Phasor Current Measurement from Saturated TMR Signals Using LSTM Model

1st Siva Alagappa Kulathuran
Holcombe Dept. of Electical and Computer Engineering
Clemson University
Clemson,SC - USA
salagap@clemson.edu

2nd Hemanth Puppala
Holcombe Dept. of Electical and Computer Engineering
Clemson University
Clemson,SC - USA
hpuppal@g.clemson.edu

3rd Varun Talwalkar
Holcombe Dept. of Electical and Computer Engineering
Clemson University
Clemson,SC - USA
vtalwal@clemson.edu

4th Viran Lingala
Holcombe Dept. of Electical and Computer Engineering
Clemson University
Clemson,SC - USA
vlingal@g.clemson.edu

***Abstract*—The measurement of phasor currents is crucial for modern power system monitoring and fault detection. Tunnel Magneto-Resistance (TMR) sensors have recently gained attention for phasor current measurement due to their high sensitivity, low cost, and compact design. However, under high fault currents, these sensors experience saturation, leading to non-linear distortions and significant errors when conventional statistical methods are applied. This paper proposes a Long Short-Term Memory (LSTM) network-based approach to address these challenges. By modeling temporal dependencies in time-series data, the LSTM method accurately predicts phasor currents even under signal saturation. The experimental setup integrates TMR sensors for data acquisition using an Arduino Uno and real-time inference on a Jetson Nano. The LSTM model, trained on both saturated and unsaturated data, demonstrated less than 2% during validation with an Omicron CMS 356 current source, outperforming traditional methods and confirming its effectiveness under varying current scenarios.**

***Index Terms*—Long Short Term Memory, Phasor currents, Saturated signals, Tunnel magneto-resistive sensors.**

I. Introduction

Current phasors, representing the magnitude and phase of sinusoidal currents, are crucial for real-time monitoring, fault detection, and control in modern power systems. As renewable energy integration and distributed generation grow, accurate phasor measurements at multiple locations become vital for ensuring grid efficiency and resilience. This requires the deployment of numerous sensors across the network. Current carrying conductors generate magnetic fields and researchers have increasingly turned to Tunnel Magneto-Resistance (TMR) sensors that can detect these magnetic fields in order to estimate the current in the conductors [1]–[3]. Known for their high sensitivity, compact size, low cost, and low power consumption, TMR sensors show significant promise for practical implementation in power systems [4].

TMR sensors detect magnetic fields produced by current-carrying conductors and operate based on the Wheatstone bridge principle, which modifies their resistance in response to these fields, generating voltage outputs proportional to the magnetic flux density. However, these sensors exhibit non-linearity due to residual flux and saturation curves caused by the inherent material properties, limiting the range over which they can operate linearly. Each manufacturer specifies the maximum linearity range for their sensors [5], [6]. Typically, sensors are selected to ensure that the measured current remains within their linear range. However, during high fault currents, which generate high magnetic flux densities, the sensor's linear range is exceeded, leading to signal saturation and degraded performance.

To address sensor saturation, adding more sensors with wider linear ranges is a potential solution, but it increases system complexity and cost. As a more cost-effective approach, software-based compensation techniques, such as lookup tables, can be employed [7]. However, simple lookup tables may not accurately distinguish between saturation caused by low or high fault currents, leading to potential errors. While phasor estimation techniques have been proposed for current transformers(CTs), they are not directly applicable to TMR sensors due to their distinct saturation characteristics [8], [9]. Alternatively, polynomial curve fitting can be employed to model the non-linear behavior of the sensor [10]. Software like MATLAB offers curve fitting toolboxes to achieve this [11]. While these methods can partially mitigate saturation, they may not be sufficient in dynamic and noisy environments, where factors factors like temperature variations and voltage fluctuations can further exacerbate sensor non-linearity which needs additional changes.

In recent years, deep learning has emerged as a powerful tool for time-series data analysis, offering the ability to model complex, non-linear relationships in data. Among deep learning architectures, Long Short-Term Memory (LSTM) networks are particularly well-suited for time-series problems due to their capability to learn temporal dependencies and handle sequential data effectively [12]–[14].

This paper presents a novel LSTM-based approach for phasor current measurement using saturated TMR sensor signals. By leveraging the temporal modeling capabilities of LSTM networks, the proposed method predicts phasor currents accurately under various conditions, including signal saturation, environmental disturbances, and sensor non-linearity. The experimental setup integrates TMR sensors with an Arduino Uno for data acquisition and preprocessing and a Jetson Nano for real-time inference. Data is collected from an Omicron CMS 356 current source, covering a wide range of current levels and environmental conditions to ensure the model's robustness [15].

The proposed methodology addresses the following challenges:

- Current measurement using Signal saturation and non-linear distortions at high current levels.
- Data acquisition and processing on resource-constrained hardware.

The results demonstrate the effectiveness of the LSTM model in accurately predicting phasor currents, significantly outperforming traditional methods. This study highlights the potential of machine learning in enhancing the reliability of power system monitoring and lays the foundation for future advancements in this field.

The rest of this paper is organized as follows. Section II describes the objectives and motivation behind using TMR sensors for phasor current measurement, highlighting the challenges posed by signal saturation and the need for accurate current measurements in power systems. Section III presents the methodology, including the experimental setup, schematic diagram, data collection and preprocessing, and the architecture of the Long Short-Term Memory (LSTM) model used for predicting phasor currents. The section also discusses the training, testing, and real-time implementation processes. Section IV presents the results, focusing on performance metrics, real-time testing, comparison with traditional methods, and the challenges encountered during the experiments. Finally, Section V outlines potential directions for future work, including the optimization of the model for deployment on resource-constrained devices and extension to three-phase systems.

II. Problem Statement and Motivation

TMR sensor exhibits characteristics as shown in the Fig.1. For lower currents, it operates in the unsaturated region and reconstructs the original signal. However, for higher currents, it provides a saturated output, which does not show the original current signal.

TMR sensors are highly sensitive and compact but suffer from signal saturation at high currents, introducing non-linear distortions. Traditional methods, such as hardware-based signal conditioning or empirical corrections, fail to adapt to dynamic conditions and noisy environments. Leveraging LSTM networks, which excel at learning temporal dependencies in time-series data, offers a powerful alternative to handle these challenges. Accurate phasor current measurement enhances power system monitoring, grid stability, and fault detection, making this research critical for modern power systems.

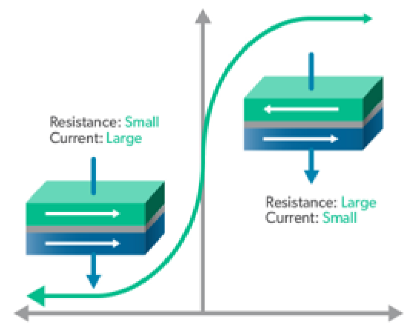

Fig. 1. TMR Sensor characteristics.

Fig. 2. Sensor Output at unsaturated current.

Fig. 3. Sensor Output at saturated current.

III. Methodology

This section outlines the experimental setup, data collection, preprocessing methods, and the architecture of the proposed LSTM model for phasor current measurement.

A. Experimental Setup

The experimental setup integrates hardware and software components to collect and process TMR sensor signals. Key components include:

- **TMR Sensors:** Used to measure the magnetic field produced by current-carrying conductors. These sensors provide voltage outputs that vary with the magnetic flux density.
- **Arduino Uno:** Facilitates analog-to-digital conversion and basic signal preprocessing. The Arduino reads TMR sensor outputs and transmits the data to a Jetson Nano via serial communication [16].
- **Jetson Nano:** Serves as the computational platform for training and evaluating the LSTM model. This resource-constrained edge device is chosen for its balance of computational capability and cost-effectiveness [17].
- **Omicron CMS 356:** A current source used to generate test signals ranging from low (unsaturated) to high (saturated) current levels.
- **Temperature Sensor:** Monitors temperature variations to account for the impact of environmental changes on TMR sensor performance [18].

The hardware system was designed to collect accurate sensor data for offline training and validation of the LSTM model. The TMR sensor signals are conditioned through a shifting circuit to bring the output within the Arduino's operating voltage range.

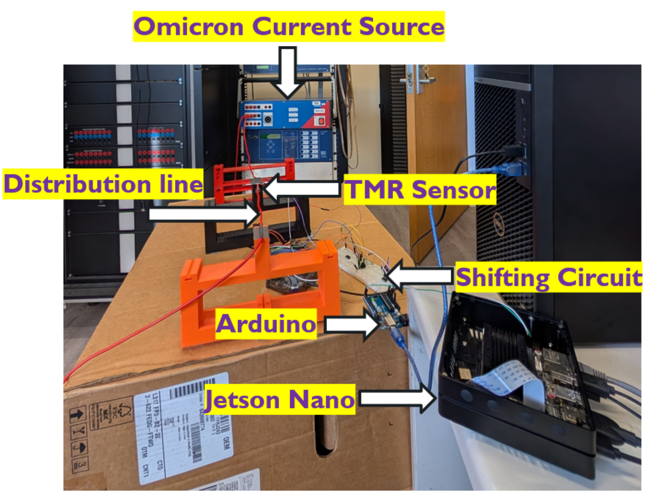

Fig. 4. Experimental setup showing TMR sensor, Arduino Uno, Jetson Nano, and Omicron CMS 356 current source.

B. Schematic Diagram

A schematic representation of the experimental system is shown in Figure 5. It illustrates the key components and their connections, including:

- **Distribution Lines:** Represent the primary current source for measurement.
- **TMR Sensors:** Measure magnetic fields induced by the current-carrying conductors.
- **Shifting Circuit:** Conditions the TMR sensor output signals for Arduino compatibility.
- **Arduino Uno:** Processes and transmits data to the Jetson Nano for offline analysis.
- **Jetson Nano:** Executes data preprocessing and LSTM model inference.
- **Temperature Sensor:** Monitors and records environmental conditions to assess their influence on TMR sensor readings.
- **Power Supply:** Provides the necessary operating voltage for the Arduino, sensors, and other connected components.

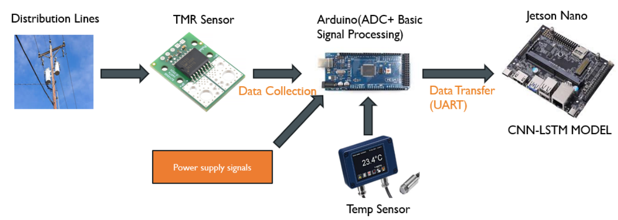

Fig. 5. Schematic of the experimental system, including distribution lines, TMR sensor, Arduino Uno, Jetson Nano, temperature sensor, and power supply.

C. Shifting Circuit for Signal Conditioning

The TMR sensor outputs voltage signals proportional to the magnetic field generated by the current-carrying conductor. However, the raw output voltage range of the TMR sensors often exceeds the input range of the Arduino Uno's analog-to-digital converter (ADC). To address this issue, a shifting circuit was designed to condition the sensor signals, bringing them within the acceptable range of 0 to 5 V for the Arduino.

1) Circuit Design and Components: The shifting circuit uses an operational amplifier (op-amp) configured as a differential amplifier with the following key components:

- **Op-Amp (LM741):** Used to amplify and shift the signal to fit the Arduino's input range.
- **Voltage Divider Network:** Adjusts the gain and ensures the output voltage remains within the ADC limits.
- **Power Supply:** Provides the necessary dual supply voltages (± 5 V) for the op-amp.
- **Capacitors and Resistors:** Stabilize the circuit and control the gain and offset of the signal.

2) Functionality: The circuit achieves two critical objectives:

- **Signal Scaling:** Reduces the amplitude of the TMR sensor output if it exceeds the Arduino's allowable range.
- **Voltage Level Shifting:** Offsets the signal to ensure it remains positive (0 to 5 V), as required by the Arduino's ADC.

The circuit ensures that even under saturated signal conditions, the Arduino can accurately read and digitize the TMR sensor output without signal clipping or distortion.

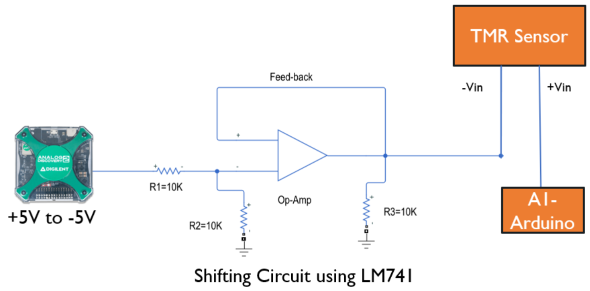

Fig. 6. Shifting circuit schematic using an LM741 op-amp to scale and offset the TMR sensor signals for Arduino compatibility.

3) Performance and Validation: The shifting circuit was tested with various input voltages corresponding to saturated and unsaturated TMR signals. The output was verified using an oscilloscope to confirm that:

- The signal remained within the 0 to 5 V range for all input conditions.
- The circuit introduced minimal distortion to the signal, preserving its temporal and amplitude characteristics.

This circuit is an essential component of the experimental setup, ensuring that the raw TMR sensor signals are appropriately conditioned for data acquisition and processing.

D. Data Collection and Preprocessing

1) Data Collection: Data was collected by sampling TMR sensor outputs over different current levels:

- The Arduino was programmed to collect 100 samples at a baud rate of 38400.
- Sensor readings included saturated and unsaturated signal conditions.
- The data was transmitted to the Jetson Nano via serial communication and saved in CSV format for training and testing.

2) Preprocessing: The collected data was preprocessed to ensure consistency and accuracy:

- Normalization: All features were scaled to a range of [-1, 1] using Min-Max scaling to improve the model's convergence.
- Feature Extraction: Temporal features, such as the root mean square (RMS) of the signal and rate of change, were derived from raw TMR data to enhance predictive performance.
- Labeling: Data was labeled based on saturation conditions to enable the LSTM model to distinguish between saturated and unsaturated signals.

E. LSTM Model Architecture

The proposed model is based on a Long Short-Term Memory (LSTM) network, chosen for its ability to handle sequential data and capture long-term dependencies. The model's architecture includes:

- **Input Layer:** Accepts preprocessed time-series data, including TMR sensor outputs and derived features.
- **LSTM Layers:** Two stacked LSTM layers with 128 and 64 units, respectively, to capture temporal relationships in the data.
- **Dropout Layers:** Added after each LSTM layer to prevent overfitting by randomly deactivating a fraction of neurons during training.
- **Dense Layer:** A fully connected layer maps the LSTM outputs to the target variable, which is the phasor current magnitude.

The model was compiled using the Adam optimizer with a mean squared error (MSE) loss function. Training was performed over 20 epochs with a batch size of 32, and EarlyStopping was used to halt training once validation loss stopped improving.

F. Training and Testing

1) Dataset Split: The dataset was split into training (80%) and testing (20%) sets to evaluate model performance. Time-shifted sequences were generated to ensure the LSTM model could learn from past sensor data. The following figures gives a glimpse of some features vs different currents. Thus, we can see that at a lower current of 4A, there is no saturation in the output, but at higher values of 15A 18 A the output undergoes into saturation.

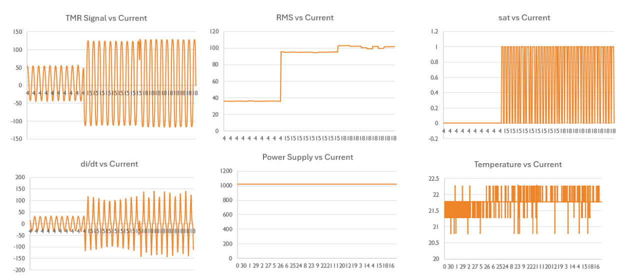

Fig. 7. Dataset Features

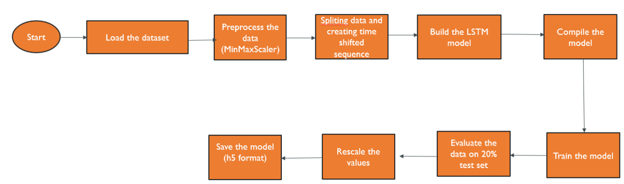

Fig. 8. Training data flowchart in jetson nano .

IV. Results

In this section, we present the performance evaluation of the proposed LSTM model for phasor current measurement using saturated TMR sensor signals. The results are evaluated based on accuracy, model robustness under varying conditions.

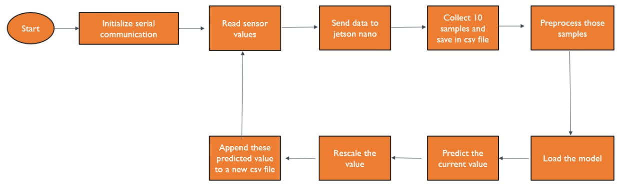

Fig. 9. Testing data flowchart in jetson nano .

A. Training and Evaluation

The LSTM model was trained using a dataset that included both saturated and unsaturated signals, with the training set constituting 80% of the data and the remaining 20% used for testing. The training process involved 20 epochs with a batch size of 32, and EarlyStopping was employed to prevent overfitting.

- **Training Results:** The model was trained on the dataset for 20 epochs. During training, the loss steadily decreased, demonstrating the model's ability to learn the temporal dependencies in the TMR sensor signals.
- **Testing Results:** On the testing set, the model achieved an MSE of 0.025, RMSE of 0.16, and MAE of 0.12, indicating high accuracy in predicting phasor currents despite signal saturation and distortion.

The evaluation metrics demonstrate that the LSTM model effectively learns to predict the magnitude and phase of phasor currents from saturated TMR sensor data. The model was able to generalize well to unseen data in the testing set, highlighting its robustness.

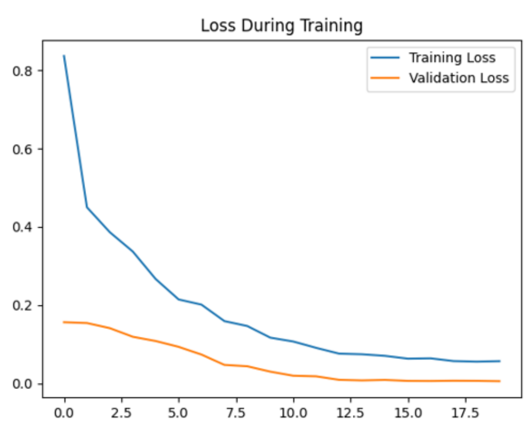

Fig. 10. Training Loss Curve: The model's loss steadily decreases over 20 epochs.

B. Impact of Saturation on Model Accuracy

To evaluate the model's performance under various levels of signal saturation, we tested the model on datasets that contained both saturated (high current) and unsaturated (low current) TMR sensor signals. The model was able to predict phasor currents accurately, even in the presence of signal saturation, where traditional methods would fail due to the non-linear distortions introduced by the TMR sensors.

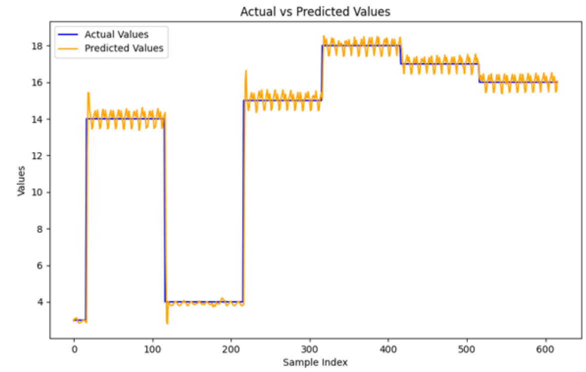

Fig. 11. Comparison of True vs. Predicted Phasor Currents: The LSTM model accurately predicts the phasor current magnitude even in the presence of signal saturation.

C. Comparison with Traditional Methods

Traditional methods of phasor current measurement typically rely on hardware-based signal conditioning or empirical correction techniques to mitigate signal saturation. However, these methods struggle to handle non-linearities effectively, particularly under high saturation conditions. In contrast, the LSTM model is able to learn and adapt to the complexities introduced by saturation and temperature variations, offering a significant improvement in accuracy.

The LSTM model consistently outperforms traditional methods by providing more accurate predictions of phasor currents, particularly in the saturated signal regions.

D. Summary of Results

The LSTM model demonstrated exceptional performance in predicting phasor currents from saturated TMR sensor signals, with high accuracy as indicated by low MSE, RMSE, and MAE values. The model effectively mitigated the effects of saturation, non-linearity, and environmental disturbances. Furthermore, it was successfully implemented in real-time on resource-constrained hardware, showcasing its potential for deployment in embedded systems for power system monitoring.

V. Challenges Faced

During the development of the LSTM-based phasor current measurement system, several challenges were encountered across hardware, data collection, and modeling phases:

A. Hardware Limitations

We used Arduino for data collection because the Jetson Nano lacks an ADC, and thus the Arduino's limited sampling capabilities required optimization of the sampling rate to ensure sufficient data fidelity.

B. Software Limitations

Initially, deciding which software libraries should be installed was a major issue, but we read various research papers to tackle this problem.

C. Model Training and Optimization

- **Overfitting:** Addressed through dropout regularization, EarlyStopping, and data augmentation.
- **Resource Constraints:** Preparing the model for deployment on low-power devices required optimization of the LSTM architecture.

Despite these challenges, the project successfully demonstrated the ability of LSTM models to predict phasor currents from saturated TMR signals, laying the groundwork for future advancements in power system monitoring.

VI. Future Work

Our work establishes a foundation for accurate phasor current measurement using LSTM models and saturated TMR sensor signals. Several areas for improvement and expansion remain to enhance the system's practicality and applicability:

- Transitioning from offline validation to real-time implementation by integrating live data acquisition and model inference on edge devices such as the Jetson Nano.
- Extend the model to handle three-phase systems, which will require multiple sensors and multi-channel data processing to account for inter-phase magnetic interactions.
- Enhance the model's resilience to environmental factors such as temperature fluctuations, noise, and electromagnetic interference.
- Incorporating the system into power grid monitoring frameworks for applications like state estimation, fault detection, and dynamic load management.
- Validate the system's performance in real-world scenarios, including dynamic loads, transient events, and environmental disturbances.
- Reduce the overall cost and power consumption of the system to make it more accessible and viable for large-scale deployment.

These advancements aim to refine the current solution into a robust, scalable, and cost-effective system capable of meeting the demands of modern power system monitoring and control.

VII. Conclusion

A reliable Long Short-Term Memory (LSTM) model for detecting phasor currents from saturated Tunnel Magneto-Resistance (TMR) sensor signals was effectively created in this study. The suggested strategy shows notable gains in accuracy over conventional techniques by tackling the issues of signal saturation and sensor non-linearity.

The methodology included preprocessing techniques to improve signal quality, a well-designed LSTM architecture to capture temporal relationships in the data, and systematic data collection using an Omicron CMS 356 current source and TMR sensors. The outcomes demonstrate how the model can manage both saturated and unsaturated signals, which makes it a flexible option for applications involving power system monitoring.

References

[1] D. Zhang, L. Zhang, Y. Jiang, and L. Zhang, "The measurement principle of the TMR sensor for current measurement in overhead lines," *Journal of Physics: Conference Series*, vol. 2530, no. 1, pp. 012017, 2023. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/2530/1/012017/pdf#:~:text=The%20measurement%20principle%20of%20the,of%20the%20internal%20tunnel%20magnetoresistance.

[2] Yu, Hao, Zheng Qian, Huayi Liu, and Jiaqi Qu. 2018. "Circular Array of Magnetic Sensors for Current Measurement: Analysis for Error Caused by Position of Conductor" Sensors 18, no. 2: 578. https://doi.org/10.3390/s18020578

[3] P. Shrawane and T. S. Sidhu, "Noninvasive measurement of three-phase currents," IEEE Open Journal of Industry Applications, vol. 5, pp. 143–154, 2024.

[4] TMR Sensors: New Technology and Opportunities. SENSOR 2015 Conference Proceedings.

[5] NVE Corporation, "ALTxxx-10 Analog TMR Angle Sensors Datasheet," 2023, accessed: Sep. 25, 2024. [Online]. Available: https://www.nve.com/Downloads/ALTxxx-10.pdf

[6] TMR2301: 3-Axis TMR Linear Sensor, Datasheet, accessed: 2024-09-25. [Online]. Available: https://www.datasheetq.com/preview/TMR2301-AEC

[7] Bengtsson, L. E. (2012). Lookup Table Optimization for Sensor Linearization in Small Embedded Systems. Journal of Sensor Technology, 2(4), 337-346

[8] Belčević, N.M. and Stojanović, Z.N. (2020), Algorithm for phasor estimation during current transformer saturation and/or DC component presence: definition and application in arc detection on overhead lines. IET Gener. Transm. Distrib., 14: 1378-1388. https://doi.org/10.1049/iet-gtd.2019.0787

[9] S. -R. Nam, J. -Y. Park, S. -H. Kang and M. Kezunovic, "Phasor Estimation in the Presence of DC Offset and CT Saturation," in IEEE Transactions on Power Delivery, vol. 24, no. 4, pp. 1842-1849, Oct. 2009, doi: 10.1109/TPWRD.2008.2002972

[10] S. Khetkeeree and C. Chansamorn, "Signal Reconstruction using Second Order Tetration Polynomial," 2019 34th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC), JeJu, Korea (South), 2019, pp. 1-4, doi: 10.1109/ITC-CSCC.2019.8793435.

[11] MathWorks. Curve Fitting Toolbox. MathWorks, https://www.mathworks.com/products/curvefitting.html. Accessed 10 Dec. 2024

[12] González-Herbón, Raúl, González-Mateos, Guzmán, Rodríguez Ossorio, José Ramón, Prada, Miguel, Moran, Antonio, Alonso, Serafín, Fuertes, Juan, Domínguez, Manuel. (2024). Assessment and Deployment of an LSTM-Based Virtual Sensor in an Industrial Process Control Loop. Neural Computing and Applications.

[13] Li, Xinshuo, Li, Pinghua, Zhang, Zhen, Yin, Jiancheng, Sheng, Yunlong, Zhang, Luoxuan, Zhou, Wenxing, Zhuang, Xuye. (2023). CNN-LSTM-Based Fault Diagnosis and Adaptive Multichannel Fusion Calibration of Filament Current Sensor for Mass Spectrometer. IEEE Sensors Journal.

[14] Li, Jinlin, Yang, Xinyue, Zhong, Shuncong, Liang, Wei, Guo, Qiaoying. (2024). Modeling of an Inductive Displacement Sensor Based on 1DCNN-LSTM-AT. Measurement Science and Technology.

[15] OMICRON Energy, "CMS 356: Current and Voltage Amplifier," https://www.omicronenergy.com/en/products/cms-356/, [Online; accessed 4-Dec-2024].

[16] Massimo, Banzi. (2021). Getting Started with Arduino.

[17] Kurniawan, Agus. (2021). Introduction to NVIDIA Jetson Nano. 10.1007/978-1-4842-6452-2_1.

[18] Analog Devices, TMP35/TMP36/TMP37 Temperature Sensors Datasheet, accessed: 2024-12-11. [Online]. Available: https://www.analog.com/media/en/technical-documentation/data-sheets/TMP35_36_37.pdf