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Islanding Detection in Microgrid Using Signal Processing Techniques Adopting a Supervised Classifier

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Abstract: The occurrence of unexpected islanding is one of the major issues in the microgrid integrated distributed generation units. The islanding issue has to be immediately solved to protect the device from faults and power quality issues. Though several techniques are established in the recent days for the detection of islanding, the ultimate aim of detecting the fault is not achieved as these approaches generate a high risk of false detection. Hence, an effective and simple signal processing approach is proposed in this article. Initially, the grid signal is preprocessed with the implementation of Wiener filter, which performs efficient restoration of desired signal. The preprocessed signal is segmented with the assistance of DCT-DOST approach, which minimizes the time-locality. After the segmentation, the extraction of features is carried out by SIFT method, which estimates the feature descriptors by extracting single or numerous dominant orientations in every key point. Finally, the supervised classification is performed by PNN, which offers rapid training process in the absence of local minima. The proposed methodology is simulated and compared with other existing approaches. It delivers less training time of $0.85\ sec$ and testing time of $0.001\ sec$. The obtained accuracy is 97.6% for islanding conditions and 98.4% for non-islanding conditions.

Keywords: *DG, DER, Islanding detection, PCC, Wiener filter, DCT-DOST, SIFT, PNN.*

1. Introduction

The integration of renewable energy sources (RES) in the energy distribution network (EDN) has gained huge attention because of the circumstances like fossil fuel depletion and clean energy demand. Hence, the grid connected renewable energy generation system has been developed to satisfy the excessive energy demand [1]. Among all RESs, the PV and wind are considered as the most promising energy resources because of having variety of advantages like easy availability and low maintenance cost. By considering the highest contribution of PV and wind source in power generation, a hybrid PV-wind based energy generation system is interconnected to the grid. While integrating the grid connected hybrid renewable energy system (GCHRES) to the distribution network, number of issues are created, among which islanding is regarded as one of the major issues [2]-[4].

The unexpected separation of the load or distributed generation system from the utility grid during the electrification is defined as islanding [5]. Due to unintentional islanding, the utility operation is stopped, which affects the voltage and frequency level of the distributed generation (DG) [6]. This islanding issue harms the reliability of the system and puts the lives of maintenance workers under risk [7, 8]. If the islanding is detected, the distributed generation system has to be immediately tripped to protect the distributed resources and loads, which are integrated with the system. The international technical organizations like IEC or IEEE revises the islanding codes and distributed generation system's interconnection codes every two to three years to emphasize the reliability of islanding detection.

According to IEEE1547.4, the solution for the "electrical islanding" is to offer electricity even in the unavailability of utility power [9, 10]. When the utilization of DG is increased, the unintentional islanding identification become difficult. In general, the islanding detection technique is capable of detecting the electric grid interruptions by separating the GC-HRES from the

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grid [11]. The immediate detection of islanding avoids the voltage instability, damage of power assets, frequency instability and power quality issues [12]. Thus, the islanding detection techniques (IDTs) have been created to address these issues [13]. The techniques of islanding detection are divided into two categories as classic and modern. The classification of IDT is illustrated in Fig. 1.

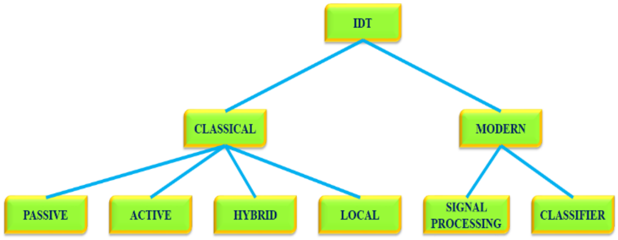


Fig. 1. Classification of IDT

Active methods possess high non-detection zone (NDZ). These Active and hybrid methods degrade the power quality of the system. The local islanding method is limited because of its high implementation cost. By choosing a suitable islanding detection technique, the islanding issues have been identified. In this concern, the modern islanding techniques like signal processing approach and classifier are utilized in the recent days. The signal processing tools extract the signal features for detecting the islanding condition whereas the classifier effectively classifies the islanding issue with high accuracy and sensitivity [14]-[17]. The classifiers delivers better performance in classifying the islanding condition by choosing a suitable threshold value [18]. Some of the popular islanding classifiers are listed as Decision tree, Static vector machine (SVM), Fuzzy logic, Artificial neural network (ANN), Artificial neuro fuzzy-inference system (ANFIS), convolutional neural network (CNN), Probabilistic neural network (PNN), etc., [19, 20].

The decision tree classifier is commonly used as it gives accurate classification result. However, it is not suitable for the applications, which have lot of uncorrelated variables. On the other hand, SVM classifiers effectively eliminates the training error but choosing a suitable hyper parameter is a difficult task in this approach. Therefore, fuzzy logic classifier is preferred as it is easily interpretable. In spite of having various benefits, it has low robustness and so it is replaced with ANN [21]. Though the ANN classifier has easy implementation, it has complicated training process. The ANFIS classifier requires no complicated mathematical models but it requires more time for the computational process. Therefore, the CNN classifier is utilized, which detects the islanding issue with high accuracy. However, it has less operational speed due to the max pool layer [22, 23]. To overcome the shortcomings of aforementioned classifiers, a PNN classifier is suggested in this work as it has high level nuisance tripping capacity.

In this work, the islanding issue is identified by utilizing a signal processing approach with PNN classifier. Initially, the grid signal is preprocessed with the assistance of Wiener filter by adopting linearity property. The preprocessed signal is segmented by DCT-DOST (Discrete Cosine Transform-Discrete Orthogonal Stockwell Transform) approach. Subsequently, the feature extraction is carried out by SIFT approach, which utilizes the regional descriptors to obtain the desired coefficients. Finally, the classification is performed by PNN approach to identify islanding conditions.

2. Proposed Detection Approach

The occurrence of unplanned islanding results in the unsynchronised impairing or reclosing of frequency and voltage control. Therefore, the DG units have to be equipped with particular schemes for the detection and prevention of islanding. The unit has to be immediately disconnected from the grid within 2 seconds of islanding. In this article, a signal processing approach is employed for the detection of islanding in DG units. The block representation of the proposed work is given in Fig. 2.

Fig. 2. Proposed block representation

Initially, the grid signal is pre-processed by the wiener filter, which plays a major part in the restoration of signals. This filter reduces the average squared distance between the centre of the anticipated signal and the filter output. It generally performs the operations like signal restoration, identification of system, channel equalization, cancellation of echo and linear prediction. The pre-processed signal is further segmented by DCT-DOST approach, which represents the frequency-time properties of the input signal. This approach indicates the coefficients of most significant low frequency components. After segmentation, the features are extracted with the help of SIFT technique, which provides rotation invariance, scale-invariability and affine invariance for maintaining high matching rate with the less noise. Finally, classification is carried out by the PNN approach for the recognition and classification of signals in power systems. It has plenty of beneficial impacts like rapid training process, absence of local minima, simple way of adding and removing training samples with maximum accuracy. Thus, the occurrence of islanding is detected with the aid of signal processing approach. The steps of this process are is clearly explained in the subsequent part.

2.1. Wiener filter for pre-processing

Various filters like mean, median and Gaussian filters are utilized for the pre-processing of input signals. However, these filters exhibit several disadvantages like generation of pseudo noise edges, poor stability and difficulty in analytically treating the effects. Hence, the Wiener filter is utilized in this approach for the pre-processing of grid signals. It is an optimized linear filter, which delivers minimum mean square error. The block illustration of the wiener filter is depicted in Fig. 3.

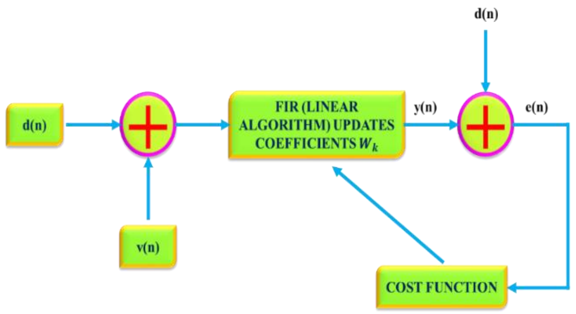


Fig. 3. Block diagram of Wiener filter

The average squared distance among the filter output and the desired signal is minimized by the computation of the coefficients. However, the coefficients of the filter for every block in N number of signal samples are estimated by considering the average signal characteristics. The relation for the input-output filter is given by,

$$\hat{a}(m) = \sum_{k=0}^{N-1} w_k\, b(m-k) \tag{1}$$

$$\hat{a}(m) = W^T B \tag{2}$$

Where, B denotes the grid signal with N number of samples and W indicates the N Number of filter coefficients.

The objective of the wiener filter is to determine the least mean square error (LSE) within the desired grid signal and filter output. The coefficients of the wiener filter are obtained through the minimization of average squared error function $E[e(m)]$. The mean square error is given by,

$$E[e^2(m)] = E[((a(m) - \hat{a}(m))^2] \tag{3}$$

The minimum mean square error (MMSE) is determined by,

$$R_{bb}W = r_{ba} \tag{4}$$

Here, $R_{bb}: E[b(m)b^T(m)]$ is the input signal autocorrelation matrix, r_{ba} is the input cross correlation matrix and $W = R^{-1}{}_{bb} r_{ba}$ is the Filter output.

Considering a noisy signal, it is given as,

$$b(m) = a(m) + n(m) \tag{5}$$

Where, (m) signifies the combined signal of clear signal $a(m)$ and noise $n(m)$

The autocorrelation matrix related to the noisy signal is expressed as,

$$R_{bb} = R_{aa} + R_{nn} \tag{6}$$

Where, R_{aa} signifies the auto correlation matrix of the signal and R_{nn} represents the auto correlation matrix of noise.

Hence, the coefficient of Wiener filter is defined by,

$$W = (R_{aa} + R_{nn})^{-1} r_{aa} \tag{7}$$

Here, r_{aa} is the input auto correlation matrix.

The Wiener filter generates a linear determination of required signal sequence from other relevant sequence and provides a solution for the issues of signal estimation. The obtained values of Peak signal to noise ratio (PSNR) and the root mean square error (RMSE) indicate the efficiency of the filter.

2.2. Segmentation by DCT-DOST

The DOST is the basic functions of orthogonal group, which provides a feasible utilization of S-transform. The DCT approach is applied to the DOST for the analysis of frequency-time distribution of grid signal. In consideration with DOST, the periodic representation of input signal is done by DFT. Hence, the signal losses its form when the coefficients are truncated. The signal tackles the coefficient truncation to maintain the required input signal shape. As the DCT computes real coefficients, it reduces the complexity in a wider range. Hence, the incorporation of DCT and DOST denotes only the most significant coefficients of low frequency. These coefficients are distributed in the frequency-time space by considering the bandwidth of frequency. The DCT-DOST is localized in space, which minimizes time-locality. Therefore, the frequency space partitioning has to be adjusted since it require frequencies of high range. It is attained with $\beta_0 = 0, \beta + n = 2^{n-1}$ due to the absence of negative frequencies. In accordance with the input signal of length 2^N, the width of the frequency partition is given as,

$$n_1 = 1 \text{ and } n_i = 2^{i-2}, for\ 2 \le i \le N-1 \tag{8}$$

The adopted algorithm is given as,

$X = dct(x)$;
$y = 0$;
For $cx\ in$ [1,1,2,4, … …]; frequency bands
$X[y{:}\, y + cy - 1]{:}\, idct1(X[y{:}\, y + cy - 1])$;
End for
Return X

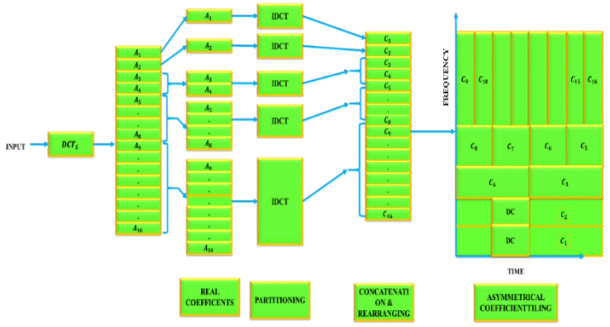


Fig. 4. Block diagram of DCT-DOST

The overall architecture of the adopted DCT-DOST is shown in Fig. 4. Initially, the input signal is applied across the N-point DCT, which performs the generation of $A_1, A_2, A_3, \ldots.. A_N$. The obtained coefficients are subdivided as the sub bands of length $[2^0, 2^1, 2^2, \ldots, 2^{N-1}]$. By considering the constraints of space, the subdivision of coefficients are performed for the length $N = 16$. The β −point inverse DCT is provided across each sub band for obtaining the finalized real coefficients, which are space localized. The β −point inverse DCT is applied for coefficient computation, which further ensures the creation of β bandwidth in frequencies along with orthogonal decomposition. In consideration with an input sequence with length$\{Y(k) = k = 0,1, \ldots.., N-1\}$, the inverse DCT operation is given as,

$$y(n) = \sqrt{\frac{1}{N}} Y(0) + \sqrt{\frac{2}{N}} \sum_{k=1}^{N-1} Y(k) cos\left(\frac{\pi(2n+1)k}{2N}\right), \text{for } n = 0,1, \ldots.., N-1 \quad (9)$$

Here, concatenation and rearrangement of frequency band width (β), time variable for time localization (τ) and frequency variable indicative of the frequency band centre (ν) are considered to generate coefficients of resultant features. The generated output is the frequency-time coefficient distribution of signal length 2^N and the coefficients are given by $C_1, C_2, \ldots\ldots, C_N$. The segmented signal is further subjected to feature extraction.

2.3. Feature extraction by SIFT

The interest points are referred as the reference locations in the corner objects. The localization of these points is significant for the applications like tracking and alignment of signals. The adoption of corner points for the determination of similar objects delivers various drawbacks. As each corner point only provides the power and position, the information, which is offered by the corner points is insufficient for representing the object. Hence, the SIFT approach is opted for the feature extraction process. In this approach, the objects are represented by utilizing the regional descriptors for performing the recognition of objects. The feature extraction using SIFT involves the following steps.

2.3.1 Detection of scale space extrema

The candidate key points are attained with the detection of extrema from the Difference of Gaussian pyramid (DoG), which indicates the Laplace of Gaussian (LoG) approximation. The minima or maxima key points are determined by the scale space of the signal and the scale space is given by,

$$L(a, b, \sigma) = G(a, b, \sigma) * I(a, b) \quad (10)$$

Here, the Gaussian convolution kernel $G(a, b, \sigma)$ is given as,

$$G(a, b, \sigma) = \left(\frac{1}{2\pi\sigma^2}\right) e^{-(a^2+b^2)/(2\sigma^2)} \quad (11)$$

Where, (a, b) denotes the pixel coordinates, σ denotes the scale factor and $L(a, b, \sigma)$ denotes the scale space.

The nearby scales are differentiated with the multiplicative factor (k) for obtaining local minima or maxima of $D(a, b, \sigma)$, which is given by,

$$D(a, b, \sigma) = \big(G(a, b, k\sigma) - G(a, b, \sigma)\big) * I(a, b) \quad (12)$$

$$= L(a, b, k\sigma) - L(a, b, \sigma) \quad (13)$$

The minima and maxima of $D(a, b, \sigma)$ are calculated by considering the sample point comparison, eight neighbours of same scale and the neighbouring pixels. A pixel is indicated as a candidate key point if it denotes a local minima or maxima.

2.3.2 Localization of key points

The stable key points are obtained in this stage. The accurate position of key points is determined by utilizing the third order Taylor polynomial. Subsequently, the key points with reduced contrast are eliminated. Finally, the key points at the edge are eliminated by utilizing the principle curvature.

2.3.3 Assigning orientation

A key point possess more than one orientation. This orientation is estimated by considering the orientation and gradient of the area around the key point.

2.3.4 Key point descriptor

The gradient magnitude and the orientation are estimated at every window sub point. An orientation histogram, which represents eight cardinal directions is determined for every sub region that depends on the magnitude of gradient. A typical key point descriptor comprises 128 elements from 16 sub-region and every sub region has 8 features.

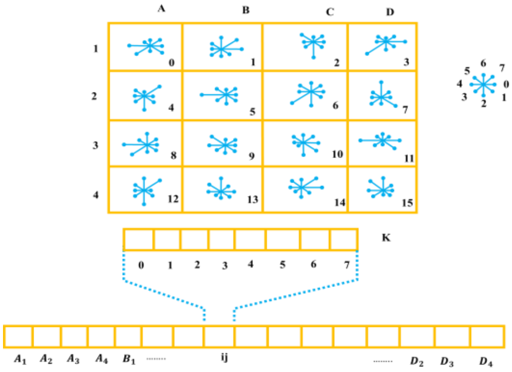


Fig. 5. SIFT descriptor representation

Fig. 5 represents the process of SIFT descriptor, in which the orientation and scale of every key point is attained from the centre location of key point. The key point size is estimated by the octave scale. Subsequently, 36 bins are created for the histogram of gradient direction, in which every bin covers 10 degrees. The magnitude of gradient m provides weightage for the gradient magnitude (θ) of every sample position. The Gaussian weighted circular window is given as,

$$m(a,b) = \sqrt{\left(L(a+1,b)-L(a-1,b)\right)^2, \left(L(a,b+1)-L(a,b-1)\right)^2} \quad (14)$$

$$\theta(a,b) = arctan\frac{L(a,b+1)-L(a,b-1)}{L(a+1,b)-L(a-1,b)} \quad (15)$$

Here, $L(a,b)$ indicates the pixel value of the position a,b; $m(a,b)$ indicates the magnitude of the gradient and $\theta(a,b)$ indicates the direction.

The features of SIFT are estimated by the extraction of single or several dominant orientations in every key point across a normalized patch. This ensures the rotation-invariant characteristics of extracted key points. The extracted feature descriptors are higher than the existing approaches.

2.4. Classification by PNN

The classification process by using PNN is regarded as a supervised learning task, which utilizes the output information as a discrete classification. By considering the islanding operation and the input parameters of the system, the classification output denotes the islanding issue. The input vector is adopted for mathematically defining the category. The network classifiers are trained by utilizing the known classification data. The major goal of PNN is to generate the relationship within the output classes and input parameters of the system. Hence, the obtained knowledge is utilized for estimating the threshold of islanding relays. The features of PNN are given as follows.

Probabilistic model like Bayesian classifiers are utilized for implementation.

- PNN offers sufficient training data.
- Offers instantaneous and faster training.
- Setting of initial weights is not required.
- No relationship exists between the recalling process and learning process.
- The network weights are not modified by the difference between the target vector and inference vector.

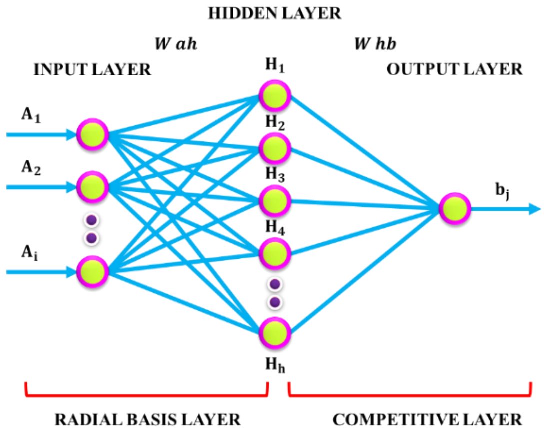


Fig. 6. PNN architecture

The PNN approach offers rapid learning speed by assuring real time signal classification and fault diagnosis. Fig. 6 represents the PNN architecture, which is comprised of competitive layer and radial basis layer. The input layer is completely linked with the pattern layer and it denotes the input features. In the training set, each pattern is connected with a single neuron. The neurons perform the weight sum execution of signal, which is received from the input layer. Consequently, this weight sum is applied to the nonlinear activation function for obtaining the neuron output. By considering the application of signal classification, the classification of training samples is performed with respect to the distribution values of probability density function (PDF). It is given represented as,

$$f_k(A) = \frac{1}{N_k}\sum_{j=1}^{N_k} exp\left(-\frac{\|A-A_{jk}\|}{2\sigma^2}\right) \quad (16)$$

In the hidden layer, the output vector H is modified as,

$$H_h = exp\left(\frac{-\sum_i\left(A_i-W_{ih}^{ah}\right)^2}{2\sigma^2}\right) \quad (17)$$

If $net_j = \frac{1}{N_j}\sum_h W_{jh}^{hb} H_h,\ N_j = \sum_h W_{jh}^{hb}$ and $net_j = max_k(net_k)$

(18)

Then $b_j = 1$; else $b_j = 0$

Where, i indicates the number of inputs, h denotes the number of hidden units, j denotes the number of outputs, k represents the number of training examples, σ indicates the smoothing parameter, N represents the number of classifications, A represents the input vector, $\|A - A_{jk}\|$

denotes Euclidean distance between A and A_{jk}, W_{ih}^{ah} indicates the weight between the input layer A and hidden layer H, W_{jh}^{hb} represents the connection weight between the output layer B and hidden layer H.

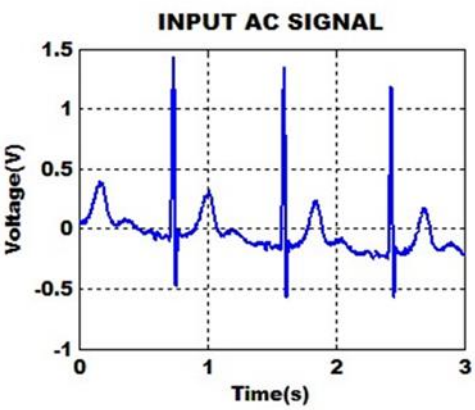
In PNN, every class has a probability of each input member and a PDF. The products of PDF is compared with the relative frequency of every input vector. The approach is utilized in real time to improve the generalization process. In the provided DG connection, the settings of island threshold are performed for a specific target location and the adopted tasks are mentioned as follows.

- A target DG is selected in the distribution network.
- The non-islanding and islanding conditions are simulated with various conditions of operations.
- The voltage and current signals are analysed at the target DG location of feature extraction.
- PNN is trained for classifying the non-islanding and islanding condition.
- PNN is validated with the remaining datasets, which are not used for the training.

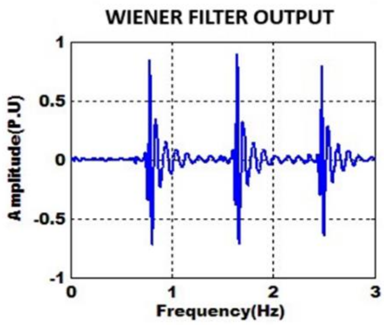
The smoothing factor is considered as a major factor for the training purpose. The reasonable range of this factor is either 0.01 to 0.09 or 0.001 to 0.009. The weights are adjusted in PNN and so this approach requires no back propagation. The total count of utilized classifiers relies on the total number of DG units in the system.

3. Results and Discussion

The simulation is carried out by the MATLAB tool. The islanding and non-islanding events depend on both the IEEE1547 standard and test practices, which are adopted by majority of the islanding relay manufacturers. The circuit breaker is closed after $0.15s$ and opened at $t = 0.3s$. Thus, it consumes reduced simulation time.



(a)



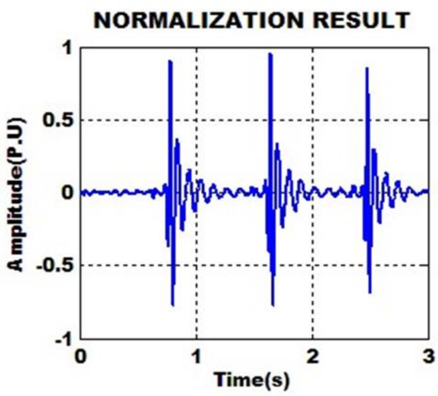
(b)

Fig. 7. (a) Input signal (b) Output of Wiener filter

Fig. 7 (a) represents the AC signal, which is given as the input for processing. Initially, the signal is pre-processed by Wiener filter and the corresponding output is given in Fig. 7 (b). The Wiener filter exhibits improved efficiency in removing noise, which is comparatively better than the other approaches. The comparison outputs are shown in Tab.1.

Table 1. RMSE and PSNR comparison

Filters	RMSE	PSNR
Median filter	33.03	5.56
Average filter	33.28	5.40
Gaussian filter	33.24	5.41
Wiener filter	34.25	4.82



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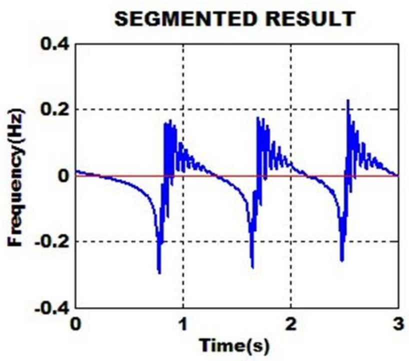
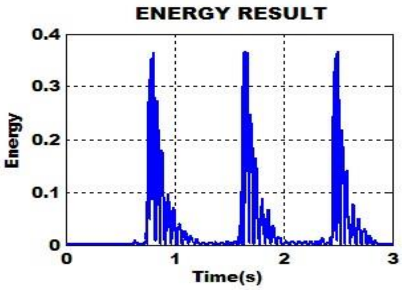


(b)

Fig. 8. (a) Normalization output (b) Segmentation output

Fig. 8 (a) denotes the normalization output and Fig. 8 (b) denotes the segmented output of DCT-DOST approach. As the generated coefficients at the output are asymmetrical and orthogonal, the computational load is reduced.



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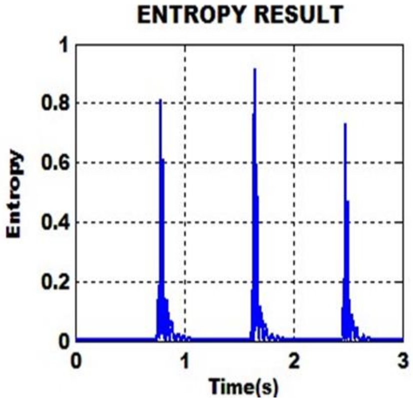


(b)

Fig. 9. (a) Energy result (b) Entropy result

Fig. 9 represents the outputs of Energy and Entropy, which are obtained by the SIFT approach.

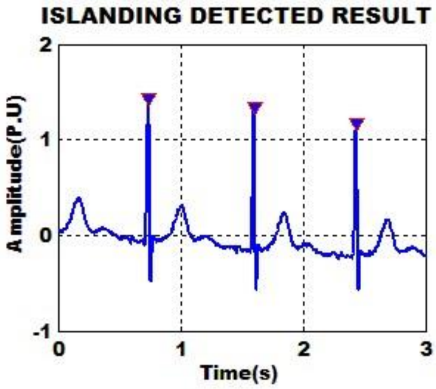
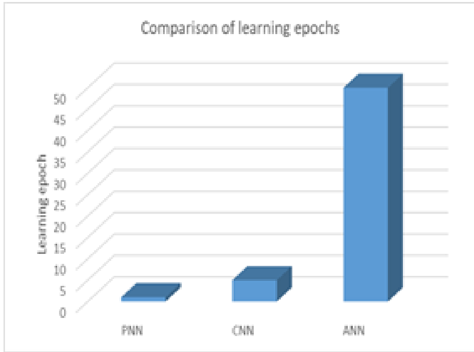
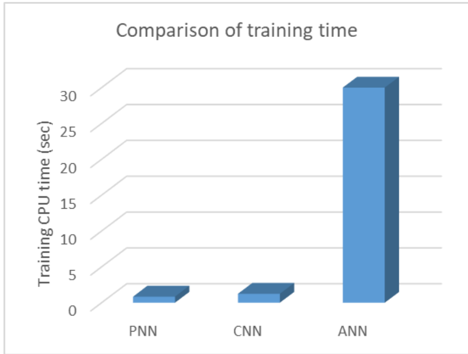


Fig. 10. Islanding detection output

Fig. 10 indicates the islanding detection output of PNN classifier. The performance of PNN in the the detection and classification of islanding is validated with testing. The testing data comprises of islanding and non-islanding events during the non-detection zone or normal conditions.



(a)



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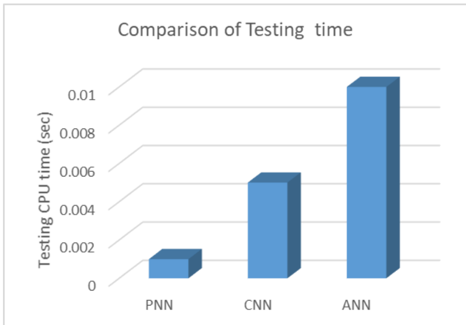

(c)

Fig. 11. Comparison results (a) learning epoch (b) training time (c) testing time

Fig. 11 indicates the comparison of proposed PNN with ANN and CNN classifiers. The PNN generates better results than the ANN and CNN with a learning epoch value of 1. The utilized training time is 0.85 sec and testing time is 0.001 sec.

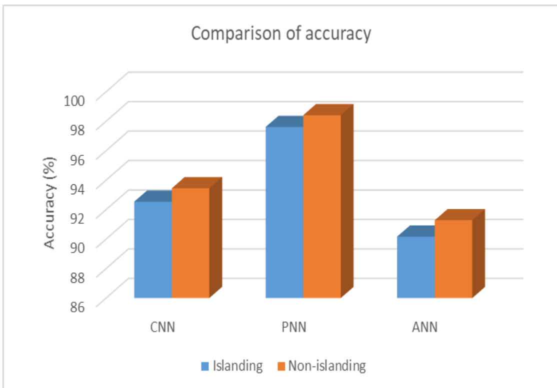

Fig. 12. Comparison of accuracy

Fig. 12 represents the comparison of PNN with ANN and CNN in terms of accuracy. The PNN is more effective with the enhanced accuracy of 97.6% for islanding conditions and 98.4% for non-islanding conditions.

Table 2. Islanding detection comparison for various faults

Faults	ANN	CNN	PNN
OC	$7.4s$	$0.82ms$	$0.65ms$
SC	$7s$	$0.8ms$	$0.6ms$
L-G	$7.8s$	$0.86ms$	$0.68ms$

Tab. 2 represents the islanding detection comparison of PNN with ANN and CNN by considering the faults like open circuit (OC), short circuit (SC) and line ground (L-G). The obtained results clearly proves that the proposed PNN consumes reduced time for the detection of islanding.

4. Conclusion

In this article, an improved method of islanding detection in DG units using signal processing approach is proposed. The denoising of input signal is performed by Wiener filter, which provides an improved solution for the signal estimation issue and generates a desired signal with linear estimation. The DCT-DOST approach is adopted for the segmentation, which aids the signal to withstand increased coefficient truncation. The feature extraction is done with the assistance of SIFT technique, which identifies the extreme points of the spatial scale along with the extraction of scale, position and rotation invariants. Finally, the supervised classification is performed by the robust PNN classifier. The most affected features are obtained in the target locations of DG and applied as inputs to PNN for the classification of islanding signals and non-islanding signals. By utilizing PNN, maximum classification accuracy of 97.6% is obtained for islanding conditions and 98.4% is obtained for non-islanding conditions. Thus, the introduced islanding approach is suitable for the DG units with actual power distribution systems.

5. References

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