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Original Article

Balanced Islanding Detection of Distributed Generator using Discrete Wavelet Transform and Artificial Neural Network

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Abstract — *Renewable Energy sources (RES) with PV array systems are most widely used nowadays. There will be some malfunctions that occur whenever RES is connected to the grid due to sudden tripping of Grid-connected circuit breakers, which causes islanding. As per IEEE standards, this islanding condition is to be detected within less than 2 sec. Islanding causes disturbances in voltage and power quality. This paper presents Artificial Neural Network and discrete wavelet transform-based positive sequence phase angle islanding method (RCPABPSVAC). This method predicts islanding detection time for various case studies in an accurate manner. In this work, Discrete wavelet transform analysis is done up to level4, and by using an Artificial Neural network algorithm, the islanding detection time is predicted online. Simulation of Positive sequence phase angle islanding method is done on Matlab 2018b platform. Discrete wavelet transform and ANN is carried using python 3.9.5.*

Keywords - *Artificial Neural Network, Discrete wavelet transforms, Islanding Detection, PV array, Rate of change of the phase angle between Positive sequence voltage and current (RCPABPSVAC).*

I. INTRODUCTION

Distributed generation technologies like wind farms and solar cells are most widely used nowadays that bring a host of challenges with benefits. The development of distributed energy resources (DER) has changed the way of power generation, transmission to the electric grid, and these can be used individually to serve the grid. Distributed generators are normally in grid-connected mode, but whenever the grid is disconnected due to any abnormal condition, then islanding will be formed [1-3]. Distributed generation systems have a persistent problem of sudden exposure of utility workers to hazards or shocks whenever the DER segment is suddenly disconnected from the rest of the system [4-6]. During islanding mode, DG continues to supply power to the remaining loads that cause utility failure.

Islanding is generally an electrical aspect that instantaneously occurs whenever the grid has undergone an interruption which has to be eliminated earliest [7-8]. The basic islanding system is shown in Fig.1. In addition to this, deviations in frequency or voltage in the islanded segment may damage electrical equipment connected to the segment [9-10].

Utility workers are exposed to life-critical dangers, severe damage to customer appliances, and unusual operation so that islanding conditions have to be detected as early as possible [11]. So, It is important to accurately detect islanding within 2 sec of their occurrence according to IEEE 1547-2003 standards [12]. Non-Detection Zone (NDZ) and interconnection standards mostly influence islanding methods.

Existing Islanding detection methods are designed based on two important parameters: (1) speed of detection (2) NDZ [13]. But the majority of islanding detection techniques are affected by large NDZs. These techniques are divided into communication, local techniques. Moreover, the local techniques are further split into active and passive techniques. Reliability is more in communication-based techniques. However, they are expensive and complex [14].

The operation of passive islanding methods depends on transient changes of PCC parameters such as current, voltage, phase displacement, frequency, harmonic distortion, etc. The main drawback with the majority of the passive methods is they are unable to identify islanding under balanced load conditions and also have a large NDZ.

Active techniques that are based on a real-time approach have won the confirmation. NDZ is very less for these techniques. However, the control circuit implemented for active methods is complex in nature and also has a slow detection time. When more inverters are connected to DG, the power quality will be affected for active islanding methods.

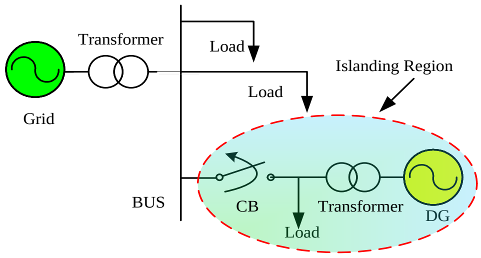


Fig 1: Islanding in integrated electrical network

Communication-based islanding detection methods are more effective than other methods, which is generally using high power systems. Communication-based islanding methods will not affect system power quality. But they are complex in nature and costlier [15].

The area of parameters where any recognition technique declines to recognize it is known as NDZ. As a result of harmonic perturbations, the hybrid and active techniques affect degrading the power quality. The convolution neural network-based deep learning technique has been presented recently, which possesses a very small NDZ [16].

II. TEST SYSTEM UNDER STUDY

A 100 kW solar system is integrated with a 120 KV major network through a DC to DC converter, voltage source inverter, filters, CB, transmission lines transformer shown in Fig. 2. The solar system has 330 solar panels, which have 66 strings of 5 series associated strings are placed in shunt to generate one-kilowatt power (66*5*305.2W= 100.7KW). Each panel has a short circuit current of 5.96 A and open-circuit voltage of 64.2 V and at 1000 W/m^2 solar irradiance and 25^{0}C ambient heat. The DC/DC structure increases the output voltage of solar panels by using MPPT techniques. This structure uses incremental conductance and an integral regulator approach for the same. This DC-DC boost converter increments the output voltage to 500 volts and gives it as input to the inverter.

The inverter increases the 500V DC voltage into 260V AC voltage at the output of the inverter. After sending it through the filters, the voltage and current harmonics are removed. The ripple-free voltage is stepped up and integrated into the 25KV feeder and 120 kV grid.

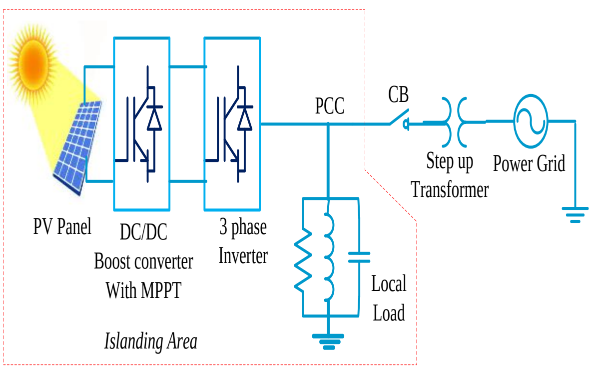


Fig 2: Grid-connected solar PV system as a Test system

The control circuit for integration is shown in Fig.3

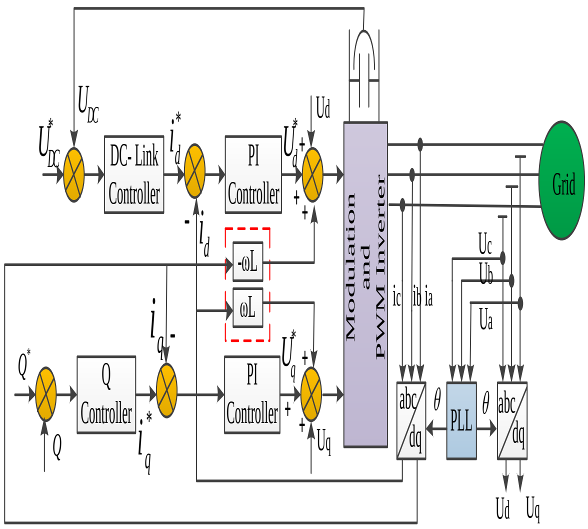


Fig 3: Control circuit for grid integration of PV system

III. WAVELET TRANSFORM AND ANN

The wavelet transform is mostly used for analyzing stationary and Non-stationary signals. In wavelet transform, a single signal is decomposed into a group of constituent signals known as wavelets. Wavelets are transient in nature and have a limited duration. Unlike Fourier Transform, Wavelet will do signal analysis in both time and frequency domains. During wavelet transform, the shape of the signal remains the same only the time changes. If the wavelets are discretely sampled, then they are called discrete wavelet transform.

A. Discrete Wavelet Transform

Wavelet transforms best suitable for signal and speech processing applications [17-18]. The wavelet transform is defined by two basic components location and scale. Wavelet transform consists of series of wavelet functions with different scales. This work represents RCPABPSVAC signals that are multiplied with wavelet functions to produce various wavelet coefficients up to level4.Daubechies4 (dB4) mother wavelet is employed due to its high performance. Here objective signal (S) is propagated through a high pass filter (HPF) and low pass filter (LPF) to determine the components of approximation (C) and detail (D). This decomposition process can be repeated until all lower resolution components are obtained. This process is known as the wavelet decomposition tree, which is represented in Fig. 4.

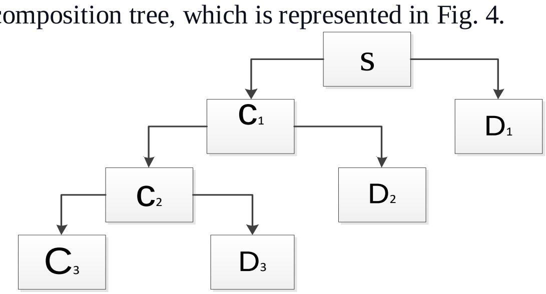


Fig 4: Wavelet Decomposition tree

The wavelet transform is divided into two different and distinct ways based on its operation: continuous (CWT) and discrete wavelet transforms (DWT) [19].

CWT of a signal is represented as

$$\text{CWT (v,x,y)}=\frac{1}{\sqrt{a}}\int_{+\infty}^{-\infty} v(t)\psi^{*}\left(\frac{t-y}{x}\right) \quad (1)$$

Here x denotes scaling (dilation), and y denotes translation (time shift) constants, respectively, and ψ^{*} It is the mother wavelet.

DWT of a signal is represented as

$$\text{DWT (v,x,y)}=\frac{1}{\sqrt{x_0^m}}\sum_k v(k)\,\psi^{*}\left(\frac{n-kx_0^m}{x_0^m}\right) \quad (2)$$

Here m and k are integer variables. X and y terms in equation 1 are substituted by x_0^m and kx_0^m.

In wavelet function, the HPF preserves the signal details, whereas coarser information of the approximation signal is represented by LPF. In this method, DWT analysis uses Daubechies level4 filter (d-4). The comparative analysis of various case studies has been done through d-4 mother wavelet transform [20]. Here d-4 has been used as the mother wavelet, which can efficiently detect transients that will be used to analyze various components during islanding.

B. Artificial Neural Network

Neural Network is a part of the Deep learning approach. Deep learning is associated with a high number of input layers and one or more output layers [21-22]. ANN consists of nodes and layers. Nodes in successive layers are interconnected by links. The output variable can be binary. ANN needs to assign certain weights to each input variable. The hidden layer takes a sum of a weighted average of these input layers and then applies a hidden activation function [23-24]. The prediction of output accuracy mainly depends on the selection of hidden layers. The details of the ANN model are shown in Table 1.

TABLE 1. ANN MODEL DETAILS

S.No	Parameter	value
1	Total neurons in the input layer	6
2	Total neurons in the hidden layer	6
3	Total neurons in the output layer	1
4	Transfer function of input and hidden layers	ReLU
5	Transfer function of the output layer	Sigmoid
6	Batch size	100
7	Number of epochs	100
8	Error threshold	0.5
9	Momentum rate	1msec/step

Activation functions are mostly used in ANN for Determining the output Yes or No. In this paper, Nonlinear active functions are used, namely Rectified Linear Unit (ReLU), Sigmoid, etc. ReLU is an activation function that is used for transforming the added, weighted inputs of the node. It will give the same input as output if it is positive, or else, it will be zero. The output layer uses a logistic function called sigmoid. Softmax active function used in case of multiclass classification.

By using the standard scalar function, all the data values are scaled in between 1 and -1. The sequential layer helps to design a model in the Keras. A dense model is used to interconnect all neurons present in side-by-side layers. A stochastic gradient descent optimization algorithm like Adam is used to compile the ANN model. Adam means an adaptive moment estimation which is used to compute the adaptive learning rate of each parameter.

The loss function is used to classify binary data. The complete data set is split into testing and training data using the fit function in ANN. Here weights will be updated after every observation, and whole training set data will be passed more than just 1 Epoch [25]. Confusion matrix: it predicts how many incorrect and correct predictions of the model. The order of the matrix is 2x2.

Accuracy measures the percentage of correct predictions made model. The Closeness of two or more measurements to each other indicates precision. The Ratio of the number of correctly Predicted observations to all observations is called Recall. F1_score indicates a better measure to use. It provides the balance between precision and Recall and also mentions any uneven class distribution.

IV. PROPOSED METHODOLOGY

In this work, the islanding detection is done based on the variation in the RCPABPSVAC signal at PCC [26]. Whenever a sudden switching circuit breaker occurs, there will be a deviation in the phase angle between positive sequence current and voltage which is detected easily by PMU (PLL Based, Positive sequence) unit even under balanced conditions. The proposed method is analyzed by discrete wavelet transform (DWT) up to level4, and also various approximate and detailed coefficients are determined. Deep learning neural network tool is used to predict islanding detection time for various case studies. It was also useful for the anti-islanding protection of distributed generators [27].

A. Discrete Wavelet Transform

Pywt. dwt is a single-level discrete wavelet transform applied to all islanding data. Haar or d-1 is applied during single-level discrete wavelet transform. Pywt. wavedec function is used for multilevel discrete wavelet transform up to level4. By using this discrete wavelet transform, we will determine energy deviations for several case studies are shown in Table. 2.

B. ANN Training

The purpose of training data is to obtain specific values of biases and weights to perform the online islanding detection. The learning process is done to get a minimum mean square error. The hidden layer neurons varied until we got a lower mean square error (MSE) [23].

Output states are labeled as 0 and 1 for normal islanding conditions. Wavelet Transform indices of the proposed method are fed to the ANN model, as shown in Fig .5.

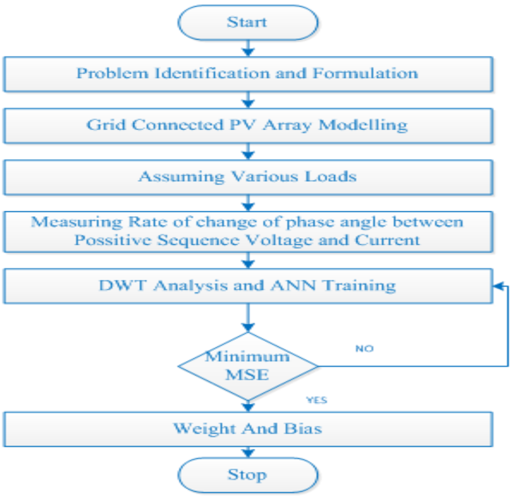


Fig 5: ANN Flow chart of islanding Detection

V. RESULTS AND DISCUSSION

For all case studies given below, the incident of islanding was created at 0.5 sec by tripping the Grid side circuit Breaker. The proposed technique will be used to detect islanding under Matlab/Simulink environment. Latter Discrete Wavelet Transform analysis is done up to level 4 using python Programming, and ANN Technique will be used to predict islanding for various case studies.

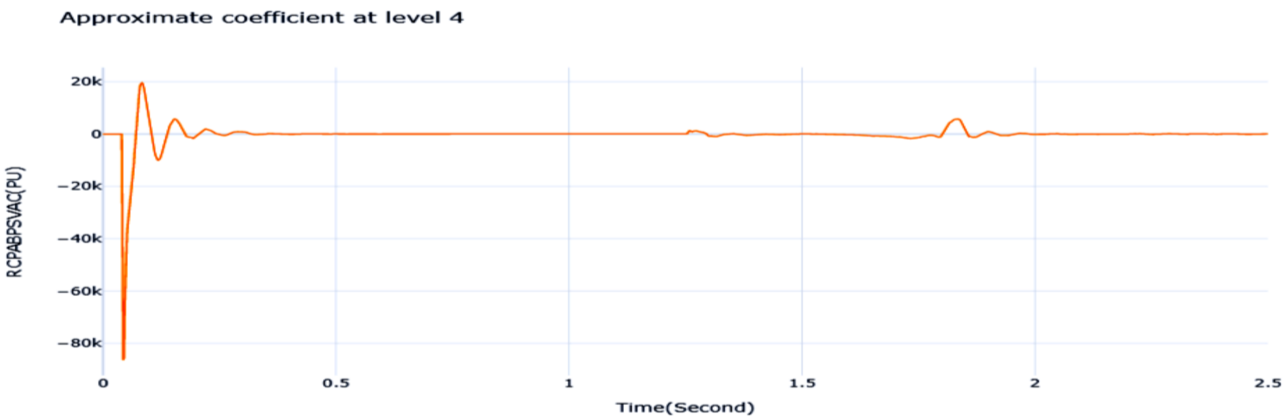
A. Normal Loading Conditions

Fig.6(a)-(e) represent both Approximate and Detailed coefficients of Daubechies wavelet family up to level 4 under very less loading conditions where load capacity is 70% of Distributed Generator capacity. Testing data and Training data have been selected depending on the level of Coefficients, and various parameters like Mean square error and Accuracy are determined.

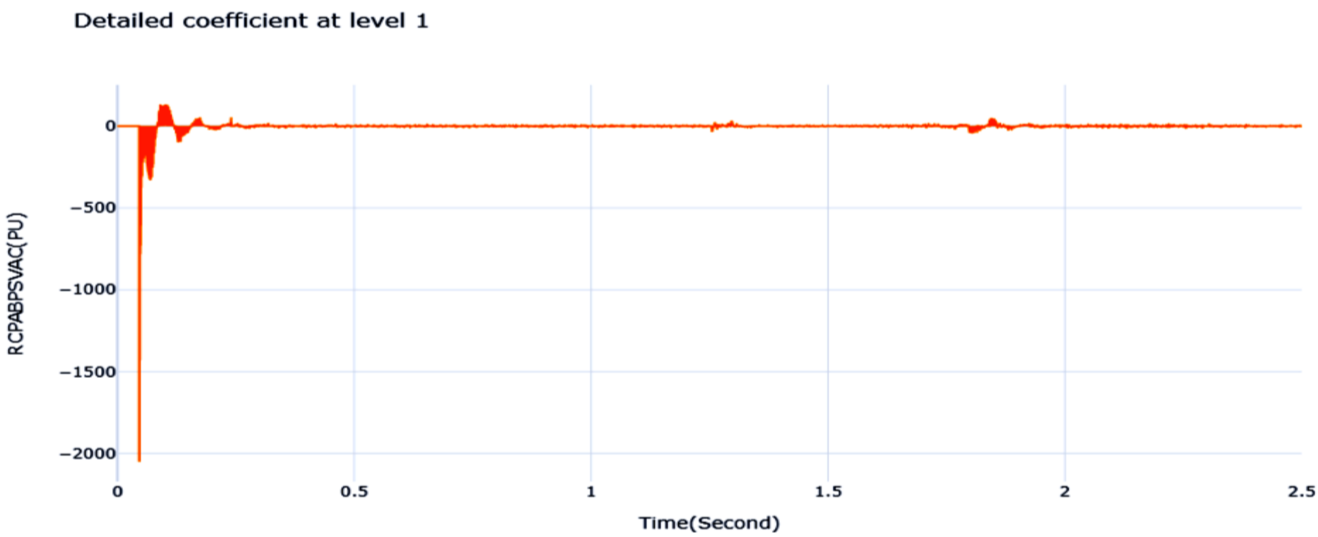
As Wavelet propagates from level1 to level4 the timing samples data decreased, which cause improvement in F1_score, Recall value, Precision and make testing Data more accurate for detecting islanding condition which is shown in Table 4. The ANN model predicted the islanding condition at 0.598 sec under normal conditions.

TABLE 2 Energy Deviation of Wavelet Coefficients for various cases

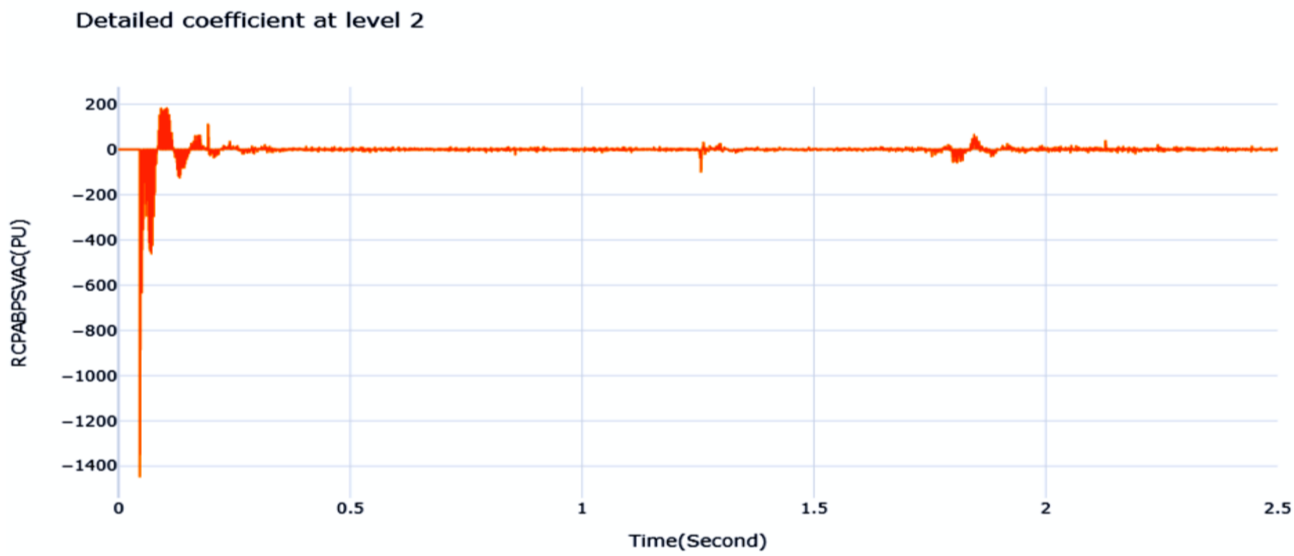
S.No	Wavelet Coefficients	Energy Deviation					
		50KW	70KW	100KW	120KW	Inductive Load Switching(50H.P)	Capacitive load Switching(10Kva)
1	Approx.Level1	16100.377	10114.56	2784.875	5796.601	28464.31	30378.44
2	Approx.Level2	32207.5809	20243.4	4044.943	11628.22	56908.22	60735.89
3	Approx.Level3	64411.903	40478.34	11212.29	23216.61	113799.4	121456.78
4	Approx.Level4	128974.4	81275	23995.92	47373.65	227656.9	242928.2
5	Detailed.Level1	0.009165	0.008566	0.008244	0.008156	0.00958	1.00e-02
6	Detailed.Level2	149.019	206.3805	2.91e+02	345.6551	166.0665	1302.823
7	Detailed .Level3	100.5102	137.3296	191.9482	227.8727	101.2602	84.90155
8	Detailed.Level4	3648.0439	5046.029	7101.0158	8442.38	4085.629	3256.739



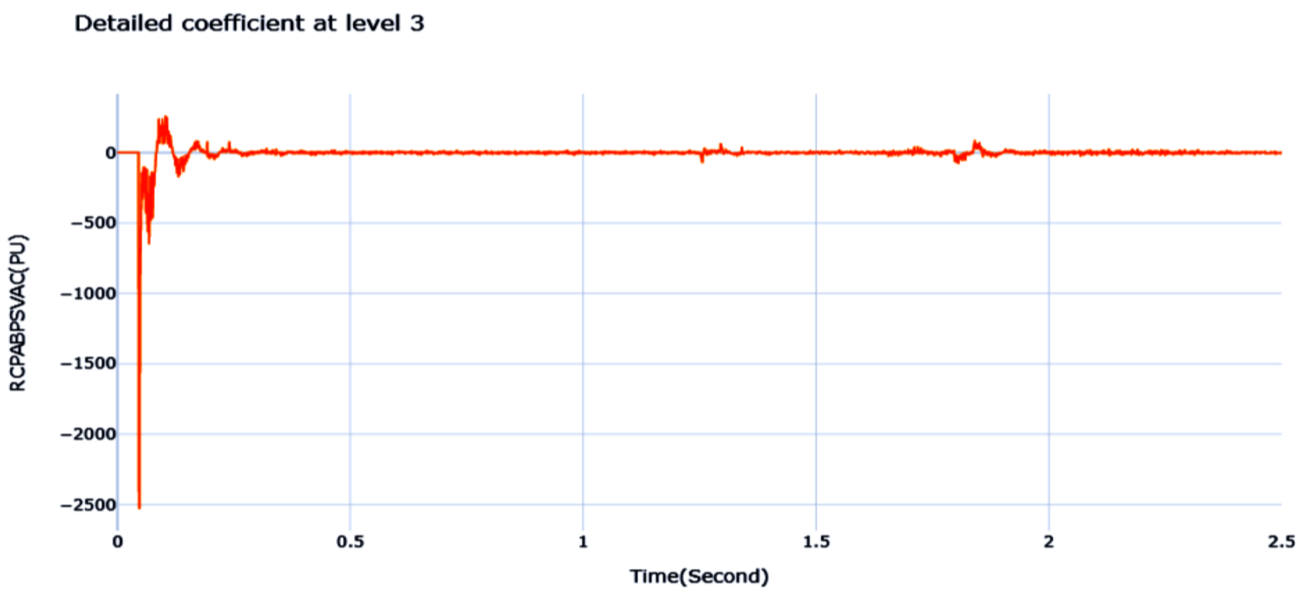
(a)


Detailed coefficient at level 1
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
0
0.5
1
1.5
2
2.5
Time(Second)

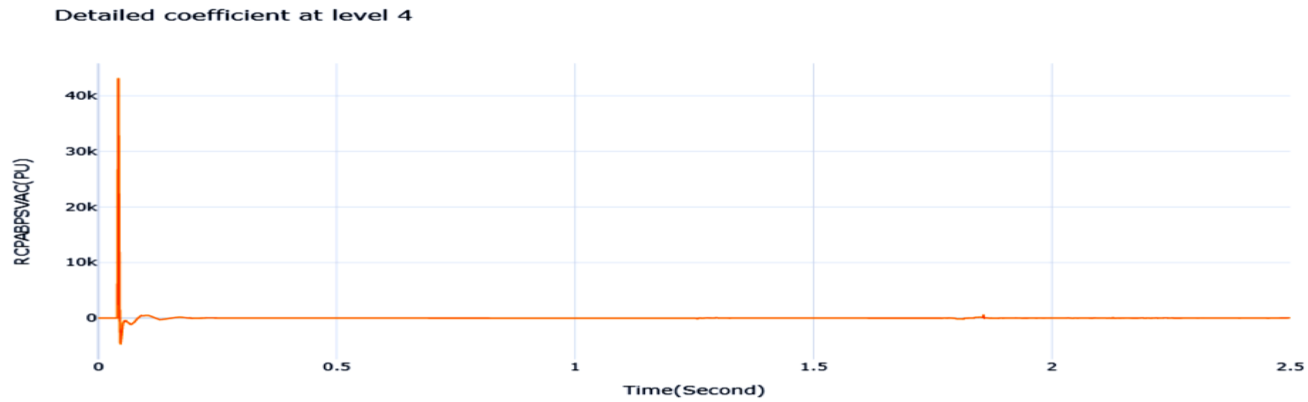
(b)


Detailed coefficient at level 2
RCPABPSVAC(PU)
200
0
−200
−400
−600
−800
−1000
−1200
−1400
0
0.5
1
1.5
2
2.5
Time(Second)

(c)


Detailed coefficient at level 3
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
−2500
0
0.5
1
1.5
2
2.5
Time(Second)

(d)



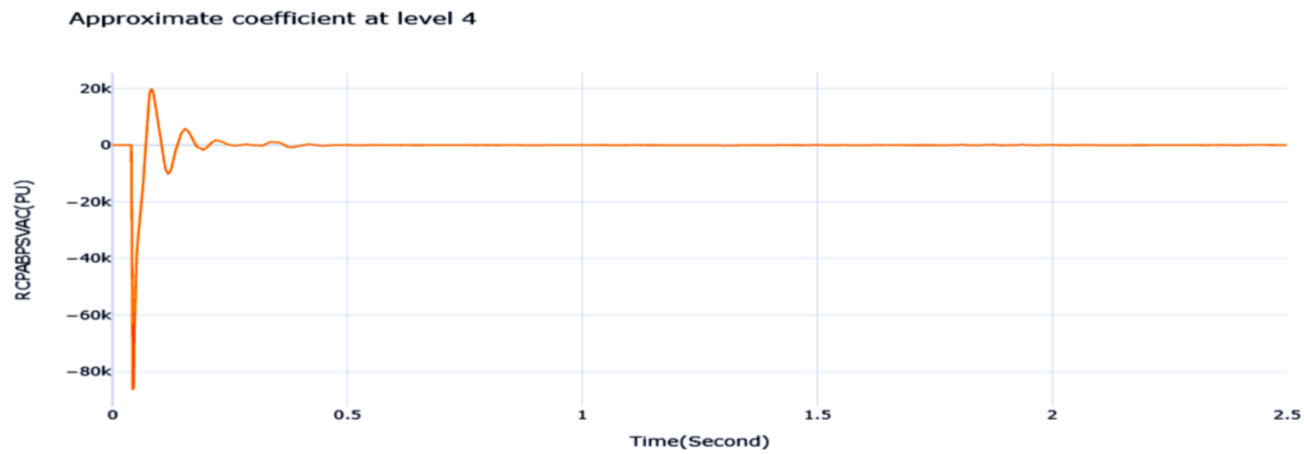
(e)

Fig 6(a): Approximate coefficient at level4 of 70KW Load and Fig. 6 (b)-(e): d1-d4 coefficients of 70KW Load.

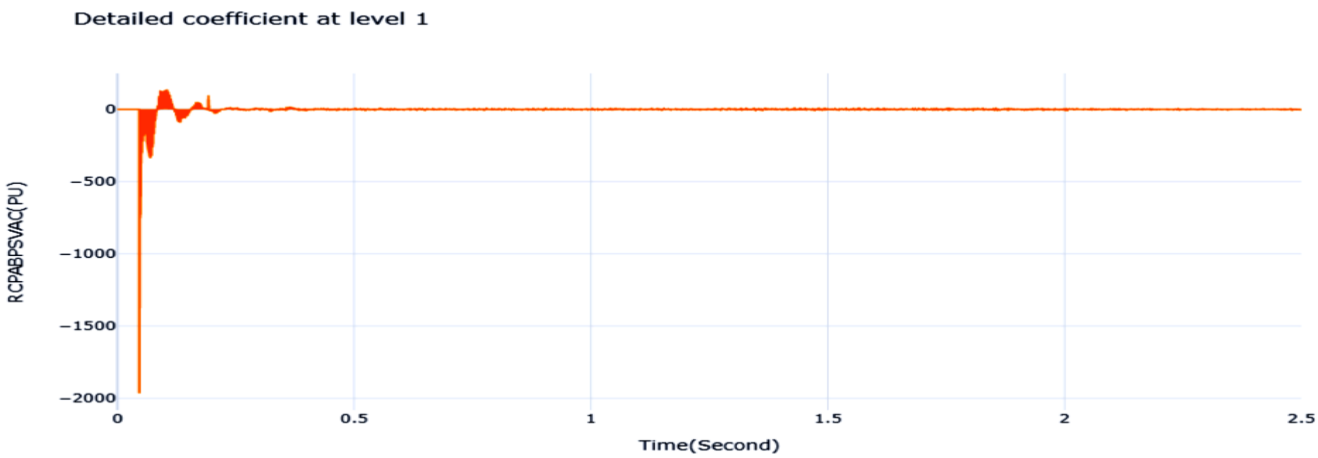
B. Balanced Loading Conditions

Fig. 7(a) -(e) represents both Approximate and Detailed coefficients of Daubechies wavelet family up to level4 under less loading conditions where load capacity is 100% of Distributed Generator capacity (Balanced loading). Testing data and training data have been selected depending on the level of Coefficients as well as various parameters like Mean square error and accuracy are determined.

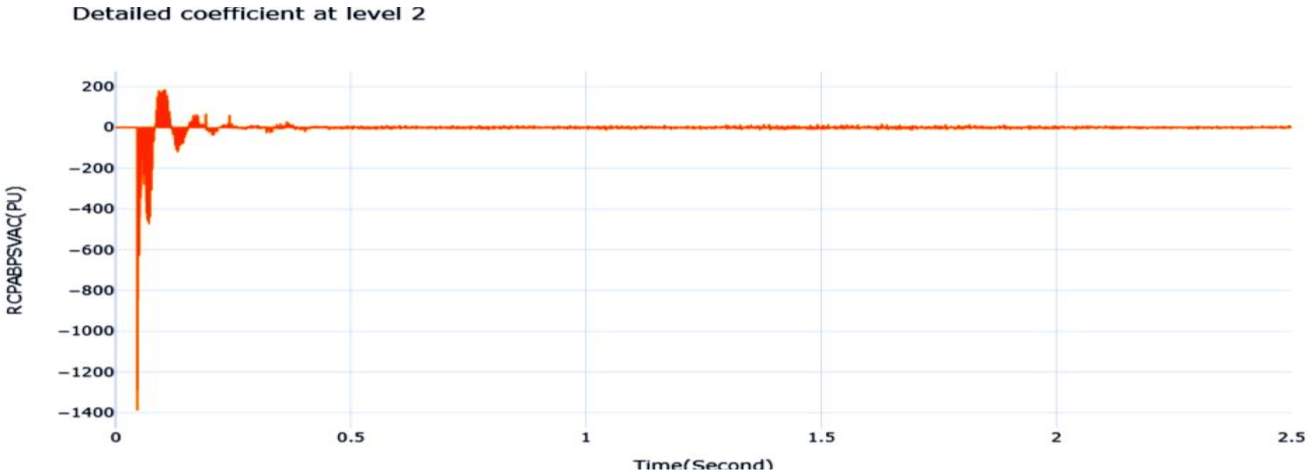
As wavelet propagates from level1 to level 4, then the data of timing samples was decreased, which causes improvement in F1_score, Recall value, Precision showed in Table 5, make testing data more accurate for detecting islanding conditions. The ANN model predicted the islanding condition at 0.522 sec under these conditions.



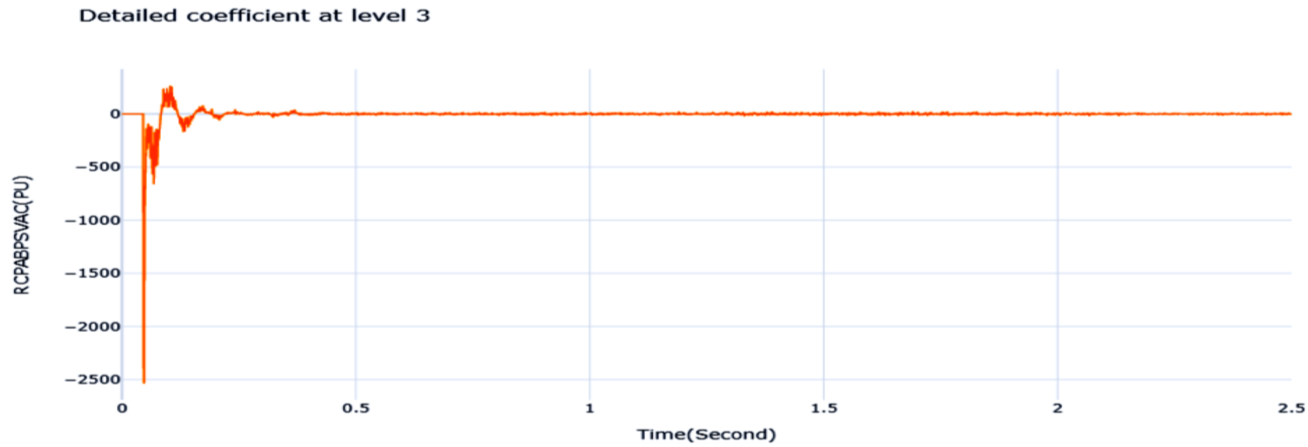
(a)



(b)



(c)



(d)

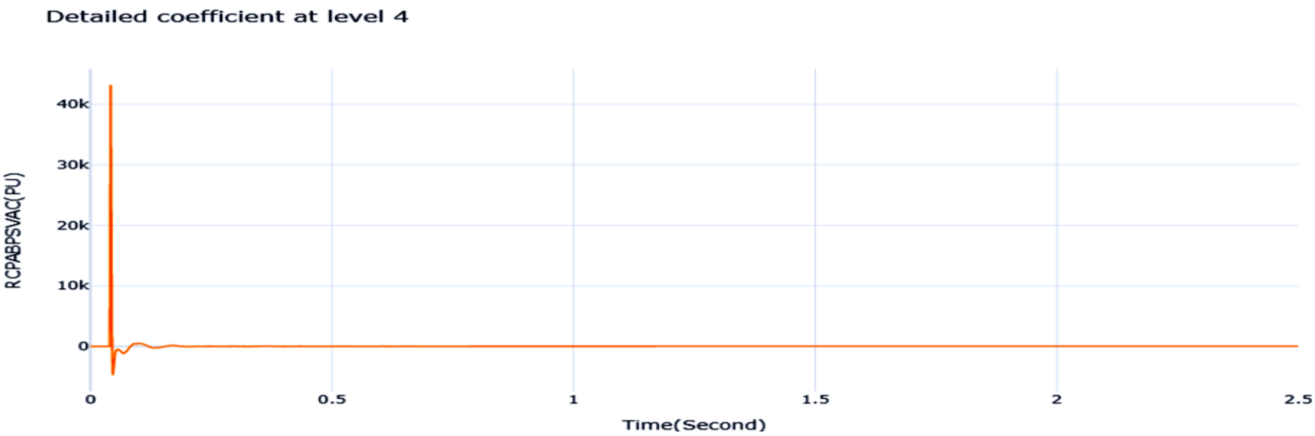
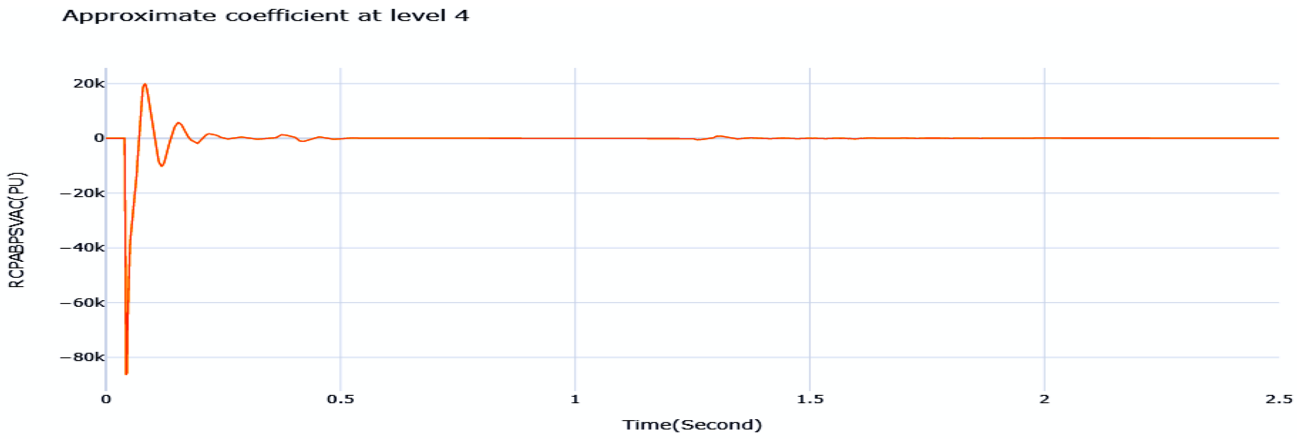


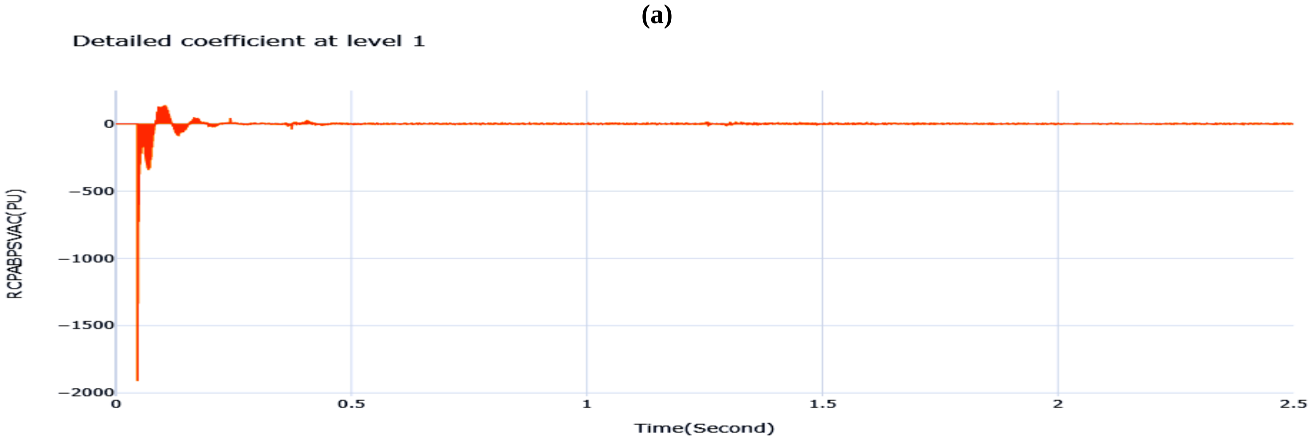
Fig 7(a): Approximate coefficient at level4 of 100 KW Load and Fig. 7 (b)-(e): d1-d4 coefficients of 100 KW Load.

C. Over Loading Conditions

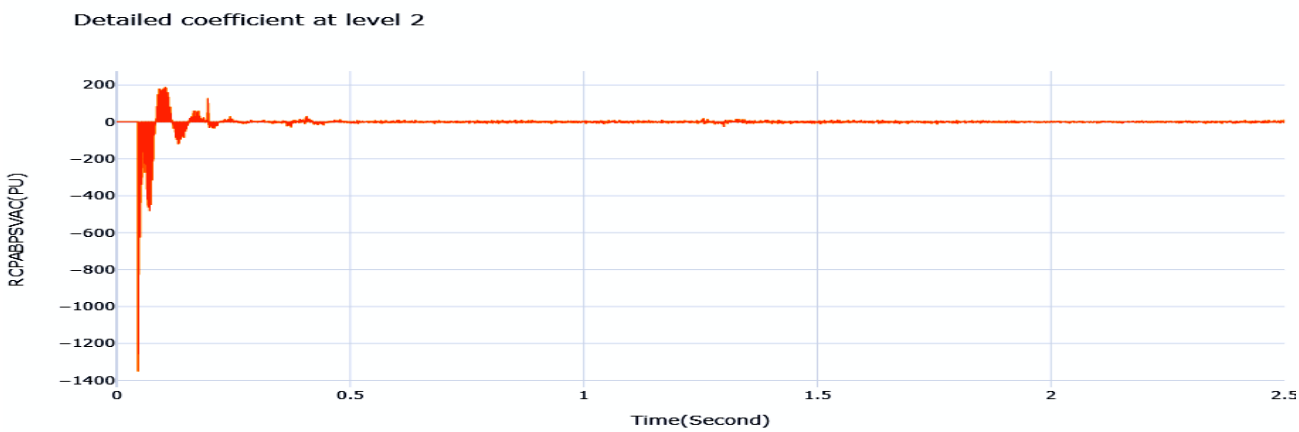
Fig. 8(a)-(e) represents both Approximate and Detail coefficients of Daubechies wavelet family up to level4 under low loading conditions where load capacity is 120% of Distributed Generator capacity (overloading). Testing data and training data have been selected depending on the level of Coefficients as well as various parameters like Mean square error and Accuracy are determined. As wavelet propagates from level1 to level4, then timing samples data decreased, which causes improvement in F1_score, Recall value, Precision, as shown in Table 6, which makes testing Data more accurate for detecting islanding conditions. The ANN model predicted the islanding condition at 0.5139 sec under these conditions.


Approximate coefficient at level 4
RCPABPSVAC(PU)
20k
0
−20k
−40k
−60k
−80k
0
0.5
1
1.5
2
2.5
Time(Second)

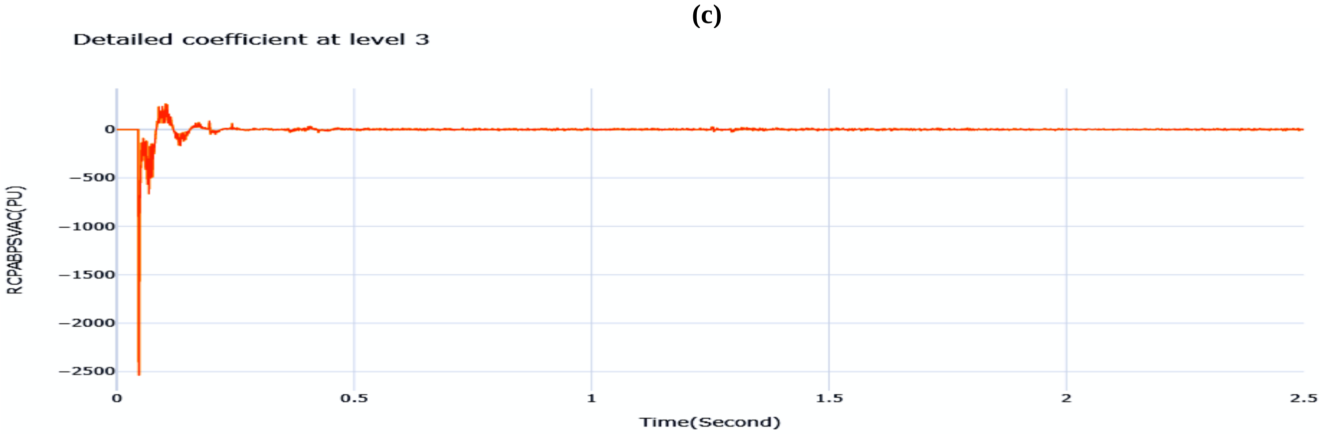
(a)


Detailed coefficient at level 1
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
0
0.5
1
1.5
2
2.5
Time(Second)

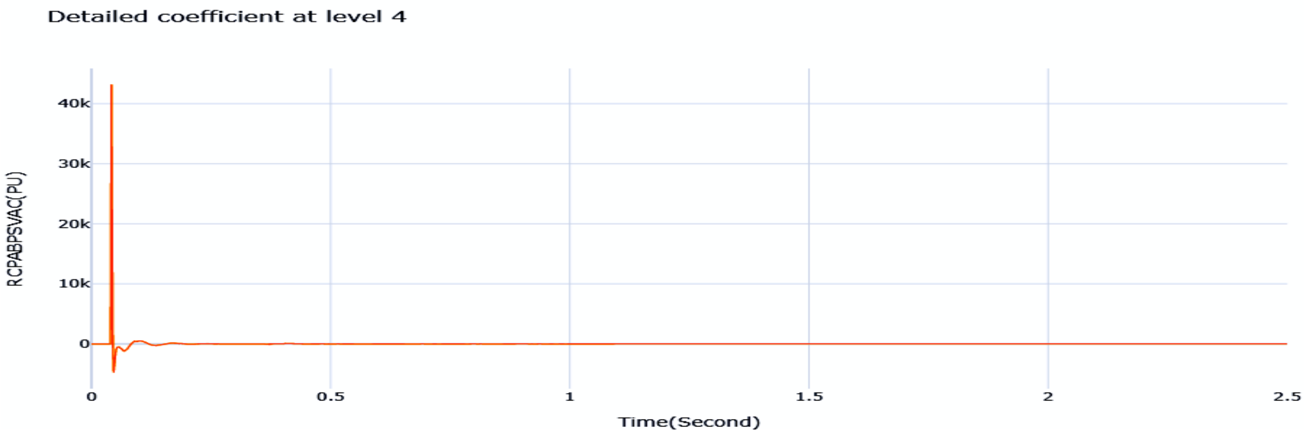
(b)


Detailed coefficient at level 2
RCPABPSVAC(PU)
200
0
−200
−400
−600
−800
−1000
−1200
−1400
0
0.5
1
1.5
2
2.5
Time(Second)

(c)


Detailed coefficient at level 3
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
−2500
0
0.5
1
1.5
2
2.5
Time(Second)

(d)



(e)

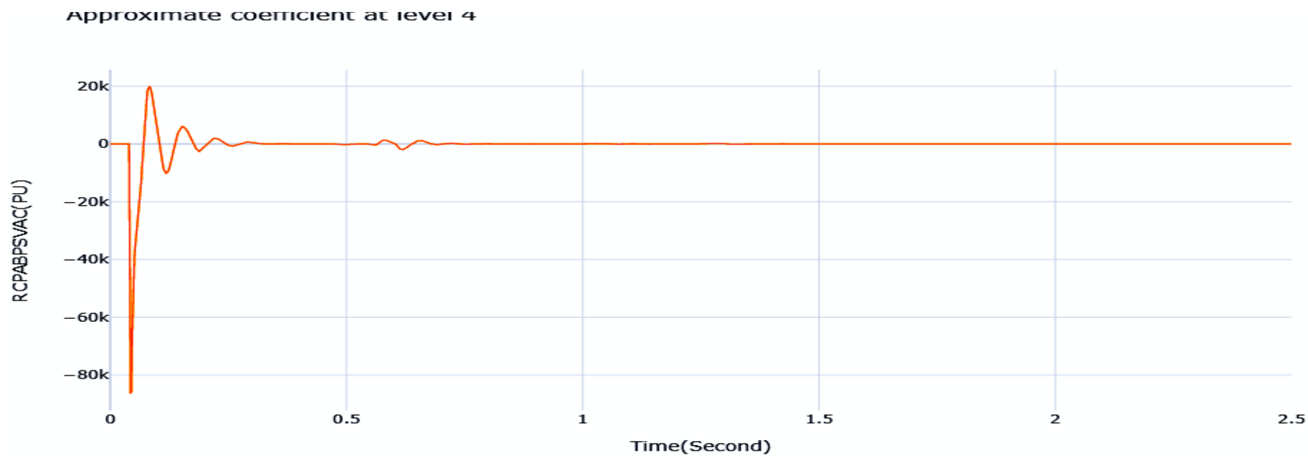
Fig. 8 (a): Approximate coefficient at level 4 100KW Load and Fig. 8 (b)-(e): d1-d4 coefficients of 120KW Load.

D. *Inductive Load Switching(Non-Islanding)*

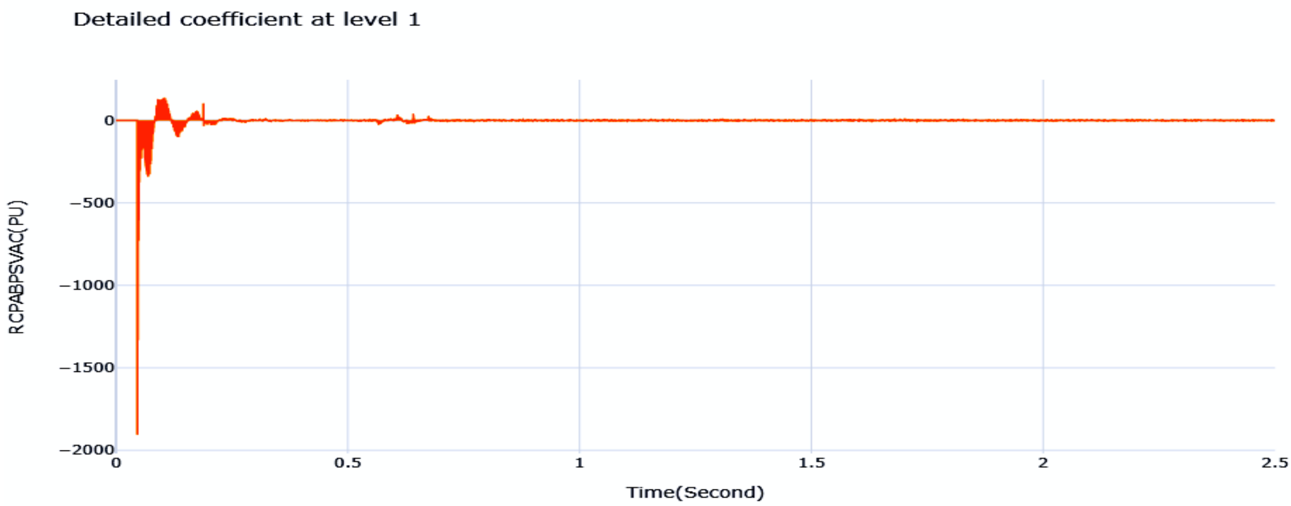
Fig. 9(a) - (e) represent both approximate and detailed coefficients of Daubechies wavelet family up to level4 under sudden switching of the inductive load circuit breaker at 0.5 sec. In this case, also wavelet coefficients are determined up to level4.

Moreover, various parameters like mean square error and accuracy are determined and tabulated in Table 7. ANN model predicted the Non-islanding condition at 0.5224 sec under balanced conditions. During Non-islanding conditions, both grid and DG will supply power to the load continuously

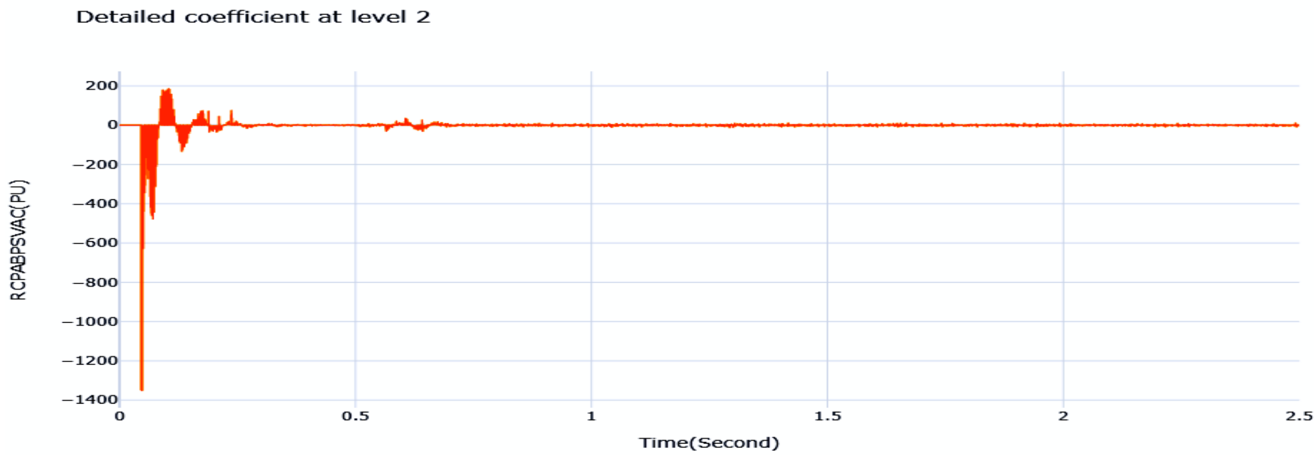
.



(a)



(b)



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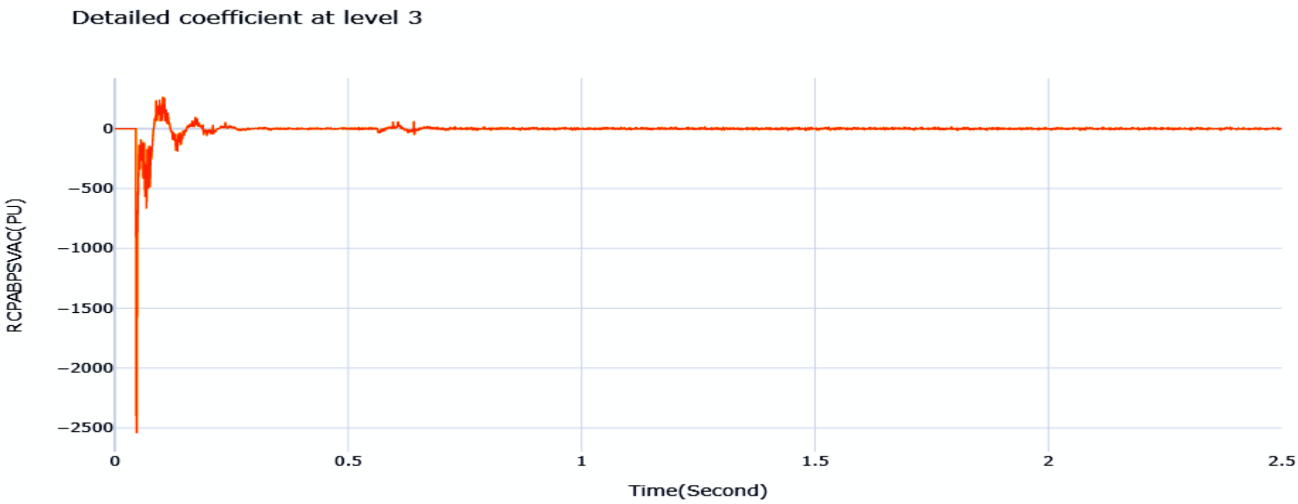
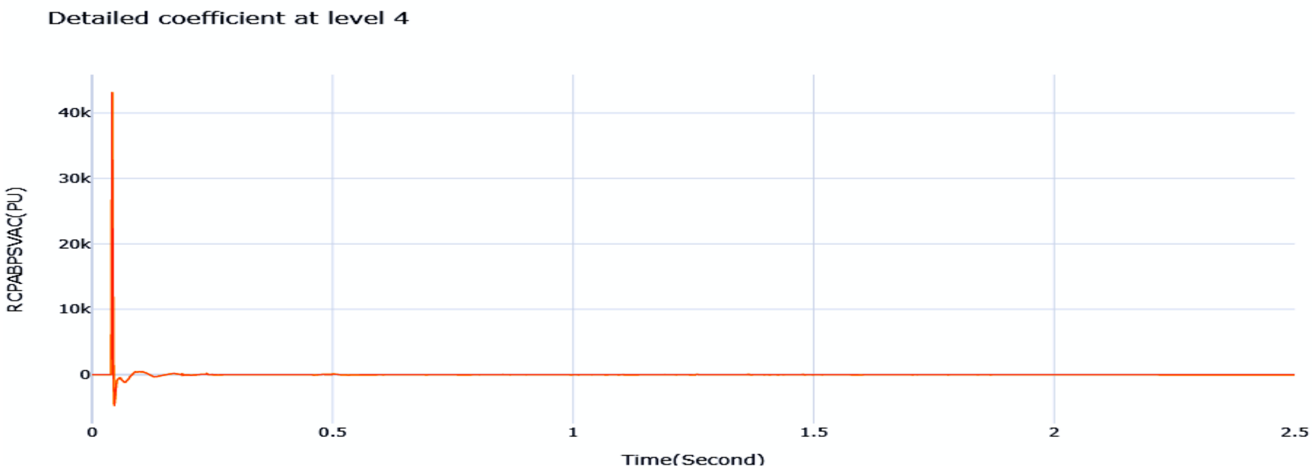


(d)

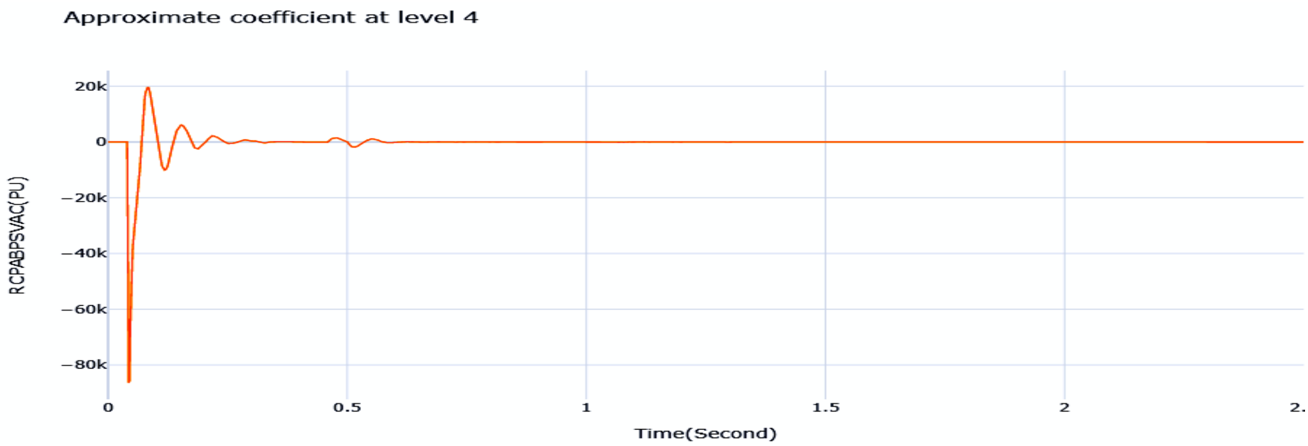


(e)

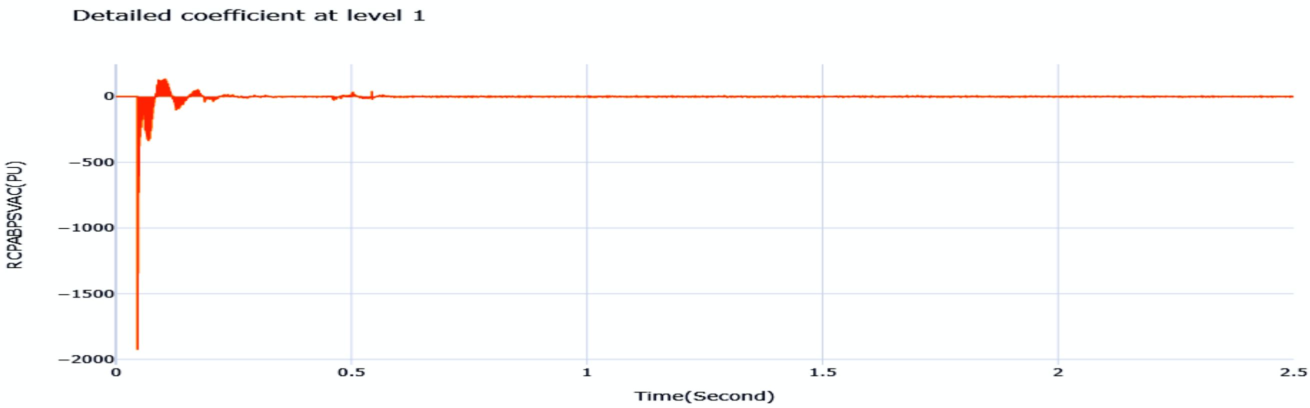
Fig. 9(a): Approximate coefficient at level4 & Fig. 9 (b)-(e): d1-d4 coefficients of Inductive load switching

E. Capacitor Switching(Non-Islanding)

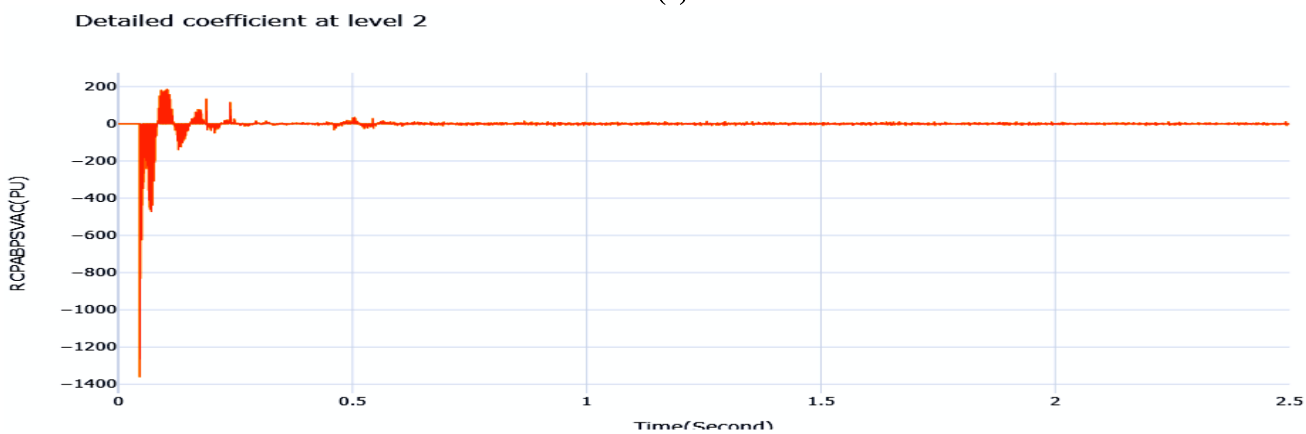
The below figures in Fig. 10(a) -(e) represent both approximate and detailed coefficients of Daubechies wavelet family up to level4 under sudden switching of the capacitor at 0.5 sec for proposed method RCPABPSVSAC. In this case, also wavelet coefficients are determined up to level4. In addition to this, various parameters like mean square error and accuracy are determined and tabulated in Table 8. ANN model predicted the Non-islanding condition at 0.515 sec under balanced conditions.


Approximate coefficient at level 4
RCPABPSVAC(PU)
20k
0
−20k
−40k
−60k
−80k
0
0.5
1
1.5
2
2.
Time(Second)

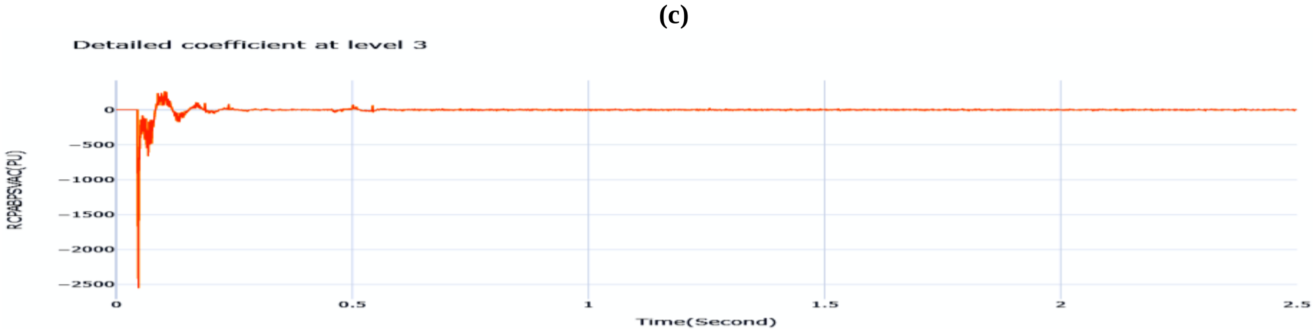
(a)


Detailed coefficient at level 1
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
0
0.5
1
1.5
2
2.5
Time(Second)

(b)


Detailed coefficient at level 2
RCPABPSVAC(PU)
200
0
−200
−400
−600
−800
−1000
−1200
−1400
0
0.5
1
1.5
2
2.5

(c)


Detailed coefficient at level 3
RCPABPSVAC(PU)
0
−500
−1000
−1500
−2000
−2500
0
0.5
1
1.5
2
2.5
Time(Second)

(d)

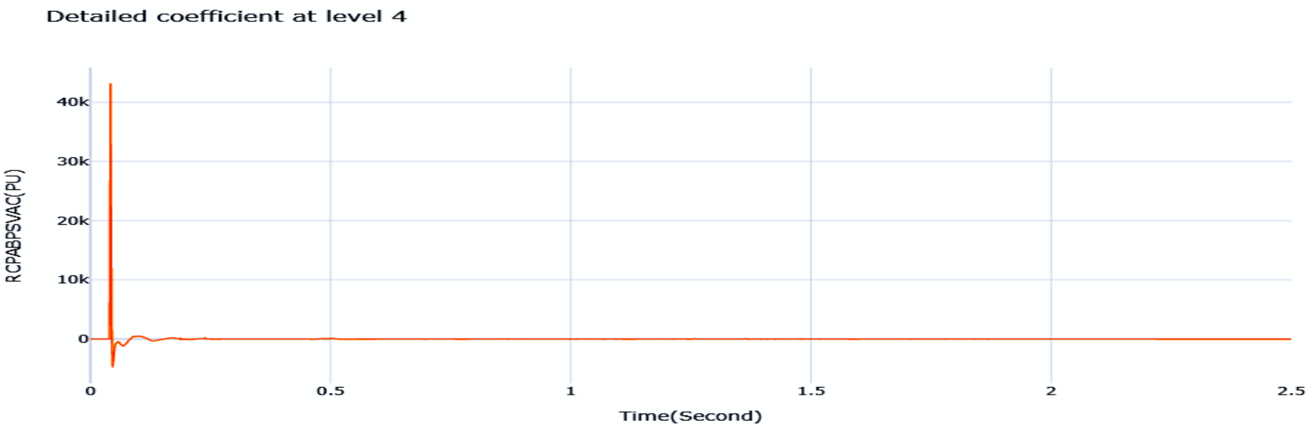


Fig. 10(a): Approximate coefficient at level4 & Fig. 10(b)-(e): d1-d4 coefficients of capacitor Switching

VI. CONFUSION MATRIX

The purpose of the confusion matrix is to specify correct and incorrect predictions of the ANN model. It is a 2x2 Matrix shown in Fig. 11.

Actual \ Predicted	No	Yes
No	TN	FP
Yes	FN	TP

Fig 11: ANN Flow chart of islanding Detection

TP: True Positives; TN: True Negatives FP: False Positives; FN: False Negatives. This confusion matrix was utilized for more analytical purposes rather than predicting the model.

$$\text{Accuracy (A)} = \frac{(TP + TN)}{TP + TN + FN + FP} \quad (3)$$

$$\text{Precision (P)} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall (R)} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1\_score} = \frac{2 * P * R}{P + R} \quad (6)$$

In the ANN model, accuracy, precision, recall, F1_score, and mean square error of wavelet coefficients were measured using equations (3)-(6). Moreover, islanding detection time was predicted for various case studies and reduced by 5msec. The confusion matrix compares actual target values with predicted values with the help of a machine learning algorithm. The confusion matrices for various wavelet coefficients are in Table 3.

TABLE 3 Confusion Matrices of Testing and Training data

S.No	Wavelet Coefficients	CONFUSION MATRIX OF TESTING DATA				
		70KW	100KW	120KW	Inductive Load(50H.P)	Capacitive load(10Kva)
1	Approx.Level1	$\begin{bmatrix}113 & 765\\52 & 1571\end{bmatrix}$	$\begin{bmatrix}341 & 537\\34 & 1589\end{bmatrix}$	$\begin{bmatrix}346 & 532\\66 & 1557\end{bmatrix}$	$\begin{bmatrix}492 & 386\\43 & 1580\end{bmatrix}$	$\begin{bmatrix}511 & 367\\48 & 1575\end{bmatrix}$
2	Approx.Level2	$\begin{bmatrix}79 & 219\\37 & 916\end{bmatrix}$	$\begin{bmatrix}176 & 122\\9 & 944\end{bmatrix}$	$\begin{bmatrix}150 & 148\\23 & 930\end{bmatrix}$	$\begin{bmatrix}153 & 145\\24 & 929\end{bmatrix}$	$\begin{bmatrix}212 & 86\\4 & 949\end{bmatrix}$
3	Approx.Level3	$\begin{bmatrix}22 & 90\\4 & 510\end{bmatrix}$	$\begin{bmatrix}68 & 44\\1 & 513\end{bmatrix}$	$\begin{bmatrix}64 & 48\\10 & 504\end{bmatrix}$	$\begin{bmatrix}35 & 77\\12 & 502\end{bmatrix}$	$\begin{bmatrix}0 & 112\\0 & 514\end{bmatrix}$
4	Approx.Level4	$\begin{bmatrix}11 & 32\\5 & 265\end{bmatrix}$	$\begin{bmatrix}18 & 25\\0 & 270\end{bmatrix}$	$\begin{bmatrix}15 & 28\\0 & 270\end{bmatrix}$	$\begin{bmatrix}18 & 25\\5 & 265\end{bmatrix}$	$\begin{bmatrix}18 & 25\\03 & 267\end{bmatrix}$
5	NORMAL	$\begin{bmatrix}1940 & 560\\1685 & 816\end{bmatrix}$	$\begin{bmatrix}1594 & 909\\1050 & 1451\end{bmatrix}$	$\begin{bmatrix}1827 & 673\\1099 & 1402\end{bmatrix}$	$\begin{bmatrix}1378 & 1122\\190 & 2311\end{bmatrix}$	$\begin{bmatrix}1541 & 959\\209 & 2292\end{bmatrix}$
		CONFUSION MATRIX OF TRAINING DATA				
6	Detail.Level1	$\begin{bmatrix}4420 & 0\\8081 & 0\end{bmatrix}$	$\begin{bmatrix}4420 & 0\\8081 & 0\end{bmatrix}$	$\begin{bmatrix}346 & 532\\66 & 1557\end{bmatrix}$	$\begin{bmatrix}3963 & 457\\7700 & 381\end{bmatrix}$	$\begin{bmatrix}4420 & 0\\8081 & 0\end{bmatrix}$
7	Detail.Level2	$\begin{bmatrix}777 & 786\\1739 & 2949\end{bmatrix}$	$\begin{bmatrix}1563 & 0\\4688 & 0\end{bmatrix}$	$\begin{bmatrix}1563 & 0\\4688 & 0\end{bmatrix}$	$\begin{bmatrix}1563 & 0\\4684 & 4\end{bmatrix}$	$\begin{bmatrix}1365 & 198\\4670 & 18\end{bmatrix}$
8	Detail.Level3	$\begin{bmatrix}454 & 99\\1524 & 1049\end{bmatrix}$	$\begin{bmatrix}553 & 0\\2573 & 0\end{bmatrix}$	$\begin{bmatrix}553 & 0\\2573 & 0\end{bmatrix}$	$\begin{bmatrix}553 & 0\\2573 & 0\end{bmatrix}$	$\begin{bmatrix}0 & 553\\0 & 2573\end{bmatrix}$
9	Detail.Level4	$\begin{bmatrix}181 & 14\\1018 & 350\end{bmatrix}$	$\begin{bmatrix}195 & 0\\1368 & 0\end{bmatrix}$	$\begin{bmatrix}192 & 3\\1363 & 5\end{bmatrix}$	$\begin{bmatrix}195 & 0\\1368 & 0\end{bmatrix}$	$\begin{bmatrix}195 & 0\\1368 & 0\end{bmatrix}$
10	NORMAL	$\begin{bmatrix}9774 & 2726\\11453 & 1048\end{bmatrix}$	$\begin{bmatrix}12500 & 0\\12501 & 0\end{bmatrix}$	$\begin{bmatrix}5019 & 7481\\5041 & 7460\end{bmatrix}$	$\begin{bmatrix}12500 & 0\\12501 & 0\end{bmatrix}$	$\begin{bmatrix}12500 & 0\\12501 & 0\end{bmatrix}$

TABLE 4 Testing Data & Training data details & performance for Normal load

S.No	Wavelet Coefficients	LOAD:70KW							
		Testing Data	Training Data	F1_Score	Recall	Precision	Mean Square Error	Testing Data Accuracy	Training Data Accuracy
1	Normal	5001	20000	0.7100	0.7505	0.6737	0.2751	72.48	55.62
2	Level1	2501	10000	0,793	0.6725	0.9679	0.3266	67.33	35.35
3	Level2	1251	5000	0.8773	0.8070	0.9611	0.2046	79.53	59.60
4	Level3	626	2500	0.9156	0.85	0.9922	0.1501	84.94	48.08
5	Level4	313	1250	0.9347	0.8922	0.9814	0.1182	88.17	33.97

TABLE 5 Testing Data & Training data details & performance for balanced loading

S.No	Wavelet Coefficients	LOAD:100KW							
		Testing Data samples	Training Data samples	F1_Score	Recall	Precision	Mean Square Error	Testing Data Accuracy	Training Data Accuracy
1	Normal	5001	20000	0.5969	0.6148	0.5801	0.3917	60.82	49.99
2	Level1	2501	10000	0.847	0.7474	0.9790	0.2283	77.16	35.35
3	Level2	1251	5000	0.9351	0.8855	0.9905	0.1047	89.52	25.00
4	Level3	626	2500	0.9579	0.9210	0.9980	0.0718	92.81	17.69
5	Level4	313	1250	0.9557	0.9152	1.0	0.0798	92.01	12.47

TABLE 6 Testing Data & Training data details & performance for Overloading

S.No	Wavelet Coefficients	LOAD:120KW							
		Testing Data samples	Training Data samples	F1_Score	Recall	Precision	Mean Square Error	Testing Data Accuracy	Training Data Accuracy
1	Normal	5001	20000	0,6127	0.6756	0.5605	0.3543	64.56	49.91
2	Level1	2501	10000	0.8389	0.7453	0.9593	0.2391	76.08	54.75
3	Level2	1251	5000	0.8633	0.8627	0.9758	0.1366	86.33	25.00
4	Level3	626	2500	0.9455	0.9130	0.9805	0.0926	90.73	17.69
5	Level4	313	1250	0.9507	0.9060	1.0	0.0894	91.05	12.60

TABLE 7 Testing Data & Training data details & performance for Inductive Load

S.No	Wavelet Coefficients	LOAD:50 H.P							
		Testing Data samples	Training Data samples	F1_Score	Recall	Precision	Mean Square Error	Testing Data Accuracy	Training Data Accuracy
1	Normal	5001	20000	0.7789	0.6731	0.9240	0.2981	73.76	49.99
2	Level1	2501	10000	0.8804	0.8036	0.9735	0.1715	82.84	34.79
3	Level2	1251	5000	0.91662	0.8649	0.9748	0.1350	86.49	25.06
4	Level3	626	2500	0.9857	0.8670	0.9766	0.1421	85.78	17.69
5	Level4	313	1250	0.9464	0.9137	0.9814	0.0958	90.41	12.47

TABLE 8 Testing Data & Training data details & performance for Capacitor Switching

S.No	Wavelet Coefficients	LOAD:10 KVA							
		Testing Data samples	Training Data samples	F1_Score	Recall	Precision	Mean Square Error	Testing Data Accuracy	Training Data Accuracy
1	Normal	5001	20000	0.7969	0.7050	0.9164	0.2335	76.66	49.99
2	Level1	2501	10000	0.8835	0.8110	0.9704	0.1659	83.40	35.35
3	Level2	1251	5000	0.9547	0.9169	0.9958	0.0719	92.80	22.12
4	Level3	626	2500	0.9017	0.8210	1.0	0.0701	82.10	82.30
5	Level4	313	1250	0.9501	0.9143	0.988	0.0894	91.05	12.47

VII. COMPARATIVE ASSESSMENT

In this work, DWT-ANN based passive islanding technique is recommended. It depends on the rate of change of phase angle between Positive Sequence voltage and current using DWT-ANN. DWT analysis is done for all case studies up to level4 (d-4), and then its approximation, detailed coefficients are determined. The purpose of these coefficients is to estimate the islanding detection time for various case studies based on the minimum square error as given in Table 9.

The values of Energy deviation vary linearly from level1 to level4 due to a decrease in the number of time samples. The proposed method detects islanding at a faster rate compared to existing procedures, as shown in Table 10. Islanding detection time will be predicted much better with level4 coefficients compared to level1 coefficients due to the reduction in samples.

From Tables 4-8, we can understand that improvement in Testing data accuracy and reduction in training data Accuracy indicates proper selection of epochs. This change in accuracy mainly depends on the epochs count and number of time approximation samples used in various case studies. If the number of epochs increased, it would detect islanding detection at a faster rate, but it reduces the accuracy of Testing Data. So selection of epochs will decide the accuracy of islanding detection. During islanding, the prediction of epochs will be such that accuracy and precision will be higher, and the Recall value will be near to unity.

TABLE 9 Islanding detection for various case studies

S.No	Islanding/Non-islanding Event	Detection time
1	70KW Load	98 msec
2	100KW Load	22 msec
3	120KW Load	13.9 msec
4	Inductive Load Switching	22.4 msec
5	Capacitor Switching	15 msec

TABLE 10 Suggested approach against existing procedures

Approach	Islanding estimation time(msec)
Rate of change of frequency[5],[2]	500
Positive sequence voltage and current [11]	100
Active rate of change of frequency [8]	200
Regulator voltage over reactive power [9]	300
Proposed Technique	Less than 100

VIII. CONCLUSION

The paper presents a WT-ANN-based islanding detection technique that depends on Mean square error for detecting islanding conditions. The energy content and standard deviation are measured for various wavelet coefficients and fed to ANN Model. It measures islanding detection time with an accuracy of 88-92% for various loads. It measures islanding detection time with an accuracy of 88-92% for various loads. The proposed islanding technique can also detect islanding under balanced conditions with zero NDZ. The main drawback of the proposed method is its islanding detection time increases drastically under low-level load conditions. The suggested approach can be realized by advanced techniques in ANN like multiple regression, Recurrent Neural networks, etc., for islanding detection without reducing the accuracy in the future.

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