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Textile Production Line Monitoring System Using Wavelet-Regression Neural Network

Nagaraj V. Dharwadkar, Department of Computer Science and Engineering, Rajarambapu Institute of Technology, India
https://orcid.org/0000-0003-3017-0011

Anagha R. Pakhare, Department of Computer Science and Engineering, Rajarambapu Institute of Technology, India

Vinothkumar Veeramani, Department of Electrical and Electronics Engineering, University College of Engineering, Birla Institute of Technology, India

Wen-Ren Yang, Department of Electrical Engineering, National Changhua University of Education, Taiwan
https://orcid.org/0000-0003-0117-1912

Rajinder Kumar Mallayya Math, BLDEA's V. P. Dr. P. G. Halakatti College of Engineering and Technology, Vijayapur, India & VTU-RRC, India
https://orcid.org/0000-0002-2855-6233

ABSTRACT

This paper presents design and experiments for a production line monitoring system. The system is designed based on an existing production line mapped to the smart grid standards. The discrete wavelet transform (DWT) and regression neural network (RNN) are applied to the operation modes data analysis. DWT used to preprocess the signals to remove noise from the raw signals. The output of DWT energy distribution is given as an input to the GRNN model. The neural network GRNN architecture involves multi-layer structures. Mean absolute percentage error (MAPE) loss has used in the GRNN model, which is used to forecast the time-series data. Current research results can only apply to the single production line, but in the future, it will be used for multiple production lines.

KEYWORDS

Discrete Wavelet Transform, Frames, Normalization, Power System, Regression Neural Network, Smart Grid

1. INTRODUCTION

The paper presents research based on the textile factory production line. For textile manufacturers, the production line's power quality and motor monitoring are essential to operational stability. The purpose of power quality and motor status monitoring is to conduct maintenance in advance to avoid system downtime or malfunctions. New long-distance transmission lines are required to harness these resources to provide an ever-growing load centre. Presumably, these new lines could be high-voltage DC (HVDC) transmission systems owned by companies that break away the standard utilities, which need small and native AC to DC converters. In recent years, many renewable energy sources are wont to generate DC (DC); during this situation, DC to AC inverters must be to interconnect the DC electricity generators to AC systems. Additionally, new power electronics-based controllers like those that the Flexible AC Transmission Systems (FACTS) will install for improving power transfer and providing voltage support are vital factors for reliable operations. Thus, the transmission during a

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future Smart Grid is going to be far more controllable, and therefore the benefits of HVDC systems and FACTS controllers will be maximized (IEEE, 2011; IEEE, 2013; IEEE, 2016).

This research also implements a monitoring system based on smart grid interoperability. The basic principle of a smart grid is to deliver a secure and robust electric system. To accomplish seamless operation for electricity generation and permit two-way power flow with communication, assimilation of energy with technology and information communication is essential. Moving towards the next generation of Smart Grid is a crucial task and requires robust design and consistent infrastructure of networks through which communication is possible to overcome flaws related to the existing system. (Amin, 2011; Germany Trade and Invest, 2014; IEEE, 2011)

This research also complies with industry 4.0 standards and implements an essential structure for a smart factory. To realize the more intelligent manufacturing processes fourth technological revolution encapsulates development trends for the future industries(Rüßmann et al., 2015), which will adapt on-board information and advanced communication technology for evolution within the supply chain and assembly line, by real-time data monitoring, tracking the status and positions of the product also by sticking to the instructions to regulate production processes.(Radziwona, 2014). Recent research specializing in the role of Industry 4.0 on the assembly and services sector of Pakistan conducted a survey questionnaire from a complete 224 employees of textile and logistics companies. Therefore, the findings revealed that Industry 4.0 has significant importance in overcoming the varied challenges of Pakistan's textile and logistics industry (Imran et al., n.d.). Industry 4.0 connects embedded system production technologies and smart production processes to pave, thanks to a replacement technological age, which radically transforms industry and production value chains and business models, e.g., Smart Factory. Some key features of Industry 4.0 are digitization, optimization, customization of production and automation, adaptation, Etc. (Burke, 2017; German Standardization Roadmap, 2018; Raafi, 2019).

One of the essential factors in the smart grid is signal processing. This factor helps the engineer and researcher figure out the exact plan, design, and complex operations in the smart grid. Since the monitoring station for the inverter can provide users with the real-time waveform, wavelet transformation is useful for analysing power quality. A wavelet transform within which waves are separate samples referred to as a discrete wavelet model. The DWT (Discrete Wavelet Transform) gives a multi-goal portrayal of the signal, which is valuable in analysing real-world signals. DWT is a fast computation wavelet transform that is based on sub-band coding.

To improve the capability of the WT (wavelet transforms) based on power quality monitoring system, many researchers proposed a de-noising approach to detecting transient disturbances in a noisy environment. Moreover, the modified approach is known as S–transform, which is useful for localization, detection, and visually classify the types of disturbances. (Dash et al., 2003; Yang & Liao, 2001)

It does not have the restrictions associated with conventional neural networks or algorithms related to neuro-fuzzy, such as convergence to local optimum points, over-fit, and under-fit queries (Masoum et al., 2010).

To evaluate the harmonics in the power system, the wavelet transform technique can be used. Conventional signal processing tools have some severe drawbacks for harmonics applications, so the wavelet transform is an engaging alternative method. Because it has superior time-frequency resolution property as well as for studying non-stationary power waveforms.

To study extensive data set analysis and the viability of operating system conditions, advanced computational intelligence methods are used. A reliable communication system must be built to handle the data exchange needs for intelligent devices at all voltage levels. This paper investigates primary methodologies for the implementation based on real waveforms rather than simulation. Wavelet neural network used for this is smaller and more efficient than immense deep learning and Convolutional Neural Network (CNN).

2. SYSTEM DIAGRAM AND DESIGN PROCEDURES

Smart grid interoperability is used as the cross-correlation factor to investigate relationships between the power system, communication system, and information system. The power system interoperability architectural perspective describes fundamental utility relationships in the current PS (Power System) as shown in fig.1. CT (Communication Technology) IAP (Interoperability Architectural Perspective) describes communication connections and relationships between utilities and subsystems. The IT (Information Technology) interoperability illustrates data and information flow through entire utilities and subsystems in the smart grid.

Fig 1 illustrates the mapping of system planning of this research for smart grid interoperability. In this figure, the textile fabrication line driving motors and inverters are related to PS IAP. The voltage and current measurement modules are related to PS/CT IAP. The connection and transmission medium from the data recording unit to the presumed server is related to CT IAP. The data storage in the presumed server is related to CT/IT IAP. The signal processing, neural network approximation, and prediction are related to IT IAP.

The textile production monitoring system for data analysis includes data collection, data transmission, data pre-processing, signal pre-processing, and training and testing of the dataset using a neural network. All the information about the smart grid system is stored in the primary device's database. Data is collected from the primary device using the remote connection process and loaded into the Personal Computer for data analysis. These CSV dataset files are loaded using Pandas Tensor flow, and after that, this process is followed by the cleaning and normalizing of the dataset. Normalization is required to reduce data redundancy and complexity of data to improve data integrity and eliminate useless data. Perform training and evaluation on this dataset for further use. Training and testing on the dataset can minimize data inconsistency and a superior perception of the model's characteristics.

Discrete Wavelet Transformation is used to perform the decomposition on a newly generated dataset, and in this process, mathematical calculations are applied to eliminate the noise from the original signals. Feed those generated values after DWT decomposition as input values to the neural network to obtain target output value as a motor speed. After that, build the model and compile it using MAPE (Mean Absolute Percentage Error).

Load CSV Data: The CSV file records DC voltage, output power, motor speed, power factor of a three-phase inverter. The inverter is installed in a textile factory to drive a production line motor. This CSV data and other information can be accessed remotely or manually. This data is used for analysis purposes, so it produces good results that have fewer errors in the future.

Three dataset files are used which contains following data:

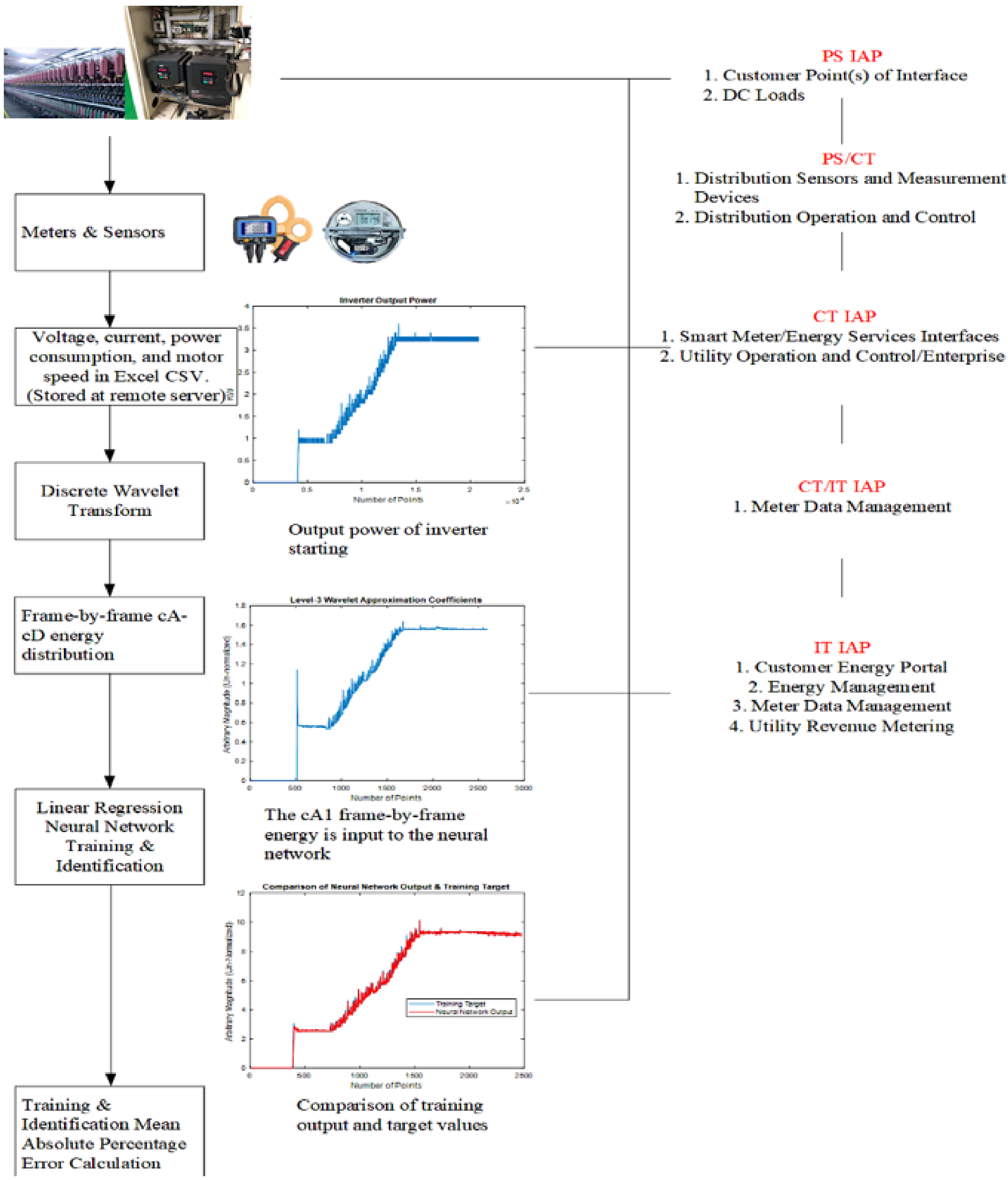
Data 1 File: Data 1 CSV file contains a dataset at the time when the motor's power supply is turned off, so it is called Maintenance mode or shutdown mode. Which means suspend any operation in the middle of the phase or after completion of that phase.

Data 2 File: Data 2 CSV file contains dataset at the time of Restart mode. It is the starting phase when we provide a power supply to the motor.

Data 3 File: Data 3 CSV file contains the data when the motor's speed is at stable mode, so it is named as stable mode.

Normalization: Normalization is a precise approach towards decomposing a dataset, which includes the decomposition of tables to reduce data redundancy. It is also known as the data preparation part, which is useful in machine learning applications and algorithms. When data has a varying scale, it is difficult to perform calculations on such data, and the applied algorithm is confused to make any predictions about distributing data. This dataset contains DC voltage, output power, motor speed, power factor where DC voltage ranges from 0-400, output power ranges from 0-5, motor speed ranges from 0-3000, and power factor ranges from 0-2.

Figure 1. Planning and Experimental Block Diagram of Proposed Method



PyWavelets: The PyWavelet is an open-source wavelet toolbox or library for wavelet transform in which the python package implementing several n-dimensional discrete wavelets transforms as well as the 1D continuous wavelet transform. PyWavelets has additional functionality that is not common in other wavelet toolboxes, such as support for dimension n > 3 and real and complex data in either single or double precision. This functionality is also useful in signal processing, time-series analysis, image processing, etc.

Wavelet Transformation: In the electrical field, signal processing is used to analyse power quality detection. In signal processing, wavelets are widely used to analyse and transform discrete data.

Wavelet transforms are classified as the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT), where DWT is used for signal coding, and the CWT is used for signal analysis. In DWT, only two filters are used in each decomposition level, one of them is a low pass filter, and the other is a high pass filter. The high pass filter is used to analyse the high frequencies, and the result is called as detail coefficient (cD), while to analyse the low frequencies low pass filter is used, and the result is called approximation coefficient (cA).

An important element in power system planning is the load forecast used to de-noise the wavelet transform integrated with neural networks.

Figure 2 shows the system's process flow, which requires an analysis of the data from the smart grid in which the user collects real-time data using the remote access method.

CSV data file consists of three input values DC voltage, Output KW, Output PF and Time, respectively. Also, the output factor Motor Speed is there. Data consists of duplicate values, some null values, so the cleaning of data is necessary before performing testing and training on the dataset to obtain the final dataset.

Noises often pollute signals required for data analysis. So, feature extraction is difficult primarily when the signal's noise has a high-frequency spectrum, which may overlap with the frequency of fault. For the decomposition of the data, approximation, and details coefficients are used, and they are in the form of cA1…cAn and cD1…cDn, respectively.

3. RESULTS AND DISCUSSION

3.1 Signal Analysis:

Signal plays a vital role when it comes to the data analysis process. Using signals, data property analysis, and observations related to change in data, quality, and quantity become easy to understand. The sampling rate of data points is 0.5 Hz; that is, the data point interval is 2 seconds.

Figure 3(a), (b), (c), (d) represents the graph of all signals for analysis purpose and further processing on them. This signal contains many null values; removing these null values will minimize the errors and complexities and produce efficient results for analysis purposes. There are different methods to eliminate and replace these null values. In this paper, the final resort method is used to delete every row or record, which contains a null value.

In fig. 3(a), when the system runs in regular mode, the power factor (PF) remains constant throughout irrespective of the change in the number of points for a certain period. As no of the points exceeds 15000, we can see a drastic change.

In start mode, PF is 0; this indicates that the current drawn at the load is very high. As no of the points reaches from 18000 to 20000, we can observe the stability in PF. The stability of PF is between 18000 to 20000, which is nothing but regular mode operation and in this fig, there is are no harmonics can be observed as regular mode operation.

When it is in shutdown mode, the PF gradually decreases from 0.55-0.4, and this remains constant until 10000 no of points. A drastic increase in PF is observed, and then from there is a gradual decrease observed in PF, which is not observed, and the system is ready for the next cycle of operation.

In fig.3(b), according to regular mode, start and shutdown mode distortion is observed for the voltage analysis. In regular mode, voltage is dropped down from 300V to 296V.

The same flickering of 296V is observed at the end of the start mode when no points are somewhere near 15000 data points.

At the end of start mode, the voltage observed is 299V, and in shutdown mode, that starts at 299V, and distorted waveform settled at 301V.

Figure 3(c) shows that the motor speed is 1230.9rpm till 6000 no of points in regular mode. Motor speed increases and remains constant till the time where no of points reaches to 20000 and known as

Figure 2. Flow Diagram

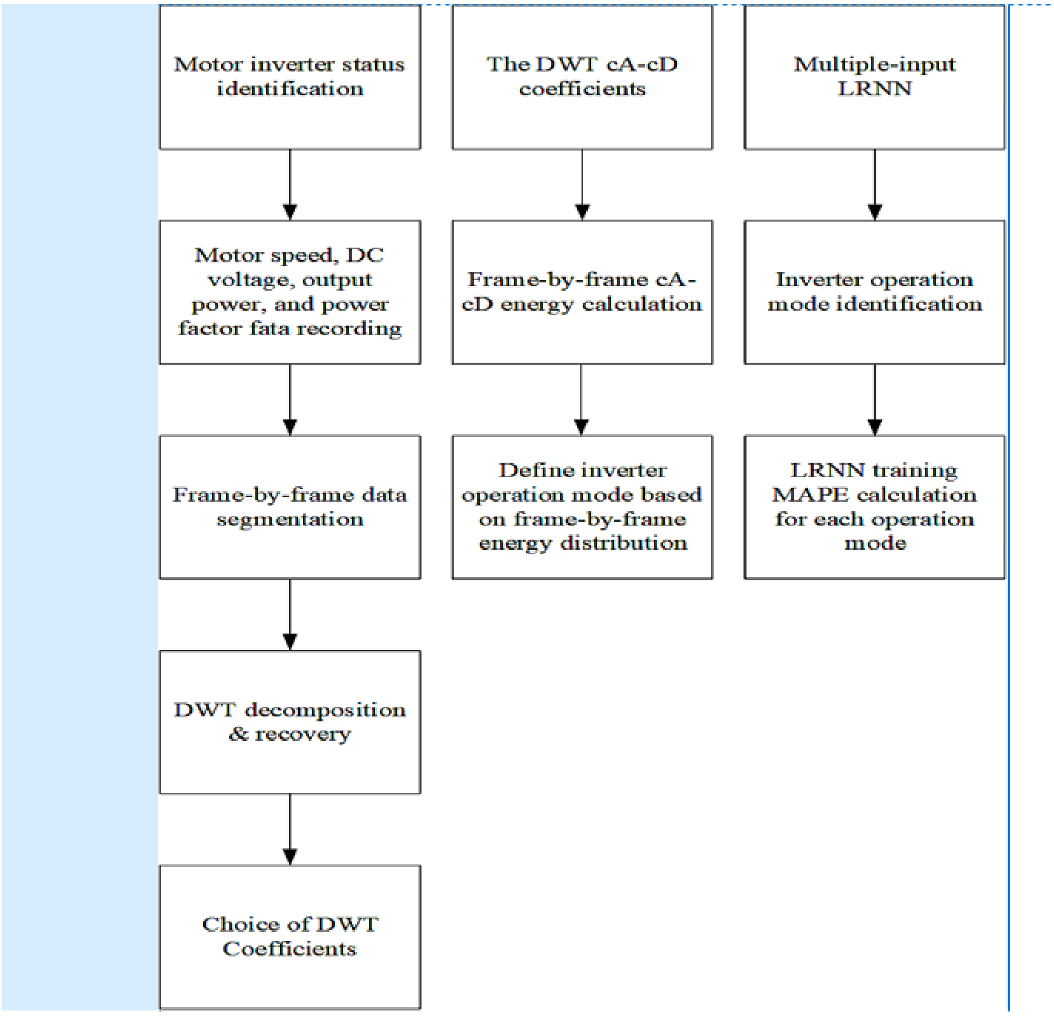
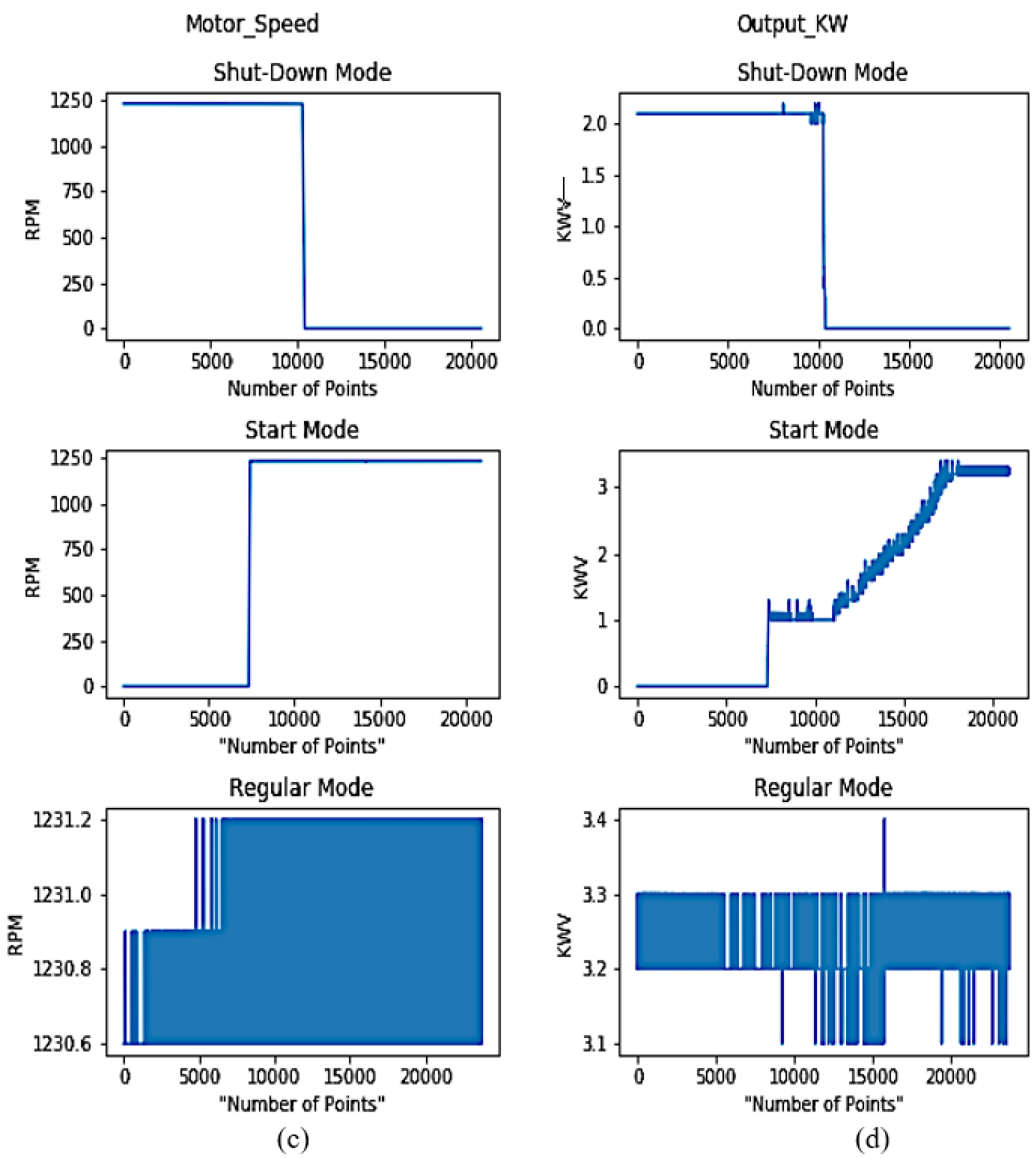


Figure 3 (a). Power factor from Data 1-3 (b). DC voltage from Data 1-3. (c). Motor speed from Data 1-3 (d). Output KW from Data 1-3



regular mode. In start mode, the motor is not gaining any speed until 6000, and from 6000 -20000, start mode is similar to regular mode and is running at speed as that of regular mode, 1231.2 rpm. Shut down mode continues start mode speed until the no of points reaches 10000. Then, the motor stops operating and is ready to operate for the next cycle.

In fig.3(d), In regular mode, power output is 3.3KW, and it remains constant. There is a stable power of 1 KW in start mode when no points are from 6000 – 11000. From 18000- 20000, start mode operates similar to regular mode with 3.3KW. Due to power loss, 2KW of output power is observed in shutting down mode till 10000 no of points. Then it is ready for the second cycle.

In the CSV file, after approximately ten thousand rows, it contains all null values of Output KW, Output PF, and Motor Speed, so this method is essential for removing null values from the dataset.

3.2 Window Function:

Before decomposition, signals are divided into frames, which helps to achieve stationarity in signals. In this process, the data block executes one frame at a time, and after that window rolling function is applied to these frames. Generally, the rolling function is used to smooth the fluctuations in the signals. Output generated after this process is fed to the discrete wavelet transform for decomposition. Window or tapering function in signal processing is used to draw smooth sampled signals. Hamming, Hanning, Blackman, Hann, etc., are different types of windows.

In this paper, the hamming window function (Proakis & Manolakis, 1996) is used.

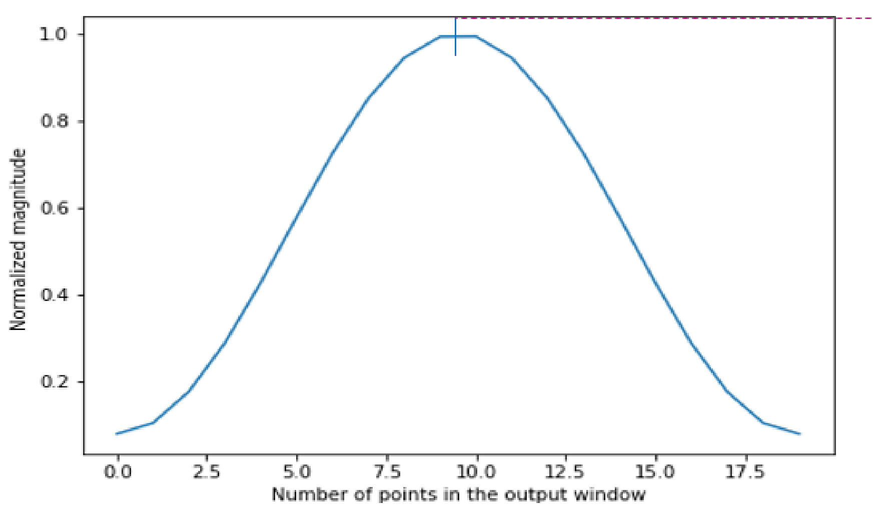
$$w\left(n\right) = 0.54 - 0.46\ \cos\left(\frac{2\pi n}{M-1}\right) \tag{1}$$

Where $0 \leq n \leq M-1$ and M is the number of points in the output window.

The Hamming window functions have a sinusoidal shape, resulting in a broad peak but low side lobes. For noise measurements, this window function is useful where there is a need for better frequency resolution, but moderate side lobes do not present a problem.

In Fig.4, datasets are first split into 200 data points per frame, the resulting splits sizes will differ from the expected value when applied on the small dataset rather than on big data, where they will be very close to exact. And then, the window function having a window size of 20(20 data points per window) is applied to each frame.

Figure 4. Hamming window function



3.3 Discrete Wavelet Transform (DWT):

The DWT has a major impact time frequency analysis for the non-linear signals. It assesses the spectrum signals of aperiodic and time-varying signals from the system. It also has ability to overcome the demerits of the fast Fourier Transforms (FFT).

A vast amount of data can be generated by a single captured event recorded for several seconds using monitoring instruments, leading to the rise of data storage and transmission. Data compression is aided by wavelet transform's ability to concentrate a large percentage of total signal energy into a few coefficients. Thus it eliminates the need for large quantities of data to be processed and reduces its costs.

Selection of appropriate Wavelet Transform: The researchers tend to neglect the choice of an appropriate wavelet filter for their application. The selection of wavelets and their special filters is important because it can cancel out aliasing effects if used correctly.
Introduction to Wavelet Families: There are several wavelet families that exist, and each one of them has a specific application. Some of the commonly used wavelet families that can be used to examine the phenomena of harmonics are Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, Meyer, Complex Wavelets, Etc.

In the CWT 2-3, the mother wavelet is widened and converted continuously over a real constant number system.(Daubechies, 1992; Gu & Bollen, 2000) Hence, it can create extensive redundant data. By replacing $\mathrm{a} = \mathrm{a}_0^{\mathrm{m}}$ and $\mathrm{b} = \mathrm{nb}_0\mathrm{a}_0^{\mathrm{m}}$, where a0 and b0 are the stationary coefficients with $a_0>1$, $b_0>0$ and m, n goes to N. Here, N is the set of positive integers. It can be defined as

$$\psi\Psi_{m,n}\left(t\right) = a_0^{-m/2}\psi\Psi\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \tag{2}$$

And the equivalent Discrete Wavelet Transform (DWT) can be defined as

$$DWT_{\Psi\psi}x\left(m,n\right) = \int_{-\infty}^{\infty} x\left(t\right)\psi\Psi_{m,n}^{*}\left(t\right)dt \tag{3}$$

In the DWT, widened wavelets' family establishes an orthonormal origin by cautious ranges of a_0 and b_0. There are some inferences of the orthonormal source. The orthonormality confirms no data errors amid the decayed signals, with the ideal picks of a_0 and b_0, a well-made algorithm known as the multiresolution signal decomposition. It decomposes a signal into several scales with diverse time and frequency resolutions. In the DWT, the process starts with transiting the discrete signal x[n] of length N over a digital low pass filter with impulse response g[n] and a digital high pass filter with impulse response h[n]. The low pass and high pass filters are called ascending and wavelet filters, respectively. The outcomes from the low pass filter are approximation coefficients of the discrete signal at the first level of the DWT tenacity. The output obtained from the high pass filter is the detail coefficients of the discrete signal at the first level of resolution of the DWT. The outcome of these filters consists of N wavelet constants, and this creates the first level of decomposition of the discrete signal and can be arithmetically expressed as,

$$\mathrm{cA}^1\left[\mathrm{n}\right] = \sum_{\mathrm{k}=0}^{\mathrm{N}-1}\mathrm{g}\left[\mathrm{k}\right]\mathrm{x}\left[\mathrm{n}-\mathrm{k}\right] \tag{4}$$

$$\mathrm{cD}^1\left[\mathrm{n}\right] = \sum_{\mathrm{k}=0}^{\mathrm{N}-1}\mathrm{h}\left[\mathrm{k}\right]\mathrm{x}\left[\mathrm{n}-\mathrm{k}\right] \tag{5}$$

The approximation constants (cA1) at the first level of resolution are used as inputs for different wavelet filters and afterward down sampled by two. The filters at the second level of resolution produce approximations and details constants of length N/2.

And this creates a second level of decomposition of the discrete signal and can be arithmetically expressed as,

$$cA^2\left[n\right] = \sum_{k=0}^{\frac{N}{2}-1} g\left[k\right] cA^1\left[2n-k\right] \tag{6}$$

$$cD^2\left[n\right] = \sum_{k=0}^{\frac{N}{2}-1} h\left[k\right] cA^1\left[2n-k\right] \tag{7}$$

The filter's third level of resolution generates sets of approximations and details coefficients of length N/4. This constitutes the third level of decomposition of the discrete signal and expressed as,

$$cA^3\left[n\right] = \sum_{k=0}^{\frac{N}{4}-1} g\left[k\right] cA^2\left[3n-k\right] \tag{8}$$

$$cD^3\left[n\right] = \sum_{k=0}^{\frac{N}{4}-1} h\left[k\right] cA^2\left[3n-k\right] \tag{9}$$

Figure 5 shows the three-level decay of a disconnected signal of the DWT. It uses the high pass filters h(n) and the low pass filters g(n) in the decaying process. If a wavelet function contests a signal's contour well at a precise scale and location, then a large change in the value will be produced. In addition to this, if the wavelet function and signals do not associate well, then a low value of alteration will be generated. The orthonormality ensures no data redundancy among the decayed signals.

The above Figure shows the DC voltage from a TECO inverter A510s connected to a textile industry load. The voltage is measured continuously using TECO Jn5 drive link software. Initially, the voltage output of the inverter is nearly 308V. Due to some fluctuations in the power supply, there is a sudden drop in the inverter's voltage, which is up to 303V, as shown in the Figure. These fluctuations may cause some change in the motor connected to the inverter, which in turn changes the motor's speed also. This small change in the voltage may significantly affect the motor output, and the discrete wavelet transform can determine this by decomposing the signal in both time and frequency domains.

Figure 6 shows the approximation waveform, which is decomposed and analysed in detail to find the amount of voltage variation in the DC supply. Figure 7 gives the detailed coefficients of the DC supply, which provides an insight to analysed the variations, and gives the information about possible fault occurrences.

A finite group of data in which an orthogonal function can be applied is known as DWT. When windows overlap, there is information redundancy in CWT, which leads to disadvantages like feature

Figure 5. DC Voltage from the Inverter

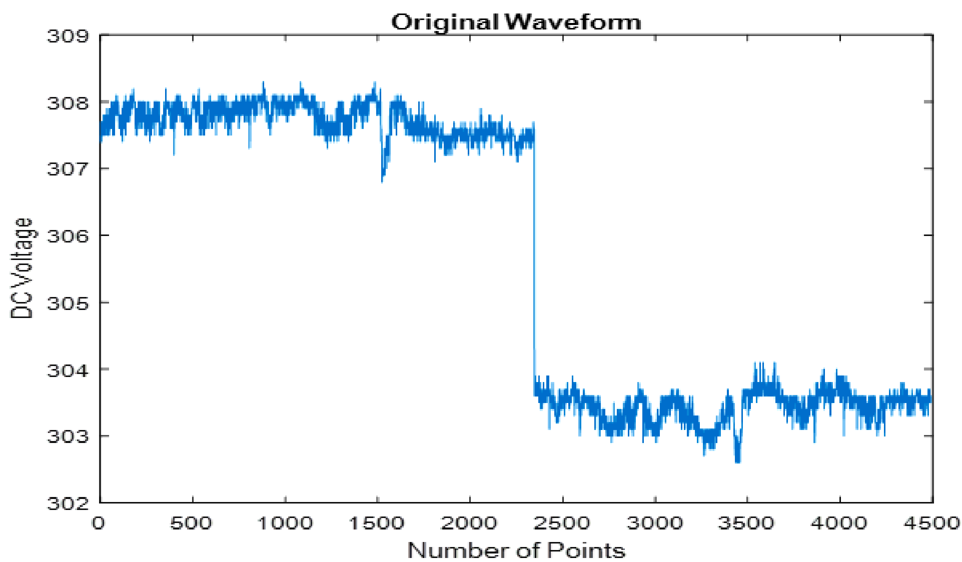


Figure 6. Decomposed signal with approximation and detail coefficients of all three levels

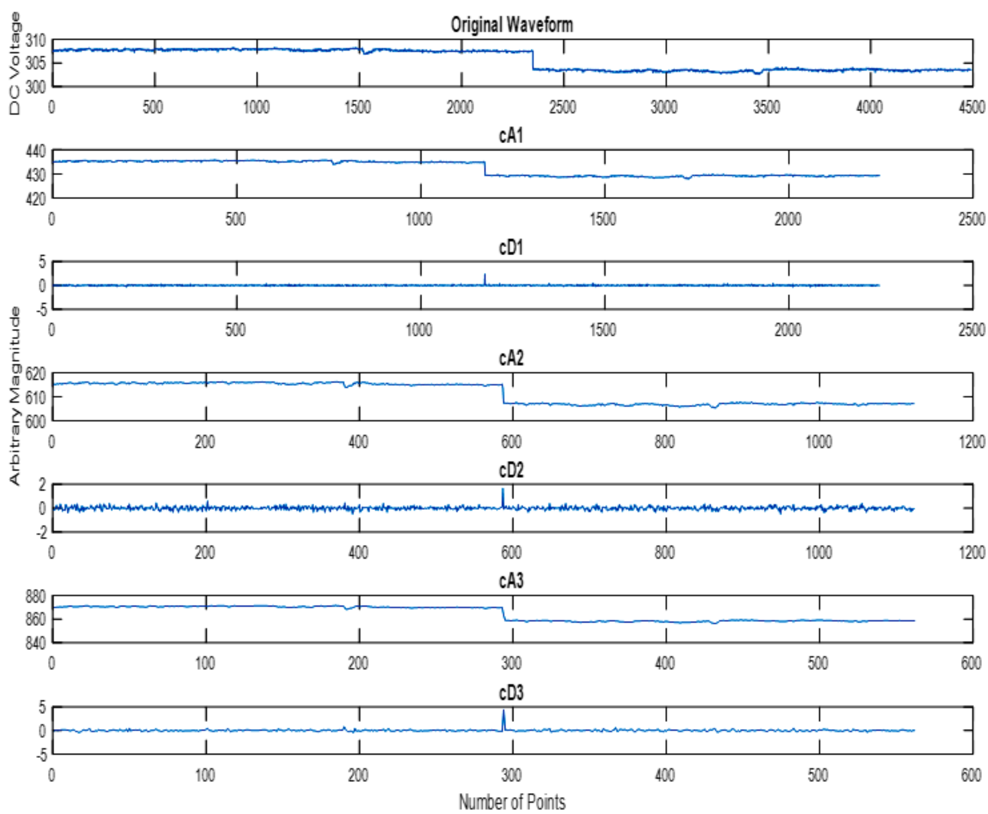


Figure 7. Approximation coefficients of the DC voltage

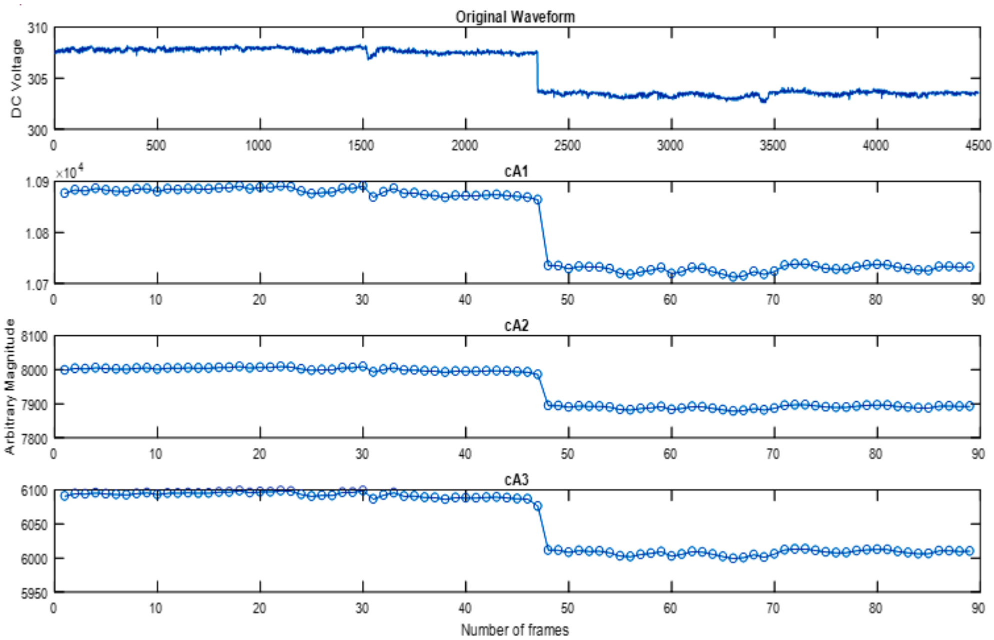


Figure 8. Detail coefficients of the DC voltage

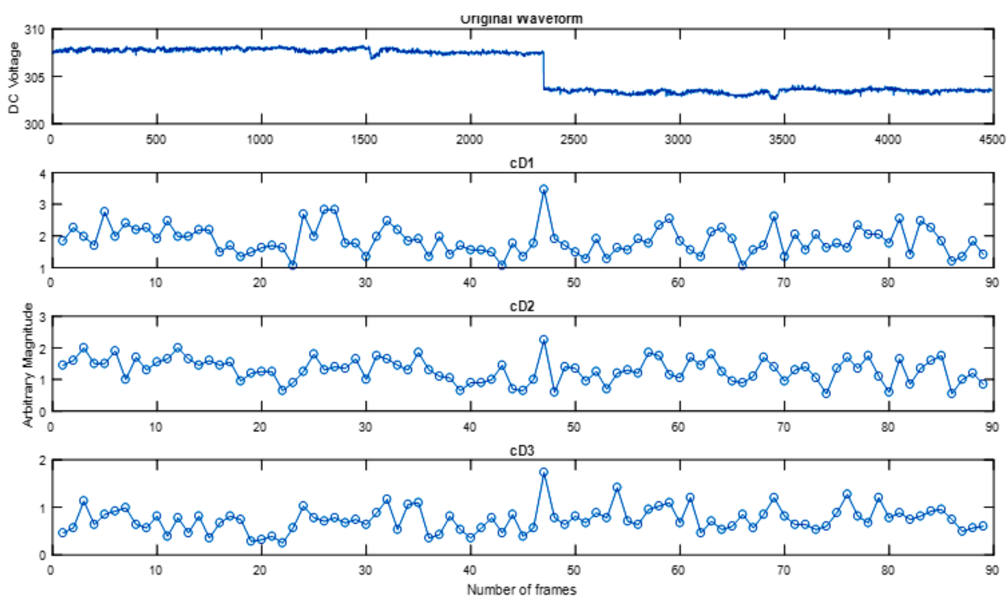
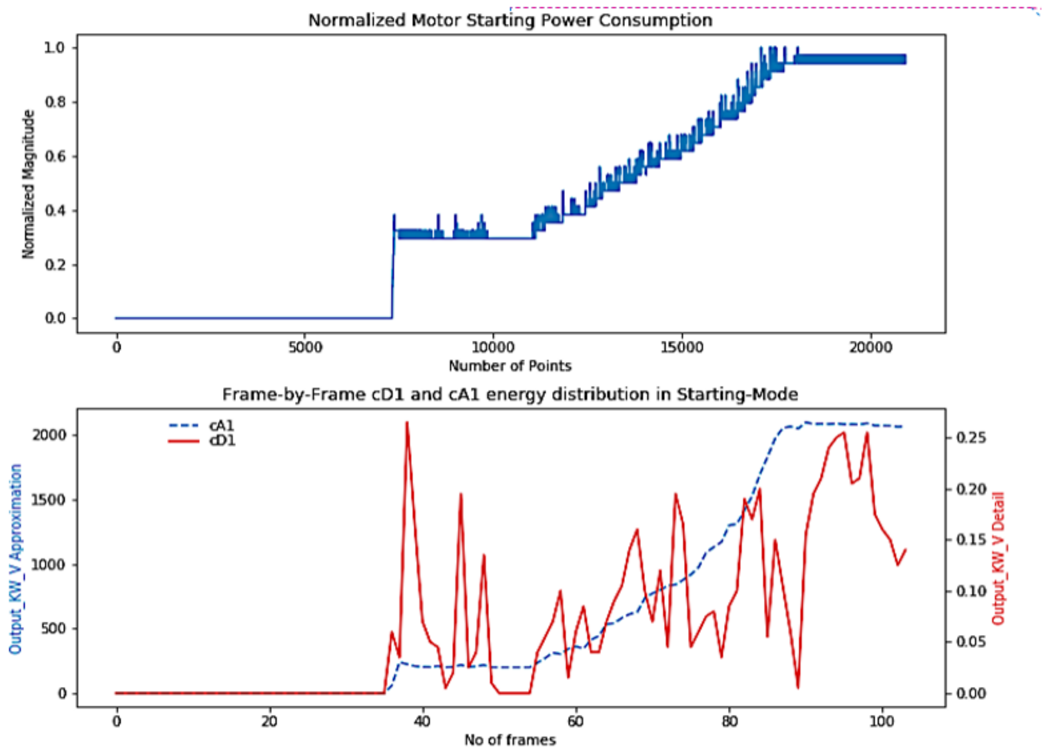


Figure 9. Frame-by-frame cA1 and cD1 energy distribution in Starting Mode (Motor power consumption in Data 2)



extraction or compression of signals. It is essential to calculate wavelet transform discretely to reduce the data redundancy.

The signal decomposition method plays a significant role in data compression and de-noising. In one level decomposition process, each frame decomposed one by one. In this paper, the PyWavelet package (Lee et al., 2019) is used for one level decomposition and recovery process.

$$cA,\ \ cD = pywt.dwt\left(x,\ \ Wavelet\_Name\right) \tag{10}$$

$$pywt.idwt\left(cA,\ \ cD,\ \ Wavele\_Name\right) \tag{11}$$

Where cA: approximation coefficient and cD is detail coefficient, x: input value for decomposition, Wavelet name: db1 (used in code). Equations (10) and (11) narrate the decomposition using PyWavelet packets and inverse decomposition process, respectively. To reconstruct the original signal, the processed coefficients are used and it called as reverse or recovery of signals.

3.4 Energy Distribution:

Based on the analysis of three files following graphs are plotted. It shows the Energy distribution system of the Data 1, Data 2 and Data 3 file. For that, it takes the summation values of both Approximation and Detail coefficient.

Figure 10. Frame-by-frame cA1 and cD1 energy distribution in Starting Mode (Inverter output power factor in Data 2)

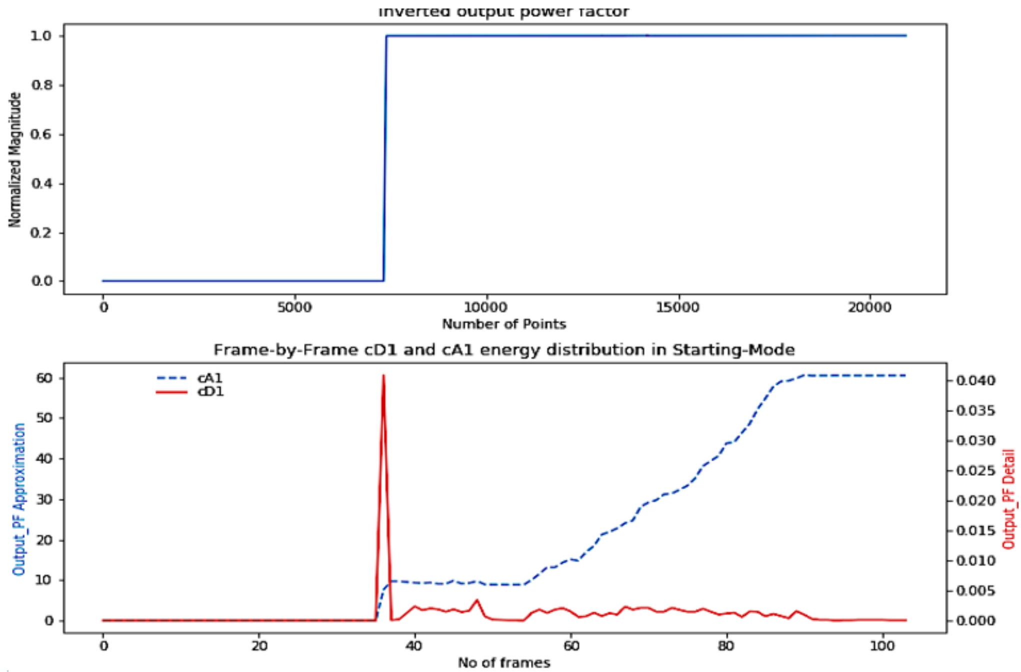


Figure 11. Frame-by-frame cA1 and cD1 energy distribution in Starting Mode (Motor speed in Data 2)

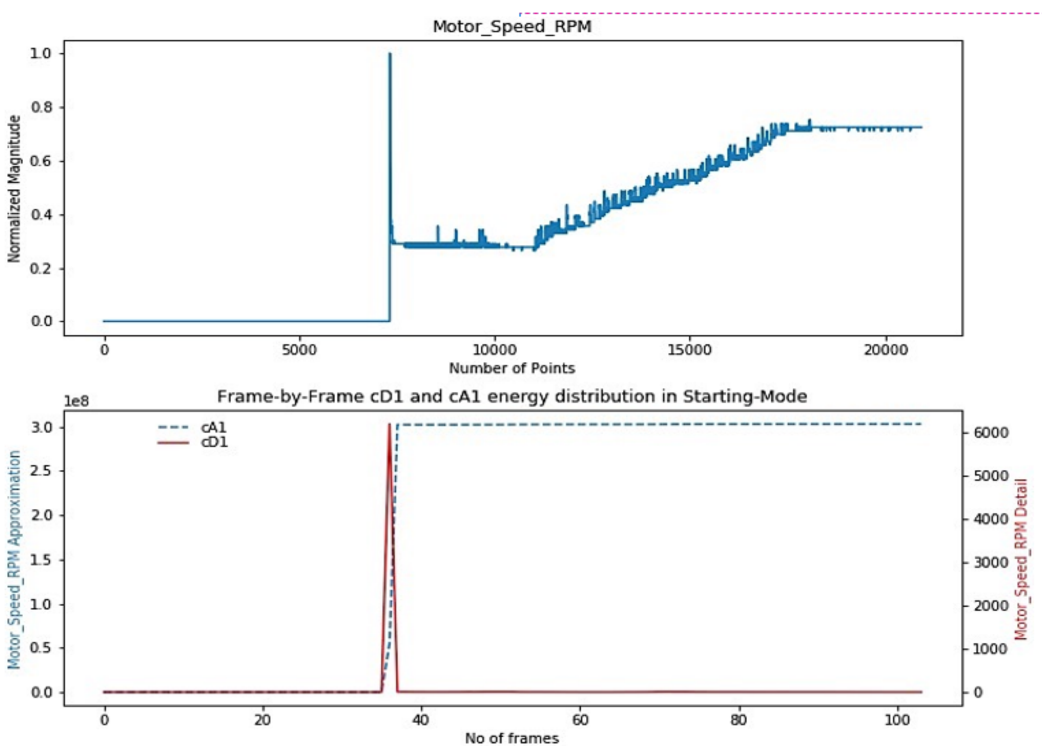


Figure 12. Frame-by-frame cA1 and cD1 energy distribution in Starting Mode (DC voltage in Data 2)

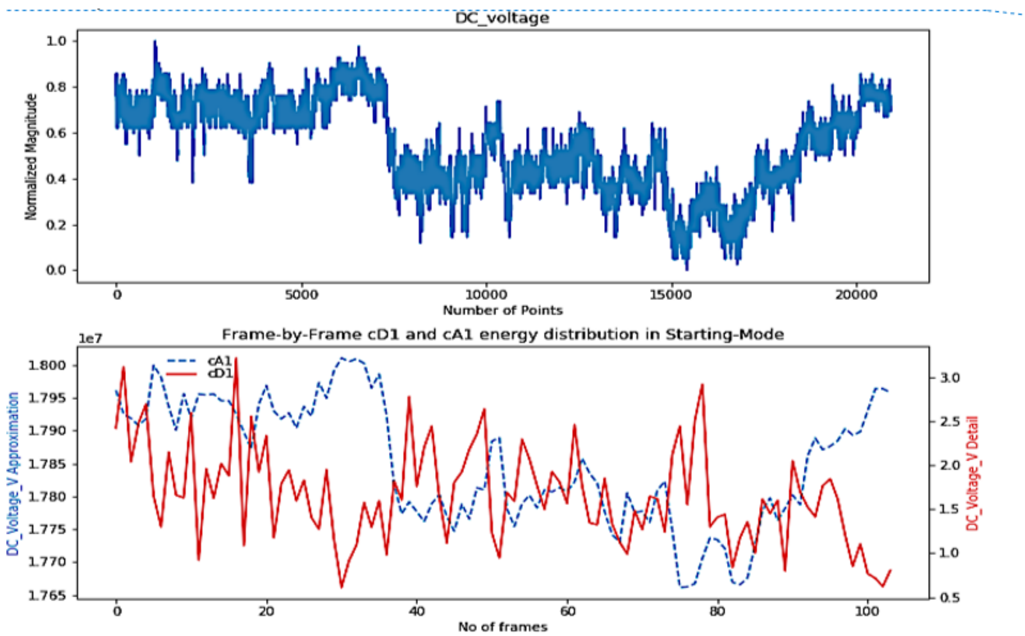


Fig.13. Frame-by-frame cA1 and cD1 energy distribution in Shut-Down Mode (Motor power consumption in Data 1)

Figure 9 to 20 shows the graphs of reconstructed signals after decomposing first frame, using Discrete Wavelet Transformation. The decomposition of the frame results in new values that are stored in the form of CSV data frames.

The first graph (top) indicates the normalized magnitude for the motor power consumption, Inverter output power factor, Motor speed, and DC voltage for Data 2, Data 1 Data 3, respectively. To examine the signals power level of these signals is observed and is proportional to its magnitude squared. Dataset is split into frames, containing 200 data points in each frame, and after applying the window function, it contains 20 data points per window. Two signals have different amplitudes with a much larger difference in their relative powers because of power's squared nature.

The Discrete Wavelet Transform (Bottom) is illustrated using the Daubechies 1 wavelet. Transient responses of DWT show that the DWT is sampling different points for the first order dB1. In this representation, they concatenate cA and cD coefficients side by side. To generate a smoother signal, detailed coefficients are exploited. Low-frequency data is retrieved by coefficients (weights) associated with the scaling function called approximation coefficients, and high-frequency information is captured by coefficients associated with the wavelet function, called detailed coefficients.

These graphs are important because they represent the states of the production line inverter. The inverter monitoring software cannot tell the states of the inverter, but it can easily be done by using a wavelet neural network. In the above graph, the red line transient cD1s tell the information about the initiation of the start and end is going to happen and fed these values as an input to the regression neural network.

3.5 Methods used for Wavelet Transformation:

Two methods can be used for wavelet transformation, but this paper focuses on the regression neural network.

Figure 13. Frame-by-frame cA1 and cD1 energy distribution in Shut-Down Mode (Motor power consumption in Data 1)

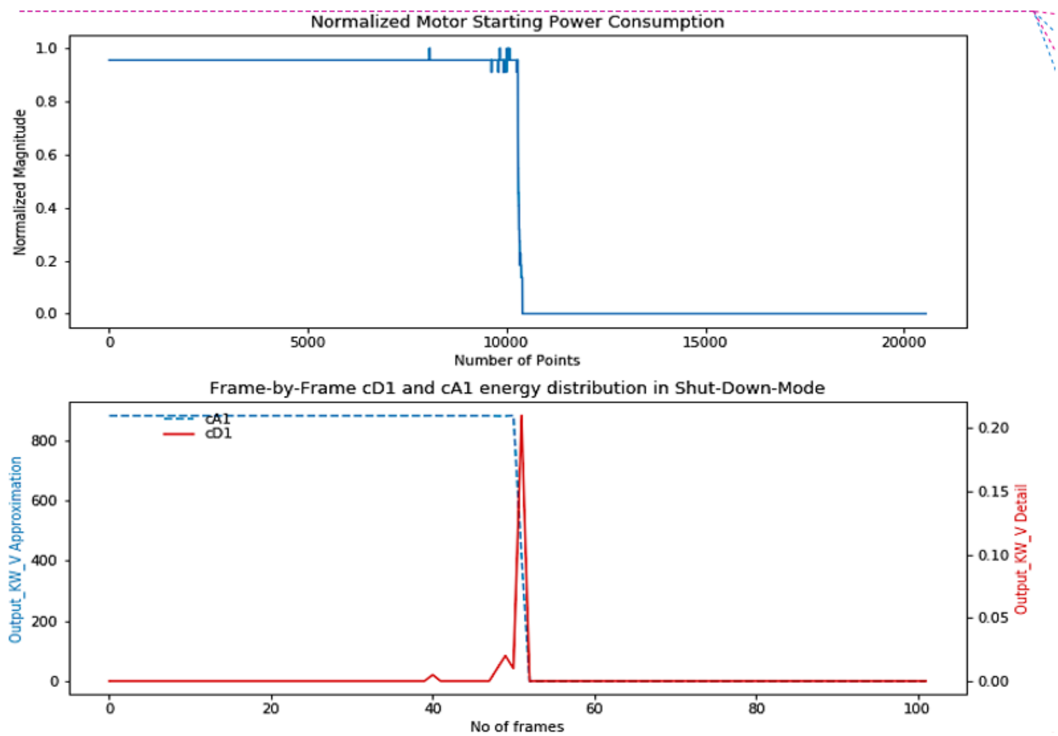


Figure 14. Frame-by-frame cA1 and cD1 energy distribution in Shut-Down Mode (Inverter output power factor in Data 1)

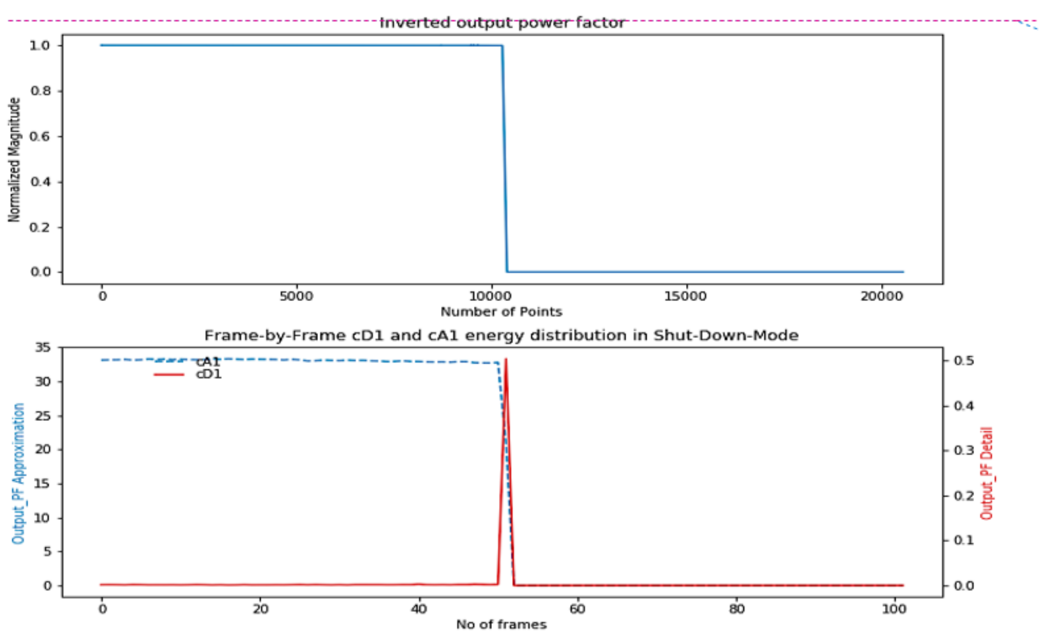


Figure 15. Frame-by-frame cA1 and cD1 energy distribution in Shut-Down Mode (Motor speed in Data 1)

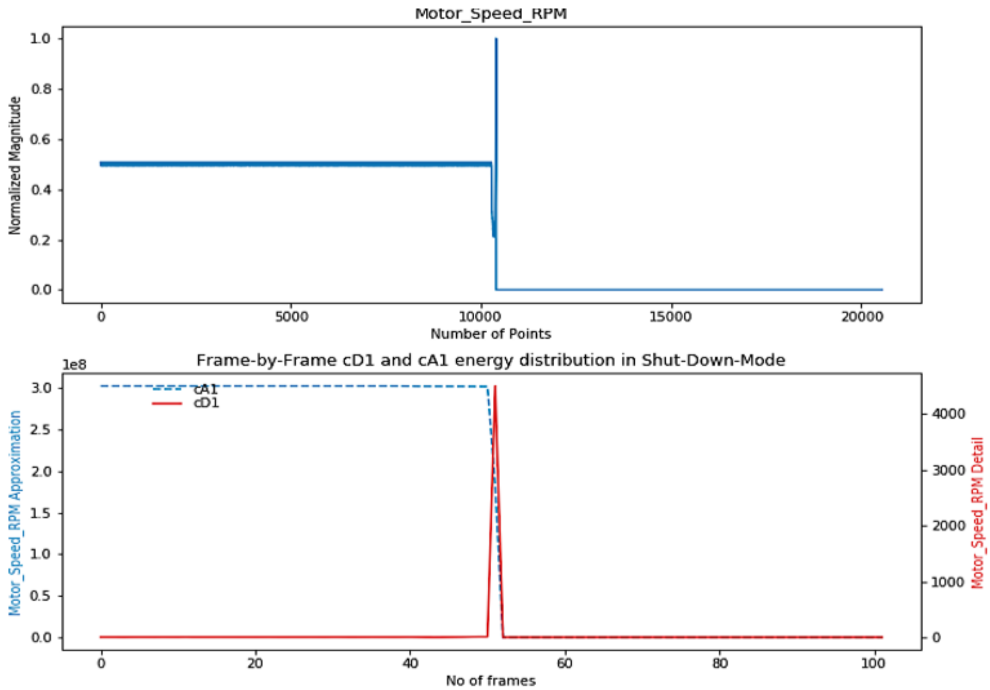


Figure 16. Frame-by-frame cA1 and cD1 energy distribution in Shut-Down Mode (DC voltage in Data 1)

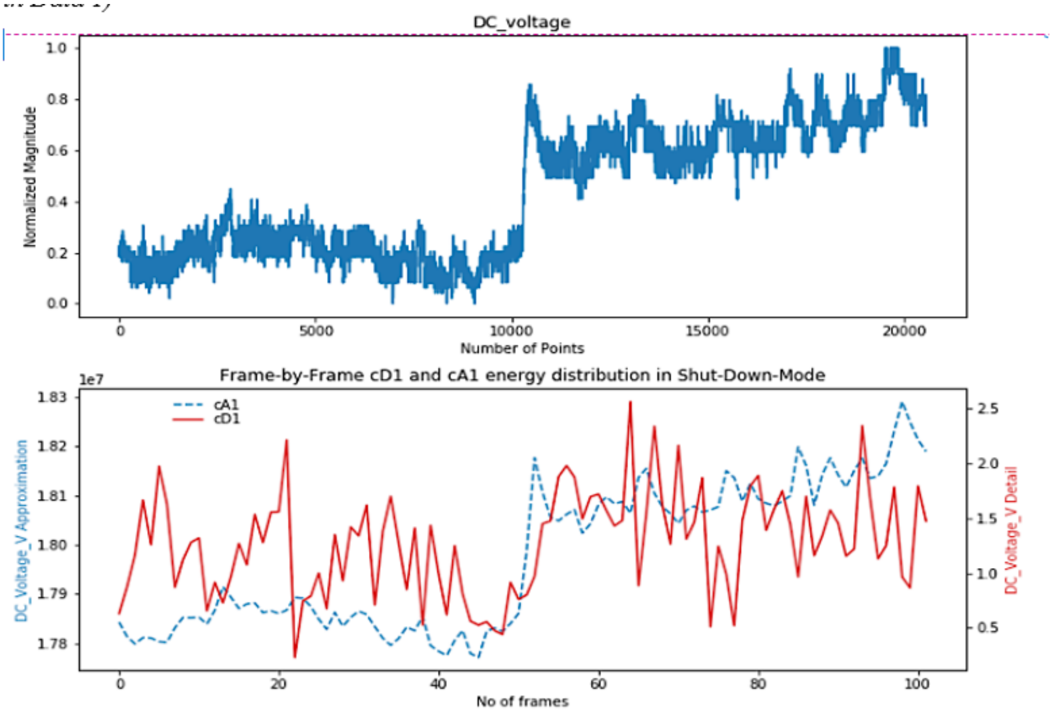


Figure 17. Frame-by-frame cA1 and cD1 energy distribution in Regular Mode (Motor power consumption in Data 3)

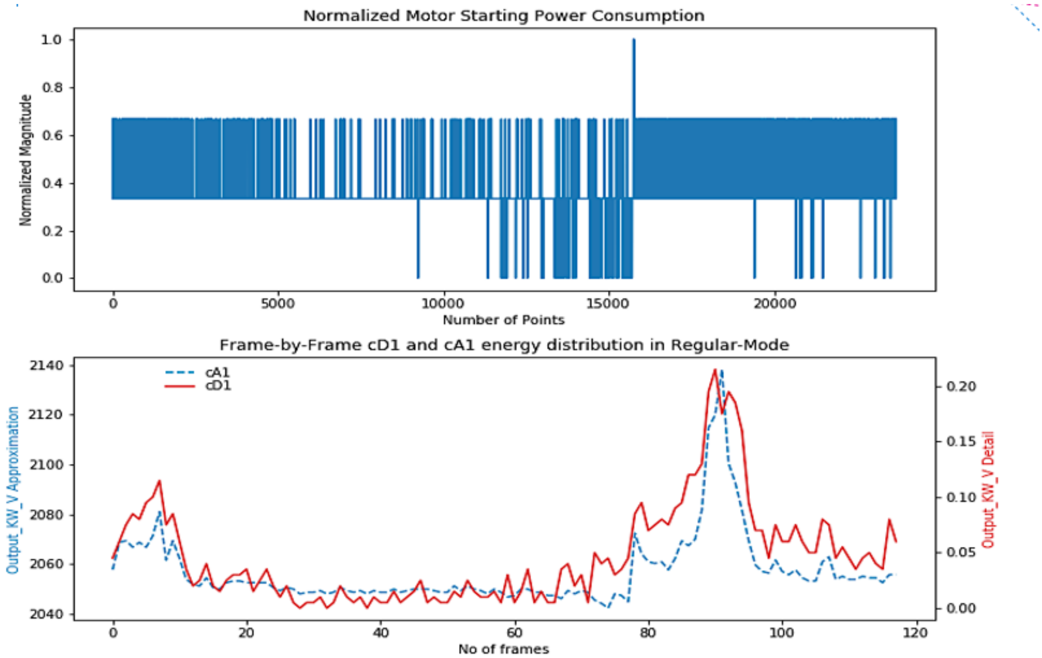


Figure 18. Frame-by-frame cA1 and cD1 energy distribution in Regular Mode (Inverter output power factor in Data 3)

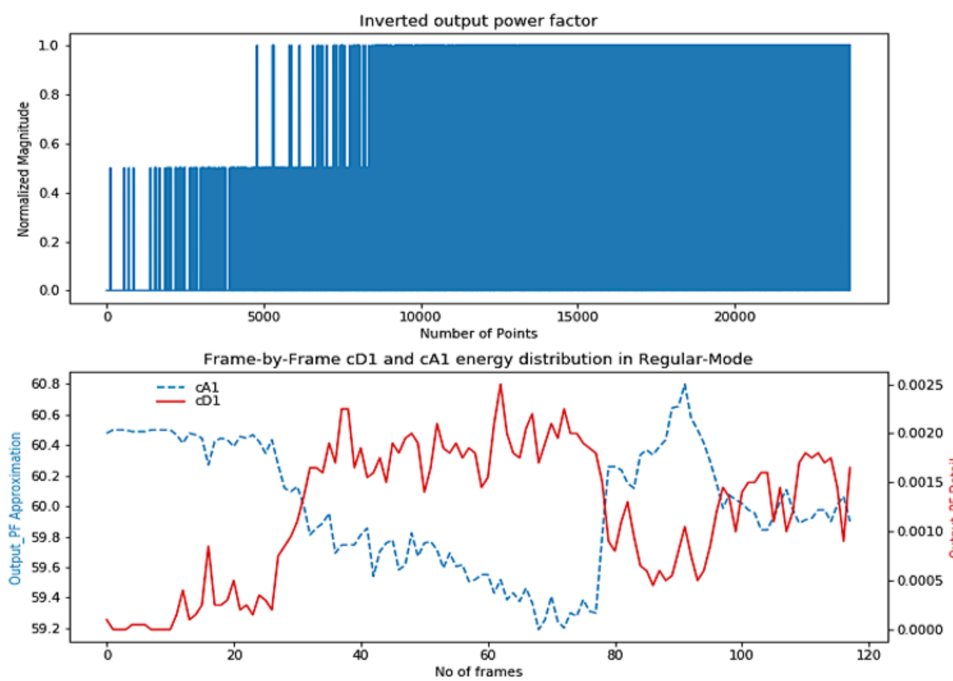


Figure 19. Frame-by-frame cA1 and cD1 energy distribution in Regular Mode (Motor speed in Data 3)

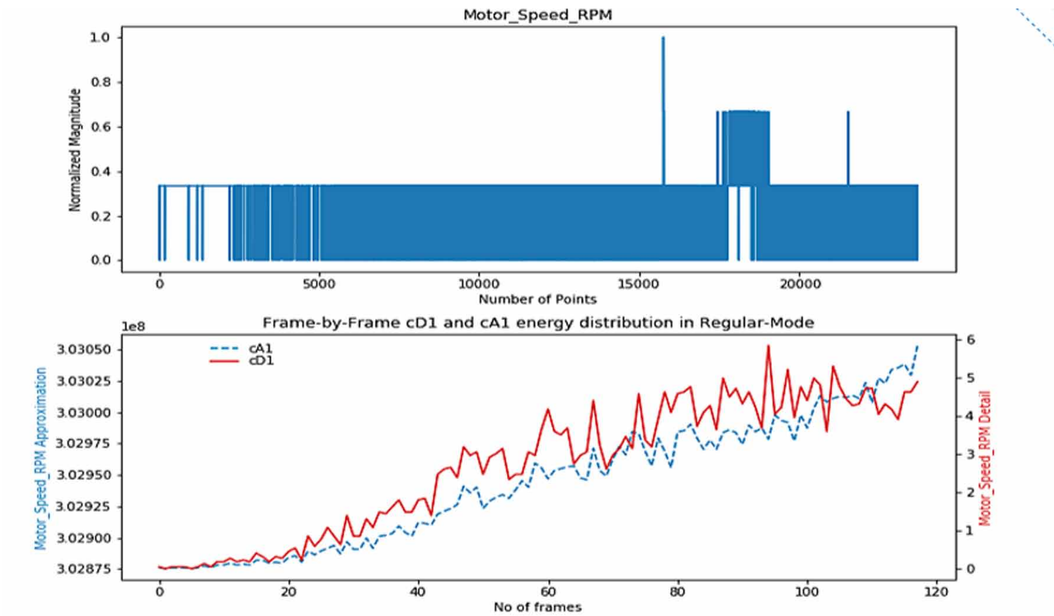


Figure 20. Frame-by-frame cA1 and cD1 energy distribution in Regular Mode (DC voltage in Data 3)

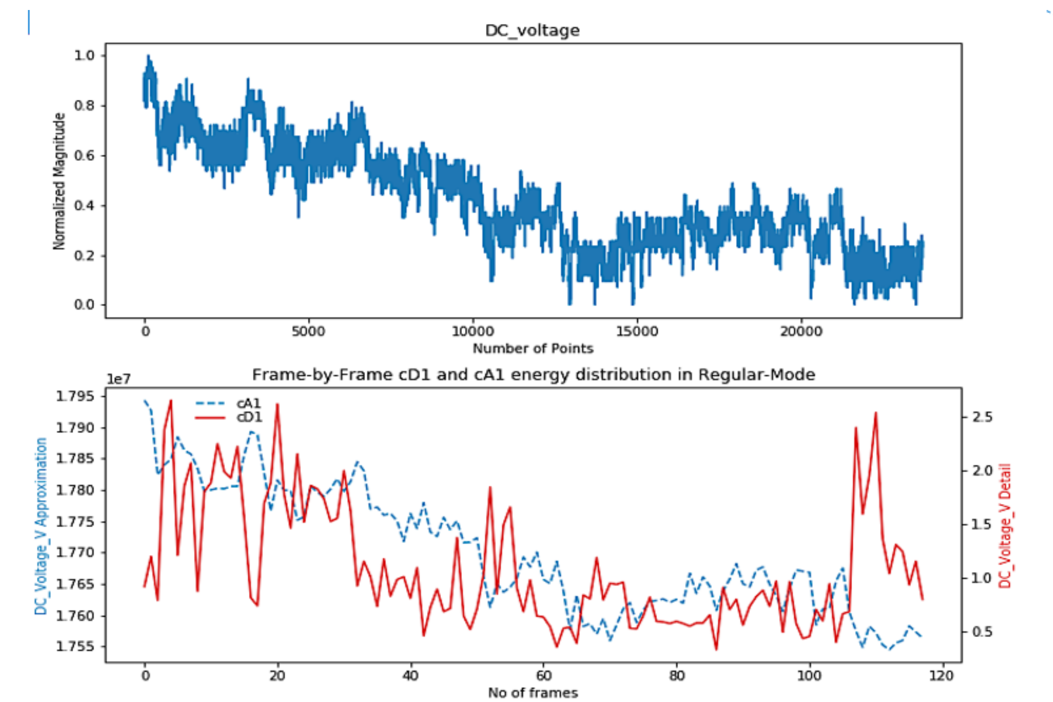
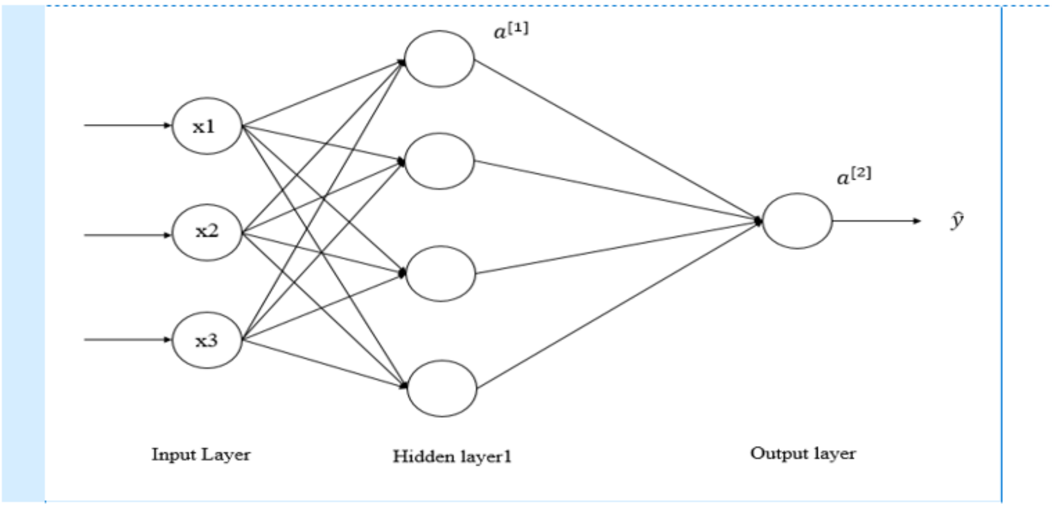


Figure 21. Neural Network Architecture Model



1. Finite Impulse Response (FIR) Filtering

FIR is a filter used in signal processing and is designed by way of finding the coefficient and filter order that satisfy requirements in the time and frequency domain. It has advantages like sophisticated design, ease in the implementation, and have a linear phase filter, which restricts the input signal for some time but does not change its phase. This filter gives a finite number of non-zero outputs, and it is more flexible than analog. Besides, this filter performs a function to block DC components and to allow AC components. As compared to a recursive filter, it requires more computation power and thus needs more memory. By looping a single instruction on the microprocessor, FIR calculations should be performed. There is no feedback in an FIR filter, which means it does not use preceding values of the output, and it guarantees that impulse response will be finite.

2. Regression using Neural Network (RNN)

A Neural Network is a flexible model that embraces itself with the data's shape so that the ablest type of regression can be picked up dynamically. A neural network consists of input layers, hidden layers (this layer uses the backpropagation method to optimize the weights of the input variables to improve the model's performance), output layers, and the number of learning iterations, and many other parameters.

Regression is a statistical approach as well as a supervised learning method to find the relationship between variables. There are different types of regression analysis like Linear Regression, Polynomial Regression, Logistic Regression, Multiple Linear Regression, Stepwise Regression Etc. (Akinwande et al., 2015; Bayer et al., 2012)

It is easy to solve the approximation problem for any function using Linear Regression Neural Network. This research applies LRNN to approximate the relationship between DC voltage, output power, motor speed, and power factor. The motor speed is the target value to be compared. The DC voltage, output power, and power factor are the inputs to the unknown motor model.

Regression Neural Network is useful for model classification and prediction. Each hidden layer has an activation function that defines the output of the neuron.

Equation for the neural network:

$$z^{[1]} = w^1 X + b^1 \rightarrow a^{[1]} = \sigma\left(z^{[1]}\right) \tag{12}$$

$$z^{[2]} = w^2 a^{[1]} + b^2 \rightarrow a^{[2]} = \sigma\left(z^{[2]}\right)$$

$$i.e\, \hat{y} = a^{[2]} \tag{13}$$

$where\ X : inputs;\ \hat{y} : output;\ w^1, w^2 : weight\ matrix;\ \ b^1, b^2 : bias\ matrix;\ a^{[2]} : neurons;$
$\sigma : activation\ function$

DC voltage, Output KW, and Output PF are the input features for the regression neural network, and the Motor Speed is the output. After loading data in the model, it splits as a training and testing set, and the size of the testing set is 20%. The training dataset is used to train the model, and the test set is used to evaluate the model. There is a need to normalize the data because it varies in different ranges; normalization speeds up the training.

The next task is to build a model; it contains one hidden layer and an output layer. RMSprop optimizer is used in the model and MAPE (Mean Absolute Percentage Error) as a loss metric.

MAPE is defined as,

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{N} \left| \frac{y_i - \widehat{y_i}}{y_i} \right| \tag{14}$$

Where N: number of training examples, y_i : actual value, y_i - $\hat{y}_i$: residual.

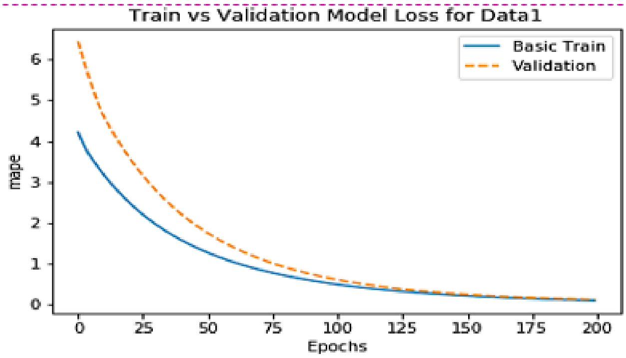
Table 1. Information related to the basic structure of Regression Neural Network.

Dataset	Number of Neurons		Execution Time	MAPE
	Input Layer	Hidden Layer		
Data 1	3	4 (one hidden layer)	5.37sec	0.1265%
Data 2	3	4 (one hidden layer)	7.00sec	0.1198%
Data 3	3	4 (one hidden layer)	10.59sec	0.1015%

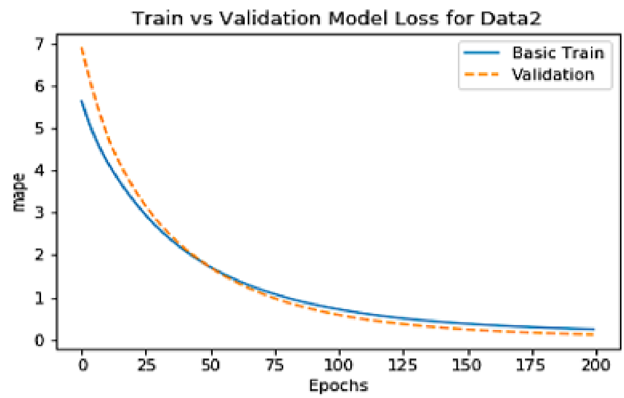
The above table explains RNN, which uses three input layers: DC voltage, output power factor, and motor power consumption. Here MAPE is calculated, which predicts the average difference between the Actual value and forecasted value. For example, for data 1, the MAPE value is 0.1265%, showing the difference between actual and predicted values. The model can predict the values accurately as it has a lower value for MAPE.

Figure 22 (a), (b), (c) define the learning curve of the model. In which training and validation curves are plotted. In this figure, the generalized model for test tells the expected model to predict the values when applied to real-world data.

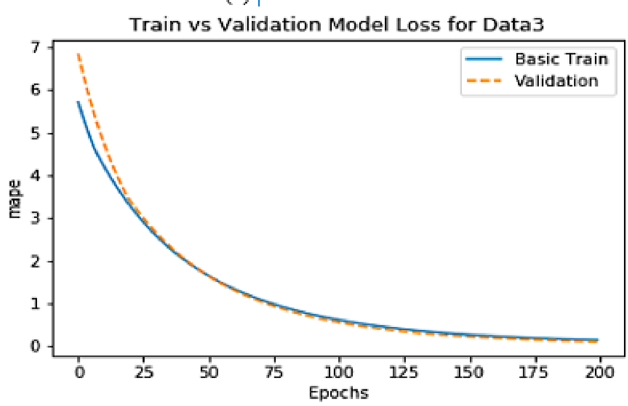
Figure 22. Graph of training vs. Validation



(a) RNN for Data 1



(b) RNN for Data 2



The training dataset is used to calculate the train learning curve, and the Validation dataset is used to calculate the validation learning curve. Learning curves are used to learn algorithms, which are used to enhance internal parameters over time. Depending on which algorithms are used, learning curves can be observed.

a) **Train Learning Curve:** Using a training dataset learning curve can calculate how well the model is learning.

b) **Validation Learning Curve:** The validation dataset is used to calculate this curve, which gives information about the model's generalization.

Mostly we can observe the Learning curve using three dynamics:

1. **Underfit:** Training loss of the learning curve known as Underfit.

The following points are essential to identify that the graph/plot is the following underfitting characteristic:

- Until the end of the training, training loss from the learning curve continues to decrease.
- When the model is not adequate to obtain a modestly low error value on the training set.
- The training loss remains flat despite training.
- It suggests that the model cannot learn the training dataset when it shows a flat line or noisy values with reasonably high loss.

2. **Overfit:** A model that has learned the training dataset too well, which essentially includes the statistical noise or irregular variations in the training dataset known as overfitting.

The following points are essential to identify that the graph/plot is the following overfitting characteristic:

- With the experience, the plot of training loss continues to decrease.
- The validation loss curve of a graph starts to decreases to a point and begins increasing again.
- If the model is trained too long, the less well it can generalize the new data, which causes an increase in generalization error, and it is measured by the performance of the model on the validation dataset.

3. **Good fit:** With a minimal gap between the two final loss values, a good fit can identify, and it exists between the overfit and underfit model.

The following points are essential to identify that the graph/plot is the following good fit characteristic:

- To the point of stability, the graph/plot of training loss starts to decrease.
- With a small gap between the training loss and a point of stability, a graph/plot of validation loss decreases.

4. CONCLUSION

This paper presented a novel approach towards the wavelet transform using a regression neural network to monitor the textile production power line system. This research shows and learns how to access and utilize the centre's data for generator stability. Furthermore, learn the strategies to reduce the risk of instability by making efficient and realistic plans and designs. Data analysis and improvement in data accuracy are essential to improve the smart grid's accuracy and performance, thus contributing to better energy efficiency in the industry sector.

DWT (Discrete Wavelet Transformation) is used to pre-process the signals to remove the raw signals' noise. Coefficients associated with wavelet function, known as detail coefficients which capture high-frequency information. The output of DWT energy distribution has been given as an input to the RNN (Regression Neural Network) model. The neural network RNN architecture involves multi-layer structures. Information related to the basic structure of RNN has been illustrated in table no 1. Mean Absolute Percentage Error (MAPE) loss matrix has been used in the RNN model, and it can predict the values accurately as it has a lower value for MAPE, which is used to forecast the time-series data. Learning curves are used to observe the internal parameters of the given dataset. A good fit is observed in our model, which means there is a minimal gap between loss values and the training values, resulting in the model's stability.

Current research results can only be applied to a single production line, with slight modifications, it can be used for multiple production lines in the future. Also, for the optimization and the arrangement of the inverter operations, it will be used.

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Anagha Rajendra Pakhare was born in India. She is pursuing her bachelor degree in Computer Science and Engineering from Rajarambapu Institute of Technology, Islampur, India. She already completed four weeks winter internship on Artificial Intelligence and Deep Learning from Bennett University, Greater Noida, Delhi. Moreover, she completed 8 months internship in Artificial Neural Network from National Changhua University of Education, Taiwan. At present, she is full time Undergraduate Researcher in Rajarambapu Institute of Technology, India. She has presented her paper on International Conference on Big Data, Machine Learning and Their Applications. (ICBMA-2020). Her area of interests are Machine Learning, Web and Software Development.

V. Vinothkumar was born in India. He received his bachelor degree in Electrical and Electronics Engineering from Anna University, Chennai in 2010. He received his Master's degree from the same university in 2013. He worked as an Assistant professor in Kongunadu college of Engineering and Technology till 2016. At present he is a full-time research scholar in Anna University. He published papers in six international journals, four international conferences. His current research area is multi-level inverters, power quality improvement and wavelet transforms.

Rajinderkumar M. Math has completed his Bachelor of Engineering degree from Karnataka University Dharwad, MTech in Digital Communication from Visvesvaraya Technological University. He is also a research scholar at Visvesvaraya Technological University, Belagavi, Karnataka, India. Currently, he holds the position of Assistant Professor in the Department of Electronics and Communication Engineering of B.L.D.E. Association's Vachana Pitamaha Dr. P. G. Halakatti college of Engineering and Technology, Vijayapur-Karnataka, India. His areas of interest include Precision Agriculture Systems, Wireless Sensor Networks (WSNs), Internet of Things (IoT), and Machine Learning (Deep Learning).