Islanding Detection of Multi-DG-Based Microgrid Using Support Vector Machine

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Abstract In the proposed study, a signal processing method known as empirical mode decomposition (EMD) and a machine learning technique called support vector machine (SVM) are combined to recognize islanding situations in a distribution generation (DG) integrated microgrid system. At first, EMD is retrieving the insight features of the voltage signal through its most informative intrinsic mode component. These feature data are collected under three different conditions, namely islanding, load switching and capacitor switching. Further, SVM classifier is trained and then utilized to segregate the class of event as islanding or non-islanding. A microgrid system is simulated in MATLAB environment, and a classification capability of more than 94% is achieved under noise-free conditions, whereas an accuracy of 91% is accomplished under 30 dB signal-to-noise ratio (SNR).

Keywords SVM · DG · Microgrid · Perceptron · Islanding detection

1 Introduction

During the last decades, several methods have been proposed for islanding detection; one of them is support vector machine. Islanding is a critical condition in which the microgrid is disconnected from the main grid, consisting of loads and DG and still carry on power distribution by the distribution generations to which network is connected [1]. Islanding causes many problems such as safety concerns, damage to customer's appliances, and inverter damage. It allows a maximum of 2 s of delay for detection of unintentional islanding [2]. A common method used in islanding detection of MGs is both over/under voltage relay and over/under frequency relay

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(or ROCOF) [3]. Islanding is defined as the lack of any monitoring signal at any given moment [4].

The signal is derived at the point of common coupling and is then compared with the set of predicted values in the passive method, meanwhile the active method detects by introducing signals at point of common coupling that is usually not considered because of the issues of power quality [5, 6]. If the algorithm gets detected by the parameters stated above in the area of separation, it determines islanding to have occurred. Scada system is monitored by switch state monitoring system, and the circuit breaker's operating status can be monitored using a SCADA system [7].

2 Support Vector Machine (SVM)

Support vector machines (SVMs) are utilized to solve problems of regression and classification, and the theory is applied in several fields of science. Classical support vector machines are based on binary classification, an approach that results in the development of the artificial neural network. The support vector machines deal with separable linear data using soft margin and kernels functions with the non-separable data [8]. Apart from hyperplane, two other lines are drawn parallel to the hyperplane, and the distance between the two parallel planes is known as marginal distance, and that type of hyperplane has to be chosen where there is the maximum marginal distance among the two parallel lines [9]. The datasets which are passing through the marginal lines which are drawn parallel to the hyperplane are known as the support vectors kernels and are used to convert low dimension to high dimension [10].

$$x_i \in R^N \quad \text{and} \quad y_i \in \tag{1}$$

The main objective is to search for an optimal hyperplane $h : y = W^T x - b = 0$ which has the maximum distance to the nearest training pattern to force the learning generalization of the machine.

$$\min_{wb} \frac{1}{2}\left(w^T w\right) \tag{2}$$

$$\text{Subjected to: } y_i\left(w^T x_i + b\right) \geq I,\ \forall i$$

Subject to the previous approach was reformulated to solve the common problem by considering relaxing optimization for defining which is so-called as the soft margin [11]. The presented problem is now written as,

$$\min_{wb} \frac{1}{2}\left(w^T w\right) + C \sum_{i=1}^{n} \varepsilon_i \tag{3}$$

3 System Under Study

The parameters are tabulated in Table 1. The proposed system investigated consists of a utility grid rated 120 kV, 50 Hz. The utility grid is configured to 25 kV bus bar and the PCC by 2 transforms-1 and 2 as shown in Ref. [12] (Fig. 1).

In Fig. 2, the line diagram of multi-DG-based microgrid is shown.

Table 1 System parameter specification

Distribution components	Specifications
Utility grid	120 kV, 50 Hz
Doubly fed induction generators	9 MW, 575 V, 50 Hz/each
Distributed line parameters	50 Hz, 10 km, 3 phase pi section R1 = 0.1153 (Ω/km), R0 = 0.413 (Ω/km) L1 = 1.05 × 10^{-3} (H/km), L0 = 3.32 × 10^{-3} (H/km) C1 = 11.33 × 10^{-9} (F/km)
Transformer-1	Side1: star grounded; Side2: delta connected 50 MVA, 120 kV/25 kV, R1 = R2 = 0.08/30 p.u., Rm = Lm = 500 p.u., L1 = L2 = 0.08 p.u.
Transformer-2 and 3	Side1: delta connected, Side2: star grounded 12 MVA, 25 kV/575 V R1 = R2 = 0.025/30 p.u., Rm = 500 p.u. L1 = L2 = 0.025 p.u. Lm = Inf

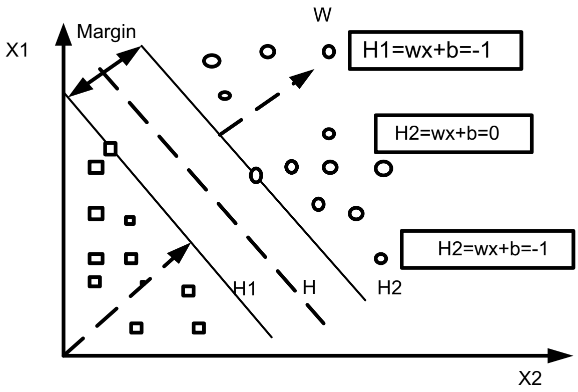

Fig. 1 Classification process of SVM

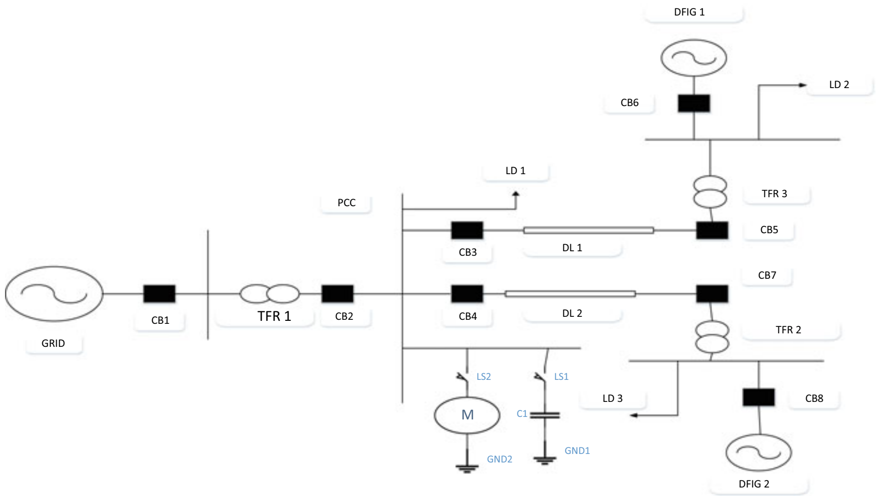

Fig. 2 Multi-DG-based microgrid

4 Empirical Mode Decomposition (EMD)

EMD is a signal processing method that empirically decomposes a time series data-based signal while preserving the time domain. In the process decomposition, the input signal is split into intrinsic mode functions (IMFs) of different bands of frequencies [13]. Any function can be decomposed into IMFs should have with: (1) there can only be one optimum between two consecutive zero crossings and at, (2) At every data point the mean of every upper and lower optimum envelops must be zero [14] (Fig. 2).

Initially, the local extremums which are indicated by $x_L(t)$ and $x_U(t)$, respectively. The mean can be determined using the equation given below:

$$m(t) = \frac{x_L(t) + x_U(t)}{2} \tag{4}$$

After then, a succession of mean elimination process will be carried out till the final IMF is obtained.

$$I_1(t) = x_i(t) - m_i(t) \tag{5}$$

$I_1(t)$ denotes the first IMF. The signal component after ith shifting is $x_i(t)$ and the ith mean is $m_i(t)$.

$$r_1(t) = x(t) - m_i(t) \tag{6}$$

With the replacement of $x(t)$ by $r_1(t)$, the same process is repeated to evolve the subsequent IMFs ($I_2(t)$, $I_3(t)$, $I_4(t)$… etc.).

$$x_R(t) = \sum_{n=1}^{N-1} I_n(t) + r_N(t) \tag{7}$$

5 Simulation and Results

The model under examination will proceed as per the flow diagram in Fig. 4 so as to recognize the two events as islanding or non-islanding (load or capacitor switching). The collection of the voltage signal took place from the point of common coupling (PCC) as displayed in Fig. 3. As we are not considering any fault cases, hence, data collected from any of the three phases will result in obtaining the same information. For instant, the phase-A data is empirically decomposed and represented within a timeframe of 0.68–0.78 s in Fig. 3 after imposing intentional islanding in the microgrid at 0.7 s. The EMD of the voltage signal results in two different IMFs. It can be noted that the IMF-1 obtained has higher frequencies and IMF-2 as of fundamental frequency.

As IMF-2 is displaying a promising correlation with the original signal, thus, it is identified as the most informative IMF and chosen for data collection purposes. A total of 1080 datasets have been stored in a database with 4 predictor variables with 540 data samples of islanding and 270 each from load switching and capacitor switching are collected, respectively, as of Table 2. Further, the machine learning classification learner will train the SVM classifier with 60% training data.

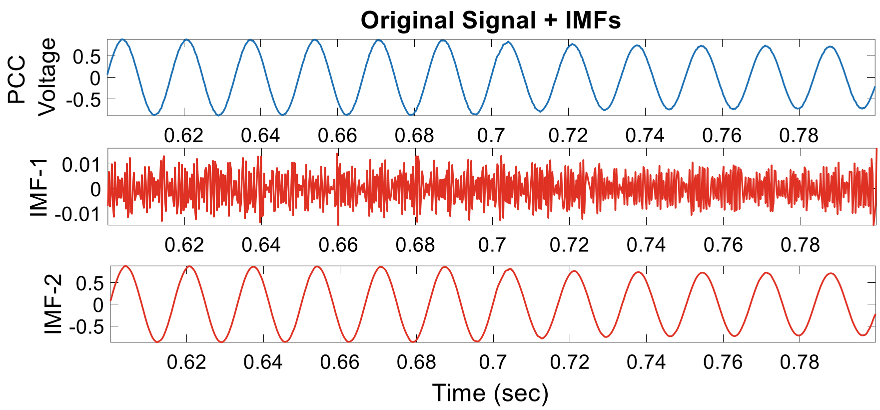

Fig. 3 Decomposed waveforms of PCC retrieved voltage signal

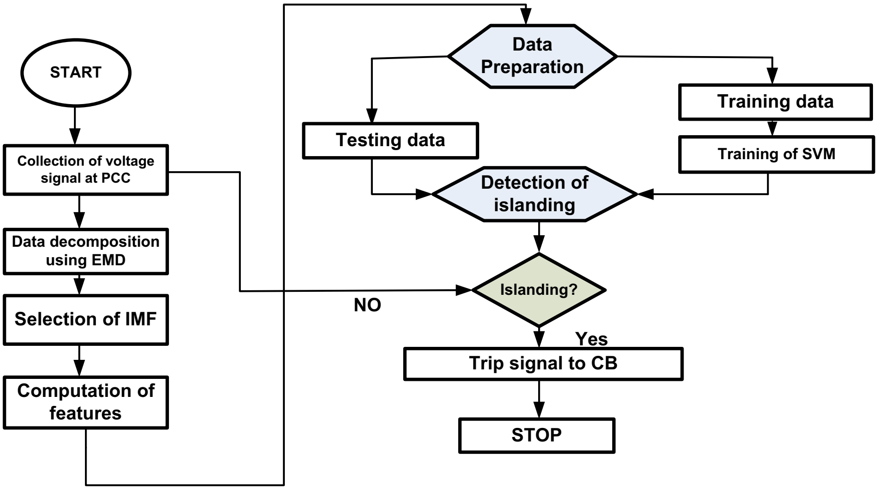

Fig. 4 Flowchart of the proposed detection method

Table 2 Samples collected from different class of events

S. No.	Event class	Collected events	Notation
1	Islanding	540	ISLAND
2	Switching of load	270	L/CSWC
3	Switching of capacitor	270	

This process is called testing. One of such performance indices is classification accuracy. The overall and individual accuracy formulae are presented in Eqs. (8) and (9), respectively.

$$\mathrm{AC_{OVR}} = \frac{\sum \text{True Predictions}}{\text{Total Number of Events}} \tag{8}$$

$$\mathrm{AC_{IND}} = \frac{\text{Truly Predicted Event of an Indivisual Class}}{\text{Total Number of Events of the Indivisual Class}} \tag{9}$$

But it is very important to determine a confusion matrix of any machine learning model to evaluate its performance indices. In simple terms, confusion matrix is a tabular representation of events predicted by the trained model which says the statistics of events truly predicted as one class and falsely predicted as another. Noise-free condition is generally an ideal condition where the power system is supposed to be dissociated from any external hindrances. A confusion matrix under such scenario can be seen in Table 3 which obtains an overall accuracy of $528 + 484/1080 = 0.937$, i.e., 93.7% where the individual accuracies are as follows,

Table 3 Noiseless condition confusion matrix

	Predicted ISLAND	Predicted L/CSWC
Truly ISLAND	528	12
Truly L/CSWC	56	484

$$\mathrm{AC}_{\mathrm{ISLAND}} = \frac{528}{540} = 0.977 = 97.7\%, \quad \mathrm{AC}_{\mathrm{L/CSWC}} = \frac{484}{540} = 0.896 = 89.6\%$$

Whereas, in the real world, there is a mere possibility for non-existence external hindrance. Electromagnetic interference, communication line presence are the main causes of obtaining polluted signals in the power line. So as to realize such a scenario in a virtual environment like Simulink additive, white Gaussian noise (AWGN) can be added to the collected signal. Mathematically, these are represented in terms of signal-to-noise ratio [12] as given in Eq. (10)

$$\mathrm{SNR(indB)} = 10 \log \frac{\mathrm{Sig}_p}{\mathrm{Noe}_p} \tag{10}$$

where Sig_p is the power of signal and Noe_p is the power of noise.

Here, a SNR of 30 dB is taken into consideration, and the respective confusion matrix is shown in Table 4. The overall accuracy is drastically got down to 88.7%, in this case, and the individual accuracies can be found as,

$$\mathrm{AC}_{\mathrm{ISLAND}} = \frac{506}{540} = 0.937 = 93.7\%, \quad \mathrm{AC}_{\mathrm{L/CSWC}} = \frac{484}{540} = 0.852 = 85.2\%$$

Moreover, the data extracted from the EMD decomposed signal is providing more accurate results to that of some published research in the field of islanding detection using SVM. A comparative analysis of the same is expressed in Table 5.

Table 4 Noisy condition confusion matrix

	Predicted ISLAND	Predicted L/CSWC
Truly ISLAND	506	34
Truly L/CSWC	80	460

Table 5 Comparison with pre-published articles

S. No.	Published article	Accuracy (in %)
1	Pattern recognition [15]	94%
2	Probabilistic NN + SVM [16]	97%
3	Proposed	97.7%

6 Conclusion

The paper proposes an EMD-based support vector machine classifier to identify the islanding condition in a multi-DG-based microgrid test system. The three basic conditions such as islanding, load switching, and capacitor switching cases simulated at various power mismatch conditions. An efficient database is prepared considering the features and cases. The capability of SVM can be enhanced by optimizing the parameters in the future study.

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