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An Islanding Detection Method Based on Wavelet Packet Transform and Extreme Learning Machine

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Abstract- In this manuscript, wavelet packet transform (WPT) with extreme learning machine (ELM) based method is proposed for detection of the islanding condition in the distribution system with the presence of multiple distributed generations (DGs). The system consists of different types of DGs like hydro turbine generator with synchronous machine and wind turbine generator with asynchronous machine. Negative sequence component based assessment and analysis of fault conditions is considered in this work. The change of energy components are calculated using WPT at different nodes and considered as feature index for a particular fault condition. Very often occurred practical islanding and non-islanding events like capacitor switching, load rejection, line to line fault, three phase fault, voltage sag and swell etc. are simulated. Based on the feature index, ELM is applied as a classifier to distinguish islanding from non-islanding events. The results are presented with comparison to other classifiers like decision tree, artificial neural network (ANN) and support vector machine (SVM). It has been found that the proposed WPT-ELM technique is highly effective to discriminate islanding events under a wide range of operating conditions from other type of disturbances in the power distribution network. The proposed scheme is fully simulated by the MATLAB/SIMULINK environment.

Keywords Negative sequence components, wavelet packet transform, islanding; decision tree, artificial neural network, support vector machine, extreme learning machine.

1. Introduction

In recent years, one of the major concerns is to meet the exponential increase of the load demand in the deregulated power sector. The most preferable solution among all alternatives for electric power generation in today's world is the placement of DGs in the distribution sector. Several types of DGs are integrated into the grid at the distribution level like photovoltaic (PV), fuel cells, micro hydro turbines, small wind turbines, biomass and geothermal energies. Despite of the many advantages of DG connection to the utility grid in the power system, there are many challenges that need to be seriously think about and one of the main issues is islanding detection. Islanding is a condition in which part of the distribution network is disconnected from the remainder of the grid while supplying the power to the local loads [1].

According to IEEE 1547-2003, the isolation time should be less than 2 sec and the related DGs shall be isolated within that period from the distribution system [2]. Majorly, islanding is divided into two categories, such as intentional islanding and unintentional islanding. Intentional islanding is occurred during fault condition which can be easily detected and removed by disconnecting the main grid from the utility system. But in the latter case a frequently unwanted tripping problem arises in the distribution system. This in turn gives rise to various problems related to power quality, safety hazard, voltage and frequency instability, and damage to the system equipment's, etc. So, it is necessary to formulate an efficient methodology to detect an islanding detection in the distribution system with high reliability at different operating conditions [2].

Local detection and remote detection techniques are very often used for the islanding detection purpose. The local detection techniques are applied based on the measured data from the DG side, while the remote detection techniques are mostly designed according to the measured data from the utility side. The latter one is more efficient between the two; however, its implementation is too expensive and less reliable. The local detection techniques can be categorized into passive detection technique [3-7], active detection technique [8-12] and hybrid detection technique [4,13-14]. Their performances are assessed according to their ability to detect and their size of non-detection zone (NDZ) in which these techniques have failed to detect islanding conditions [2,15].The passive methods are usually simple and easy to implement and do not introduce any disturbance by harmonic injection and stability issues like active methods. An attempt has been made in this paper to formulate a passive method with an assumption that small NDZ is allowed. Time–frequency transform based passive islanding techniques have been recently suggested by various authors. Wavelet transform and S- transform have been applied for islanding detection [7,16-19]**.** The major drawback of wavelet transform is its batch processing steps, which results to introduction of delay. Wavelet transform is basically a time-scale analysis and is non-adaptive in nature. On the other hand, although the S-transform can perform multi-resolution analysis of retaining the frequency information, one cannot expect the predetermined Gaussian window to fit all signals. Moreover, it is more time consuming compared with other time –frequency based methods.

In this paper, an attempt has been made to use WPT with ELM as a classifier to detect the islanding operation. The used WPT provides better frequency and time variation resolution through uniform frequency subbands. A new feature index "change of energy" at different nodes is calculated using WPT for detection of various islanding and non-islanding faults. For classification an advanced ELM based classifier is used because of its better accuracy and much faster execution than SVM and other recently used classifiers [20]. Various practical fault cases which are occurring very often in the distribution system are simulated in this study like capacitor switching, load rejection, line to line fault, three phase fault, voltage sag and swell etc. Then, this feature index at different node is used as a feature vector to train the different data-mining approach to classify the islanding events from other non-islanding events and provide comparisons of performance between them. The results are also analysed with different noisy conditions. It has been found that, compared with other time-frequency based techniques, the proposed method is very simple, straight forward and easy to implement with small computational time.

The major contributions of this study towards islanding detection problem are : (1) application of WPT for feature extraction instead of using other popular signal processing techniques like wavelet transform and s-transform etc. (2) use of ELM for classification and detection of islanding condition. (3) annalysing the application of the above techniques under nine different very often occured practical operating conditions. (4) presentation of extensive comparative results with recently published and well proved techniques.

This paper is organized as follows; the theory behind WPT and feature extraction are discussed in Section 2, the studied system model is introduced in Section 3, evaluation of the proposed approach for islanding detection is given in Section 4. Lastly, the conclusion drawn from the study is given in section 5.

2. Wavelet Packet Transform (WPT)

The word "Wavelet" has discovered from a French origin word "ondelette" which means a small wave. If an arbitrary function $S(x)$ is considered in wavelet analysis, then the baby wavelets at different versions of $S(x)$ are obtained by the process of translation and compression (dilation). In the next step, when these wavelets are compared with the original signal, a set of coefficients (approximate and detail) are obtained at different frequencies and time. This way continuous wavelet transform (CWT) can be formulated. The discrete wavelet transform (DWT) can be formulated by the process of dilation and translation of the mother wavelet discretely. Due to the high bandwidth of the signal, it is difficult to process feature extraction of the signal component during this period. When the mother wavelet is dilated and translated discretely, then this is known as the discrete wavelet transforms (DWT) [16, 21].

To avoid such types of problem and for better frequency resolution, the decomposition process is carried out by decomposing both detail and approximate coefficient simultaneously at each level. This process is called as Wavelet Packet Transform (WPT). The upper level of WPT gives a better time resolution; whereas the lower level gives a better frequency resolution.

The original signal is decomposed to 'n' level as shown in Fig. 1. for WT and WPT respectively. The signal can be represented as (A1,D1),(A1,D2,D1),(A3,D3,D2,D1) for WT and for the WPT the original signal can be decomposed to 2^n node like a40, d41, a42, d43, a44, d45, a46, d47, a48, d49, a410, d411, a412, d413, a414 and d415 for WPT. So, WPT provides a better frequency resolution and control of features than WT. Mathematically, the orthogonal decomposition of the given function $S^n(x)$ can be stated as:

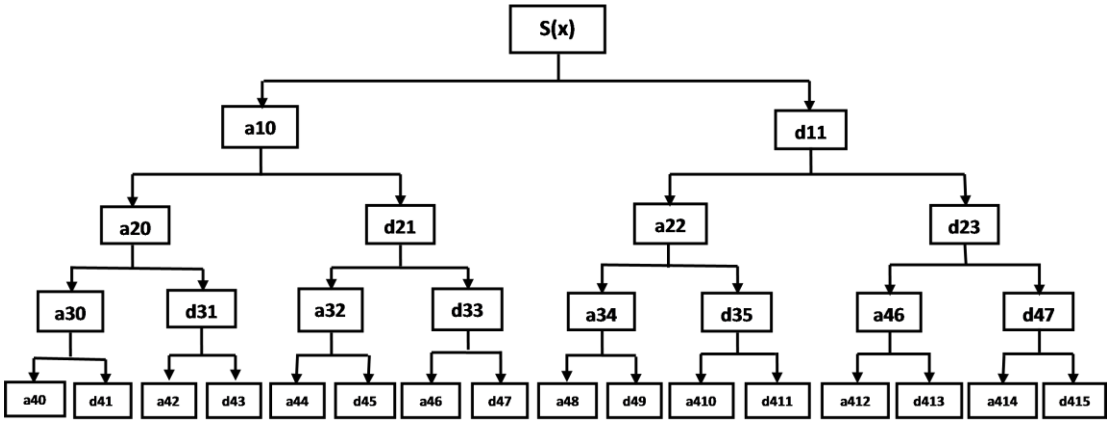
$$S^n_{i,j}(x) = 2^{-j/2} S^n(2^i x - j) \tag{1}$$

Where $n = 0,1,2...,(2^{-i} - 1)$ denotes as the frequency parameter (node number) and 'i' is level of decomposition (depth of parameter) in the wavelet packet tree. Here 'j' denotes the position parameter (sampling time) that belongs to the set of integer number.

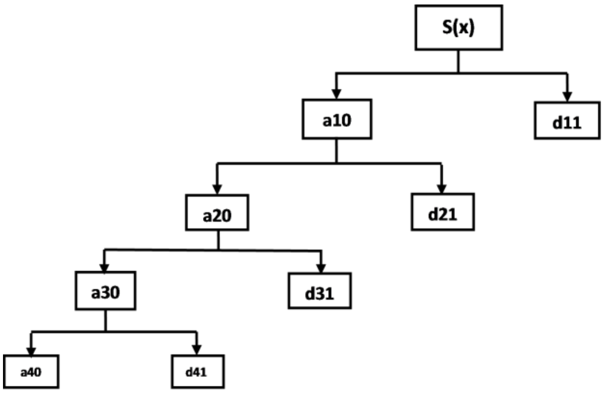
The total energy of the signal at node j can be calculated as:

$$E_j = \sum_{k=1}^{\infty} \left| WPTcoff_j(k) \right|^2 \tag{2}$$

Where '$WPTcoff_j$' is the WPT coefficient for node j.



(a)



(b)

Fig. 1. The 4th level decomposition tree (a) WPT (b) WT

Change of energy index ($COEI_j$) for different node is found out by the following expression

$$COEI_j = E_{fj} - E_{Aj} \tag{3}$$

Where E_{fj} is the total energy for one cycle ahead of the fault inception and E_{Aj} is the total energy for one cycle before the inception of the fault.

3. System Studied

In this paper, to investigate all the proposed method, a multi DG radial distribution system is considered as shown in Fig. 2. Two numbers of DGs one as hydro turbine and governor system with a synchronous generator (DG1) and another is a wind turbine with a synchronous generator (DG2), are integrated to the grid at the point of common coupling (PCC).The DG1 consists of a 10 MW synchronous generator connected to a 79 KV grid through a 30 KM, 13 KV feeder and DG2 consists of a 1.5 MW asynchronous generator driven by wind turbine connected to a 79 KV grid through a 30 KM, 13 KV feeder. Two loads L1 and L2 are connected to the PCC bus. The detail of the generators, transformers, DGs, distribution lines and loads are mentioned in the Appendix. The relays are placed at the DG end to collect the voltage/current signal for both islanding and non-islanding conditions. The sampling frequency of the system studied is 2.4 kHz with 40 numbers of samples in one cycle on the 60 Hz base frequency. The voltage and current signals are extracted at the targeted DG position (DG-1, DG-2).

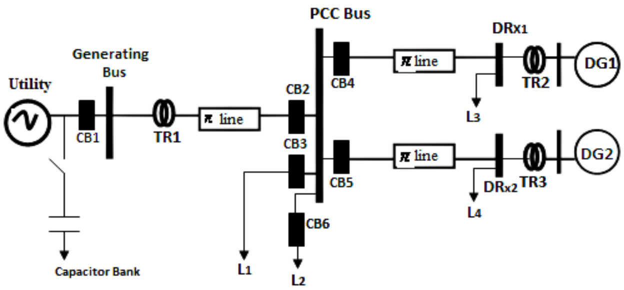


Fig. 2. The single line diagram of the studied Power Distribution system with multiple Distributed generating system (DGs).

4. Evaluation

4.1. Case Studies:

Total nine numbers of different cases are considered in this study and are listed in Table 1. The first case (C1) is the islanding condition in which the grid source is disconnected from the DGs by opening the circuit breaker (CB1). The next three cases (C2, C3 and C4) are dealing with different fault conditions. The C5 case is considered to be the effect of sudden load change due to connection of L3 and L4. The C6 and C7 represent the voltage sag and swell conditions respectively. The C8 is denoted for the tripping of one of the DG other than targeted DG. The last case C9 is the capacitor switching case.

Table 1. Different types of case studies

Case	Types of Cases
C1	Islanding condition
C2	Single-line to ground fault
C3	Three-phase fault
C4	Double line to ground fault
C5	Sudden load change
C6	Voltage sag
C7	Voltage swell
C8	Tripping of one DG
C9	Capacitor switching

4.2. Classification of Events

In this section the intelligent ELM classifier used for the islanding detection is discussed. Feedforward neural networks are optimal classifiers for nonlinear mappings that employ a gradient descent method for weight and bias optimization. The major limitations of a traditional neural learning algorithm include:

i. Appropriate learning parameter value is difficult to decide because small value gives slow convergence and high value leads to instability and oscillation around optimum value.
ii. Application of gradient decent method for weight modification usually takes longer time for convergence.

To improve the inherent slow learning ability of traditional optimization methods, the ELM technique is used to train a single layer feed forward neural network (SLFNN). Fig. 3. shows the architecture of SLFNN. The weights connecting inputs to hidden nodes are chosen randomly assigned and never updated during the learning process. However, the weights between hidden nodes and outputs nodes are calculated numerically in one step.The ELM approach has several motivating and important features like: 1) Extremely fast learning speed 2) Smallest training error and norm of the weights. 3) Use of learning algorithm to train SLFNs with non-differentiable activation functions. 4) Not having problem like local minimum, improper learning rate and over fitting, etc.

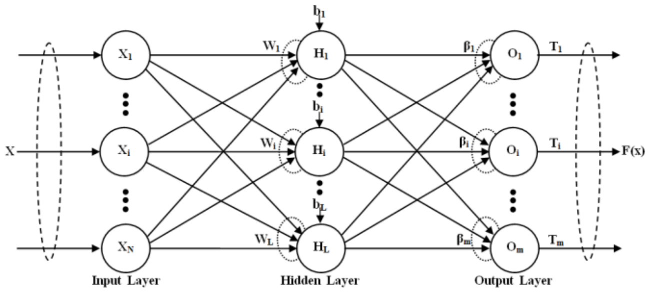


Fig. 3. Single-hidden layer feedforword network

With N training samples (x_i, t_i), L hidden nodes and the Kernel function G, the mathematical model of the SLFNs is

$$\sum_{i=1}^{L}\beta_i g_i(x_n) = \sum_{i=1}^{L}\beta_i G_i(w_i,b_i,x_n) = t_j, \qquad n = 1,....,N. \quad (6)$$

Equation (6) can be written as:

$$\mathrm{H} * \beta = \mathrm{T} \quad (7)$$

Where H, β and T are the hidden layer output matrix, output weight matrix of classifier and target vector respectively.

$$H = \begin{bmatrix} H(x_1) \\ \vdots \\ H(x_N) \end{bmatrix}_{N\times L} = \begin{bmatrix} G(w_1,b_1,x_1) & \cdots & G(w_L,b_L,x_1) \\ \vdots & \cdots & \vdots \\ G(w_1,b_1,x_N) & \cdots & G(w_L,b_L,x_N) \end{bmatrix}_{N\times L} ;$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \quad and \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{N\times m}$$

The minimum absolute least square result is empirically resolute using Moore-Penrose “generalize” inverse $H^{\dagger}$ [22-24]:

$$When\ N<L: \beta = H * T = H^T\ (\frac{I}{\lambda} + HH^T)^{-1}T \quad (8)$$

$$When\ N > L: \beta = H * T = (\frac{I}{\lambda} + H^T H)^{-1}\ H^T T \quad (9)$$

A small positive small value I/λ is added to the diagonal of H^*H^T or $H^{T*}H$ to calculate output weight vector β to avoid non-singularities and better performance.

The output $f(x)$ of ELM classifier can be obtained by taking a new sample x with sign kernel function is:

$$\mathrm{f(x) = sign\ h(x)}\,\beta$$

$$f(x)_{N\times N} = sign\ h(x)\ H^T\ (\frac{I}{\lambda} + HH^T)^{-1}\ T \quad (10)$$

$$f(x)_{L\times L} = sign\ h(x)\ (\frac{I}{\lambda} + H^T H)^{-1}\ H^T T \quad (11)$$

To satisfy universal approximation [25] of ELM, the hidden layer kernel function G(w,b,x) can be utilize for nonlinear piecewise continuous functions. A various kind of hidden layer kernel function can be implemented, which is not restricted to

Sigmoid kernel function

$$G(w,b,x) = \frac{1}{1 + \exp(-w.x + b)} \quad (12)$$

Gaussian kernel function

$$G(w,b,x) = \exp(-b\|x-w\|^2) \quad (13)$$

Hard limit kernel function.

$$G(w,b,x) = \begin{cases} 1 & if\ w.\ x\text{-}b\ \geq 0 \\ 0 & otherwise \end{cases} \quad (14)$$

Multi quadrics kernel function

$$G(w,b,x) = \|x - w\|^2 + b^2 \quad (15)$$

It is not essential that the hidden layer kernel function h(x) is always known. The ELM uses other Kernel function which can be able to provides a better generalised solution for SLFNs.

4.3. Result and Discussions

For each of the nine cases as described above the three phase voltages are extracted at the targeted DG location. Then these voltage signals passed through the sequence analyzer to extract the negative sequence component. Negative sequence voltage components are carried out in all the nine cases. For the simulation, sampling frequency of 3.8 kHz and system frequency is 60 Hz are considered. Four levels of decomposition are carried out by WPT, which provide sixteen nodes in the wavelet decomposition tree. The sub-band ensures a frequency bandwidth of 120 Hz, which is closer to the fundamental frequency of 60Hz. The

Daubechies 10 (db10) is used as mother wavelet to perform this analysis because of good performance compared to other wavelet functions.

Fig. 4. (a)-7 (a) show the negative sequence voltage signal for C1, C3, C5 and C6 respectively. Fig. 4. (b) - 7 (b) indicate the WPT coefficient at node four for case C1, C3, C5 and C7 respectively. In the same way the coefficient for node two are shown in Fig. 4. (c)–7 (c). The same observations are also analyzed for other cases and the results are not shown in this paper due to space limitations. The results indicate that the coefficient at node four and node two are highly identifiable under an islanding case from other non- islanding cases.

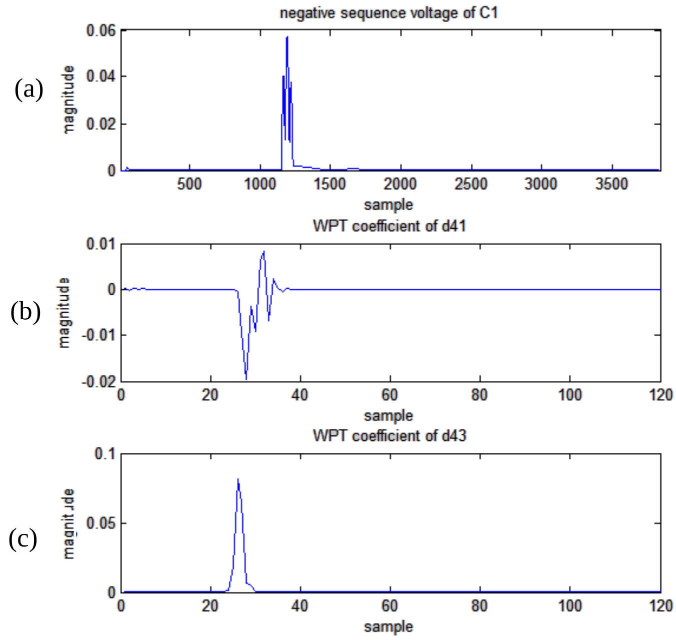


Fig. 4. Voltage signal for islanding case C1 (a) Negative sequence voltage (b) WPT coefficient at node two (c) WPT coefficient at node four.

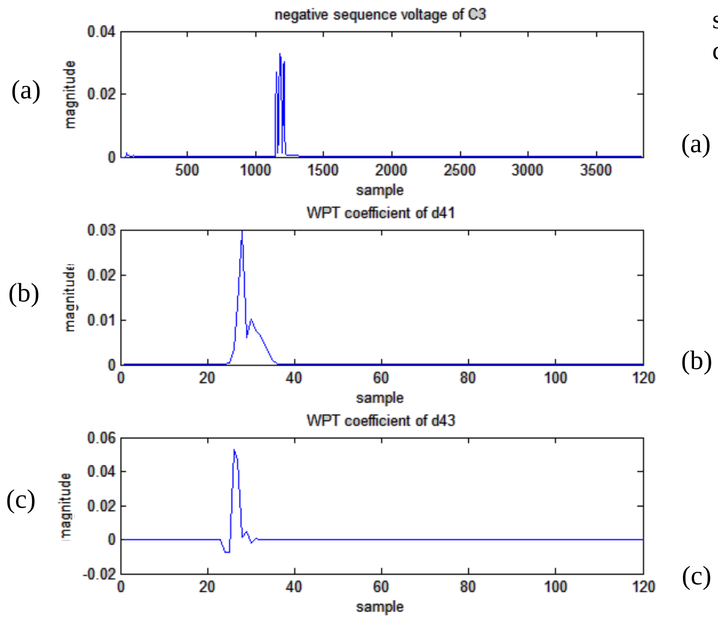


Fig. 5. Voltage signal for islanding case C3 (a) Negative sequence voltage (b) WPT coefficient at node two (c) WPT coefficient at node four.

Fig. 8. and 9. show the change of the energy index (COEI) at each node (node four and two) respectively. The change in energy index has been attenuated in the rest of the sixteen nodes and is not displayed in the result due to page limitation. For case C1, 200 sampled data and all other cases from C2-C9 100 number of samples data are generated. All the events are simulated in the model separately as by changing active and reactive power mismatch up to 50% and 5% respectively for islanding case C1, changing fault resistance 0 to 200 Ω for case C2, C3 and C4, changing load parameter for case C5, 10 to 80% sag for case C6, 10 to 80 % swell for case C7, and capacitor switching from 0.5MVar to 10 MVar in case C9.

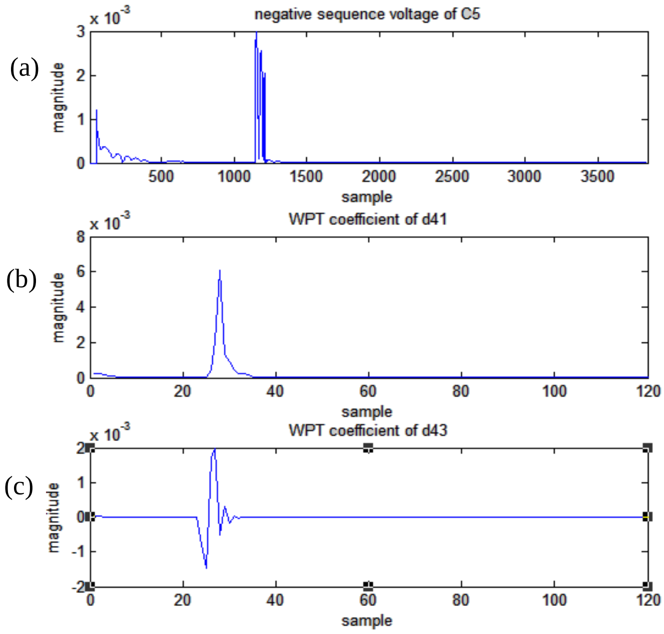


Fig. 6. Voltage signal for islanding case C5 (a) Negative sequence voltage (b) WPT coefficient at node two (c) WPT coefficient at node four.

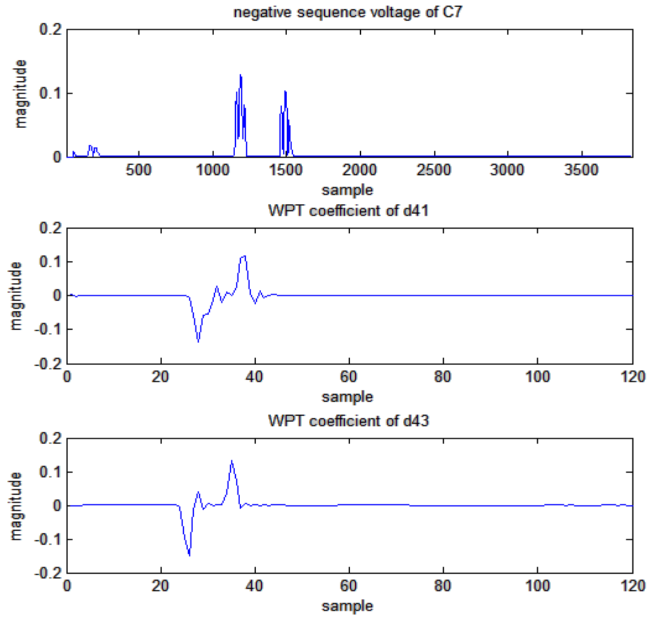


Fig. 7. Voltage signal for islanding case C7 (a) Negative sequence voltage (b) WPT coefficient at node two (c) WPT coefficient at node four.

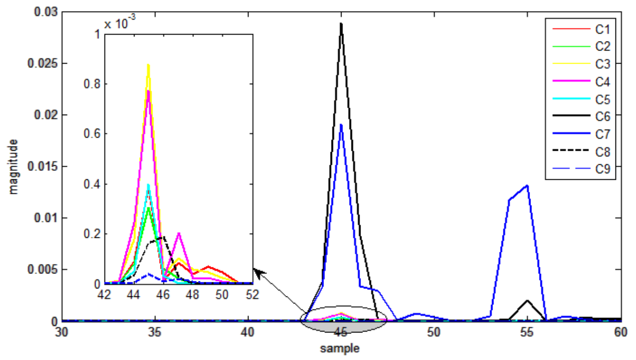


Fig. 8. Change of energy index at node four.

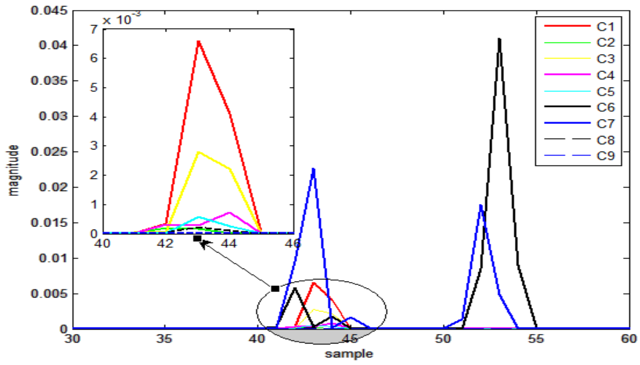


Fig. 9. Change of energy index at node two.

Table 2. Change of energy index for node four and two at target location DG1

Cases	COEI at node Four		COEI at node Two	
	Max	**Min**	**Max**	**Min**
C1	0.010404	0.007206	0.000385	0.000353
C2	0.002864	8.14 x e-6	0.000613	1.81 x e-5
C3	0.005154	0.000232	0.016581	1.12 xe-5
C4	0.003038	5.61 x e-5	0.005539	2.83 xe-5
C5	0.000575	1.73 x e-5	0.0004	2.99 x e-5
C6	0.037167	0.006238	0.025119	0.00564
C7	0.040971	0.007246	0.028851	0.005222
C8	0.000225	3.19 x e-6	0.000188	8.75 x e-7
C9	2.55 x e-6	2.48 x e-7	3.93 x e-5	7.34 x e-7

The maximum and minimum values of COEI at node four and two for different case at a target DG location DG2 bus are shown in Table 2. Table 2 clearly indicates the COEI for islanding case C1 is always a higher value compared to other cases except voltage swell case C7.So by checking the same change of energy index at node two, the index value for islanding case is smaller from case C7. Based on the above analysis a threshold value for node four is chosen as 0.007 and for node two is to be 0.005.The complete flowchart of the proposed decision tree method is shown in Fig. 10. Table 3 and Table 4 depict the performance of WPT-DT based islanding detection technique with and without noisy condition. It is clear from the table that the accuracy of islanding detection is quite good for normal (without noise) condition where at 30 dB noisy condition the accuracy is decreased to 70%. The impact of changing target DG location on the performance of the method is also investigated and depicted in table 3 and 4.

Table 3. Performance of the DT based approach for islanding detection. (without noise)

Events	Islanding detection	Non-islanding detection	Accuracy,%
Target DG location 1			
Islanding	100	0	100
Non-islanding	0	400	100
Target DG location 2			
Islanding	98	2	98
Non-islanding	0	400	100

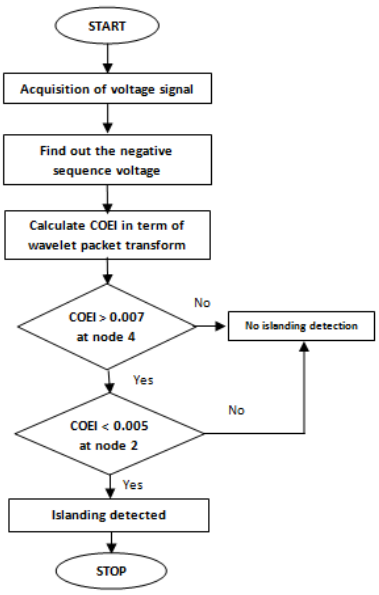


Fig. 10. Flow chart of the DT method for islanding detection

Table 4. Performance of the WPT-DT based approach for islanding detection with noisy condition.

Events	Accuracy,%			
	Normal Condition	With (SNR) 50dB	With (SNR) 40dB	With (SNR) 30dB
Target DG location 1				
Islanding	100	100	88	70
Non-islanding	100	99.25	93.5	88.25
Over all	100	99.33	92.88	86.22
Target DG location 2				
Islanding	98	98	88	68
Non-islanding	100	99	92	86.25
Over all	99.95	98.88	91.55	84.22

*The test data set include 100 islanding cases and 400 non islanding cases.

The further islanding classification process is realized with multi-layer perceptron (MLP) neural network, where resilient back propagation (RPROP) is used as learning algorithm. Out of total data, 50% is used for training and 50 % is used for testing for the classifier. The overall performance of ANN is shown in Table 5. It is evident from Table 5 that the dependability level of classification of islanding with other non-islanding events is 100%, 100%, 94% and 88% of normal (without noise) and noisy condition(with SNR 50db,40db,30db) respectively. Also, this technique detect non-islanding events with accuracy (security level) 100%, 100%, 94%, 92.25% for normal (without noise) and noisy condition with SNR 50db, 40db, 30db respectively.

Table 5. Performance of the WPT-ANN based approach for islanding detection with and without noisy condition.

Events	Accuracy,%			
	Normal Condition	With (SNR) 50dB	With (SNR) 40dB	With (SNR) 30dB
Target DG location 1				
Islanding	100	100	94	88
Non-islanding	100	100	94	92.25
Over all	100	100	94	91.77
Target DG location 2				
Islanding	100	100	94	86
Non-islanding	100	100	96.25	94
Over all	100	100	96	93.11

*The test data set include 100 islanding cases and 400 non islanding cases.

The overall performances of SVM for islanding classification with respect to non-islanding events are shown in Table 6. It is evident from Table 6 that the proposed method gives 100%, 100%, 94% and 87% and 100%, 100%, 94.25%, 92.5% security level for normal (without noise) and noisy condition(with SNR 50db,40db,30db)respectively.

Table 6. Performance of the WPT-SVM based approach for islanding detection with and without noisy condition.

Events	Accuracy,%			
	Normal Condition	With (SNR) 50dB	With (SNR) 40dB	With (SNR) 30dB
Target DG location 1				
Islanding	100	100	90	87
Non-islanding	100	100	92.5	94.25
Over all	100	100	92.22	93.33
Target DG location 2				
Islanding	100	100	92	86
Non-islanding	100	100	96.25	92.5
Over all	100	100	95.77	91.77

*The test data set include 100 islanding cases and 400 non islanding cases.

Table 7. Performance of the proposed WPT-ELM based approach for islanding detection with and without noisy condition

Events	Accuracy,%			
	Normal Condition	With (SNR) 50dB	With (SNR) 40dB	With (SNR) 30dB
Target DG location 1				
Islanding	100	100	94	92
Non-islanding	100	100	97.25	96
Over all	100	100	96.88	95.55
Target DG location 2				
Islanding	100	100	94	92
Non-islanding	100	100	96	96
Over all	100	100	95.77	95.55

*The test data set include 100 islanding cases and 400 non islanding cases.

Table 8. Comparison of performance of different islanding detection technique

Islanding Detection Techniques	Over all Accuracy (%)			
	Normal Condition	With (SNR) 50dB	With (SNR) 40dB	With (SNR) 30dB
Proposed methods				
ELM-WPT	**100**	**100**	**96.88**	**95.55**
Other existing methods				
WPT-DT	100	99.33	92.88	86.22
WPT-ANN	100	100	94	91.77
WPT-SVM	100	100	92.22	93.33
Review paper				
ANN based technique [26]	99.1	NA	NA	NA
ANN based technique [27]	97.77	NA	NA	NA
SOM neural network [28]	97.92	NA	NA	NA

Over/under voltage [29]	78.81	NA	NA	NA
Over/under frequency [29]	90.24	NA	NA	NA
ROCOF based technique [29]	93.81	NA	NA	NA
Intelligent based relay [30]	83.33	NA	NA	NA
MPNN [31]	97.4	NA	NA	NA
Fuzzy and DT based technique [32]	100	NA	NA	NA
ANFIS based technique [33]	100	NA	NA	NA
DT and DWT technique [19]	96.43	NA	NA	NA
Universal detection with SVM and NN [34]	100%	NA	NA	NA
RBF and DT [35]	100%	NA	NA	NA

In this paper, the islanding classification is further analyzed by a new classification technique ELM. The overall performances of ELM for islanding classification with respect to non-islanding events are shown in Table 7 by using sigmoid kernel function. It is evident from Table 7 that the overall accuracy of classification of islanding with other non-islanding events is 100%, 100%, 96.88% and 95.55% for normal (without noise) and noisy condition(with SNR 50dB,40dB,30dB) respectively. Also this technique detects non-islanding events with accuracy 100%, 100%, 95.77%, 95.55% for normal (without noise) and noisy condition(with SNR 50dB,40dB,30dB) respectively, for changing the target DG location from DG1 to DG2.

Table 8 summarizes the performance comparison of the different methods of detection on islanding events. It is clearly revealed that the proposed method ELM-WPT shows the highest reliability and performance by 100%, 100%, 96.88%, 95.55% overall classification accuracy for ideal condition, with SNR 50 dB, 40dB and 30dB respectively.

5. Conclusion

This paper presents a new approach using wavelet packet transform and extreme learning machine for islanding detection in micro-grid system. The proposed wavelet packet transform technique has several merits over CWT and DWT at a higher frequency level, and provided greatly distinguish features which easily discriminate the islanding events from non-islanding one. A new feature index named "Change of Energy Index" (COEI) is extracted to quantify the change in energy at each wavelet packet transform subband. Here, nine case studies are considered and all the cases it has been found that, when islanding occur, this feature index is capable to distinguish islanding from non-islanding events. Further, using this feature index COEI, an ELM classifier has been trained and tested to measure its performance and accuracy to detect islanding conditions. A comparative analysis of the proposed approach WPT-ELM has been presented with techniques like WPT-DT, WPT-ANN, WPT-SVM and other existing methods. The results demonstrates better performance and justifies its practical application in real time power system for islanding detection.

Appendix:

<table>
<tr><th colspan="2">System Elements</th><th colspan="4">Model Parameter</th></tr>
<tr><td colspan="2">Source data (Generator)</td><td colspan="4">Rated short-circuir power(MVA): 1000 ; Rated Voltage(KV): 79 ; Base Voltage(KV): 79 ; Frequency(Hz):60</td></tr>
<tr><td colspan="2">Transformer data(TR1)</td><td colspan="4">Rated Voltage(KV): 79/13 (Dyn1); Rated(MVA): 10 ; Winding resistance (R1&R2) (pu): 0.00375 ; Frequency(Hz): 60 ; Winding inductance (L1&L2) (pu): 0.1 ; Magnetizing inductance (Xm) pu: 50</td></tr>
<tr><td colspan="2">Transformer data(TR2)</td><td colspan="4">Rated Voltage(KV): 13/13 (Dyn1); Rated(MVA): 10 ; Winding resistance (R1&R2) (pu): 0.00375 ; Frequency(Hz): 60 ; Winding inductance (L1&L2) (pu): 0.1 ; Magnetizing inductance (Xm) pu: 500</td></tr>
<tr><td colspan="2">Transformer data(TR3)</td><td colspan="4">Rated Voltage(KV): 0.4/13 (Dyn1) ; Rated(MVA): 10 ; Winding resistance (R1&R2) (pu): 0.00375 ; Frequency(Hz): 60 ; Winding inductance (L1&L2) (pu): 0.1 ; Magnetizing inductance (Xm) pu: 500</td></tr>
<tr><td colspan="2">DG1(HTG) Generator of DG1:simplified synchronous machine</td><td colspan="4">Rated power(MVA): 10 ; Rated Voltage(KV): 13 ; Inertia Const(pu): inf ; Internal resistance(pu): 0.01466 ; Reactance (pu): 0.22</td></tr>
<tr><td colspan="2">DG2(Wind Turbine) Generator of DG2:asynchronous machine</td><td colspan="4">Rated MVA: 1.5 ; Rated KV: 0.4 ; Inertia Const(pu): 0.48; Frequency(Hz): 60; Stator resistance,R_s (pu): 0.016; Rotor resistance,R_r (pu): 0.015; Stator inductance,L_s (pu): 0.017; Rotor inductance,L_r (pu): 0.156; Mutual inductance ,L_m (pu): 3.5</td></tr>
<tr><td colspan="2">Transmission Line data (pi line)</td><td colspan="4">R_0 (Ω/km): 0.0424 , R_1 (Ω/km): 0.0135, X_0 (H/km): 1.39e-4, X_1(H/km): 4.9869e-5,C_0 (F/km): 5.01e-9, C_1 (F/km): 11.33e-9 Length of line :TL1:20km,TL2:30km,TL3:30km</td></tr>
<tr><td colspan="2">Loading Data</td><td>Normal Loading Data PCC bus load L1</td><td>PCC bus load L2:</td><td>Normal Loading Data DG1 bus load L3:</td><td>DG2 bus load L3</td></tr>
<tr><td rowspan="2">Types of loads</td><td>Active power (MW)</td><td>4.7</td><td>4.7</td><td>3.8</td><td>0.75</td></tr>
<tr><td>Reactive</td><td>1.8</td><td>1.8</td><td>2</td><td>0.414</td></tr>
</table>

	power (MVAr)				

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