A Deep CNN Approach for Islanding Detection of Integrated DG with Time Series Data and Scalogram

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Abstract

The ever increasing demand of electricity leads to the advancement of Distributed Generation (DG). Almost the DG sources are renewable in nature. One of the major complications with high penetration of DG sources is islanding. The islanding may damage the clients and their equipment. As per the IEEE 1547 DG interconnection standards, the islanding will be identified in a period of two seconds and the DG must be turned off. In this paper an advanced islanding detection process stand on deep learning technique with Continuous Wavelet Transforms (CWT) and Convolution Neural Networks (CNN) is implemented. This approach basically transformes the time series information into scalogram images, later the images are used to train and to test the islanding and non islanding events. The outcomes are correlated with the Artificial Neural Networks (ANN) and Fuzzy logic methods. The comparison shows that the proposed deep learning approach efficiently detects the islanding and non islanding events.

1. Introduction

The high integration of DG systems makes the power system network further complex. One of the major complications as a result of such DG assimilation is islanding. It is a situation where DG feeds the regional loads after disconnecting from utility grid [1]. It can be intentional or unintentional. The intentional islanding arises with the maintenance of utility. The unintentional islanding may cause due to utility grid failure or uncertainties in the power network [2]. It not only damages the customer appliances and personal but also makes the grid cumbersome [3]. Considerable islanding detection approaches are recommended by the researchers. They are briefly described here.

The passive methods encounter the situation by regularly auditing the passive parameters at the point of common coupling (PCC) and comparing it with the predefined threshold value [4]. The passive parameters are voltage, current, frequency, impedance, phase angle etc. If the parameter exceeds the specified value, the method affirms the islanding [5]. However, they have been suffering from massive non detection zone (NDZ) and complexity in fixing threshold values [6–7]. To overcome these demerits, active methods are suggested. In active methods, a low frequency harmonic signal is continuously injected and the parameters at PCC are monitored [8]. In grid connected affair the injected signal will not affect the monitored parameters, but in the islanding case it leads to the discrepancy in the observed guidelines. The perticuler discrepancies have been used to find the islanding [9–10]. These recommendations have no NDZ, but they are degrading the quality of power [11]. To eliminate the drawbacks of active methods, hybrid methods are proposed. They are the aggregate of active and passive approaches [12]. When the passive method suspects the islanding case, the active approach confirms it [13]. These methods have no NDZ and effect power quality less compared to active methods [14]. The remote islanding approach find the islanding by collecting data from utility and DG [15]. Various signal processing approaches have been proposed by the researchers which reduce the NDZ and enhances the performance of the passive methods by extracting the hidden features from the passive parameters [16–18]. Artificial intelligence learning models classify the islanding and non islanding events without threshold settings efficiently [19]. They do not have NDZ but large data is required for training the models [20]. It is compulsary to produce an accurate islanding detection technique due to advancements in smart grid technology and the complexity of the power system network in the future.

This paper presents a new IDM based on deep learning. This method uses CWT and CNN. First, the time series data obtained at PCC is transformed toward the scalogram illustrations with CWT which contain the data of various islanding and non islanding events. Later the scalogram images will be used to train the proposed CNN model. This is the second attempt of applying image processing techniques for the classification of the islanding cases. The remaining part of the paper is organized as per the following aspects. Segment 2 describes the practise of transforming time series input toward scalogram illustrations. Segment 3 describes the test system and data set preparation. In Section 4 the designing and training of CNN is presented. The results and discussions are illustrated in Section 5. Section 6 presents the conclusion.

2. Time Series Data To Scalogram Image Conversion

This section presents the operation of transforming time series signal towards the scalogram appearances. The signal data of (1) is used to prepare the basic scalogram image [21]. It is one second duration composed of two different frequencies 10 Hz and 200 Hz near ampiltudes 15 and 25 respectively. The amplitudes and frequencies are randomly selected for illustrating the explanation. This approach uses the wavelet transform of a signal.

$$f(t) = 15\sin(2\pi \times 10 \times t) + 25\sin(2\pi \times 200 \times t)$$

1

The wavelet transform of any signal $f(t)$ can be specified as

$$X(u, s) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-u}{s}\right)dt$$

2

In wavelet transforms, the time frequency energy density of a signal is a scalogram. In simple words, a scalogram is a observable impersonation of wavelet transform, to what end x, y and z axis produce the time, frequency and magnitude in color gradient respectively [22]. The scalogram of time series results represented in Eq. (1) is depicted in Fig. 1. It is obtained by applying the CWT with Morse wavelets. From Fig. 1 it has two frequencies 10 Hz and 200 Hz and two amplitudes 15 and 25 respectively. In this manner any time series data can be converted into scalogram images. It is generally known that any supervised learning requires, data set for training of the network and testing. In this paper, the data set is prepared with scalogram images of different time series events. The next section describes the test system and data set preparation for the training of CNN in detail.

3. Test System And Data Set Preparation

Large training information is needed for testing of any supervised learning methods. For problems related to image classifications, standard data sets are available. No such standard data sets are available for islanding detection methods. Hence, a standard test system is appropriate for developing the sufficient data set. A 100 KW grid integrated PV source shown in Fig. 2 is considered to create such a data set. This model has been adopted in such a way to satisfy the proposed work. The simulations are borned in the MATLAB/Simulink plotform. At t = 0.4s, by opening the Circuit Breaker (CB) the islanding event is created. The phase angle between positive sequence component of voltage and current at PCC is acquired for 6 cycles at 1000 samples per second. A PC with an i5 processor, 8 GB RAM, Windows 10 operating system is used to get these simulations. For producing the image data set different islanding and non islanding events are validated and their results are recorded as time series plots. CWT is applied to each time series data, for the generation of scalogram images. The scalogram of phase angle between positive sequence component of voltage and current at PCC for grid integrated and disconnected operations is shown in Fig. 3. It is clearly observed against the scalogram illustrations, there is a good variation among the islanding and non islanding images. The image classification technique is applied to these images for the detection of events.

Most of the passive approaches are failed to detect the islanding cases when there a zero or small power variation among the DG and the load in the islanding situation. This situation is taken into account and different islanding capsules at nearly worst power mismatches are studied and included in the data set. The data set also includes several islanding cases and non islanding cases such as switching of loads, capacitor banks, short circuit faults and motor switching events. A total of 300 islanding and non islanding are generated for data set creation. Which include 150 islanding and 150 non islanding events. All events are listed in Table. II.

4. Methodology And Cnn Design

This segment presents the methodology, architecture and training perticulers of CNN. Figure 4 represents the steps in the proposed islanding detection process. The phase angle between positive sequence component of voltage and current is acquired at PCC in time series form. This knowledge is transformed into scalogram pictures.

The scalogram pictures are given as input to the already ecperienced CNN for classification of events. For any supervised learning methods, the feature extraction is crucial for workout and examination. The accuracy of the approach depends on these features. In deep learning the CNN naturally extracts these features from the input pictures. It has multiple layers, most of the layers are used for feature extraction and only the concluding minority layers are used for analysis. The general structure of CNN is depicted in Fig. 5. and various slabs of CNN are shortly described here [23–24].

4.1 Convolution layer

In deep learning the convolution is a mathematical operation on two functions. Among the two functions, one function is an image in the form of pixels at the point on the picture and the other function is the kernel. Both are characterized as a cluster of numbers. The multiplication of these two arrays accord the outcome. The filter is now moved to another position on the image which is decided through the stride duration. The convolution is continued as far as the total picture has covered. The output of these computations is an activation map. Unlike the artificial neural networks where all input neurons are connected to all the output neurons, CNN has sparse connections, which means only the input neurons have only a few connections with the next layer neurons. The convolution activity is represented by the $*$ operator. Output $f(x)$is characterized when the input $I(x)$is convoluted with the kernel $K(x)$as (3)

$$f(x) = (I * K)(x)$$

3

If takes only integer attitudes, the discretized convolution can be defined as (4), which assumes the one dimensional convolution

$$f(x) = \sum_{a} I(a). K(x - a)$$

4

The two dimensional convolution with input $I(a, b)$and filter $K(m, n)$is illustrated as (5)

$$f(x) = \sum_{m} \sum_{n} I(m, n). K(a - m, b - n)$$

5

By commutative law filter is flipped and Eq. (5) is corresponding to (6)

$$f(x) = \sum_{m} \sum_{n} I(a - m, b - n). K(m, n)$$

6

Neural networks appliance the cross-correlation operation, it is same as the convolution operation without flipping the filter, the Eq. (6) changes to (7). Figure 6 shows the convolution operation in detail

$$f(x) = \sum_{m} \sum_{n} I(a + m, b + n). K(m, n)$$

7

4.2 Rectified Liner Unit (ReLu) Layer

The activation function at the yeild of the convolution lamination is linear naturally. The activations are commonly happen through the ReLu unit, for getting the nonlinear transformation. There are different types of activation functions; few among the familiar functions are tanh, sigmoid and Rectified Linear Unit (ReLu). In this CNN architecture, ReLu activation function is used at the output of previous layers. It can be represented as Fig. 7

Here, is the input to the neuron. It gives the output as zero if the input is negative and it gives the same output if the input is a positive value. This layer simplifies the calculations and accelerates the designing, and it advices to escape the fading gradient problems.

4.3 Pooling Layer

The pooling sheet lower the resolution of the extractions. This layer produces the extractions strong counter to distortion and noise. Here are four type of pooling, they are max pooling, average pooling, L2 normalization and sum pooling. In these classifications, the input is seperated into non overlapping two dimensional zones. For max pooling the maximum value of zone values is considered as output. For average pooling the average of zone values is considered as output and for sum pooling the sum of all values in the zone is considered. The proposed approach uses the max pooling layer.

4.4 Softmax Layer

Softmax layer provides the probabilities of all classes for n dimensional input real numbers vector. These probabilities are used for classification. Mathematically it can be represented as (8)

$$x_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

8

All the determined contingencies are in the dimention of zero and one. The importance of this function is it can add the entire probabilities up to one.

4.5 Fully connected layer

These are the output layers of the CNN. This layer produces the output classification. Eevery neuron in a fully connected layer has a connection with all neurons in the last layers. All the features received from the previous layers are weighted together to produce the specific classification output in this layer. The combination of these layers varies for different applications.

4.6 Design of CNN for islanding detection approach

In this paper, the CNN is constructed for the classification of different islanding and non islanding events. Several aspects are taken into account while constructing the CNN. The seusequent steps are initially supported. During the training process, all the hyperparameters are uninterupted initially. This will help in identifying the number of layers required for good efficiency. Once the statistics of slabs are identified, the variation of hyperparameters is identified for optimal values and they are fixed while designing CNN. It is initially started with a single layer. Every layer of CNN implements three operations such as convolution, ReLu activation and max pool operation. Once the CNN is designed and excecuted successfully for a single layer, the other layer is added and the same operations are repeated until it gets high accuracy. The response for the number of layers on accuracy found that eight layers architecture has good accuracy compared to five and seven layers. Hence eight layers architecture is fixed for the CNN design for classification of islanding and other events. Once it is fixed, the next step is the investigation of the size of filters. It is found that 3×3 kernel has good output compared to 5×5 and 11×11 kernels. The variation of learning rate and momentum with stochastic gradient descent with momentum method is verified. The learning rate of 0.001 accord good outputs in terms of accuracy and loss. The CNN design parameters and data set information is listed in Tables.I and Table.II respectively. The complete generic details of the CNN architecture are presented in Table.III.

Table.I: CNN design parameters

Training parameters	Design Value
Optimizer	Stocastic gradient decent with momentum
Momentum	0.2
Learning rate	0.001
Maximum epochs	15
Mini batch size	10
Loss function	Cross entrophy
Weight initialization	Random
Convolution layers	5
Kernals	3*3, 5*5, 11*11
Drop out	0.5
Stride	2
ReLu	5
Max pooling layers	5
Fully connected layer	3

5. Results And Discussion

The constructed structure is experienced with 75% of data and tested with 25% of data. The 25% of data is completely unseen by the designed network. The data set contains the islanding events and various non islanding events. The non islanding events includes load switching, capacitor switching, feeder switching, fault switching for ON/OFF cases. In all these cases the time series data is transformed into scalogram pictures. The voltage varions for islanding and non islanding events are reflected as colour gradients in the scalogram images. The few testing scalograms are depicted from Fig. 9 to Fig. 13. Total of 65 (25 islanding + 40 non islanding) cases are tested. Out of all the testing cases only 3 cases are wrongly predicted. Tha accuracy and loss plots training and validation are depicted in Fig. 14 for 50 epochs.

Table.II: Different scalograms simulated for data set preparation

Events	Number of cases
Islanding	**110**
Near zero power loading	40
Large and medium loading	70
Non islanding	**148**
Capacitor switching (ON)	10
Capacitor switching (OFF)	10
Induction motor switching (ON)	10
Induction motor switching (OFF)	10
Load switching (ON)	10
Load switching (OFF)	10
Various types of fault switching	8
Grid connected (Out of islanding area)	80

Table III: Customized CNN model generic details

Layer name	Type	Kernel Size	Output	Parameters
Input-1	Input Layer	–	256 x256 x 3	0
conv2d-1	convolution + ReLU	5 x 5	256 x 256 x64	321
batch_norm-1	Batch normalization	–	256 x 256 x64	256
max_pooling2d-1	MaxPooling	2 x 2	128, 128, 64	0
conv2d-2	convolution + ReLU	5 x 5	128 x 128 x 128	9930
batch_norm-2	Batch normalization	–	128 x128 x 128	512
max_pooling2d-2	MaxPooling	2 x 2	64 x64 x128	0
conv2d-3	convolution + ReLU	5 x 5	64 x64 x 256	36234
batch_norm-3	Batch normalization	–	64 x64 x256	1024
max_pooling2d-3	MaxPooling	2 x 2	32 x 32 x256	0
glob_ave_pool2d-1	Global Average pooling	–	256	0
Dropout-1	Dropout		256	0
Dense-1	Fully connected layer + softmax		2	524
Total params: 47,891 Trainable params: 46,905 Non-trainable params: 986				

6. Conclusion

This paper presents a novel islanding detection method with with CWT and CNN. The time series data of phase angle between PSV and PSC obtained from simulink are transformed into scalogram images. The data set is prepared with 258 events of islanding and non islanding cases. 75% of data set has been used for training the CNN and remaining 25% (65 Cases) is used for testing. Out of tested 25 islanding and 40 non islanding cases only three non islanding cases is wrongly predicted. This method has an accuracy 95.4%. It has been found that the deep learning based CNN can detect the islanding classifications effectively compared to machine learning approaches.

Declarations

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Conflict of Interest: The authors declare that they have no conflict of interest

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Figures

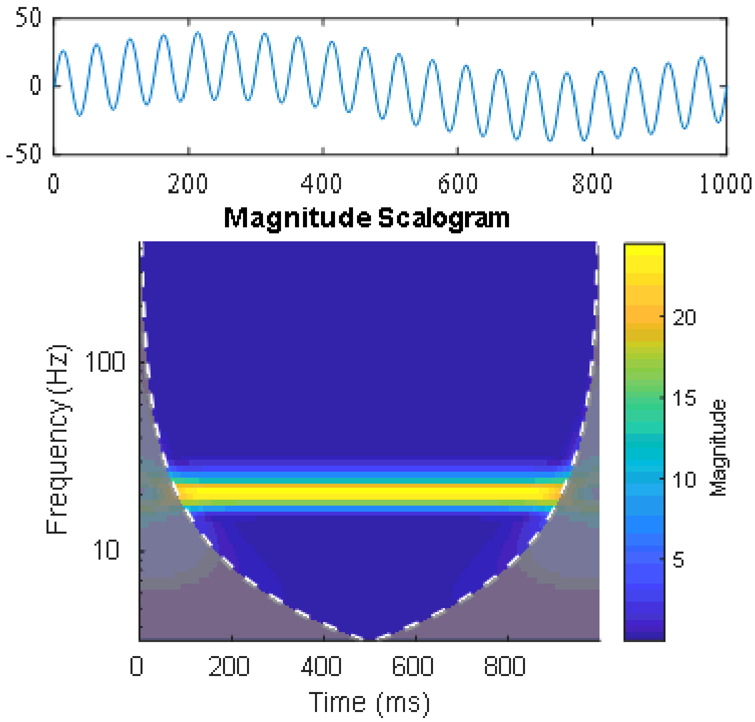

Figure 1

Scalogram image of equation (1)

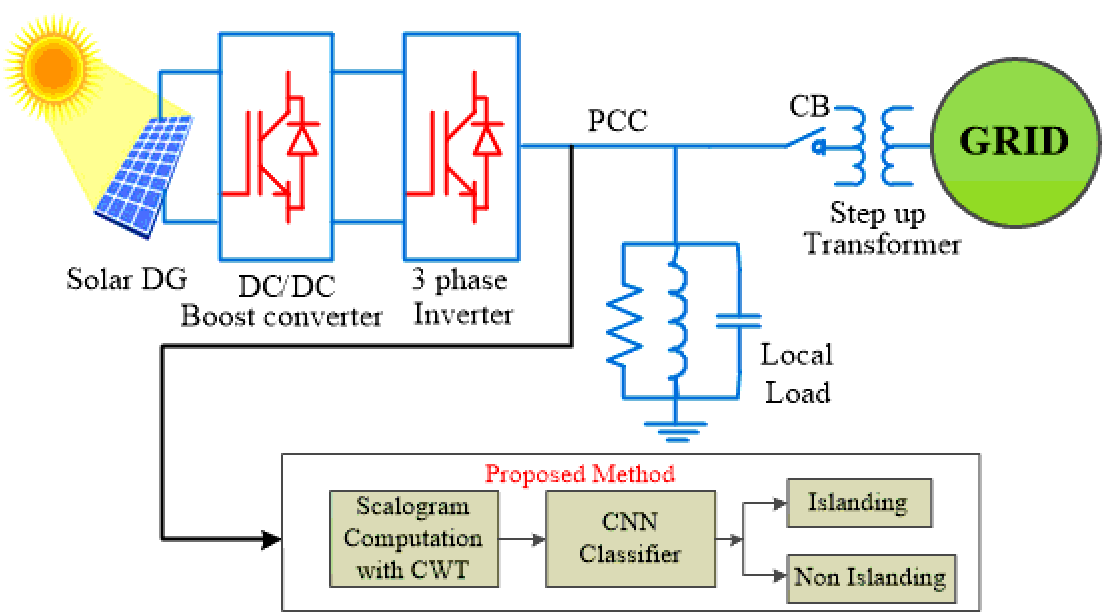

Figure 2

Test system for implementation of the proposed method

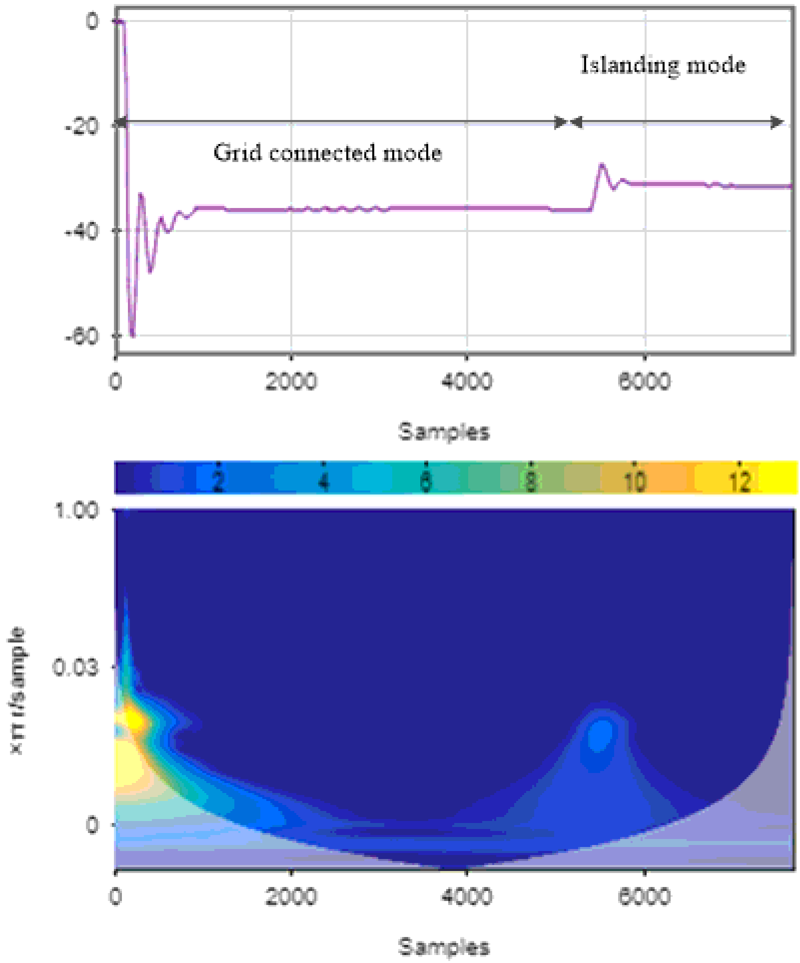

Figure 3

Scalogram image variation for grid connected and islanded data

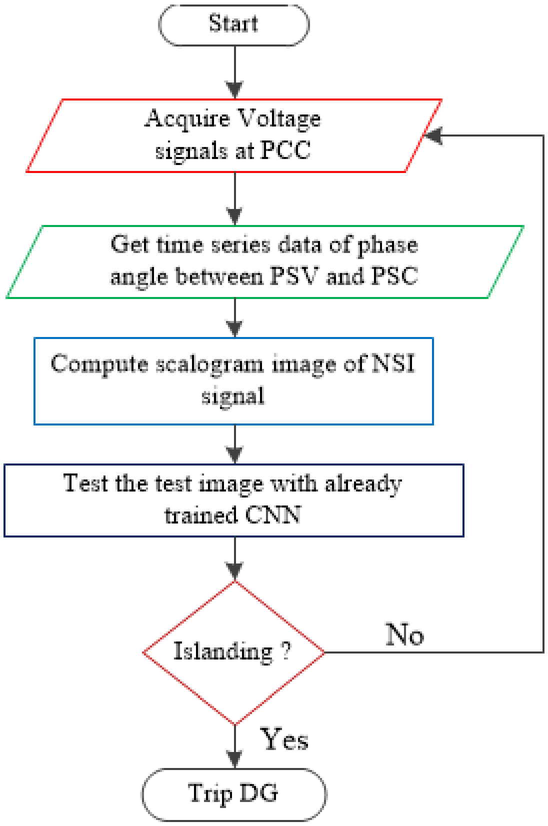

Figure 4

Flow chart of the proposed method

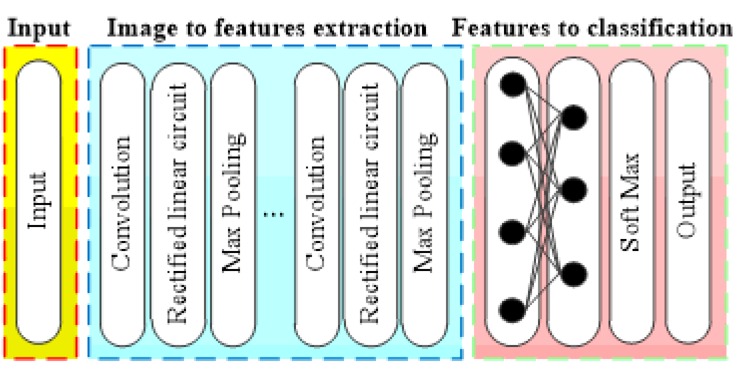

Figure 5

Familiar design of CNN

Figure 6

Convolution operation in CNN

Figure 7

ReLu activation function

Figure 8

Different pooling operations with 2×2 filter and stride 2

Figure 9

Islanding case for 100% of load

Figure 10

Islanding case for 80% of load

Figure 11

Islanding case for 50% of load

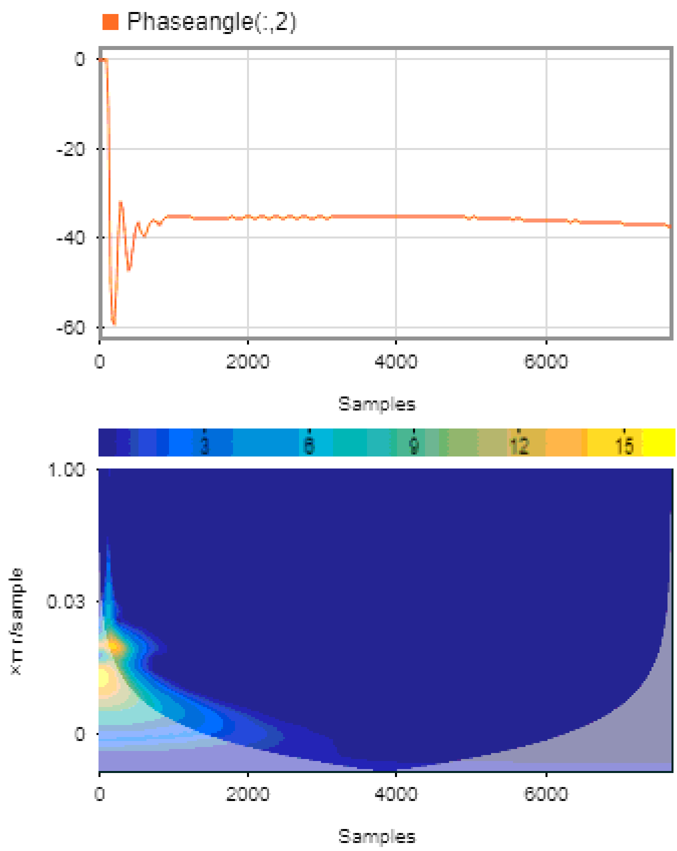

Figure 12

Non islanding case of capacitor switching

Figure 13

Non islanding case of induction motor switching

Figure 14

Accuracy and loss plots for training and validation