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A Comparative Analysis of Intelligent Classifiers for Passive Islanding Detection in Microgrids

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***Abstract*—This paper proposes a passive islanding detection technique for distributed generations in grid-connected microgrids and presents a comprehensive comparative analysis of intelligent classifiers for passive islanding detection application. The proposed method utilizes pattern recognition techniques in classification of underlying signatures of wide variety of system events on critical system parameters for islanding detection. Case study on a grid-connected microgrid model with different types of distributed generations is performed to evaluate the proposed method and compare the classifier performances. Test results demonstrate the effectiveness of the proposed method in detection of islanding events.**

***Index Terms*--Decision trees, islanding detection, microgrids, naïve-Bayes, neural networks, support vector machines.**

I. Introduction

Integration of distributed generation (DG) resources with electric power systems (EPS) offers potential solution to energy security and reliability with minimum environmental impacts. However, several technical considerations are required in system planning and operation processes for DG integration. Inadvertent islanding is one of the major issues associated with DG integrations. IEEE Std. 1547 defines islanding as “A condition in which a portion of area electric power system (EPS) is energized solely by one or more local EPSs through associated points of common couplings (PCC) while the portion of area EPS is electrically isolated from rest of the area EPS”. IEEE Std. 1547 recommends isolation of DGs within a maximum of 2 seconds in events of island formation [1]. Although islanded operations may be able to enhance reliability by supplying local loads and reducing downtime when supply from area EPS is unavailable, but several operational and safety considerations including power quality standards, voltage and frequency controls, and safety hazards are required before such operations can be realized in practice.

The concept of microgrids allows such self-governing system operations. A microgrid is essentially a distribution network consisting of a cluster of DG resources and loads with advanced controls, protections and energy management system to operate in grid-connected mode, islanded (autonomous) mode and ride through between the two modes. Transition from grid-connected mode to islanded mode requires fast and accurate islanding detection as the primary step. Islanding detection techniques are generally divided into three main categories, namely active, passive and communication based techniques. Communication based islanding detection methods mainly use “transfer trip” or “power line signaling” in order to detect islanding conditions. These methods require extensive communication infrastructures and hence expensive. Active techniques rely on perturb and observe methods. Although active methods have smaller non-detection zones (NDZ) compared to passive techniques, they cause degradation of power quality and require complex control for perturbation injections [2-3]. Passive islanding detection methods rely on local measurements of system parameters (such as- voltage and current) and detects islanding events by locating abnormalities in those system parameters. Several passive islanding detection methods have been proposed in literature [4-12]. Passive islanding detection methods do not degrade power quality, but these methods suffer from a larger non-detection zone (NDZ). Especially, in presence of power balance in the island (i.e. generation and load are approximately balanced in the islanded section of the system).

This paper investigates passive islanding detection based on pattern recognition techniques and presents a comprehensive comparative analysis of pattern recognition techniques based classifiers for passive islanding detection in distributed generation (DG) from microgrid standpoint. The passive islanding detection method is based on extraction of a unique set of critical system features from voltage and current measurements at target DG locations, and utilization of intelligent classifiers for detection of islanding events. The set of system features were selected to enhance islanding detection accuracy in presence of multiple types of DG units, under different system operating and loading conditions. A detailed case study on grid connected microgrid model implemented with IEEE 13 node distribution feeder system is performed to validate the effectiveness of the proposed islanding detection

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method and evaluate the performances of five different intelligent classifiers based on pattern recognition techniques for the proposed islanding detection application.

The paper is organized as follows. Principles of pattern recognition based classification methods are presented in Section II. Section III describes the proposed passive islanding detection method. Section IV describes the test system model. In Section V, case study results are presented, and performance of the classification methods are compared and analyzed. Finally, Conclusions are presented in Section VI.

II. CLASSIFICATION METHODS

This paper investigates five different classification techniques: (1) Decision Trees, (2) Naïve-Bayes, (3) Support Vector Machines, (4) Multilayer Perceptron Neural Networks, and (5) Radial Basis Function Neural Networks. [15] A brief overview of these methods is presented in this section.

A. Decision Trees

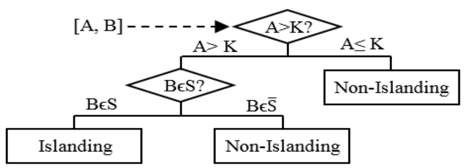

Figure 1. A simple illustrative decision tree.

Decision trees (DT) belong to a class of pattern recognition tools capable of extracting useful information from large data set and provide assistance in classification of input vectors into discrete categories. The classification algorithm combines hyperplanes parallel to coordinate axes to approximate multiple separation boundaries for splitting a complex decision process into a collection of simple decision processes [13]. The DT algorithm initiates with “Root Node” which contains the complete learning set (LS). Each of the “Internal Nodes” tests a critical attribute (CA) and each “Arc” corresponds to an attribute value. The learning process is achieved by recursively splitting the learning set (LS) into two purer subsets according to the critical splitting rule (CSR) at each of the internal nodes. The “Terminal Node” represents the predicted class of an input vector [14, 15]. DT classifiers offer robustness, ease of interpretation and implementation compared with other popular pattern recognition tools.

B. Naïve-Bayes Classification Method

The Naïve-Bayes classifier is a probabilistic classifier method based on Bayesian theorem with strong independence assumptions. NB classifiers are particularly suitable for classification tasks where the dimensionality of the input data is high. In Naïve-Bayes classification model, the final classification is derived from posterior probability of an event which is computed from prior probability and likelihood. The posterior probability and likelihood of an event c_i among a set of possible outcomes $C = \{c_1, c_2, c_3, \dots, c_n\}$ for a given set of predictor $X = \{x_1, x_2, x_3, \dots, x_n\}$ can be expressed as follows.

$$p(c_j|X) = \frac{p(c_j)p(X|c_j)}{p(X)} \tag{1}$$

$$p(X|c_j) = \prod_{k=1}^{n} p(x_k|c_j) \tag{2}$$

where $p(c_j \mid X)$ is the posterior probability of class membership, i.e., the probability that X belongs to c_j. Naïve-Bayes classifiers can be trained very efficiently in a supervised learning setting and require small amount of training data to estimate parameters necessary for classification.

C. Support Vector Machines

Support vector machines (SVMs) are based on the concept of decision planes which define decision boundaries. SVM classifiers perform classification by constructing hyperplanes in a multidimensional space to separate cases of different classes. An optimal hyperplane is constructed by minimizing an error function through iterative training algorithm, which maximizes the separation margin between different classes. For a set of input vectors X_i and vector of classes Y_i, the training process involves minimization of the error function presented in (3) subjected to the constraint presented in (4).

$$\frac{1}{2}w^T w + C\sum_{i=1}^{k} \xi_i \ ; \ \xi_i > 0, i = 1,2, \dots, k \tag{3}$$

$$Y_i(w^T \phi(X_i) + b) \geq 1 - \xi_i \tag{4}$$

where, C is the capacity constant corresponding to the penalty factor for error term ξ_i, w is the vector of coefficients, b is the bias constant. The kernel function $\phi(x)$is applied to transform data from input vectors to feature space. The kernel function can be linear, polynomial, radial or sigmoid functions.

D. Artificial Neural Networks

Artificial neural networks (ANN) are highly sophisticated modeling technique which have been successfully applied across diversified classification problems in the domain of power systems. ANN architecture consists of input layer, hidden layers (pattern and summation layers) and output layer. Two different types of ANNs are investigated in this paper.

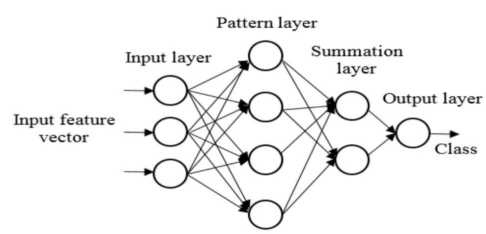

Figure 2. Generic artificial neural network architecture.

1) Multilayer Perceptrons (MLP): MLP architecture offers simplicity and capability to model functions of almost arbitrary complexity. In MLP architecture, nodes are arranged in a layered feed-forward topology. Each node is modeled as sigmoid functions and performs a biased weighted sum of their inputs. The response function is modeled by dividing up the pattern space into hyperplanes and computing the Euclidian distance of the test case from the line of sigmoid-cliff. Output is generated by passing the nodal outputs through a transfer function (called activation function).

2) Radial Basis Function Networks: Radial basis function (RBF) networks model the response function using Gaussian functions and divides the pattern space using hyperspheres.

Therefore, in radial basis function networks, hidden layer nodes are modeled as radial units which are nonlinear and a single hidden layer with sufficient number of nodes is capable of modeling any function. The network output is a linear combination of the outputs from hidden layer radial nodes which are weighted sum of the Gaussian functions.

III. ISLANDING DETECTION METHODOLOGY

The conceptual model of the proposed islanding detection methodology is presented in Fig.3. The method relies on extraction of critical system features by post-processing voltage and current waveforms obtained at target DG locations, and detection of event specific signatures associated with these critical features through the application of classification methods based on pattern recognition techniques. Knowledge base (KB) for training and testing the classifiers is generated through extensive offline event simulations to capture the essential characteristics of the system.

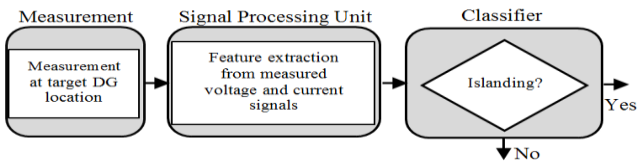

Figure 3. Conceptual model of the proposed islanding detection scheme.

TABLE I. CRITICAL FEATURES USED IN ISLANDING DETECTION

$x_1^i = \Delta V_i$	Voltage deviation (V) under ith event;
$x_2^i = (\Delta V/\Delta t)_i$	Rate-of-change of voltage (V/sec) under ith event;
$x_3^i = \Delta f_i$	Frequency deviation (Hz) under ith event;
$x_4^i = (\Delta f/\Delta t)_i$	Rate-of-change of Frequency (Hz/sec) under ith event;
$x_5^i = P_i$	Active power output (Watts) at target DG location under ith event;
$x_6^i = (\Delta P/\Delta t)_i$	Rate-of-change of active power output (Watts/sec) at target DG location under ith event;
$x_7^i = Q_i$	Reactive power output (VARs) at target DG location under ith event;
$x_8^i = (\Delta Q/\Delta t)_i$	Rate-of-change of reactive power output (VARs/sec) at target DG location under ith event;
$x_9^i = (\Delta f/\Delta P)_i$	Change in frequency with respect to DG active power output (Hz/Watts) under ith event;
$x_{10}^i = (\Delta V/\Delta Q)_i$	Change in voltage with respect to DG reactive power output (V/VARs) under ith event;
$x_{11}^i = VTHD_i$	Total harmonic distortion in voltage under ith event;
$x_{12}^i = CTHD_i$	Total harmonic distortion in current under ith event;
$x_{13}^i = \left(\frac{\Delta(\delta_V - \delta_I)}{\Delta t}\right)_i$	Rate-of-change of phase angle deviation (ROCPAD) at target DG location under ith event;
$x_{14}^i = \left(V_2/V_1\right)_i$	Voltage unbalance at target DG location under ith event.

In this paper, a set of 14 features have been selected for the classification purpose which is used for supervised learning of five different types of classifiers. Table I lists all the independent system features used in islanding detection.

A wide variety of system disturbances leading to islanding and non-islanding events have been considered in offline simulations. The islanding events include all possible tripping of circuit breakers leading to islanding situations, islanding in area EPS transmission network or loss of distribution line, and sudden loss of power at PCC with area EPS. Non-islanding events considered include tripping of circuit breakers not leading to islanding situations, abrupt changes in loadings at target DG locations, at PCC and in overall microgrid, and capacitor bank switching. These events have been simulated under various operating states of area EPS and microgrid.

The methodology of the proposed passive islanding detection approach can be outlined according to the flow diagram presented in Fig.4.

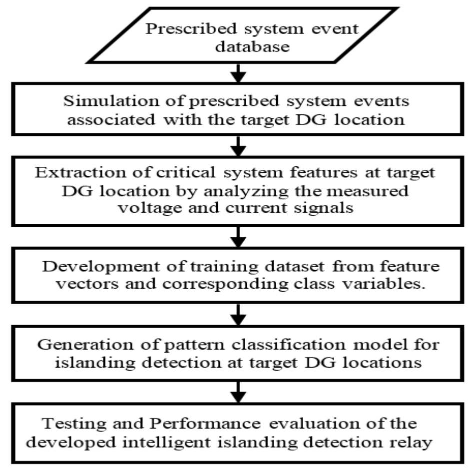

Figure 4. Outline of the proposed passive islanding detection scheme.

IV. TEST SYSTEM MODEL

The test system model is developed using Matlab/Simulink platform. A brief overview of the grid-connected microgrid model used as the test system is presented in this section.

A. Main Grid Model

The main grid is modeled as 4-generator, 2-area system described in [16]. The system has a relatively small size but is able to exhibit typical power system dynamics. Thus, interactions between main grid and microgrid can be studied.

TABLE II. TWO AREA SYSTEM MODEL OVERVIEW

Generators	G-1: 700MW,185MVar G-2: 700MW, 235MVar	G-3: 719MW, 176MVar G-4: 700MW, 202MVar
Load	Bus-7: 967MW, 100MVar	Bus-9: 1767MW, 100MVar
Shunt Capacitors	Bus-7: 200MVar	Bus-9: 350MVar

B. Microgrid Model

The microgrid model is implemented using IEEE 13 bus distribution system model with two different types of distributed generators (i.e. diesel generator and PV array) and one storage unit (i.e. battery). The 13-bus test feeder system is operated at 4.16kV with unbalanced loads (both single-phase and there-phase loads) and shunt capacitor banks to model a representative distribution system. The microgrid model is connected to area-2 of the main grid model.

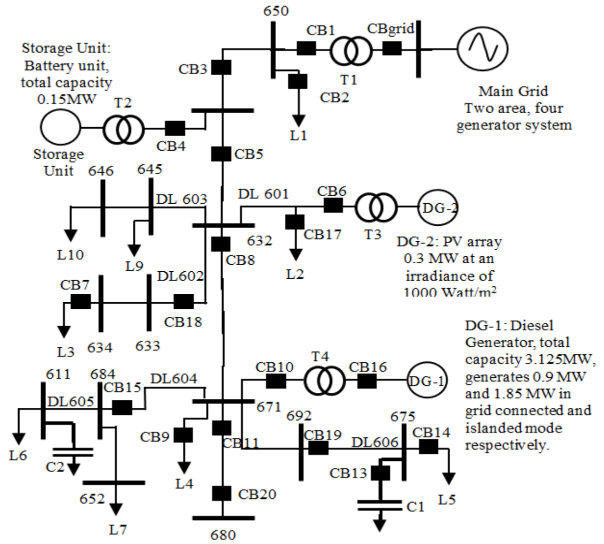

Figure 5. Microgrid model implemented in IEEE 13 node distribution feeder.

V. Case Study Results and Analysis

In this case study, a total of 162 islanding (I) cases and 324 non-islanding (NI) cases were simulated under 27 different operating conditions (i.e. EPS loading, microgrid loading) to generate the measurement database at target DG locations (at PCC of the DG unit with microgrid). Voltage and current signals at target DG locations were sampled at 60 Hz. The set of critical system features presented in Table I was extracted from the measurement dataset and data model for setting the islanding detection relay at target DG location was developed.

Based on the data model, five different classifiers explained in Section II were developed using "Waikato Environment for Knowledge Analysis (WEKA)" [17] data mining platform. For each of the classification methods, three different classifiers (i.e. separate classifiers for DG-1 and DG-2, and common classifier for both DGs) were developed.

Two different testing methods -a) K-fold cross validation and b) percent split were applied to test the classifiers. K-fold cross validation method partitions the original dataset into K subsets and performs K iterations. In each iteration, (K-1) subsets are used as training sets and a single subset as validation set. Each of the K subsets is used as the validation set once in the process and results over K iterations are averaged to generate the final result. In this paper, 10-fold cross validation method is used for the evaluation of the developed classifiers. In percent split method, entire dataset is divided into a learning set (LS) for training and a test set (TS) for testing the classifiers. This study uses 70% of the data set as the training set and remaining 30% of the data set as the test set in percent split validation method.

Merits of the selected critical system features were evaluated in WEKA. Table III presents the average merits of the selected critical features for classifier training. Results indicate that voltage unbalance (VU) has the highest merit among the selected features. This is mainly due to the fact that islanding scenarios suddenly change DG loading conditions and even in scenarios of minimum DG load variations due to islanding, VU varies because of the changes in network topologies caused by islanding events. List of features with higher merits towards classifier training also include ΔV/ΔQ, ΔV/Δt, ΔV, Δf/ΔP, Δf/Δt, VTHD and CTHD. Since DGs are operated at unity power factor, islanding events can possibly lead to lack of reactive power and subsequent voltage variations. Hence variations in indices like ΔV/ΔQ, ΔV/Δt, ΔV can be utilized for accurate identification of islanding events. Moreover, abrupt changes in loading conditions might introduce shifts in the operating frequency, and harmonics in voltages and currents in the network. Hence indices like Δf/ΔP, Δf/Δt, VTHD and CTHD can be monitored and utilized in classifier training for successful islanding detections.

TABLE III. Average Merit of Features in Classifier Training

Feature	Average Merit	Feature	Average Merit
VU	0.901	CTHD	0.690
ΔV/ΔQ	0.881	Δf	0.68
ΔV/Δt	0.881	ROCPAD	0.674
ΔV	0.881	ΔP/Δt	0.653
Δf/ΔP	0.843	ΔP/Δt	0.566
VTHD	0.823	ΔQ/Δt	0.485
Δf/Δt	0.691	Q	0.305

Figure.6 presents the distribution of the values of system features with highest merits towards classifier training corresponding to the 18 events (5 islanding events and 13 non-islanding events) under a certain system operating condition.

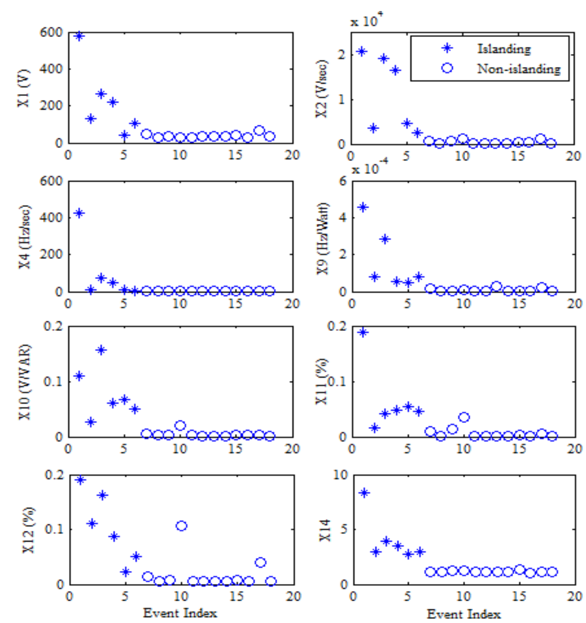

Figure 6. Distribution of system feature values corresponding to the 18 system events simulated under a certain operating condition.

A. Decision Tree Classifiers

Decision tree classifiers were developed using J48 decision tree algorithm in WEKA. Table IV and Table V summarize the performances of developed DT classifiers. In cross validation method, obtained average classifier accuracy is 96.55%, average dependability index (i.e. islanding detection accuracy) is 97.01 and average security index (i.e. non-islanding detection accuracy) is 96.31. In percent split method, average classifier accuracy is 97.53%, average security index is 98.14 and average dependability index is 97.24. In general, DT classifiers offer higher dependability index compared to security index.

TABLE IV. DT PERFORMANCE (10-FOLD CROSS VALIDATION)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	324	96.30	96.71	3.29
	I	162	97.53		
DG2	NI	297	96.97	97.17	2.83
	I	162	97.53		
Common classifier	NI	621	95.65	95.77	4.23
	I	324	95.98		

TABLE V. DT PERFORMANCE (LS-70% VS. TS-30%)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	98	97.96	97.94	2.06
	I	48	97.92		
DG2	NI	92	97.82	98.55	1.45
	I	46	100		
Common classifier	NI	197	95.94	96.11	3.89
	I	86	96.51		

B. *Naïve-Bayes Classifiers*

Table VI and Table VII present classification results with Naïve-Bayes classifiers. In cross validation method, average classifier accuracy is 92.76%, average dependability index is 85.6 and security index is 96.53. In percent split method, average classifier accuracy is 93.53%, average dependability index is 91.52 and average security index is 94.45.

TABLE VI. NAÏVE-BAYES PERFORMANCE (10-FOLD CROSS VALIDATION)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	324	96.91	93.62	6.38
	I	162	87.04		
DG2	NI	297	97.98	93.03	6.97
	I	162	83.95		
Common classifier	NI	621	94.69	91.64	8.36
	I	324	85.80		

TABLE VII. NAÏVE-BAYES PERFORMANCE (LS-70% VS. TS-30%)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	98	94.89	94.52	5.48
	I	48	93.75		
DG2	NI	92	94.56	93.48	6.52
	I	46	91.3		
Common classifier	NI	197	93.90	92.58	7.42
	I	86	89.53		

In general, Naïve-Bayes classifiers have lower overall classification accuracies compared to DT classifiers and also suffer heavily from inaccuracies in detection of islanding cases.

C. *Support Vector Machines*

SVM classifiers were developed using linear kernel function in LIBSVM toolbox [18]. Table VIII presents results from cross validation study, in which average classifier accuracy is 85.27%, average dependability index is 82.8 and average security index is 86.52. Evaluation results from percent split approach is presented in Table IX. In this method, average classifier accuracy is 86.35%, dependability index is 83.82 and average security index is 87.54. Test results indicate, SVM classifiers have less accurate performance compared to other classification methods studied in this paper.

TABLE VIII. SVM PERFORMANCE (10-FOLD CROSS VALIDATION)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	324	90.12	88.27	11.73
	I	162	84.57		
DG2	NI	297	85.86	85.84	14.16
	I	162	85.80		
Common classifier	NI	621	83.57	81.69	18.31
	I	324	78.09		

TABLE IX. SVM PERFORMACNE (LS-70% VS TS-30%)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	98	90.82	89.04	10.96
	I	48	85.42		
DG2	NI	92	88.04	87.68	12.32
	I	46	86.96		
Common classifier	NI	197	83.76	82.33	17.67
	I	86	79.07		

D. *Multilayer Perceptrons*

Classification results for MLP classifiers trained with back-propagation algorithm are presented in Table X and Table XI.

TABLE X. MLP PERFORMANCE (10-FOLD CROSS VALIDATION)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	324	97.53	97.32	2.68
	I	162	96.91		
DG2	NI	297	98.31	97.82	2.18
	I	162	96.91		
Common classifier	NI	621	96.13	95.87	4.13
	I	324	95.37		

TABLE XI. MLP PERFORMANCE (LS-70% VS. TS-30%)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	98	100	98.63	1.37
	I	48	95.83		
DG2	NI	92	98.91	97.82	2.18
	I	46	95.65		
Common classifier	NI	197	97.96	96.46	3.18
	I	86	93.02		

For cross validation study, average classifier accuracy achieved is 97%, average dependability index is 96.4 and average security index is 97.32. For percent split method, obtained average classifier accuracy is 97.64%, average dependability index is 94.83 and average security index is 98.96. MLP based classifiers provide better security as compared to dependability as evident from the study results.

E. *Radial Basis Function Networks*

Results for RBF network based classifier are presented in Table XII and Table XIII. In cross validation study, obtained average classifier accuracy is 94.03%, dependability index is 94.54 and security index is 93.75. In percent split method, the average classifier accuracy is 94.7%, dependability index is 94.11 and security index is 94.31.

TABLE XII. RBF PERFORMANCE (10-FOLD CROSS VALIDATION)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	324	94.75	94.85	5.15
	I	162	95.05		
DG2	NI	297	93.26	94.11	5.89
	I	162	95.68		
Common classifier	NI	621	93.24	93.12	6.88
	I	324	92.90		

TABLE XIII. RBF PERFORMANCE (LS-70% VS. TS-30%)

Classifier Type	Actual Class	Total Cases	% Correct	Classifier Accuracy	Misclassification Rate
DG1	NI	98	93.88	95.89	4.11
	I	48	95.83		
DG2	NI	92	95.65	94.92	5.08
	I	46	93.48		
Common classifier	NI	197	93.40	93.29	6.71
	I	86	93.02		

Classifiers implemented with decision trees and multiplayer perceptrons offer higher accuracies compared to other methods studied in this paper. Although MLP classifiers have slightly better overall classification accuracies, but decision trees provide higher dependability index in the classification process. This points to a reduced chance of missing an islanding event in the detection process. Classifiers based on RBF networks have better performance than Naïve-Bayes classifiers but both classifiers are less accurate than MLP and DT classifiers. Moreover, Naïve-Bayes classifiers are significantly less accurate in classifying islanding cases.

VI. CONCLUSION

An intelligent classifier based passive islanding detection method for DG islanding detection in microgrids is investigated and a comprehensive performance analysis of five different classifier techniques is presented. Three different classifiers were developed for each of the classification methods. A detailed case study on a grid-connected microgrid model consisting of both synchronous and inverter based DGs indicates that the proposed method can detect islanding events with high degree of accuracy and reliability. Among the classification methods considered, multilayer perceptron and decision tree based classifiers offer best performances. Overall classification accuracy for MLP classifiers is slightly higher than the DT classifiers. However, DT classifiers offer higher dependability in islanding detection which is critical, since the cost of misclassifying an islanding case as non-islanding is often larger than misclassifying a non-islanding case. Moreover, DT classifiers offer ease of implementation with the easily interpretable rules defining decision boundaries. Test results also shows that, classifiers trained separately for each DG unit have better performances compared to the common classifiers. The classifier performances can be further improved by enhancing the knowledge base used to develop the classifiers. Further investigations may include studying the effects of reducing the number of features by selecting only important features in the classification process and varying the sampling rate in preparation of measurement database.

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