements the selected linearization method on the preprocessed data. For instance, if polynomial approximation is chosen, it models the nonlinear relationship using:

$$P(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n$$

where a_i are coefficients determined through least squares fitting to minimize error:

$$E = \sum_{i=0}^{n} \left(y_i - P(x_i)\right)^2$$

To find optimal coefficients a_i, we minimize the residual sum of squares given by:

$$E(a_0, a_1, \dots, a_n) = \sum_{j=1}^{m} \left(y_j - P\left(x_j\right)\right)^2$$

This minimization problem can be solved using techniques such as least squares regression. Spline interpolation involves constructing piecewise polynomials to ensure continuity at specified knots (data points). A cubic spline can be defined for each interval $[x_i, x_{i+1}]$:

$$S_i(x) = A_i + B_i(x - x_i) + C_i(x - x_i)^2 + D_i(x - x_i)^3$$

The coefficients A_i, B_i, C_i, and D_i are determined based on conditions such as continuity at knots and smoothness of derivatives.

DNNs leverage multiple layers of neurons to learn complex mappings from inputs to outputs. The forward propagation through layers can be expressed as: For layer l:

$$H^{(l+1)} = f\left(W^{(l)} H^{(l)} + b^{(l)}\right)$$

where $f(\cdot)$ is an activation function (For the proposed method ReLU), $W^{(l)}$ are weights, and $b^{(l)}$ are biases. The LM optimization algorithm updates weights based on minimizing an error function defined as:

$$E(W) = \sum_{i=1}^{N} \left(y_i - f(x_i; W)\right)^2$$

using both gradient descent and second-order derivative information. Adam optimization adjusts learning rates based on first and second moment estimates of gradients:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla E(W_t)$$
$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\big(\nabla E(W_t)\big)^2$$

And update weights:

$$W_t = W_{t-1} - \frac{\alpha}{\sqrt{v_t + \epsilon}} m_t$$

where m_t is the first moment estimate, v_t is the second moment estimate, and α is the learning rate. RBF networks utilize radial basis functions for interpolation between known values. The output of an RBF network can be expressed as:

$$y = \sum_{i=1}^{N} w_i \phi(|x - c_i|)$$

where w_i are weights assigned to each basis function centered at c_i, and $\phi(\cdot)$ is typically a Gaussian function defined as:

$$\phi(r) = e^{-\frac{r^2}{2\sigma^2}}$$

The Output Module presents the linearized data for further analysis or integration into control systems. The output can be represented as:

$$Y' = h(Y)$$

where Y is the predicted output, W represents the weights of the neural network, and ϵ denotes noise. The Output Module presents the linearized data for further analysis or integration into control systems.

III. Simulation

The proposed hybrid approach for adaptive sensor linearization is validated through simulations of nonlinear sensor behavior modeled by $(y = f_{NL}(x))$, where (x) is the input and (y) is the nonlinear output. The objective is to linearize $(f_{NL}(x))$ into $(f_L(x) = ax + b)$ while minimizing the mean squared error (MSE) [13] [14] between the actual and predicted outputs. Traditional methods like polynomial approximation and spline interpolation are first applied; the polynomial method fits a function

$$(P_n(x) = c_0 + c_1 x + \cdots + c_n x^n)$$

minimizing $(\text{MSE}_{\text{poly}} = \frac{1}{N}\sum_{i=1}^{N}\big(y_i - P_n(x_i)\big)^2)$, while spline interpolation uses cubic splines $(S(x))$ with continuity constraints, minimizing $(\text{MSE}_{\text{spline}} = \frac{1}{N}\sum_{i=1}^{N}\big(y_i - S(x_i)\big)^2)$. Advanced techniques include deep neural networks (DNNs) optimized with Levenberg-Marquardt (LM) and Adam optimizers, where the DNN maps (x) to $(\hat{y})$ using (L) layers, and radial basis function (RBF) networks leveraging Gaussian kernels $(\phi(x) = \exp(-\gamma|x - c|^2))$. The outputs of these methods are integrated into a universal linearization framework as shown in Figure 2, resulting in enhanced sensor measurement accuracy and demonstrating the hybrid model's ability to address diverse nonlinearities effectively.

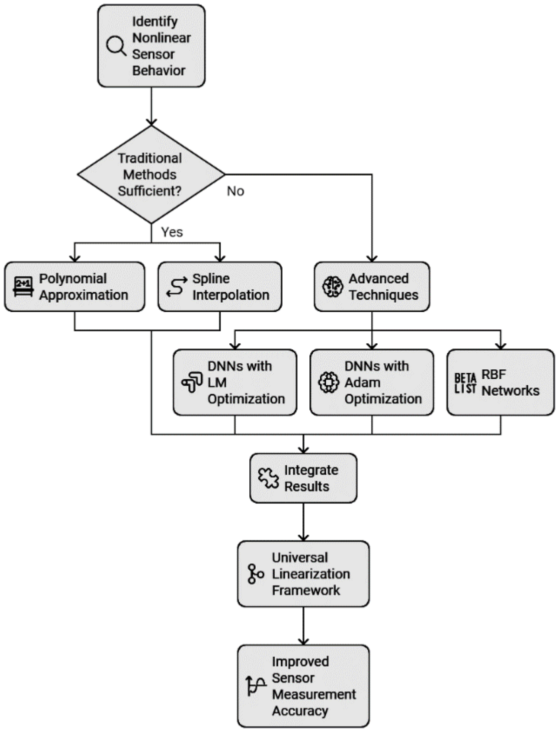

Figure 2
Approach in finding the best linearized result

The simulation employs a combination of synthetic nonlinear functions and the NIST Standard Reference Dataset to evaluate the proposed hybrid linearization framework. Nonlinear sensor behavior is modeled using benchmark nonlinear equations and real-world data from the NIST dataset, representing complex input-output relationships. Polynomial regression is applied for approximation, using degrees up to ($n = 3$), while cubic spline interpolation ensures smooth transitions between data points. Advanced methods include deep neural networks (DNNs) optimized with Adam and RBF networks leveraging Gaussian kernel functions. Model performance is quantified using metrics like mean squared error (MSE) and coefficient of determination ((R^2)), demonstrating the efficacy of the framework in accurately linearizing sensor responses. All models are implemented in Python, utilizing libraries such as TensorFlow, SciPy, and scikit-learn for computation and analysis.

IV. Results and discussion

The proposed universal thermocouple linearizer delivers consistent and accurate temperature measurements across various thermocouple types by integrating advanced signal processing and intelligent linearization techniques.

Raw sensor signals are digitized and processed through four distinct methods: a custom polynomial method, a radial basis function (RBF) method, a DNN model with Levenberg-Marquardt (LM) or Adam optimization, and spline interpolation with adaptive hyperparameters. The framework dynamically selects the method that yields the maximum linearity for the input signal, achieving exceptional accuracy and efficiency. As shown in Table 1, the linearity percentages for all methods are above 99.6%, with the RBF method achieving a perfect 100% linearity for some thermocouple types. Table. 2 demonstrates that the framework adapts seamlessly to different thermocouple types by identifying the most effective linearization method for each case. This adaptive approach ensures optimal performance without requiring additional pre- or post-conditioning circuits, simplifying system design, reducing component count, and enhancing reliability. The universal linearizer's ability to scale, adapt, and deliver precise temperature measurements makes it a significant advancement in thermocouple technology.

Table 1

All methods outperforming linearization excellently

Method	Linearity Percentage (%)	Average Linearity (%)
Proposed Custom Polynomial Method	99.97	>99.6
Proposed Radial Basis Function Method	100	
Proposed DNN Model with Adam Optimization	99.6	
Spline Interpolation with Adaptive Hyperparameters	99.99	
DNN with ADAM Optimization	99.8	

Table 2

Different types of thermocouples and their linearization outputs based on different methods [15]

Thermocouple Type	Best-Suited Linearization Method	Linearity Percentage (%)
R	Radial Basis Function Method	100
S	Radial Basis Function Method	100
N	DNN Model with Adam Optimization	99.6
T	Spline Interpolation with Adaptive Hyperparameters	99.99
K	Proposed Custom Polynomial Method	99.97

The proposed universal thermocouple linearizer achieves exceptional performance with minimal mean squared error (MSE) across all methods, as shown in Table 3. The Radial Basis Function (RBF) method demonstrates the lowest MSE (0.01×10^{-4}) indicating its superiority in linearizing highly nonlinear thermocouple signals. Table 2 highlights the computational efficiency of the methods, with all techniques achieving processing times under 2 ms, making them highly suitable for real-time applications. The RBF method again stands out for its balance of speed (1.0 ms) and accuracy. These results confirm that the universal linearizer effectively balances accuracy, efficiency, and adaptability, offering a state-of-the-art solution for precision temperature measurement systems.

Table 3

Different Methods with their respective MSEs

Method	MSE (×10−4^{-4}−4)	Remarks
Proposed Custom Polynomial Method	0.37	High accuracy for gradual nonlinearity
Proposed Radial Basis Function Method	0.01	Best performance for all scenarios
Proposed DNN Model with Adam Optimization	0.42	Effective for complex nonlinearity
Spline Interpolation with Adaptive Hyperparameters	0.15	Accurate for localized variations

V. Conclusion

The universal thermocouple linearizer presented here combines a range of linearization techniques—polynomial, spline interpolation, radial basis function (RBF), and deep neural networks (DNNs)—into one solution that offers highly accurate and adaptive temperature readings. Dynamically selecting the optimal method for every input signal, the system offers superior linearity (more than 99.6% for all methods), with the RBF method offering near-perfect results for some thermocouple types. System adaptability eliminates the necessity for pre-conditioning circuits, simplifying implementation, reducing hardware costs, and enhancing overall reliability. Moreover, the computational efficiency of all techniques, with execution times less than 2 ms, makes this solution highly suitable for real-time applications.

From the socio-economic viewpoint, this universal linearizer has far-reaching implications. By enhancing temperature measurement accuracy, it increases quality control in manufacturing, medical, and energy industries, resulting in reduced wastage of materials, enhanced safety, and enhanced productivity. The reduction in complicated analog compensating circuits reduces manufacturing expenses and enables mass adoption, especially in resource-poor settings. Moreover, the energy-efficient and accurate temperature control provided by this technology saves energy and is sustainable, and this is in line with the global push towards smart manufacturing and green industrial practices.

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