

Online Learning-based Islanding Detection Scheme for Grid-Connected Systems

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Keywords

«Distributed generation », «Islanded operation», «Machine learning », and «Fault detection ».

Abstract

Data aggregation in smart grids is a key component for emergency responses during abnormalities in the grid. To efficiently utilize the aggregated data, and achieve fast identification of these abnormalities, this paper develops an online islanding detection approach. The development of the technique is realized with an online learning algorithm implemented using the large-scale support vector machine (*LaSVM*). The algorithm adopts a classification problem for islanding detection in grid-connected systems by considering a set of independent variables and unknown variables. The independent variables are related to the known islanding events in the grid-connected system, and the unknown variables are related to the dynamics of the grid operating in real-time. The proposed approach solves this problem by training the known and unknown variables and identifying new instances through sequential minimal optimization. The training and validation results provided indicate 99.8 % accuracy for islanding detection under standard operating conditions of the grid-connected system.

Introduction

Reliable, sustainable, and resilient electric power systems are essential for modern societies. These goals require the distribution and diversification of power sources, which could be facilitated by smart grids [1]. These smart grids enable bi-directional communication between the control units and the end-loads, contrary to the traditional utility grid that uses unidirectional power transmission. Generally, there are two operational modes for the distributed generation systems operating in the smart grid, i.e., islanded and grid-connected modes. The DGs transition between these modes is an

example of time-sensitive events that require high priority in the queuing systems to reduce processing and detection time. Islanding may present a lot of adverse impacts on the power system as it may damage the DG by the influx of unregulated voltage with poor power quality and imbalance in frequency. To smoothen out the transition between both the mode of operation and fasted abnormality identification and islanding detection algorithm is necessary. Traditionally, the approaches utilized to detect these events are categorized as passive, active, and hybrid [2], and are mostly dependent on measuring multiple electrical characteristics.

Besides, the islanding detection can also be done either by remote or locally communication techniques [3]. Most remote techniques comprise the methods such as transfer trip, supervisory control, and data acquisition (SCADA), in which the parameters are transferred to a centralized control unit for operational decisions. Even though the method is highly reliable however the cost of communication is very high, and the cyber threats have also increased exponentially in recent years. Generally, the active and the passive islanding detection techniques are adopting local communication [4]. In the active islanding detection technique[5], a small perturb is added to the system parameter and observed for changes to determine the system operation. The active detection technique has an advantage such as a small non-detection zone and low cost of implementation, however, the introduction of perturb in signal may cause an increase in the noise and impact the overall harmonics in the system. Whereas in passive islanding detection [6], the different operating parameters of the system are monitored to identify any abnormality in the system. The implementation of the method is easy and very cost effective however the selection of threshold can be a concern and may lead to a false alert in case of a transient.

Further, to overcome these drawbacks islanding detection using artificial intelligence techniques has emerged based on certain machine learning algorithms [7]. Further, in [8] a Fuzzy Logic technique that is developed via the Decision Tree algorithm is proposed. The proposed technique was tested on data with and without noise, which performed perfectly with a 99.8 % of islanding detection rate. The authors in [9] extracted 62 features from voltage and current signals and trained the support vector machine classifier. In [10], the Neural network-based islanding detection technique is introduced to accurately classify the fault and prepare the system for disconnecting in case of fault.

All these techniques proved to be efficient when tested for single islanding scenarios. But for multiple or simultaneous islanding conditions, these techniques showed misclassification with a long classification time.

To overcome these elements, this paper develops a single parameter-based islanding classification approach using online learning methods. The proposed approach measures the voltage at the point of common coupling (PCC) and extracts its features to train with the large-scale support vector machines (*LaSVM*). The major contributions of this research are:

- Single measured parameter-based islanding classification approach for fast and accurate islanding detection.
- Online learning approach for accurate detection of multiple islanding events.

Further, the paper is organized as follows: In Section II, the system modeling is discussed with a focus on grid abnormalities and grid codes to overcome those abnormalities. In Section III, the information related to the classification problem along with the training algorithm is discussed in detail. In Section IV, the implementation of the developed algorithm is realized, and the corresponding results are discussed. Finally, the conclusion is provided in Section V.

System Modeling

Unintentional islanding may cause damage to the DGs and loads or even cause safety concerns to the maintenance personnel. Hence the system needs to be designed such that the fault is identified efficiently and the controller response to the fault clearance is adequate before the DGs are disconnected from the grid. An overview of the generalized grid-connected PV system is presented in Fig.1.

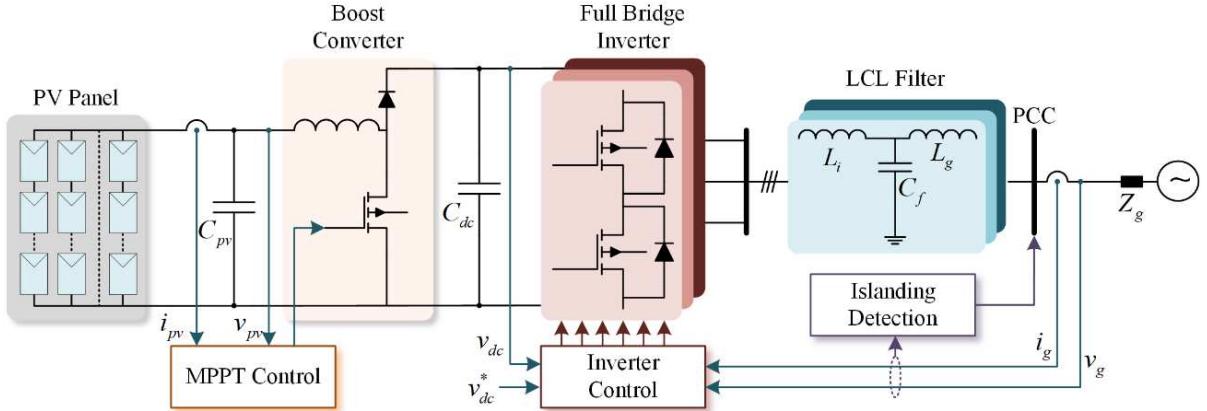


Fig. 1: Layout of three-phase grid-connected PV system. (v_{PV} and i_{PV} are the voltage and current measured at the PV output, v_{dc} is the DC link voltage and v_{dc}^* is the reference DC link voltage, C_{pv} is the DC link capacitance, L_g are grid side filter inductance, C_f is the filter capacitance, and v_g and i_g are the measured three-phase voltage and current at the point of common coupling)

System Controller Design

The control of the grid-connected inverter must be designed such that the power converter can support the utility in abnormal conditions and the system can operate independently of DGs if the fault persists after a certain duration as specified by the grid standards. The controller intends to regulate the inductor current (i_{Lg}) of the LCL filter by tuning the magnitude and the phase angle of the capacitor voltage (v_{Cf}). The fluctuation in the magnitude and phase angle of the of the i_{Cf} tend to determine the active and reactive response of the grid inductor (i_g) as illustrated in Fig. 2.

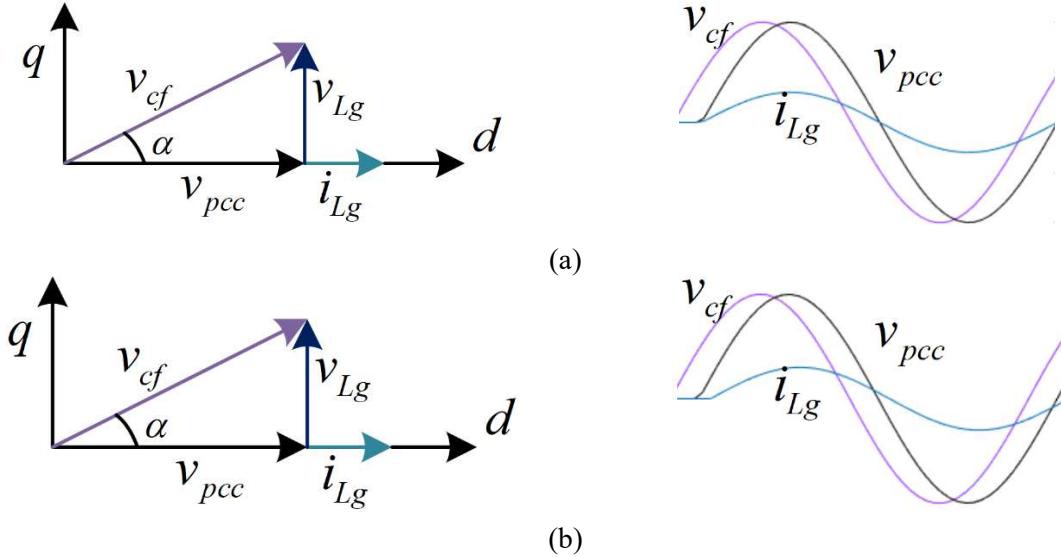


Fig. 2: Phasor representation of controller implementation. (a) Active power injection (b) Active and reactive power injection

It can be observed from Fig. 2, initially the i_{Lg} is present in the q -axis, hence resulting in active power injection, whereas the fluctuation in the magnitude and phase shift of the i_{Cf} corresponding to the v_g has resulted in a shift of v_{Lg} and further pushed i_{Lg} into d -axis with a phase shift of β . As a result, v_{Lg} has both d and q components are present and active as well as reactive power injection is taking place at such instance. The control scheme comprises two loops where the inner loop controls the voltage of

the capacitor whereas the outer loop is responsible for the inductor current control. The detailed representation of the control scheme is presented in Fig .3.

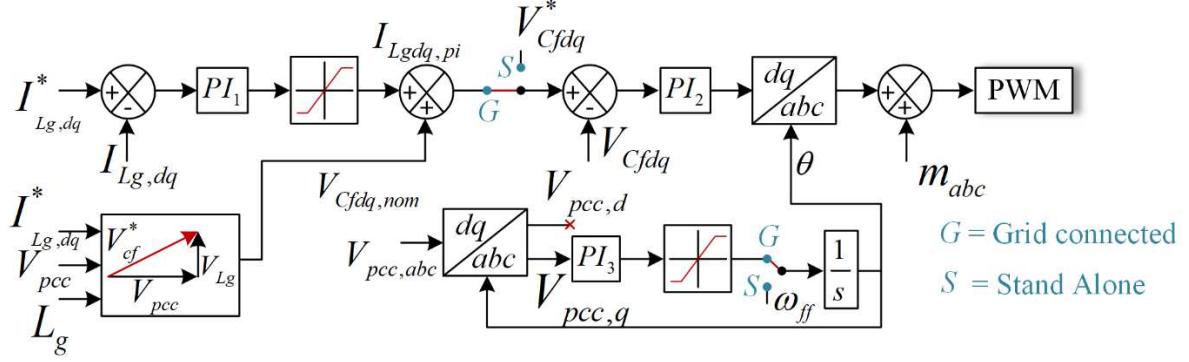


Fig. 3: Control block diagram

The nominal d and q components of capacitor voltage are represented as:

$$V_{Cfd,nom} = V_{pcc,d} + V_{Lg,d} = V_{pcc,d} + i_{Lg,q}^* \times \omega L_g \quad (1)$$

$$V_{Cfd,nom} = V_{Lg,q} = i_{Lg,d}^* \times \omega L_g \quad (2)$$

The capacitor voltage reference (V_{Cf}^*) can be achieved by adding the compensation value with the nominal value of the current controller as represented in (1) and (2). The phase-locked loop (PLL) and grid inductor controller are confined by the limiter to provide a stable voltage to the load during the fault clearance time. The limiter range is set up as per the grid standards (IEEE 1547) and can range as follow:

$$-0.1V_{g,peak} \leq I_{Lgdq,com} \leq 0.1V_{g,peak} \quad (3)$$

$$-0.01\omega_{nom} \leq \omega_{com} \leq 0.01\omega_{nom} \quad (4)$$

During the grid-connected mode of operation, the inverter tends to supply power to the load and the utilities, whereas during the clearance time, PLL and grid inductor control are saturated, and the capacitor voltage controls the inverter operation. In most cases, the Islanding detection algorithm only monitors the magnitude and frequency of voltage at PCC which may lead to false identification at times. Hence the new islanding detection algorithm aims to utilize the multiple features for more accurate and efficient fault identification.

Grid Parameters and Abnormalities

The Islanding approach provides additional protection to the DGs and protects the system from complete blackout. Islanding detection also aims at improving the operating condition of the power system and protecting the power electronics components from damage. Various grid standards have been formulated to regulate the operation of DGs with the utility. By specifying different integration requirements and various operating constraints, the distribution companies along with the manufacturers have come up with the grid codes for the smooth operation of the system. Further, these grid standards also protect the DG components during a grid abnormality as well as the life of line workers on maintenance duty. The multiple standards corresponding to the abnormality detection and DGs disconnection have been formulated by the different countries in association with the distribution companies in the region. The grid standards stipulate parameters for the grid forming/feeding and supporting aspects of the DG [11]. Few of the most used grid codes for the islanding detection are: UL1741 [12], IEEE 1547 [13], IEC 62116 [14], and IEEE 929 [15]. The codes are selected by the utilities and the government depending on the load that is to be supplied. Hence it

is expected by the power system to follow one of the above grid standards and disconnect DGs from the utilities in case of system abnormalities.

The DGs while integrated with the utility is susceptible to faults that can damage the local load in case of unintentional islanding. A few of the most commonly occurring abnormalities in the grid-connected DG operation are discussed in the Table. 1.

Table I: Normal and abnormal operating conditions at the grid side

Class	Condition	Cause and Impact	State
NO	Normal Operation	The voltage at PCC (v_{pcc}) is within the limits specified by the grid standards.	Not Islanded
F1	Asymmetrical Faults	Voltage dips are generated at v_{pcc} .	Islanded
F2	Faults due to Impedance	Violation in power transferring capacity of the system.	Islanded
F3	Frequency Mismatch	The frequency exceeds the permissible limit.	Islanded
F4	Harmonics	Voltage transient is observed at v_{pcc}	Islanded
F5	Grid synchronization fault	A mismatch between distributed generation voltage and grid voltage.	Islanded

Classification Algorithm

Classification Problem: The classification problem estimates the value of an unknown class variable depending on the known values of one or more independent variables. For developing an islanding detection logic (IDL) for a grid-connected inverter, the independent variables deal with information related to the known islanding events, and the unknown variables are based on the dynamics of the grid operating in the real time. The sequence of elements in the independent variables is given as $\{\mathcal{F}, \mathcal{C}\}$ where \mathcal{F} is an ordered list of known data for abnormalities affecting the grid voltage, and \mathcal{C} corresponds to the labeled class for predicting a given hypothesis. Consider the projection of the d independent variables to a \mathcal{D} -dimensional feature space, the ordered list of known data for i^{th} attribute is termed as \mathcal{F}_i . For a given unknown hypothesis with the feature set \mathcal{U}_t , the output is estimated as:

$$\mathcal{C}_t = f(\mathcal{U}_t, \mathcal{D}, \text{parameters}), \quad (1)$$

where \mathcal{C}_t is the class estimated for the features of the unknown hypothesis, and *parameters* indicates the kernels used for transforming the input test data into higher dimensional feature space. Generally, these parameters are set during the monitoring process or learned by a classifier based on the nonlinearity of the known islanding data. To solve this classification problem, the independent variables are trained with support vector machines inspired by their online learning advantages.

Online Support Vector Machine: Generally, linear SVMs were used in the literature to achieve online learning with both linear and nonlinear data [16]. For linear data, the linear SVMs on the primal representation are identified to be efficient and scalable and their weight vectors can be efficiently computed without the need for external kernels. In the case of nonlinear data, this situation changes as the weight vectors cannot be expressed explicitly, and kernels are required for transforming the data into a higher dimensional feature space. This problem requires the frequent optimization of the duality principle [17] during the training process. To achieve this, the *LaSVM* is adapted which is a dual

representation algorithm that employs optimization schemes to achieve higher accuracies quickly [18]. Generally, the *LaSVM* maintains a set of support vector indices \mathcal{J} which correspond to α non-zero coefficients. Further, whenever a new instance is provided, the *LaSVM* performs two operations, Process, and Reprocess. The Process operation performs a sequential minimal optimization to develop a violation pair from the variables corresponding to the new instance and the variables from the current set of support vector indices \mathcal{J} . This operation adds new support vectors to the current support vector indices \mathcal{J} . Similarly, the Reprocess performs a sequential minimal optimization to develop a most violation pair from any two variables available in the current set of support vector indices \mathcal{J} . This operation eliminates the unnecessary support vectors to keep the current support vector indices \mathcal{J} as small as possible. The Algorithm 1 presents the pseudo-code of *LaSVM*.

Algorithm 1: pseudo-code of *LaSVM*

- | | |
|----------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Step 1:</i> | Initialization |
| | <ul style="list-style-type: none"> • Seed \mathcal{S} with variables from each class \mathcal{C}. • Set $\alpha \leftarrow 0$ and initiate the gradient g |
| <i>Step 2:</i> | Online Episode |
| | <ul style="list-style-type: none"> • Predefine the number of episodes to repeat the process. • Select feature set \mathcal{F}_i • Compile and run Process(\mathcal{F}_i) • Run Reprocess |
| <i>Step 3:</i> | Finalizing |
| | <ul style="list-style-type: none"> • Repeat the Reprocess in <i>Step 2</i> till the convergence criteria are achieved. |
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To achieve multi-class SVMs with the *LaSVM*, the *LaRank* is used as an extension. The operation of *LaRank* for dual objective optimization is given as

$$\text{maximize}_{\beta} \sum_{i=1}^l \beta_i^{\mathcal{C}_i} - \frac{1}{2} \sum_{i,j} \sum_{\mathcal{C}=1}^d \beta_i^{\mathcal{C}} \beta_j^{\mathcal{C}} k(\mathcal{F}_i, \mathcal{F}_j) \quad (2)$$

$$\text{subject to } \beta_i^{\mathcal{C}_i} \leq \mathcal{R} \delta_{\mathcal{C}, \mathcal{C}_i}, 1 \leq i \leq l, 1 \leq \mathcal{C} \leq d \quad (3)$$

$$\sum_{\mathcal{C}=1}^d \beta_i^{\mathcal{C}} = 0, 1 \leq i \leq l \quad (4)$$

where $\beta_i^{\mathcal{C}}$ is the coefficient of violation pair $(\mathcal{F}_i, \mathcal{C})$, \mathcal{R} is the regularization parameter, and δ is the Kronecker symbol. Further, the *LaRank* modifies the support patterns and support vectors such that the Process and Reprocess operations are extended. In this modification, for a support vector $(\mathcal{F}_i, \mathcal{C})$ whose coefficients are $\beta_i^{\mathcal{C}}, 1 \leq i \leq l$, are non-zero, there exists some $\mathcal{C}, 1 \leq \mathcal{C} \leq d$, for all the patterns of \mathcal{F}_i . The extended operations of Process and Reprocess are given as, Process New, Process Old, and Optimize. The Process New operation performs a sequential minimal optimization to develop a violation pair from two variables in a feasible direction corresponding to the new instance. Further, the Process Old operation performs a sequential minimal optimization to develop the most violation pair from the variables corresponding to a randomly selected support pattern. Lastly, the Optimize operation performs similar to the Process Old operation but developed the most violation pair from the support vectors associated with the support pattern. Moreover, the derivative of the dual objective optimization function in (2) concerning the coefficient $\beta_i^{\mathcal{C}}$ gives:

$$g_i(\mathcal{C}) = \delta_{\mathcal{C}_i, \mathcal{C}} - \sum_j \beta_j^{\mathcal{C}} k(\mathcal{F}_i, \mathcal{F}_j). \quad (5)$$

This identifies that, the gradient $g_i(\mathcal{C})$ is reliant on the coefficient of each class \mathcal{C} individually. Further, the Process Old operation only works on d gradient computations due to the equality constraints with the added variables. To speed up these computations, the sparseness of the support vectors is exploited, resulting in the need for a new implementation for the effective computation of the gradients. To achieve this, the *LaRank* only stores and updates the current support vector gradients. This improves the computation speed and minimizes the memory requirement.

Classifier Training

The proposed classifier is trained with the abnormalities simulated on a 15 kW three-phase grid-connected PV system as shown in Fig. 1. As mentioned in Table. 1, one normal operating condition, and 5 abnormal operating conditions are simulated to develop the known islanding scenario dataset. The flow diagram of the online learning process along with the action of *LaSVM* for islanding detection is given in Fig. 4. During a new instance in the system, the trained model adapts the process and reprocess approach through the sequential minimization optimization as discussed in Algorithm 1.

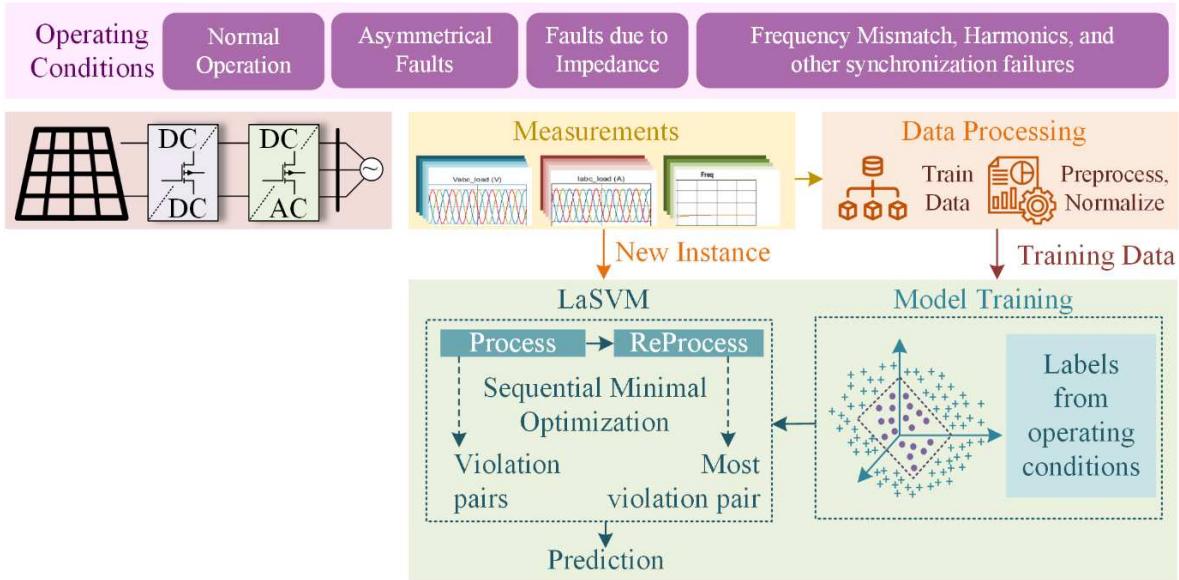
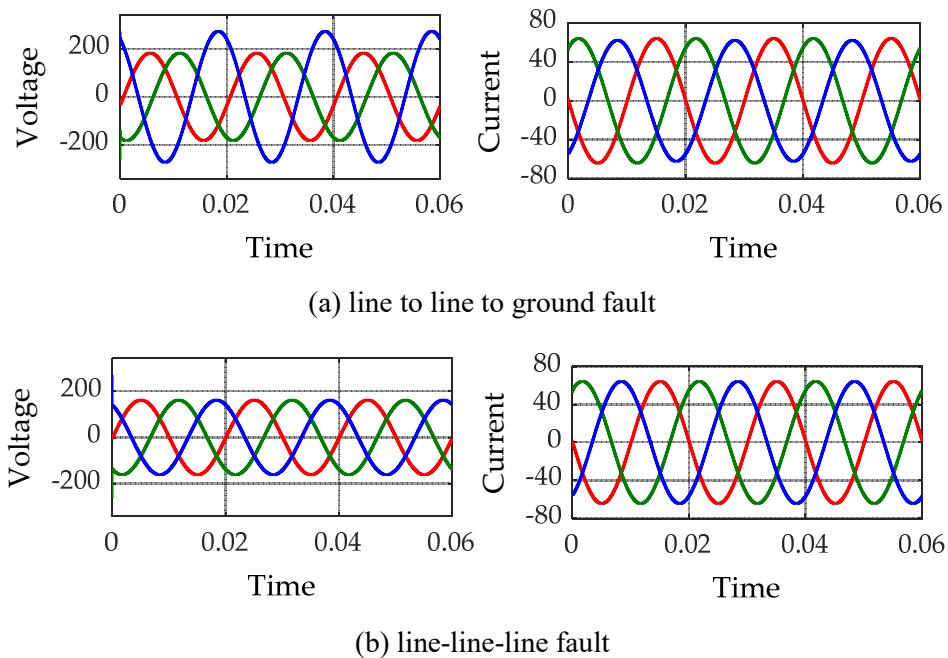
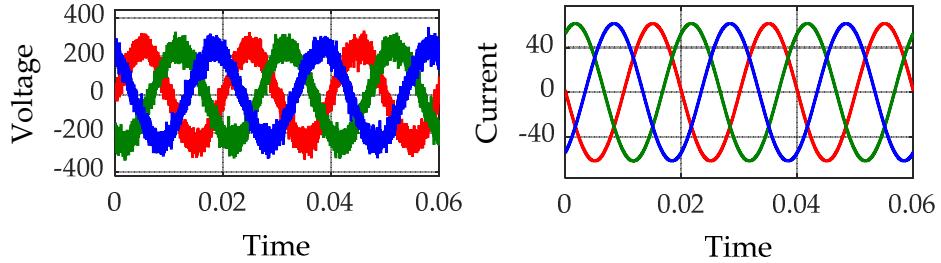


Fig 4. Flow diagram for online islanding detection in a grid-connected system





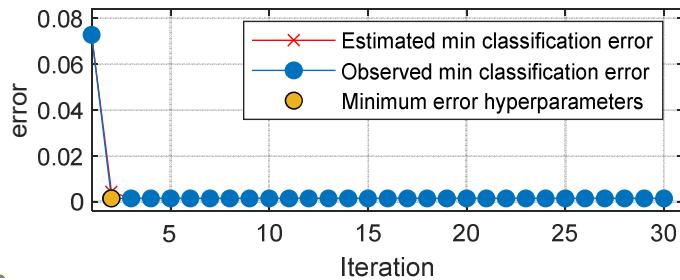
(c) Harmonics injected at the point of common coupling through grid side abnormalities

Fig 5. Sample plots of voltage and current measured during various grid abnormalities

A brief overview of the known variables used in the learning process is provided through the voltage and current measurements in Fig. 5. The data obtained from the preprocessing approach for different abnormalities are labeled with their corresponding classes to model the online SVM. The online SVM classifier is trained with C++ programming with the source code containing a C library for implementing the kernel cache, and the extended Process New, Process Old, and Optimize operations. The additional C++ programs *LaSVM* and *LaRank* are used to run the classifier training with the online SVM for multi-class classification. Initially, the known and unknown variable data is handled by splitting it into training and testing datasets. Each feature/value pair in the training data set has a target value separated by a space character which is used for making predictions with the unknown hypothesis in the testing condition. The corresponding data is trained with *LaSVM* and the corresponding results are shown in Fig. 6.

	F1	1448				
F2		511	2			
F3			511			2
F4				512		1
F5					513	
NO				1		512

(a) Classification of samples



(b) Misclassification error

True Class	F1					
	F2	100.0%	0.4%			
	F3		99.6%			0.4%
	F4			99.8%		0.2%
	F5				100.0%	
NO				0.2%		99.4%
PPV	100.0%	100.0%	99.6%	99.8%	100.0%	99.4%
FDR			0.4%	0.2%		0.6%
	F1	F2	F3	F4	F5	NO
	Predicted Class					

(c) Positive prediction and false detection rate

Fig. 6: *LaSVM* classifier training results

A total of 4013 samples are trained with 6 different classes. The online SVM formulates the violation pairs between the support variables with the processed data to form the support vectors and train the classifier according to the classes. The classifier is trained for 30 episodes. The classification samples in Fig. 6 (a) indicate 4 misclassified samples in the training data set. Further, the minimum classification error is plotted as shown in Fig. 6 (b) to identify the estimated and observed error during the training and testing process with the trained classifier. The minimum classification error is computed by the optimization process when considering all the sets of hyperparameter values tried so far, including the current iteration. This estimate is based on an upper confidence interval of the current classification error objective model observed after the best point hyperparameter [19], [20], and randomly performs the error checks by increasing the confidence limit after certain iterations. The best point hyperparameter indicates the region where the training process is optimized, and the minimum classification error indicates the episode where the classifier obtained maximum accuracy. The result in Fig. 6 (c) indicates the positive predictive value and false detection rate in % for the truly and falsely classified samples. The *LaSVM* is identified to have a training and validation accuracy of around 99.8 % with only 6 misclassified samples.

Conclusion

In this paper, an online learning algorithm is applied using the large-scale SVMs for approximative training of islanding scenarios in the grid-connected system. The training process is evaluated with a simulated three-phase grid-connected system. It adapted the *LaRank* paradigm to achieve fast approximation while classifying an untrained or new data set. Based on the results it is identified that the developed approach accurately trains and classifies different islanding scenarios for simultaneous abnormalities and achieved 99.8 % training and validation accuracy. The trained classifier has a detection speed of 0.4 sec for detecting known abnormalities. The results suggest that implementing online classifiers for islanding detection can provide a well-performing and robust way of obtaining approximation solutions with a good trade-off between accuracy and time.

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