WAVELET-DRIVEN MACHINE LEARNING TECHNIQUES FOR THE VERIFICATION OF ANALOG & MIXED SIGNAL CIRCUITS

A PROJECT REPORT

Submitted by

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BONA FIDE CERTIFICATE

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ABSTRACT

Analog Mixed-Signal (AMS) circuits are vital in modern electronics, bridging analog and digital domains for high-performance applications like smartphones and portable devices. Integration of analog and digital components on a single chip, driven by advancement in semiconductor technology, enables efficient real-time signal processing. However, AMS circuit verification poses significant challenges due to the complexity of integrating analog and digital circuitry.

This works explores the use of Machine & Deep Learning techniques to enhance AMS circuit verification by analyzing Discrete Wavelet Transform of time-domain datasets. The proposed models aims to uncover intricate circuit behaviors, reducing verification time and manual effort. This integration of wavelet based analysis with machine & deep learning algorithms seeks to streamline the verification process, improve reliability, and meet the growing demands of the semiconductor industry.

A benchmark dataset consisting of 150 files from an Operational Amplifier (Op-Amp) circuit was used to build and evaluate the model. Among the models that has been experimented Regression Transformer got the highest SNR of 34.11 dB, R2 score of 0.09984 and an MSE of 0.0007 has been obtained in the prediction of the output waveform. Although other experimented models showed similar metrics, the Transformer's encoder-decoder design handled sequential data better, resulting in more accurate predictions.

TAMIL ABSTRACT

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LIST OF SYMBOLS AND ABBREVIATIONS

AMS	Analog Mixed-Signal
CMOS	Complementary Metal-Oxide-Semiconductor
CSV	Comma Separated Value
DB	Daubechies
DL	Deep Learning
DWT	Discrete Wavelet Transform
FinFET	Fin Field-Effect Transistor
FFN	Feed Forward Network
FFT	Fast Fourier Transform
FPGA	Field-Programmable Gate Array
GPU	Graphical Processing Unit
IC	Integrated Circuits
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MSE	Mean Square Error
ML	Machine Learning
MLP	Multi Layer Perceptron
R2	R-Squared
RNN	Recurrent Neural Networks
SNR	Signal-to-Noise Ratio
SPICE	Simulation Program with Integrated Circuit Emphasis
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

This introductory chapter presents the need and idea for a tool/framework to verify AMS (Analog Mixed-Signal) circuits and discusses how this could impact IC design engineers and the semiconductor industry in general. It also gives a compelling background & problem statement that forms the basis of this project. Additionally, the chapter defines the objectives and scope of the project.

1.1 BACKGROUND

Analog Mixed-Signal (AMS) circuits are a crucial part of modern-day electronics, as they help bridge the gap between analog and digital systems. AMS circuits combine both analog and digital components onto a semiconductor chip, leveraging the advantages of each. While traditional circuits focus on either analog or digital processes, AMS circuits use the best of both to optimize chip performance.

With the growing popularity of smartphones and portable electronics, the need for AMS circuits has increased significantly. Moore's Law [1], which states that the number of transistors on an IC doubles approximately every two years, has played an important role in the evolution of Analog Mixed-Signal Circuits. The miniaturization and integration of transistors, as predicted by Moore's Law, is closely linked to the rise of AMS circuits.

As demand grows for more complex and high-performing systems, AMS circuits enable the seamless integration of analog and digital components on a single chip, allowing efficient real-time signal processing from the environment and fast digital computation.

There's no denying that advanced semiconductors are propelling us into a new realm of power, performance, and area (PPA) optimization. AMS designs leverages advanced technologies like FinFET, ensuring improved integration density and superior transistor performance. But with the rapid evolution of AMS circuits, the demand for thorough verification methods to ensure their reliability and optimal performance has also become increasingly essential.

Verification AMS circuits takes lot of manual effort, substantial computing, system expert knowledge and time to ensure that the design meets both the company's specification and global standards. The verification challenges associated with integrating analog and digital circuits often result in engineers discovering bugs only after silicon fabrication, leading to unnecessary costs, a higher risk of IC failures, under-performance, and extended timelines for delivering the ICs.

1.2 PROBLEM STATEMENT

Verification of AMS circuits is essential, particularly for ensuring safety in highly sensitive systems. It plays a key role in identifying parasitics within the integrated circuits (ICs) that can impact device performance. Among the major causes of failure in mixed-signal design electromigration and voltage drop, making it crucial for designers to understand these additional complexities. Currently, the methods used to verify the stability and correctness of AMS circuits largely depend on manual verification by engineers, who spend considerable time analyzing each component and its interconnections, as well as their overall effect on the entire circuit. While testing digital circuitry can be largely automated, this is not the case for analog circuits and, consequently, for AMS circuits as well.

1.3 OBJECTIVE

Leveraging the extensive data from analog simulation waveforms enables the effective application of Machine Learning (ML) techniques to model the intricate relationships between input, component, and output parameters in analog circuits. Conversion of waveforms data into wavelets since AMS circuits exhibit nonlinear, time-variant nature and wavelets help to analyze the signals in both frequency and time domains. Development of a Machine Learning model that incorporates wavelet transforms for signal analysis. The models will exploit the wavelets' ability to capture both time and frequency domain characteristics, thus helping a much more clear understanding of the circuit behavior.

Development of a unifying model which would comprises of both time domain waveform and frequency domain waveform, where wavelets can be used to determine both domains.

1.4 SCOPE OF WORK

The scope of creating an ML & DL-based model for verifying AMS circuits involves several key aspects that aim to enhance the traditional, manual verification process. First, the model would focus on automating the detection of issues such as parasitics, electromigration, voltage drops, and design rule violations, which are critical in ensuring the reliability and performance of AMS circuits. By leveraging simulation data and real-world measurements, these models can be trained to recognize patterns that signal potential circuit failures or performance degradation, giving engineers with early insights during the design phase. This would not only speed up the verification process but also reduce the risk of costly errors being discovered later in silicon fabrication.

Additionally, these model could integrate into existing workflows by supplementing traditional simulation tools, like identifying complex issues that might otherwise require extensive manual effort. The model's ability to learn from previous designs and testing data could improve the accuracy and efficiency of verification over time. While digital circuit testing is more automated, AMS circuits due to their analog nature require specialized handling, making ML an ideal solution to bridge this gap and ensure robust and timely verification. This approach ultimately aims to reduce verification time, improve design reliability, and lower the cost of development for complex AMS circuits.

1.5 ORGANIZATION OF REPORT

This section gives an overview of the project structure. It outlines what each chapter will cover and the ordering sequence. This serves as a roadmap to understand how the project develops.

Chapter 2: This chapter provides a summary of the literature review that highlights the earlier research in the field of AMS and Digital Circuit Verification. It also offers an extended survey on how these ML & DL models can be used to predict time-series data and how these can be implemented to the objective of this project.

Chapter 3: This chapter covers the project's system design, dataset generation, preprocessing and the need for converting time-domain signals into wavelets. It also discuss the models that are used for the predicting outputs, their general design and how they are modified for regression.

Chapter 4: This chapter covers the machine learning algorithms and conversion of time-domain to discrete wavelet transform and the necessary metrics to evaluate the machine learning models.

Chapter 5: This chapter displays the project's final outcome, comparing the models to identify the best among them and future enhancements to improve output predictions from AMS circuits.

Chapter 6: This chapter summarizes the key findings of the project, highlighting the effectiveness of predicting output from AMS circuits. It also discuss the limitations that were observed. Additionally, this chapter outlines future work that could further enhance the prediction capabilities.

CHAPTER 2

LITERATURE SURVEY

This chapter explores the application of machine learning techniques in the verification of AMS circuits. It justifies the use of DWT, evaluation methodologies, and metrics by exploring existing research. Additionally, it analyzes how various techniques and concepts enhance the scores of evaluation metrics. Through this literature review, a thorough understanding of the current state of AMS circuit verification in both academia and industry is provided.

2.1 OVERVIEW

The literature survery aims to provide an overview of the previous reserach on voltage prediction methods in mixed signal circuits, particularly focusing on the application of wavelet analysis.

Dhurga Devi et al. [2] proposed a Machine Learning based waveform prediction using Discrete Wavelet Transform for the verification of Analog and Mixed Signal Integrated Circuits, which acts as the base for the objective of the problem. The dataset used in this study is simulated from Cadence ® Spectre ® where the circuits is designed as instructed in the analog benchmarking circuits [3]. By simulating the circuits on different Process, Voltage and Temperature (PVT) corners, they were able to generate a dataset of 150 files.

The authors have converted the input data and output into Daubechies Wavelet DB4 with eleven levels of decomposition. The transformed input data along with some relevant metadata was input to a random forest model. The study also explored various verification methods such as Conventional Method (CM), Multimodal Method (MM) and Waveform segmentation Method (WSM) which were discussed in [4].

Evaluation Metrics such as Signal to Noise Ratio (SNR), R2 score and Root Mean Square Error (RMSE) and Mean Square Error (MSE) were used for evaluating the performance of ML model. Apart from the quantitative metrics, a visual waveform evaluation also considered as an evaluation method of the ML model where it offers a graphical contrast between the actual and predicted output. The DWT based learning model has an improved average SNR of 25 dB across the three methods than were discussed in previous studies that relied solely on raw transient analysis data [4]. The RMSE and MSE yields a prediction of 0.01 which makes them very reliable for regression. Furthermore, The R2 score also gets very close to 1, suggesting very good regression performance for the input data.

2.2 PREDICTION METHODS IN AMS CIRCUITS

In the world of voltage prediction methods for analog and mixed-signal circuits, several notable studies have contributed to advancements in modeling techniques and verification processes.

Samantha Alt et. al [5] utilized Support Vector Machines (SVM) as a data-driven modeling technique to achieve high accuracy and significant speed improvements over traditional simulation methods like SPICE. Their work presents an innovative approach in creating transient voltage behavioral models for complex analog and mixed-signal circuits. The proposed methodology involves partitioning larger circuits into functionally independent segments, allowing for the creation of intermediate behavioral models that can be simulated more efficiently. This partitioning is based on a channel-connected component graph that identifies input-output relationships within the circuit. By running simulations on the full un-partitioned netlist, the authors ensure continuity between partitions.

The authors describe a systematic approach to data capture, where transient behaviors are recorded at uniform intervals across the entire circuit before partitioning. This data is then used to train SVM models, which can handle a large number of inputs and discover trends from small datasets. The regression function is formulated to predict outputs based on captured behaviors, incorporating state variables for enhanced accuracy. Experimental results demonstrate that the proposed partitioning and modeling technique achieves 95% accuracy in behavioral predictions while providing a three orders of magnitude speedup compared to traditional SPICE simulations. The authors emphasize effectiveness of SVMs in modeling complex circuits, noting their ability to capture strongly correlated relationships among sub-circuits.

Fuyong Zhang et al.[6] introduces a fault detection approach for analog circuits using wavelet characteristics and one-class KNN algorithm. This method not only determine the circuit state, but also locate the faulty components and identify the fault classes. Traditionally fault detection methods struggle to effectively identify faults due to complex nature of these circuits. But this proposed method uses wavelet features from circuit signals that uses one-class KNN for multi-class classification. Furthermore, the four-op-amp biquad high-pass filter circuit is chosen as the experimental circuit to implement the simulation experiments of fault detection.

Chen et al. [7] emphasizes the need for a machine learning-based verification for the reliability of the AMS circuits and to achieve significant speedup in design closure. They suggest that once the ML model is trained it can be deployed on advanced hardware platforms like GPUs, FPGAs and ASICs to accelerate inference time. Furthermore, they authors have also discussed the challenges associated with implementing design for reliability in AMS circuits.

Dhanasekar et al. [4], proposed a framework with statistical preprocessing, waveform segmentation and circuit partition technique to process the raw transient signal analysis data to build a machine learning models. These model selects the method got better output from all the process corners, voltage and temperature. The dataset used mirrors that discussed in [2], but relies raw signal data instead of the DWT.

This [4] study also heavily emphasizes on using the Signal to Noise Ratio as a critical evaluation metric since it assesses the noise is present in the output signals compared to input signals. A Higher SNR indicates clearer data transmission, lower error rates and better overall performance. It also serves as a vital measure of how well the signal can be recovered or processed.

The proposed technique of data segmentation (circuit partition and waveform segmentation) outperformed the conventional method and multimodal method which were discussed earlier. This work also proved its ability to find the outliers and proposing the framework to be a better verification framework than traditional verification methods. However, the authors noted challenges in making accurate predictions under PVT corners and suggested future work involving frequency domain representation combined with time-domain representation to enhance prediction accuracy further. Although results were improved with DWT as discussed in [2] but still the authors believe that creating a unified waveform model could yield even better accuracy.

2.2.1 USE OF SNR AS AN EVALUATION METRIC

Gordon [8] explores various metrics and techniques for evaluating mixed-signal circuits, with a special focus on testing the analog portion of these devices, discussing key metrics such as Signal-to-Noise Ratio (SNR) and related testing techniques. T. B. Cho et al. [9] implemented low-voltage, high-speed pipeline ADC converter in CMOS technology. They used SNR as a evaluation metric and have achieved high SNR, implying the effectiveness in mixed-signal application of ADC.

Mohamed et al. [10] propose an SNR estimator based on recurrent neural network (RNN) for optical fiber communication links. Their method jointly estimates the linear and non-linear components of communication links using SNR as a critical evaluation metric.

The Article from Analog Devices ® [11] highlights the importance of Signal-to-Noise-plus-Distortion (SINAD) and SNR in selection of mixed-signal components for digital communication systems. The literature reviewed emphasizes the importance and relevance of using SNR as a evaluation metric to ensure optimal performance in mixed-signal applications.

2.2.2 USE OF DISCRETE WAVELET TRANSFORM

Rioul et al. [12] provide an overview of wavelet theory and its application in signal processing focusing on Continuous Wavelet Transform, Discrete Wavelet Transform and Multiresolution Analysis. It discusses applications in areas such as speech and image compression as well as pattern recognition. Additionally, the paper compares wavelet transforms with Short-Time Fourier Transform (STFT) and Gabor Transform, highlighting the differences between waveform representations in time-frequency and time-scale domains.

Karim et al. [13] explore Fast Fourier Transform (FFT) and Wavelet Transform for signal compression. They highlight that wavelets outperform FFTs because wavelets provide time-frequency localization, while FFT only offers frequency information, losing the temporal localization of frequencies. This makes wavelets particularly effective for better analysis and compression in scenarios where both time and frequency characteristics are preserved.

2.3 SUMMARY OF STUDY

The reviewed literature provides valuable insights into how verification for AMS circuits is conducted. A common theme across the studies is the emphasis on the need for a unified signal model that integrates both time-domain and frequency-domain information to reduce noise and improve prediction accuracy. Additionally, the literature highlights the advantage of using Discrete Wavelet Transform (DWT) over raw transient data in machine learning models, as DWT preserves critical signal features while enhancing prediction accuracy. Therefore, combining these two approaches—developing a unified waveform model that leverages both time and frequency domains—emerges as a promising research direction.

CHAPTER 3

SYSTEM DESIGN OF WAVELET-DRIVEN MACHINE LEARNING TECHNIQUES FOR THE VERIFICATION OF ANALOG AND DIGITAL MIXED CIRCUITS

This chapter deals with the design and prediction of OP-AMP circuits using Machine Learning & Deep Learning techniques. It also discusses the system architecture that has been implemented to find the best model that can be used for the prediction of output voltage in the circuits.

3.1 DATASET GENERATION

The objective of this machine & deep learning model is to map the function **Y = f(X,C)** and predict Y, where Y represents output space, X denotes input space and C refers to Component space, which include process parameters as mentioned in Equation 3.1.

$$Y = f(X,C) \tag{3.1}$$

The dataset derived from Operational Amplifier (OP-AMP) datasheet from Texas Instruments, designed as per the Analogue Benchmarking Circuit Suite [3] as shown in figure 3.1 and configured in voltage follower mode as per the Figure 3.2.The dataset generation occurs in the Cadence ® Spectre ® circuit simulator tool as shown in Figure 3.3.

The process parameters include Process (P), Temperature (T)

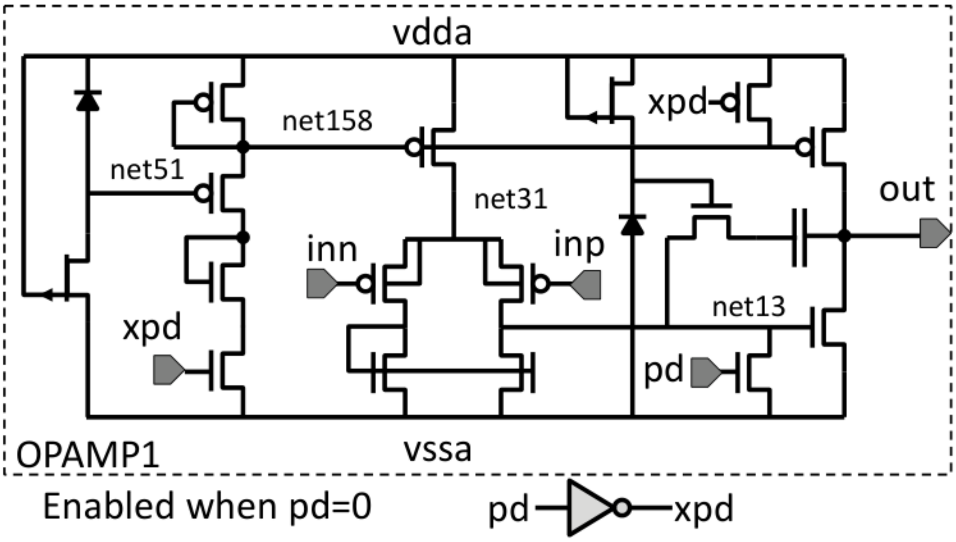

Figure 3.1: Schematic Circuit Diagram of OpAmp from the analog benchmark circuit suite

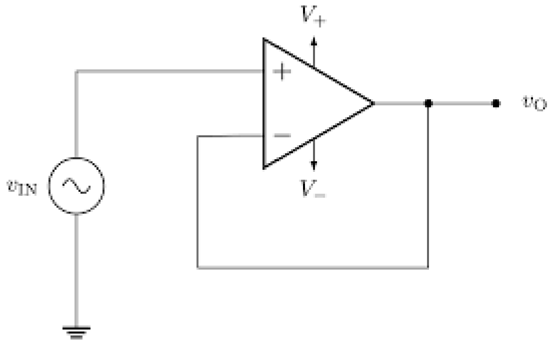

Figure 3.2: Schematic Diagram of OpAmp

and Voltage (V) which can be varied in the tool. Process parameters consists of configurations such as SS(SlowSlow), FF(FastFast), SF(SlowFast), FS(FastSlow) and Typical; three supply voltages – 3V, 3.3V, 3.6V; and temperature ranging from -55°C to +125°C in increments of 10°C. These variations results in 150 unique files, representing distinct combinations of the parameters,with each combination having 15,000 instances (rows) of time domain samples, each lasting 125μs time duration and with a uniform time interval of 1ns. These files are saved in a *.csv* format, ensuring compatibility

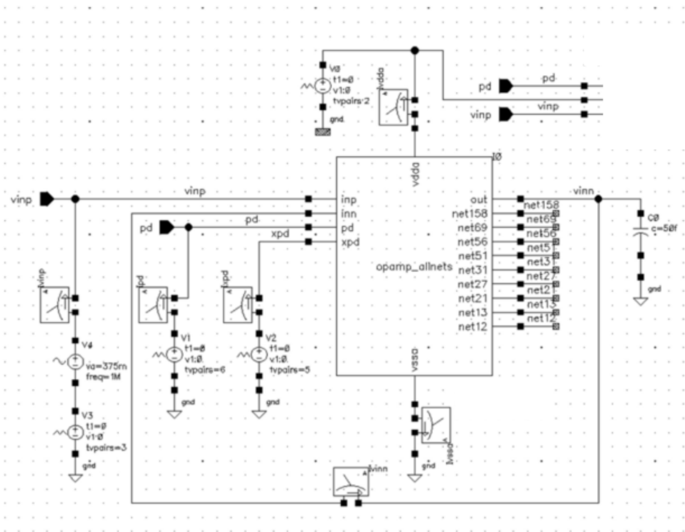

Figure 3.3: Simulated circuit in Cadence ® Spectre ®

with various programming languages and tools while being lightweight and interoperable .

3.2 DATASET PREPROCESSING

Input data preprocessing involves steps like label encoding process attributes (FF, SS, FS, SF, Typical) for machine learning and extracting parameters such as temperature, voltage, and wavelet signal coefficients (vdd, vinp, pd, xpd, vinn) from the dataframe. These parameters are converted to NumPy arrays for compatibility with Python-based workflows and split into training and testing sets for model evaluation.

3.3 WAVELET TRANSFORMATION

The wavelet transform is an advanced mathematical approach for signal analysis, that facilitates detailed time-frequency utilization. Both Wavelets and Fast Fourier Transform (FFT) are common methods used for signal compression. however, datasets are converted into wavelet transforms instead of FFT because wavelets provide time-frequency localization, while FFT only offers frequency information, losing the temporal localization of frequencies [13].

Wavelet analysis reveals signal characteristics across scales by convoluting a signal with compact, oscillatory wavelet function that can be scaled and translated. This process uncovers both high and low frequency details over time, making it effective for analyzing non-stationary signals, such as those found in semiconductor circuits and power electronics, where transient responses are critical [14].

The Wavelets transform decomposes signals into components that are localized in both time and frequency, referred to as **" time-frequency atoms"**. This decomposition forms an orthogonal basis for signal representation, allowing for adaptive tiling of the time-frequency plane for better resolution at varying scales and frequencies.

Considering Heisenberg Uncertainty principle in wavelet analysis, it limits the simultaneous precision of time and frequency measurements. Wavelet atoms aims to achieve a balance between these uncertainties [15].

Figure 3.4 illustrates a three-level wavelet decomposition process. The input signal $x[n]$ is successively decomposed at each level using a pair of filters, $g[n]$ (high-pass) and $h[n]$ (low-pass). After each filtering operation, the signal is downsampled by a factor of 2 ($\downarrow 2$).

The input and output features are decomposed into Discrete Wavelet Transforms (DWT) using PyWavelets (PyWT) library, which allows for various levels of wavelet decomposition. The Daubechies wavelet with 4 vanishing

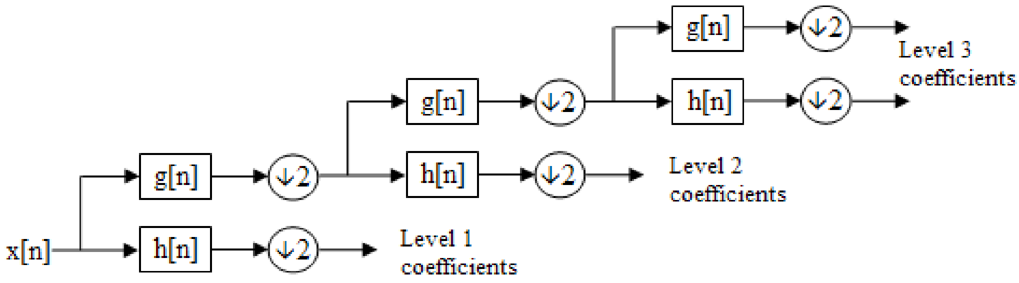

Figure 3.4: Wavelet decomposition up to three levels using iterative filtering and downsampling

moments (DB4) is employed for this process, utilizing twelve levels of decomposition. The resulting decomposed data is saved in .csv format

3.4 SYSTEM ARCHITECTURE

The methodology to learn and predict the voltage output (Vinn) waveform wavelets is shown in the Figure 3.5. The learning utilizes Random Forest algorithm as a Machine Learning approach, along with Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks as Deep Learning models. The resulting models produce a mapping function *f*.

3.4.1 RANDOM FOREST

Random Forest is a versatile and robust machine learning algorithm widely used for regression and classification tasks. It operates as a meta-estimator by fitting multiple decision tree regressors on different sub-samples of the dataset. For regression, Random Forest predicts numerical values by averaging the outputs of individual decision trees, thereby improving predictive accuracy and reducing the risk of overfitting. Figure 3.6 shows how a random forest regressor works, where the input and output data are processed

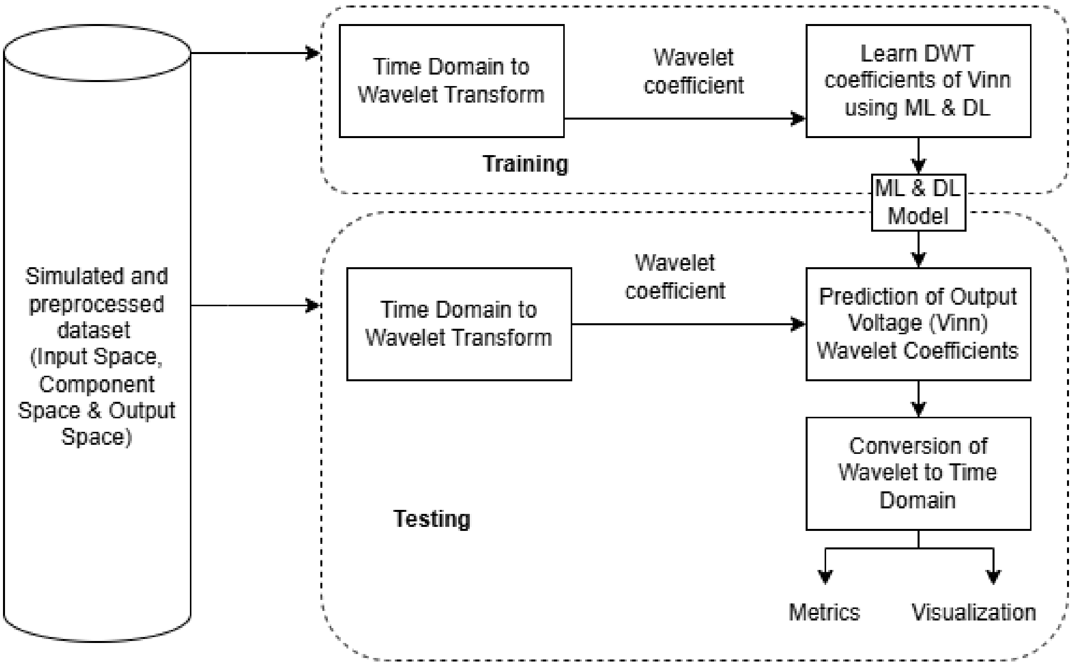

Figure 3.5: Training and Testing of Wavelet Coefficients

through multiple decision trees configured with *n* estimators to balance accuracy and computational efficiency.

As an ensemble learning method, Random Forest combines the predictions of multiple decision trees using a technique called Bootstrap Aggregation, or bagging. This approach enhances prediction stability and accuracy by reducing variance. Each decision tree is trained on a specific sub-sample of the data, and the final output is aggregated: for classification tasks, it is determined through majority voting, while for regression tasks, it is the mean of all tree outputs. This aggregation ensures the model is less reliant on any single decision tree, leading to more robust and reliable predictions.

Random Forest is not only robust but also highly flexible, capable of handling large datasets with multi-dimensional features. It can effectively manage missing data and maintain accuracy without requiring significant data preprocessing.

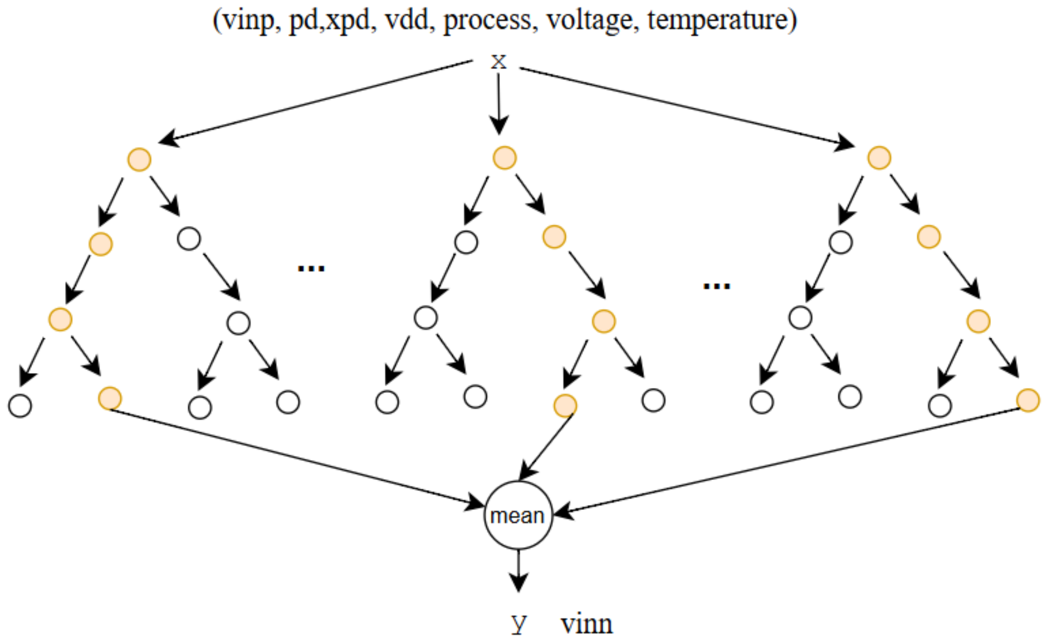

Figure 3.6: Random Forest Regression

3.4.2 MULTI-LAYER PERCEPTRON

Multi Layer Perceptron (MLP) is a type of artificial neural network that consists of multiple layers of neurons arranged in a hierarchical structure. It is one of the simplest neural network and used for supervised classification and regression. MLPs are good at learning complex relationship that exists between independent and dependent variables.

The core principle behind MLPs is backpropagation, a key algorithm that iteratively adjusts the network's weights and biases to minimize prediction error. During training, input data is fed through network, and the resulting error, quantified using a loss function such as MSE and propagated backward from the output layer to the input layer. This process, guided by an optimization algorithm, iteratively updates the model's parameters over successive cycles (epochs), improving its prediction accuracy.

In this problem objective, all input space variable and component space variables (vinp, pd, xpd, vdd, process, voltage & temperature) are treated as independent variables, while the resultant output space variable (vinn) is dependent variable as illustrated in Figure 3.7.

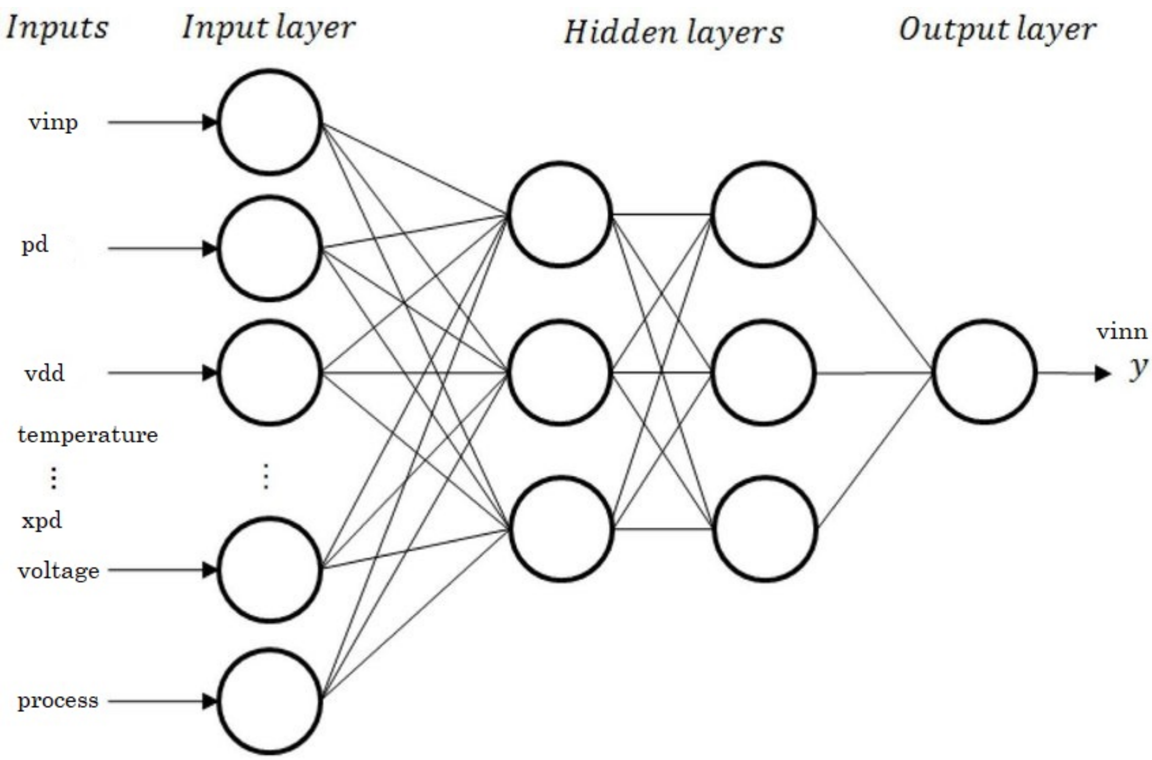

Figure 3.7: Multi-layer Perceptron Regression

3.4.3 LONG SHORT-TERM MEMORY

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to address sequence dependency in input data. Unlike standard RNNs, which suffer from gradient exploding or vanishing problems due to their reliance on continuous data transmission through internal loops, LSTMs incorporate a unique architecture with three gates: input gate, output gate, and forget gate. These gates enable LSTMs to selectively retain or discard information, effectively solving gradient-related issues and allowing the network to remember important information over extended sequences

In the training process, input sequence data is fed into the LSTM network, where weights are adjusted iteratively using backpropagation and optimization algorithms. By minimizing a loss function such as Mean Squared Error (MSE) over successive epochs, the model learns to capture and predict patterns within the data. The basic LSTM architecture is depicted in Figure 3.8.

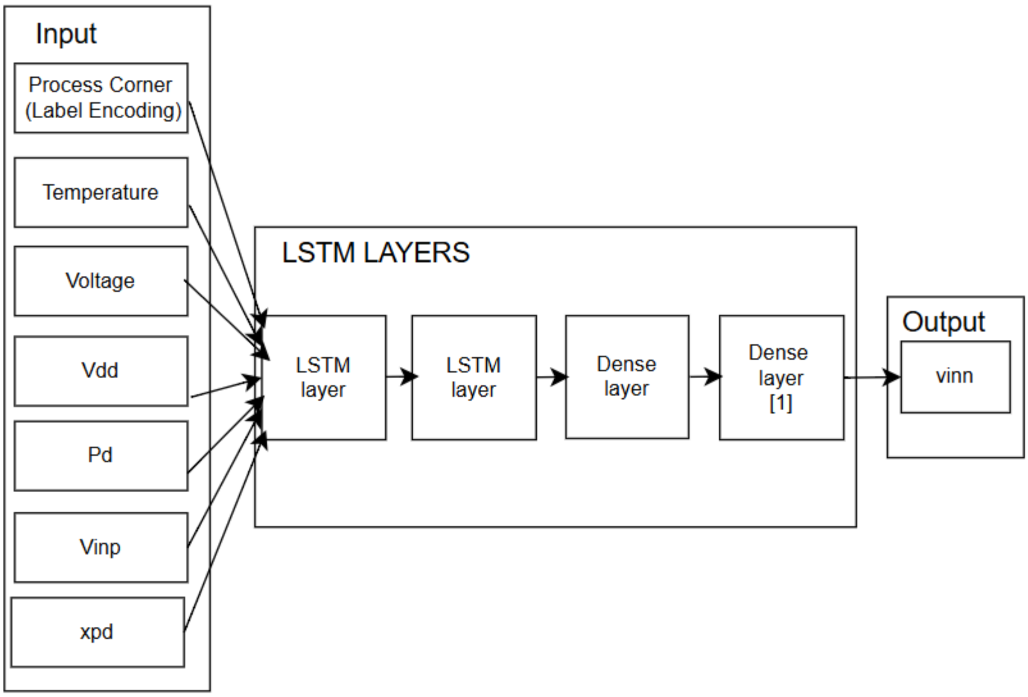

Figure 3.8: LSTM architecture for output voltage prediction

3.4.4 REGRESSION TRANSFORMER

Regression Transformers are powerful models for working with sequences. They use attention mechanisms instead of RNNs or LSTMs to process data. These models often have an encoder to understand the input sequence and a decoder to produce continuous outputs for tasks like regression. Attention mechanisms have become an integral part of compelling sequence modeling and transduction (language translation, speech-to-text) models in various tasks, allowing modeling of dependencies without regard to their distance in the input or output sequences[16].

Encoder and Decoder are the most important components of a transformer. Encoder is composed of an input layer, a positional encoding layer and n numbered identical encoder layers. The input layer maps the input data to a vector of dimension d_{model} through a fully connected network, which ensures a multihead attention mechanism. Positional encoding with sine & cosine functions is used to encode sequential information in time series data. These vectors is fed to the encoder layers. Each encoder layer consists of two sub-layers: self-attention sub-layer and fully-connected feed-forward sub-layer. And each sub-layer is followed by a normalization layer.

Decoder design is very similar to the design of encoder with some key differences. The input of the decoder starts with the last data point of the encoder, which is mapped to a d_{model}-dimensional vector. Apart from self-attention and feed-forward layer each decoder layer contains a sub-layer that applies self-attention over the encoder epochs. The output layer maps the final decoder layer's output to the target time sequence[17].

Time series tasks, such as forecasting, anomaly detection, & classification, benefit significantly from the transformer's ability to handle both short-term and long-term relationships. Techniques such as positional encoding allow transformers to effectively integrate temporal information into their computations. Recent advancements include adaptations like learnable positional encodings [18] and timestamp based embeddings [19] to account for the periodicity and seasonality inherent in time series data. Furthermore, innovations like sparse and hierarchical attention mechanisms have been introduced to address the computational challenges of processing long sequences while preserving accuracy [20].

CHAPTER 4

IMPLEMENTATION OF OUTPUT WAVEFORM PREDICTION FOR OP-AMP CIRCUITS USING MACHINE & DEEP LEARNING TECHNIQUES

This chapter discusses the implementation of converting a time-domain waveform into the Discrete Wavelet Transform (DWT). This chapter also discusses the creation of machine and deep learning algorithms used to predict the output voltage.

4.1 CONVERSION OF TIME-DOMAIN TO DWT

Conversion of time-domain signals into wavelets is essential for analyzing signals with time-varying frequency characteristics. As disscussed in literature survey wavelets could analyze signals signals in both time and frequency domains simultaneously than FFTs.

The dataset that has been saved from the circuit simulation tool contains time-domain data and other net-based parameters. The dataset spans around 150 files with 15,000 instances. All time-varying data from this dataset should be transformed into wavelet representations, while preserving the metadata unchanged. The transformed data, along with the preserved metadata, should then be saved into separate files. In this conversion process, Daubechies4 (db4) wavelet transform is applied with 12 levels of decomposition.

Algorithm 4.1 Time-Domain to Wavelet Transformation

Input: Time-domain data and metadata (process,voltage & temperature) columns
Output: Wavelet data and preserved metadata into a new file

1. LOAD the *time-domain* folder
2. SET wavelet as *db4* and level as *12*
3. SELECT the columns that need to be transformed and columns that need to be used as metadata
4. **function** WAVELET_TRANSFORM(dataframe, columns, wavelets, level)
5. USE Pywavelets' *wavedec* function to decompose the signals
6. CONCATENATE all the converted wavelet coefficients into one single column
7. **return** *concatenated_coeffcients*
8. **end function**
9. SAVE all the metadata columns and converted columns into a new .csv file

4.2 CONVERSION OF DWT TO TIME-DOMAIN WAVEFORM

Since all predictions are made in the DWT domain, the data must be converted back to the time domain to compare the original and predicted waveforms. While comparisons can be made directly in the DWT domain, they may not provide accurate waveforms for visual inspection and other metrics.

Since there are 150 files it would be easier to do the entire folder rather than converting each file or column. Figure 4.1 shows a sine wave signal with 32 instances is converted to a DWT waveform using the db4 wavelet with 5 decomposition levels and its reconstruction back to original time-domain waveform.

Algorithm 4.2 Conversion of DWT to time-domain

Input: DWT waveform of predicted output voltage
Output: time-domain waveform of predicted output

1. LOAD the *predicted_output* column
2. SET wavelet as *db4* and level as *12*
3. **function** WAVELET_RECONSTRUCITON(dataframe, columns, wavelets, level)
4. USE Pywavelets' *waverec* function to reconstruct the signals
5. **return** *time_domain_predicted_output*
6. **end function**
7. SAVE or PLOT the time-domain of predicted output.

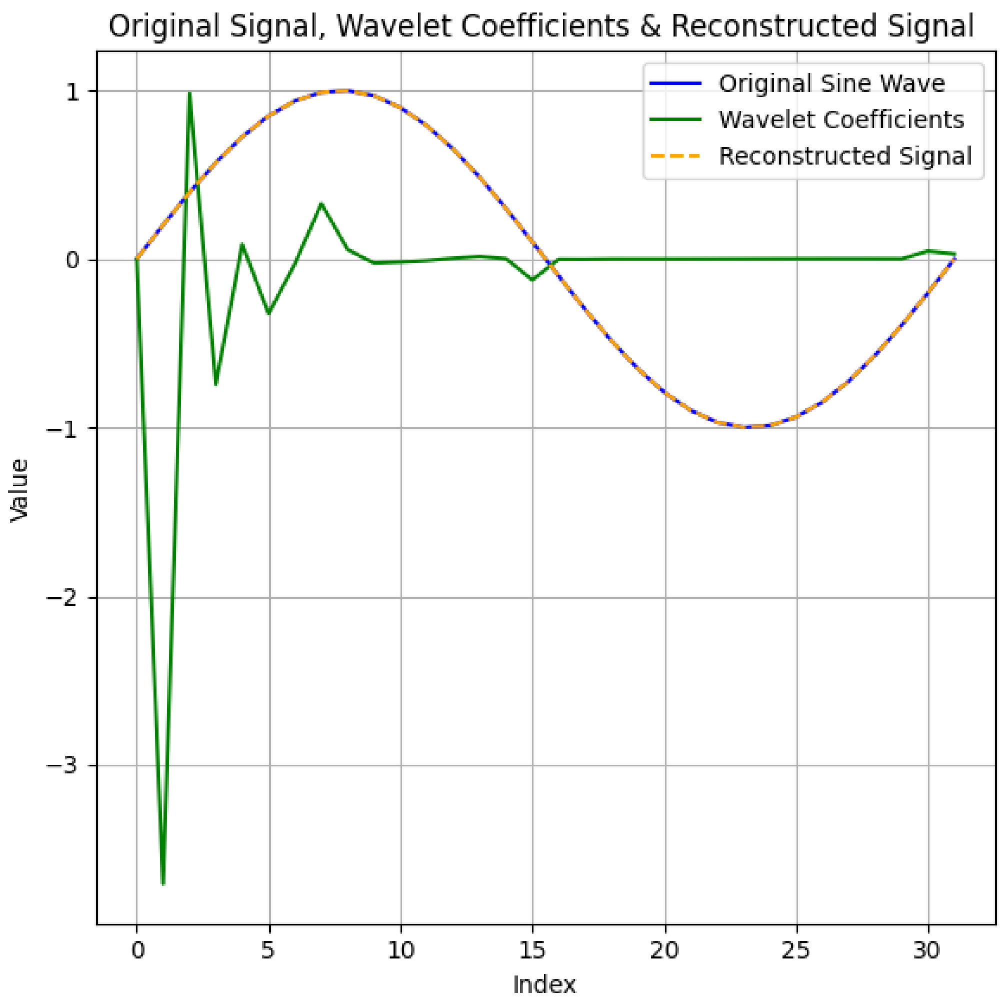

Figure 4.1: A sine wave of 32 instances is converted into DWT and reconstructed back to sine wave signal.

4.3 ALGORITHM FOR RANDOM FOREST MODEL

The Random Forest model is implemented by constructing an ensemble of decision trees estimators, each trained on a randomized subset of data (controlled by the random_state parameter) and aggregating their predictions to enhance accuracy and reduce overfitting. It can be efficiently built using the *RandomForestRegressor* function from scikit-learn.

Algorithm 4.3 Random Forest Model

Input: DWT waveform of input, component and output space
Output: output space prediction

1. LOAD the *input_data* columns as xtrain & *output_data* column as ytrain
2. USE scikit-learn *RandomForestRegressor* function and set the hyperparameters as *n_estimators = 1000* & *random_state = 42*.
3. INITIATE and TRAIN the model.
4. CALCULATE the RMSE, R2 & SNR for the model.
5. SAVE the RF model
6. CALL the model to predict the output voltage of a test case
7. RECONSTRUCT the wavelet transformation into time-domain as per the Algorithm 4.2
8. PLOT the original waveform and predicted waveform
9. CALCULATE the RMSE, R2 &SNR for this particular test case

4.4 ALGORITHM FOR MULTI-LAYER PERCEPTRON

Multi-Layer Perceptron is typically built by organizing neurons into multiple layers, input layer , one or more hidden layer and output layer. In this four dense layer has been used with 64,32,16,1 neurons respectively and activation function *relu* is used for all the dense layer except for the final dense layer where *linear* is used. Adam optimizer is utilized to optimize the model, and MSE is chosen as the loss function to evaluate its performance. Figure 4.2 gives the summary of the MLP model

Algorithm 4.4 Multi-Layer Perceptron Model

Input: DWT waveform of input, component and output space
Output: output space prediction

1. LOAD the *input_data* columns as xtrain & *output_data* column as ytrain
2. DEFINE *Sequential* model from Tensorflow and create 4 Dense layers with 64, 32, 16, 1 neurons with activation function *relu* for the first three dense layer, *linear* is used for final layer
3. COMPILE the model with Adam Optimizer and select MSE as a loss function.
4. TRAIN the model & CALCULATE the RMSE, R2 & SNR.
5. SAVE the MLP model
6. CALL the model to predict the output voltage of a test case
7. RECONSTRUCT the wavelet transformation into time-domain as per the Algorithm 4.2
8. PLOT the original waveform and predicted waveform
9. CALCULATE the RMSE, R2 &SNR for this particular test case

Model: "sequential"

Layer (type)	**Output Shape**	**Param #**
dense (Dense)	(None, 64)	512
dense_1 (Dense)	(None, 32)	2,080
dense_2 (Dense)	(None, 16)	528
dense_3 (Dense)	(None, 1)	17

Total params: 3,137 (12.25 KB)

Trainable params: 3,137 (12.25 KB)

Non-trainable params: 0 (0.00 B)

Figure 4.2: MLP model summary

4.5 ALGORITHM FOR LONG SHORT-TERM MEMORY

The LSTM model uses a sequential architecture, consists of two LSTM layers with ReLU activation functions to capture temporal dependencies within input sequence data. The dense layer uses tanh activation function and the final dense layer contains 1 neuron with a linear activation function for continuous sequential output prediction.

Algorithm 4.5 Long Short-Term Memory Model

Input: DWT waveform of input, component and output space
Output: output space prediction

1. LOAD the *input_data* columns as xtrain & *output_data* column as ytrain
2. DEFINE *Sequential* model from Tensorflow Keras and initialize two LSTM layers with 64 neurons and *ReLU* activation function. Followed by a Dense Layer with *tanh* function. The final Dense layer contains single neuron and *linear* activation function.
3. COMPILE the model with Adam Optimizer and select MSE as a loss function.
4. TRAIN the model & CALCULATE the RMSE, R2 & SNR.
5. SAVE the LSTM model
6. CALL the model to predict the output voltage of a test case
7. RECONSTRUCT the wavelet transformation into time-domain as per the Algorithm 4.2
8. PLOT the original waveform and predicted waveform
9. CALCULATE the RMSE, R2 &SNR test case

4.6 ALGORITHM FOR REGRESSION TRANSFORMER

Regression Transformer uses an encoder-decoder architecture, where each contains multi-head attention layers and FFN layers. The encoder layer and decoder layer is built very similarly where in decoder layer encoder level attention is given as input. Input embedding is done for input variables and target embedding is done for target variables. Adam optimizer is used for optimization and MSE is used as a loss function of the model.

Algorithm 4.6 Regression Transformer

Input: DWT waveform of input, component and output space
Hyperparameters: number of layer, hidden dimensions, droupouts, heads.
Output: output space prediction

1. LOAD the *input_data* columns as xtrain & *output_data* column as ytrain
2. RESHAPE the input features to *sequence_length, feature_dim*
3. CREATE *Encoder* layer with self-attention mechanism, feed-forward network and layer normalization. Include dropout if needed.
4. CREATE *Decoder* layer very similar to encoder but with cross-attention from encoder output and level attention
5. CREATE *Positional Encoding* to input and target sequences
6. STAKE multiple encoder and decoder layers to build the transformer architecture.
7. MAP the decoder's output to a linear layer to match the output (vinn)
8. INITIALIZE the hyperparameters, loss function (MSE), optimizer (Adam)
9. TRAIN the model & CALCULATE the RMSE, R2 & SNR.
10. SAVE the Regression Transformer model
11. LOAD the model to predict the output voltage of a test case
12. RECONSTRUCT the wavelet transformation into time-domain as per the Algorithm 4.2
13. PLOT the original waveform and predicted waveform
14. CALCULATE the RMSE, R2 &SNR for test case

CHAPTER 5

RESULTS AND PERFORMANCE ANALYSIS

This chapter discusses the results of output voltage prediction of an OP-AMP using wavelet transform in Random Forest, Multi Layer Percepton, LSTM and Transformers. It also includes the use of evaluation metrics for performance analysis and presents a comparative analysis of the different types of models.

5.1 OP-AMP CIRCUITS – INPUT AND OUTPUT TIME-DOMAIN AND WAVELET WAVEFORMS

Figure 5.1 illustrates the input attributes of the Operational Amplifier (vinp, vdd, pd, xpd) and the output attribute (vinn) in time-domain waveform.

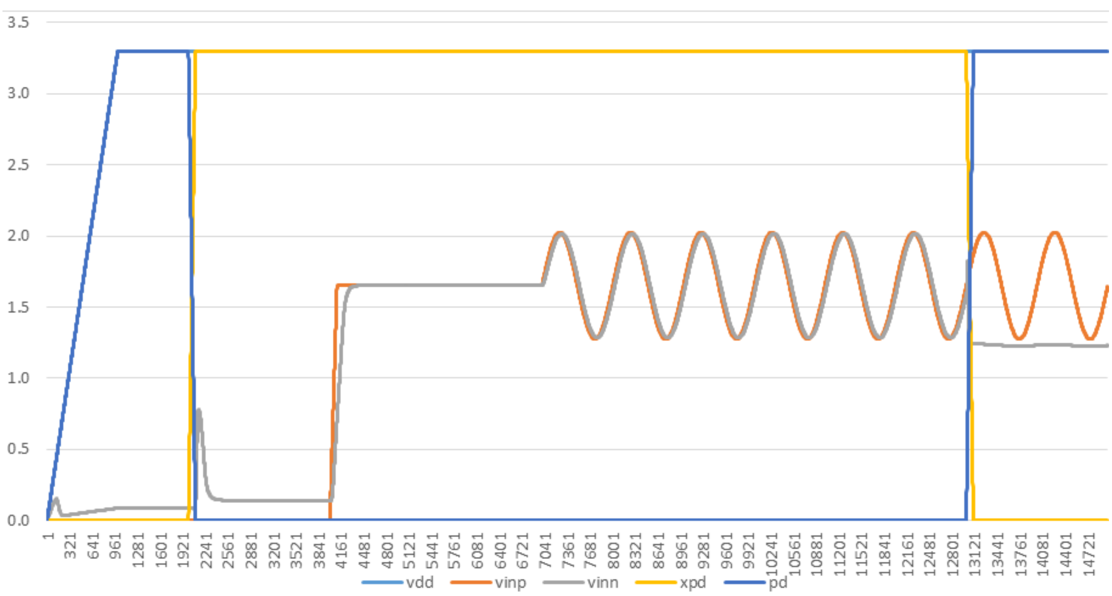

Figure 5.1: OP-AMP Input & Output time-domain waveform

Figure 5.2 illustrates the output variable (vinn) in time-domain waveform and its converted wavelet coefficients. The wavelets used in conversion is Daubechies (DB4) with 12 levels of decomposition

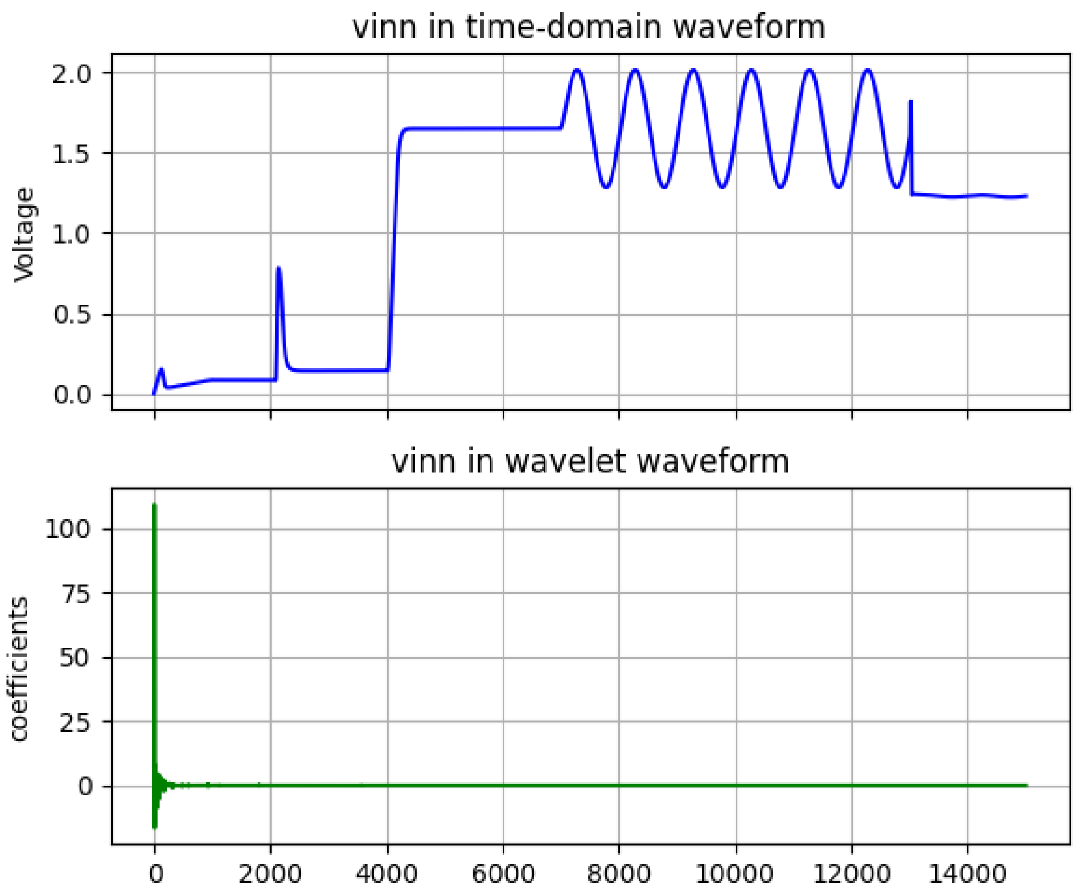

Figure 5.2: output variable (vinn) in time-domain waveform & wavelet waveform

5.2 EVALUATION METRICS FOR PREDICTION

The regressed predicted output voltage is evaluvated using following metrics and parameters: Mean Average Error (MAE), Mean Square Error (MSE), R2 Score, Signal-to-Noise Ratio (SNR).

Mean Absolute Error (MAE): MAE is the average magnitude of the absolute differences between predicted and actual values.Lower MAE indicates better predictive accuracy. The formula for MAE is given in Equation 5.1

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5.1}$$

where n refers to the number of observations, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

Mean Square Error (MSE):MSE calculates the average squared difference between predicted and actual values.Like MAE, a lower MSE indicates better accuracy, but MSE penalizes larger errors more heavily due to squaring.The formula for MSE is given in Equation 5.2

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5.2}$$

R2 Score (Coefficient of Determination): R2 measures how well the regression predictions approximate the real data points. Formula for R2 is given in equation 5.3 where $\bar{y}$ is mean of actual values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5.3}$$

When R2 = 1, it indicates that the model is a perfect fit and explains all the variability in the data. If R2 = 0, it means the model does not explain any of the variability in the data . When R2 $<$ 0, it signifies that the model performs worse than simply predicting the mean of the data.

Signal-to-Noise Ratio(SNR): SNR compares the level of the desired signal to the level of background noise. Higher SNR indicates a cleaner signal with less noise. Values are often expressed in decibels (dB). Formula for SNR in decibels is given in equation 5.4

$$\text{SNR (dB)} = 10 \cdot \log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right) \tag{5.4}$$

5.3 PREDICTION IN RANDOM FOREST MODEL

Random Forest model were used to predict the output voltage based on the input parameters. After training the RF model with 100 n estimators it gave an MSE of 0.0207, MAE = 0.0698 and R2 = 0.9549.

Performance Evaluation: As a test case, dataset of typical process, voltage of 3.6V and 45°C is used. The predicted vinn produces MAE = 0.0577, MSE = 0.1293 and R2 Score = 0.9714 and SNR = 21.28 dB. The output waveform between original and predicted values for the same dataset is shown in Figure 5.3

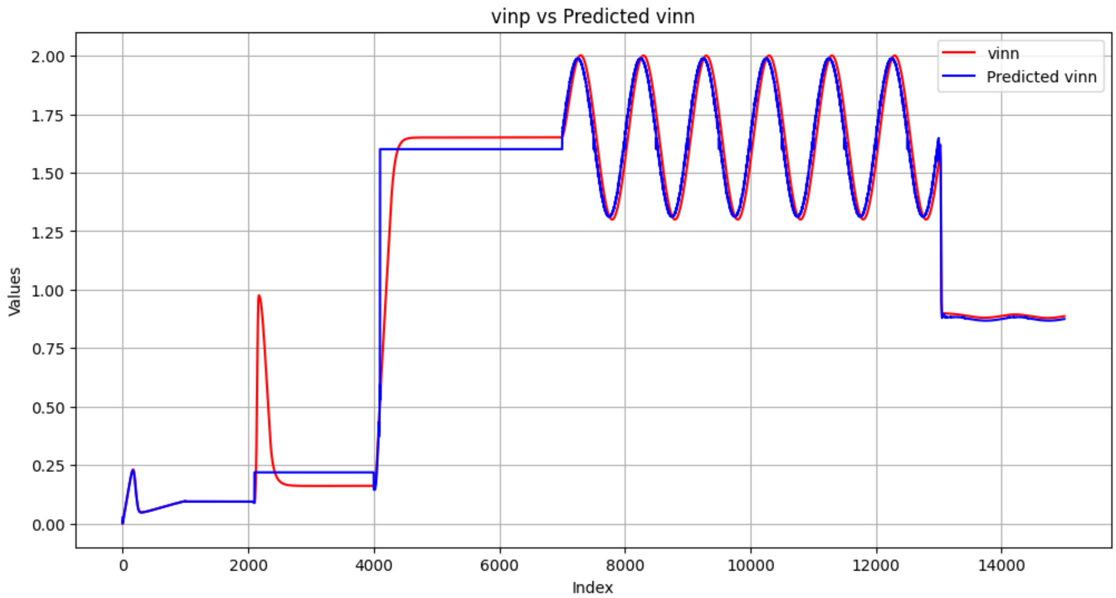

Figure 5.3: RF Model Original vs Predicted – Typical 3.6V 45°C

5.4 PREDICTION IN MULTI-LAYER PERCEPTRON

The Multi-Layer Perceptron model is trained with the DWT of the input, component, and output waveforms. It consists of 4 dense layers with 64, 32, 16, and 1 neuron, respectively, using the Adam optimizer.

Performance Evaluation: As a test case, As a test case, dataset of typical process, voltage of 3.6V and 45°C is used. The predicted vinn produces MAE = 0.0382, MSE = 0.0065, R2 Score = 0.9855 and SNR = 24.47dB. The original and predicted waveform in time-domain is shown in Figure 5.4.

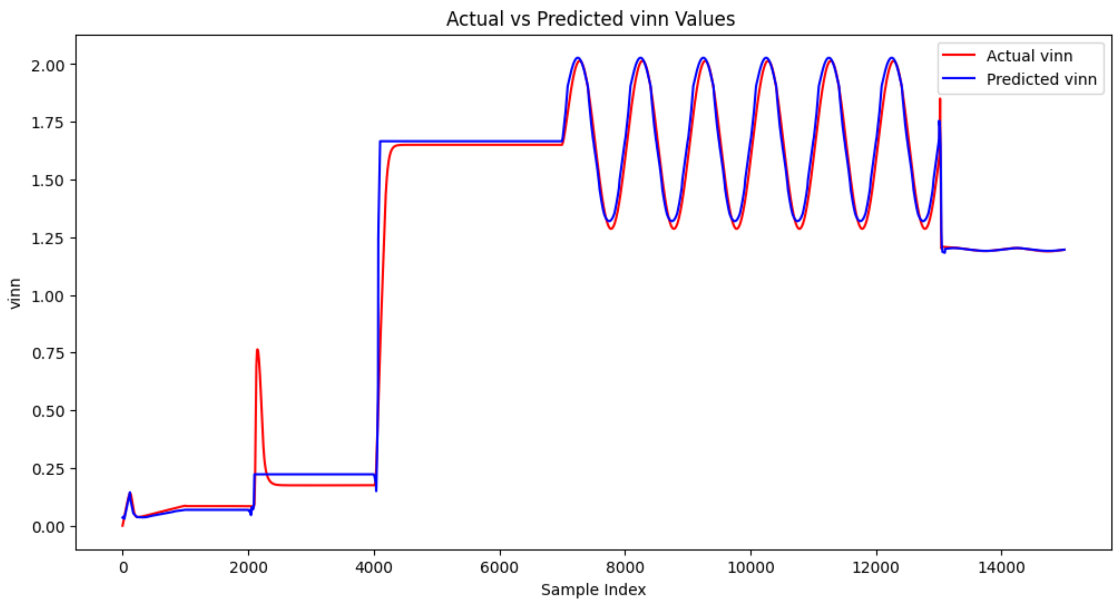

Figure 5.4: MLP Model Original vs Predicted – Typical 3.6V 45°C

5.5 PREDICTION IN LONG SHORT TERM MEMORY

The LSTM model is trained on wavelet-transformed circuit simulated data. Its architecture includes 2 LSTM layers, each with 64 neurons, followed by a dense layer with 256 neurons. and a final dense layer consists of a single neuron for regression output.

Performance Evaluation: As a test case, As a test case, dataset of typical process, voltage of 3.6V and 45°C is used. The predicted vinn produces MAE = 0.0419, MSE = 0.0048, R2 Score = 0.9892 and SNR = 28.54dB. The original and predicted waveform in time-domain is shown in Figure 5.5.

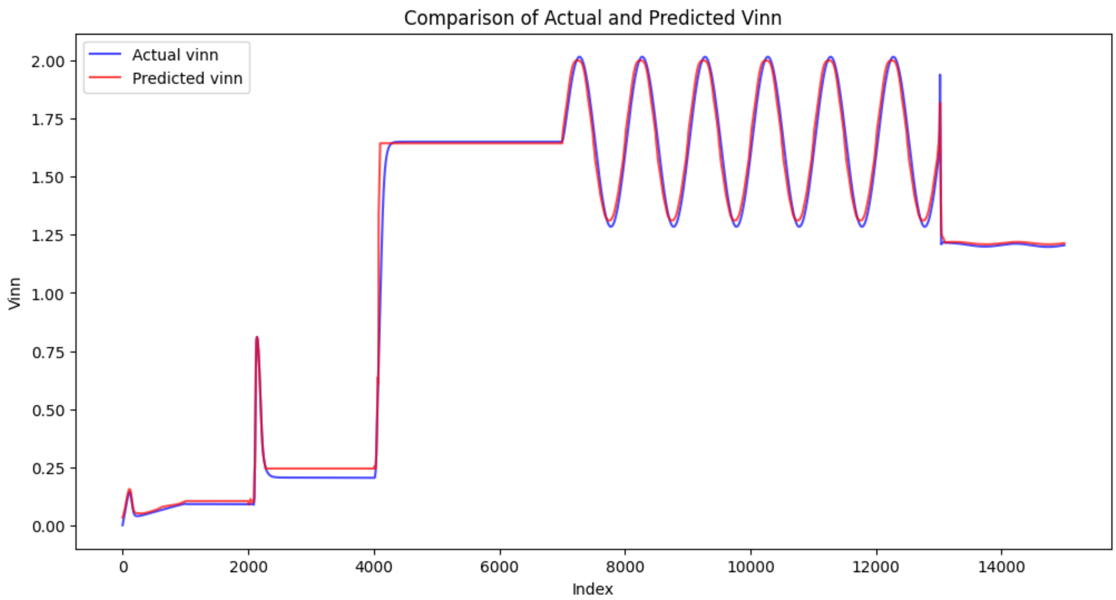

Figure 5.5: LSTM Model Original vs Predicted – Typical 3.6V 45°C

5.6 PREDICTION IN REGRESSION TRANSFORMER

Regression Transformer is made of encoder and decoder.The encoder includes multiple multihead attention layer followed by a feed forward network. The decoder, features a multi-head attention layer for the encoder's output, an input embedding layer for the input, its own multi-head attention layer, and a feed-forward network layer.

Performance Evaluation: As a test case, As a test case, dataset of typical process, voltage of 3.6V and 45°C is used. The predicted vinn produces MAE = 0.0230, MSE = 0.0007, R2 Score = 0.9984 and SNR = 34.11dB. The original and predicted waveform in time-domain is shown in Figure 5.6.

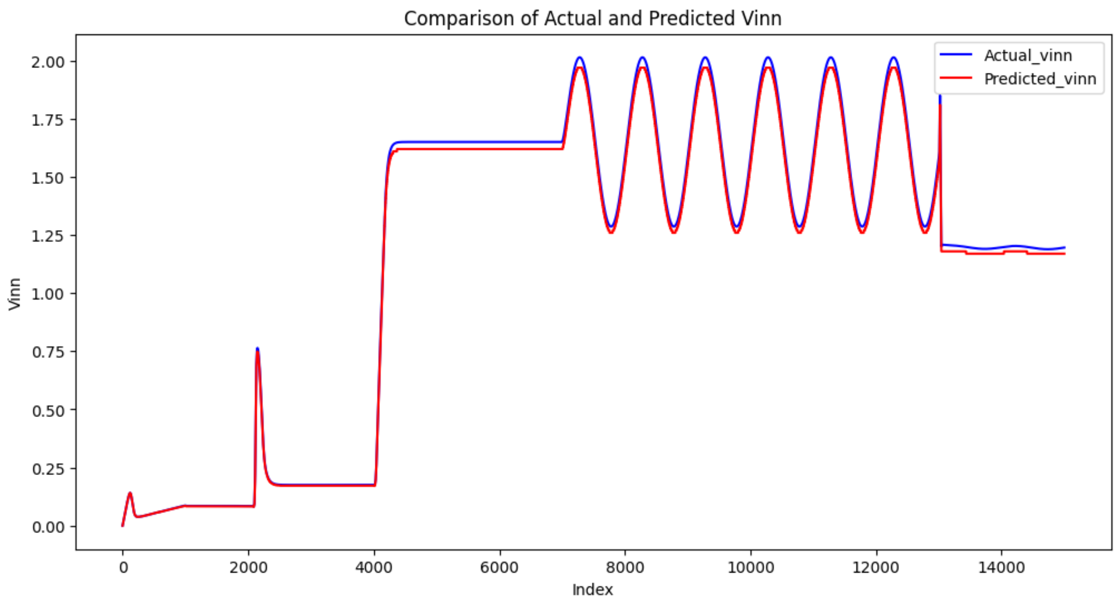

Figure 5.6: Regression Transformer Model Original vs Predicted – Typical 3.6V 45°C

5.7 COMPARISON BETWEEN MODELS

Table 5.1 provides a comparison of various models used for output voltage prediction, highlighting the superior performance of the Regression Transformer. Lots of reason contribute to its effectiveness, including the utilization of the multi-head attention mechanism, which enhances the model's ability to capture complex relationships in the data. Additionally, it benefits from its encoder-decoder architecture, allowing it to better handle sequential data and make more accurate predictions.

Table 5.1: Comparison between the ML & DL models for prediction

Model	MAE	MSE	R2	SNR
Random Forest	0.0577	0.1293	0.9714	21.28dB
Multi-layer Perceptron	0.0382	0.0065	0.9855	24.47dB
Long Short Term Memory	0.0419	0.0048	0.9892	28.54dB
Regression Transformer	**0.0230**	**0.0007**	**0.9984**	**34.11dB**

CHAPTER 6

CONCLUSION AND FUTURE WORKS

6.1 CONCLUSION

The proposed framework uses discrete wavelet transform to compress the signals and utilizes machine learning & deep learning algorithms to build models to predict output voltage on unseen simulations. Although the Random Forest model achieved an R2 score of 0.97, it struggled to capture the variability in the data effectively.

Similarly, the Multi-Layer Perceptron (MLP) model attained a higher R2 score of 0.9855 but still failed to capture the initial variability in the data. Both models were able to capture the functional part of the signal very well but faced challenges in accurately predicting the supply-on phase and enable-assertion phase.

Deep learning models like LSTM and Regression Transformer significantly improved performance. The recurrent neural networks in LSTM enabled it to retain important information over time, enhancing its ability to handle sequential data. On the other hand, the multi-head attention mechanism in the Transformer captured the variability in the data more effectively. Its encoder-decoder architecture proved highly successful, showcasing the Transformer's capability to process time-series and sequential data while managing both short-term and long-term relationships. Additionally, the use of SNR as an evaluation metric proved insightful, as it measured the model's ability to differentiate between signal and noise,, further evaluating the built models.

Ultimately, Transformers performed best across all metrics, as shown in Table 5.1, proving their effectiveness for this task.

6.2 FUTURE WORKS

Further enhancement to the current framework can be achieved by exploring datasets and employing techniques such as waveform segmentation which might be a bit more complex but able predict each sub-segmented waveform more accurately. Advanced model architectures, like Transformers integrated with waveform segmentation, could deliver superior performance.

The scope of data can also be expanded beyond time-domain data to include AC analysis data simulated from the tool. Incorporating this into the system could create a unified model, boosting the overall performance of the framework.

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