

ISLANDING DETECTION IN A MULTIPLE DISTRIBUTED GENERATION SYSTEM USING DECISION TREE

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ABSTRACT

In this paper, a method for islanding detection based on analysis of transient state signals is provided. Decision tree (DT) is trained for classifying the transient events off-line and used to test in online for islanding detection. The required features for classification are extracted through discrete wavelet transform (DWT) of signals and reduced the total extracted features by FFS algorithm. The proposed method is then tested on Standard 39- bus system using MATLAB.

Key words: Distributed Generation, Islanding Detection, Decision trees

I. INTRODUCTION

Recently, due to numerous advantages the distributed generations (DGs) using renewable energy sources have become one of the main power generations. Islanding detection is an important consideration in distributed systems connected to distribution generators [1].

Islanding is the situation in the distribution network becomes disconnected from the grid and is powered by Distributed generators. The following Fig. 1 shows the general view of electrical Islanding. There are various customer loads between these two electrical power sources. The essential task of an islanding detection protection is to find accurately the time of islanding event and to disconnect the DG.

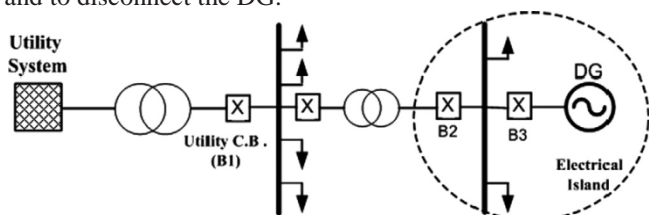


Fig. 1. A general view of electrical islanding.

Islanding is an undesirable situation since it is a potentially dangerous condition for the maintenance personnel and may cause damage to the DG and loads in the case of unsynchronized reconnection of the grid due to phase difference between the grid and DG [2]. Therefore, it has become a mandatory feature specified in the IEEE Std. 1547.1, IEEE Std. 929-2000, and UL1741 standards.

Several Islanding detection techniques can be found in literature divided into passive and active ones. Hybrid methods combine the advantages of passive and active approaches and can be applied as an alternative. The main advantage of active methods is their relatively small NDZ and the main disadvantage, however, is power quality problems due to their direct influence on the power

system. Passive techniques rely on monitoring the power system's behaviour by measuring system parameters. This is an advantage but many other non-islanding disturbances will produce transients that mimic very closely to those of an islanding event. Passive techniques do not have power quality problems and are generally quite cheap to install but they have large NDZs. However they cannot ensure guaranteed operation under all islanding situations [3-23].

Classification-based techniques have been recently proposed in the literature for islanding detection. An intelligence-based method is investigated in Ref. [24], which uses the decision-tree (DT) classifier, but with complex set of 11 features for classification, including total harmonic distortion of current/voltage, gradient of the product of voltage and power factor, etc. It has only 83.33% islanding detection accuracy.

In this paper, it is attempted through study and analysis of a real distribution system, an optimum algorithm with higher accuracy and speed (lower computation) than previous techniques is obtained. The method involves extraction of signal energies in different levels of DWT as features. It uses decision tree (DT) as a classifier to identify the islanding condition.

The rest of the paper is organized as follows: Section II provides the theory of the DWT and feature extraction. The proposed method was explained in Section III. Section IV presents the simulation results and the last section touches upon the conclusion.

II. ISLANDING DETECTION USING DECISION TREE

Voltage and current transient signals of a power system are believed to have unique characteristics that signify the cause of transient event. The method proposed here is based on this fact that transient state has certain characteristics which can be used to present a new method to distinguish the island occurrences from the other ones. Of course the features presented in transient signals are not directly diagnosed. So there should be a process to extract these features to speed up response in classifying. To this end, wavelet transform seems to be suitable.

Some important classification methods include support vector machines, neural network and decision tree. Although studies have been carried out to compare them [33], due to a number of factors and possibilities, we cannot definitely state which method has a preference in every way. The method proposed uses DT for pattern recognition and classification. Figure2 shows the block diagram of the proposed system.

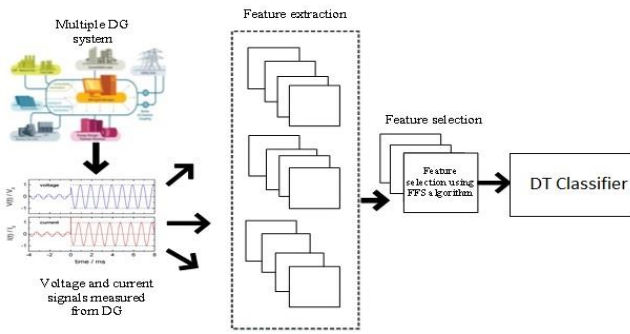


Figure 2: Block diagram of the proposed system

From figure2 it is visible that from various location of microgrids the current and voltage is measured to ensure that the grid was working in a protective condition. The number of available features are extracted from the decomposed voltage and current signals by Wavelet transform which makes the computation of feature extraction process less complex with reduced computation time. The features that can be extracted from the features are like voltage unbalance, frequency deviation, voltage and current harmonic distortion, power factor etc. Based on these extracted features the trained DT classifier detects the islanding and non-islanding conditions in the microgrid. To prove the importance of our proposed method a system model has to be considered which is explained in the following section.

A. System Model

The voltage is measured at the PCC point and fed to the Phase Locked Loop (PLL) to determine the frequency (f) and the phase angle (ϕ). In addition the current at the PCC is measured and fed in to the transformation components. After extracting the dq components of the current are compared and the differences between them were used as an input to the proportional-integral controller. Finally, in order to control the inverter-based DG switches, the frequency with the output of the proportional-integral controller were used as input to the pulse width modulation (PWM). Figure3 shows the model for a test system with a DG connected at the point of common coupling (PCC).

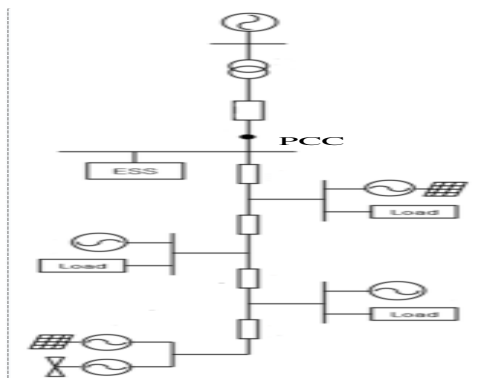


Figure 3: A model system

There are two different DG types that will be connected to the system: synchronous-based DG and inverter based DG. Tripping of main circuit breaker (CB) for islanding conditions, Opening of any breakers between the power system and DG, Loss of power on the PCC bus, sudden load change at the target DG location, tripping of other DGs apart from the target one are some of the

conditions that makes islanding. The above conditions are simulated under possible variations in operating loading at normal, minimum and maximum loading conditions. Table 1 shows the test system parameters and the specifications used for simulation.

Table 1: Test system simulation parameters

Simulation parameters	Specifications
Transformer	100KVA, 24.9 KV/480V
Simulation frequency	1.6 KHz
Number of samples	32
Sampling frequency	50 Hz
External grid	Grid represented by 120KV source and 1000MVA
L1	Load with 15 MW and 3 MVar
L2&L3	Load with 8 MW and 3 MVar
DG1&DG2	1200 Vdc
Line 1	25KV with 10km length
Line 2&Line 3	25KV with 20km length

B. Features extraction by DWT

DWT is used as a means for processing of transient signals. Using DWT, a signal can be decomposed into some signals in different frequency bands which are known as wavelet coefficients. It is more suitable for analysis of transient states in comparison with other frequency methods such as Fourier transform (FT). A suitable study of Fourier and wavelet transforms can be obtained in Ref. [33]. DWT of a signal $f(k)$ is defined in mathematical relations (1) and (2) as DWT

$$DWT_{\phi} f(p, q) = \sum_k f(k) \cdot \phi_{p,q}^*(k) \rightarrow(1)$$

$$\text{Where } \phi_{p,q}(k) = \phi\left(\frac{k}{a_o^p} - nb_0\right) \left(a_o^p\right)^{-1/2} \rightarrow(2)$$

$a_o > 1$ and $b_o > 0$ are fixed real values and p, q are the positive integers. The DWT analyses a signal by decomposing the signal into a course approximation and detail information. The course approximation is decomposed again to obtain the details of the next level and so on. At each level of successive decomposition the parameter p in equation (2) is incremented to increase the frequency resolution [34]. A DWT of discrete time sequence $x(n)$ of length N is essentially a decomposition of the spectrum of $x(n)$. The orthogonal sub-bands are defined by

$$2^{-(m+1)} T^{-1} \leq \omega \leq 2^{-m} T^{-1}, m = 1, 2, \dots, J \rightarrow(3)$$

Where T is the sampling period associated with $x(n)$ and J represents the total number of decomposition levels.

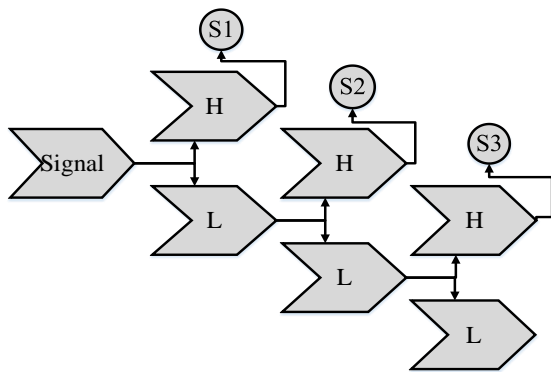


Figure 4: Decomposition of signals

Figure 4 shows the three level decomposition of the input signals, which results the wavelet coefficient of the input signal at each level. In figure 3 the S1, S2 and S3 represents the signal coefficients resulting at each level. As the signal $x(n)$ passes through the low pass and high pass filter the signal decomposes into coefficients. The scaling and wavelet coefficients at different levels which are resulting from DWT is expressed by the following equation respectively.

$$S_m(n) = \sum_n l(2n-k)S_{m-1}(k) \quad \rightarrow(4)$$

$$W_m(n) = \sum_n h(2n-k)S_{m-1}(k)$$

At level m , both $S_m(n)$ and $W_m(n)$ are composed of 2^m coefficients and the resulting decomposed signals are represented as $[w_1, w_2, \dots, w_j, S_j]$ which is the DWT of signal $x(n)$. From the decomposed signal $[w_1, w_2, \dots, w_j, S_j]$ the available features are extracted which supports to test the classifier to detect islanding. Table 2 shows the accessible features extracted from the decomposed signals and their equivalent expressions.

Table 2: Extracted features in our proposed method

Features	Expression
Rate of change of voltage	$\Delta V / \Delta t$
Rate of change of frequency	$\Delta f / \Delta t$
Magnitude of -ve sequence	Max(magnitude)
Magnitude of +ve sequence	Min(magnitude)

Rate of change of power	$\Delta P / \Delta t$
Current THD	$(\sum_{h=1}^H I_h^2)^{-1/2} \times (I_1)^{-1}$
Voltage THD	$(V_2^2 + V_3^2 + \dots)^{1/2} / V_1$
VU	$1 - [rms(V_1) / rms(V_{avg})]$
Power factor	P/S
Rate of change of VU	$1 - (VU_{avg,t} / VU_{avg,s})$

The reasons for extracting the above features are, these features show rapid changes in them when islanding is present in DG. Feature vectors required for classification were extracted from the transient current and voltage signals etc. The features extracted from the decomposed signal is of the form $\{f_1, f_2, f_3 \dots f_n\}$, where n is the total number of features extracted such features are utilized for further recognition to detect islanding by DT is explained in the next section.

C. FFS algorithm

In the forward methodology, the procedure begins with an unfilled arrangement of components and includes one element at once. The expansion of a component depends on the data pick up, so the element that boosts the data increase chose and the procedure is rehashed until the quantity of elements required is come to. Among the all extracted features just the ideal features are chosen utilizing forward feature selection strategy, which give great exactness feasible in shortest time. All the features separated from the information signals is taken as contribution for the feature selection algorithm. Consider the aggregate number of highlight separated as N and the feature selection algorithm partitions the N number of inputs into number of subsets and locate the best and ideal component from the subsets.

Forward selection finds the best features from the N features. According to onward selection, the finest detachment with m features of $X(1), X(2) \dots X(n)$, while all in all the best list of capabilities is the champ out of the entire above step.

Collect the number of features (N) extracted from the specific input signals.
 Shuffle the extracted features.
 Break it into P subsets
 For each subset ($i = 0, 1, \dots, P-1$)
 Let Outer Trainset (i) = all subsets except i .
 Let Outer Testset (i) = the i 'th subset
 Let Inner Train (i) = randomly chosen 70% of the Outer Trainset (i).
 Let Inner Test (i) = the remaining 30% of the Outer Trainset (i).
 For $j = 0, 1 \dots n$
 Search for the best feature set with j components
 End loop of (j).
 Let OuterScore (i) = RMS score of the selected feature set on Outer Testset (i)
 End of loop of (i).
 Return the mean Outer Score

Algorithm: Steps for FFS

III. DECISION TREE (DT) BASED CLASSIFIER

Pattern recognition is a learn-by-example mathematical tool, which is extremely useful for those problems that cannot be solved with analytical methods. DT is a type of pattern recognition tool, and is capable of classifying input vectors into discrete categories such as {0, 1}. It is based on the principle that many separation boundaries can be approximated by combinations of hyper-planes that are parallel to the coordinate axes. Therefore it can break down a complex decision-making process into a collection of simple decisions [35]. The main advantage of DT is fast training compared with other popular pattern recognition tools. DTs are widely used in many diverse areas. A decision tree can be learned by splitting the source feature set into subsets. This process is recursively repeated on each derived subset. For instance, Fig. 5 shows a possible binary partitioning using hyper-planes perpendicular to the feature axes of the space with three classes, W1–W3 and two features, f1 and f2.

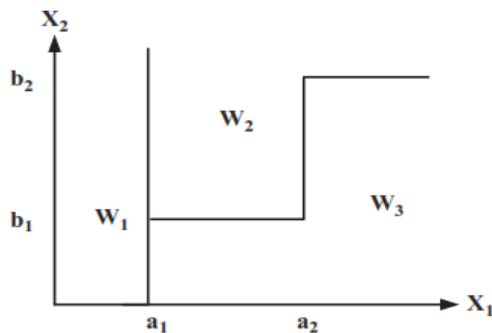


Figure5:Feature Space

Fig. 6 indicates corresponding decision tree; both provide 100% correct classification of the labelled samples. All the interior nodes correspond to the features and arcs to the child give possible values of each feature. The predicted class of a target feature is represented by a leaf of the tree. The depth of a node is the length of the path from the root to the node. In a decision tree for each node m, N instances reach m and N.

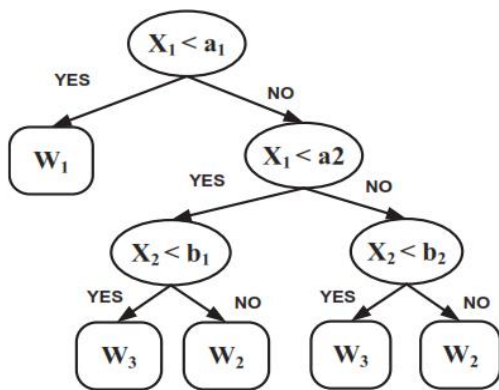


Figure6 Decision Tree

IV RESULTS AND DISCUSSION

This section presents the simulation results of our proposed islanding detection and fault current reduction method. Our proposed method is tested on standard IEEE 39 bus system using MATLAB platform.

A. Simulation Results

The voltage and current signals are measured from different locations of the microgrid to test islanding. The voltage and current signals are taken as input signals

for further processing. The voltage and current signals measured from the particular location of the bus system is shown in figure 7.

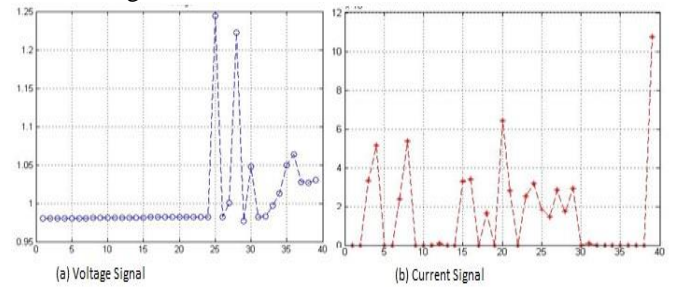


Figure 7: Voltage and Current signals

The measured voltage and current signals are decomposed into wavelet co-efficient by means of discrete wavelet transform (DWT). This results in reduction of computational complexity for further processing. The decomposed voltage and current signal resulted from DWT is shown in figure 8.

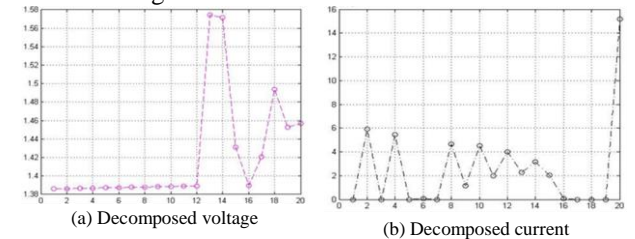


Figure 9: Decomposed signal

The features are extracted from the above decomposed signal and given as input to the trained classifier. The DT classifier classifies the location of the bus by the two classes such as islanding or non-islanding as output. The classification result of the test bus system is shown in table 3.

Table 3: Classification results

Cases	Results
Islanding	10
Non-islanding	29

B. Parameter Evaluation

The performance of our proposed islanding detection method is evaluated in terms of sensitivity, specificity, Positive predictive value, Negative predictive value, false positive rate, false negative rate, false discovery rate, Accuracy, Decision Time. Table 4 shows the contingency table for the classification.

Table 4: Contingency table

Actual classes	Predicted value	
	Islanding	Non-Islanding
Islanding	TP (8)	FP (2)
Non-Islanding	FN (0)	TN (29)

Where TP is the number of true positive pixels, FP is the number of false positive pixels, TF is the number of true negative pixels, and FN is the number of false negative pixels. The parameter values of our proposed SVM classifier based on the above Contingency table is given in table 5.

Table 5: Parameter values of DT classifier

Sensitivity (%)	100
Specificity (%)	93.54
PPV (%)	80
NPV (%)	100
Accuracy (%)	94.87

1. **Sensitivity**- is calculated by:

$$Sensitivity = \frac{TP}{TP + FN} \rightarrow(5)$$

2. **Specificity**- is calculated by:

$$Specificity = \frac{TN}{TN + FP} \rightarrow(6)$$

3. **Positive predictive value (PPV)** - is calculated by:

$$PPV = \frac{TP}{TP + FP} \rightarrow(7)$$

4. **Negative predictive value (NPV)** - is calculated by:

$$NPV = \frac{TN}{TN + FN} \rightarrow(8)$$

5. **Accuracy**- is calculated by:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \rightarrow(9)$$

C. Comparisons

In our test system model there are 8 islanding and 31 non-islanding locations. The TP, TN, FN and FP values are calculated based on the output of the classifier. Figure 10 shows the comparison of our proposed DT classifier with ANN SVM classifiers.

Figure 9 shows the comparison of our proposed DT classifier with existing classifiers namely ANN and SVM in terms of accuracy, sensitivity, specificity, PPV, NPV, FPR, FDR and FNR. By this we come to know that our proposed classifier is better than the existing classifiers with high accuracy and precision. Also the classification in DT is done within simple computational steps. So we prefer DT classifier to detect islanding in microgrids with less effort and high exactness with least Decision Time.

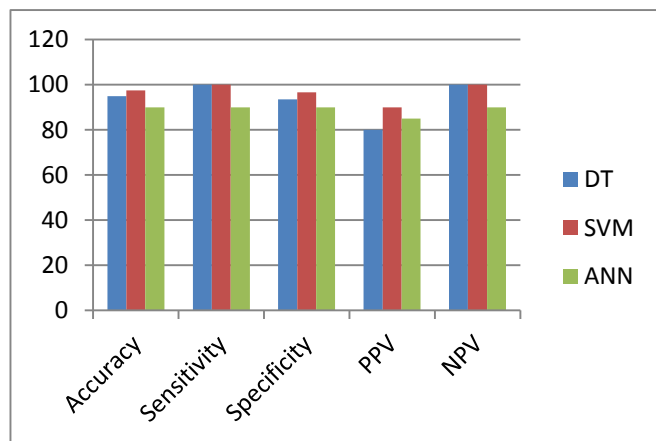


Figure 10: Parameter Comparison of DT, SVM and ANN classifiers

The comparison between the detection times of our proposed classifier with the SVM and ANN classifier is shown in table 6.

Table 6: Detection time comparison

Types of DG	Inverter DG		Synchronous DG		Multiple DG	
	All features	Select ed features	All features	Select ed features	All features	Select ed features
ANN	0.88s	0.30s	0.81s	0.20s	0.76s	0.26s
SVM	0.9	0.4	0.88	0.25	0.8	0.3
DT	0.35s	0.19s	0.38s	0.18s	0.6s	0.24s

D. Discussion

A new method for islanding detection of distributed generation in view of DT classifier is proposed in this paper. The strategy uses 21 conceivable components separated from the input signals to order any conceivable islanding operation. These components were chosen utilizing FFS algorithm to secure discovery of islanding operation even under numerous sorts of DG. This procedure was tried on a distributed generation system that incorporates different distributed recourses with long circulation circuits.

In case of DT only used for the islanding detection task, the scheme is based on an offline decision-making process where final implementation is based on the threshold values of the corresponding features of DT output. But in the proposed approach, DT is used for selecting classification boundaries, which are based on various derived features. Thus, for final implementation, only four features are selected and fed to the classifier for islanding detection. The proposed DT classifier is easier to implement for online islanding detection compared to DT only, since DT is an offline data mining algorithm. Thus, the superior approximation capabilities of the DT over crisp classifiers help to develop the relay to meet the real time application with wide range of uncertainties.

The results indicate that this technique can be used to optimize the detection threshold values of existing islanding detection techniques. For all the above estimations the datasets utilized for our proposed classifier is same as that of the datasets utilized by alternate classifiers to make an examination between our proposed routines with the current techniques. From the above examinations and comparisons it is clear that our proposed classification strategy is proficient and produce results with less identification time and high exactness. So we can say our proposed method is a best technique for islanding discovery in DGs.

V. CONCLUSION

In this paper we have proposed Decision Tree to islanding detection in systems with Multiple DGs. By the utilization of this FFS algorithm the ideal features are chosen from the quantity of separated elements. This makes the design simple and rate up the classification procedure. Likewise this approach prompts high accuracy with a predetermined number of components. An exploratory result demonstrates the adequacy of our

proposed strategy and it is obvious that the distribution system is ensured by precisely distinguishing the islanding condition with good accuracy and high speed.

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