A Fuzzy Rule-Based Approach for Islanding Detection in Distributed Generation

S. R. Samantaray, *Member, IEEE*, Khalil El-Arroudi, Geza Joós, *Fellow, IEEE*, and Innocent Kamwa, *Fellow, IEEE*

***Abstract*—The proposed method develops a fuzzy rule-based classifier that was tested using features for islanding detection in distributed generation. In the developed technique, the initial classification boundaries are found out by using the decision tree (DT). From the DT classification boundaries, the fuzzy membership functions (MFs) are developed and the corresponding rule base is formulated for islanding detection. But some of the fuzzy MFs are merged based upon similarity the measure for reducing the fuzzy MFs and simplifying the fuzzy rule base to make it more transparent. The developed fuzzy rule-based classifier is tested using features with noise up to a signal-to-noise ratio of 20 dB and provides classification results without misdetection, which shows the robustness of the proposed approach for islanding detection for distributed generations in the distribution network.**

***Index Terms*—Decision tree, fuzzy rule base, islanding detection, similarity measure.**

I. Introduction

INTEGRATIONS of distributed generations (DGs) in the distribution network is expected to play an increasingly important role in the electric power system infrastructure and market. As more DG systems become part of the power grid, there is an increased safety hazard for personnel and an increased risk of damage to the power system. Despite the favorable aspects grid-connected DGs can provide to the distribution system, a critical demanding concern is islanding detection and prevention. Islanding is a condition where the DG supplies power and is not under the direct control of the utility.

Islanding detection techniques may be classified as passive or active. Passive techniques use information available at the DG side to determine whether the DG system is isolated from the grid. The advantage of passive techniques is that the implementation does not have an impact on the normal operation of the DG system. Active techniques introduce an external perturbation at the output of the inverter. These tend to have a faster response and a smaller nondetection zone compared to passive approaches. However, the power quality (PQ) of the inverter can be degraded by the perturbation.

Manuscript received November 27, 2008; revised April 20, 2009. First published May 18, 2010; current version published June 23, 2010. Paper no. TPWRD-00884-2008.

S. R. Samantaray, K. El-Arroudi, and G. Joós are with the Department of Electrical and Computer Engineering, McGill University, Montreal, QC H3A 2A7, Canada (e-mail: sbh_samant@yahoo.co.in; khalil.elarroudi@mail.mcgill.ca; geza.joos@mcgill.ca).

I. Kamwa is with the Hydro-Quebec/IREQ, Power System Analysis, Operation and Control, Varennes, QC J3X 1S1, Canada (e-mail: kamwa.innocent@ireq.ca).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TPWRD.2010.2042625

Different method for islanding detection techniques [1]–[10] have been reported in recent years. Some of the papers provides [2], [3] detailed review of islanding detection for DGs in distributed networks. The islanding detection based upon the rate-of-change of power signal [1], the rate-of-change of voltage and change in power factor [8], the vector surge technique [5], the rate-of-change of frequency [6], the phase-shift method [7], the harmonic impedance estimation technique [8] have attracted wide spread attention. For ROCOF relays, the rate of change of frequency is calculated within a measurement window and used to detect islanding operation. The ROCOF relays, however, may become ineffective if the power imbalance in the islanded system is less than 15%, resulting in a high risk of false detection [6].

The proposed approach is based on the passive method of islanding detection considering the data mining approach. The method includes building a simplified and robust fuzzy classifier initialized by the decision tree (DT) [11]–[15] for islanding detection. As a result of the increasing complexity and dimensionality of classification problems, it becomes necessary to deal with structural issues of the identification of classifier systems. Important aspects are the selection of the relevant features and determination of effective initial partition of the input domain. Moreover, when the classifier is identified as part of an expert system, the linguistic interpretability is also an important aspect which must be taken into account. The first two aspects are often approached by an exhaustive search or educated guesses, while the interpretability aspect is often neglected. Now the importance of all these aspects is recognized, which makes the automatic data-based identification of classification systems that are compact, interpretable, and accurate.

DT-based classifiers perform a rectangular partitioning of the input space while the fuzzy models generate nonaxis parallel decision boundaries. Hence, the main advantage of rule-based classifiers over crisp DTs, is greater flexibility of the decision boundaries. Therefore, fuzzy classifiers can be more interpretable compared to DT classifiers. Generally the initialization steps of the identification of the fuzzy model become very significant. Common methods for such as grid-type [16] partitioning and rule generation on extrema initialization [17], result in complex and noninterpretable initial models. To avoid such problems, a crisp decision tree, having high performance and computational efficiency, is proposed for initial partitioning of the input domain for the proposed fuzzy model.

In the proposed approach, two major steps are involved. In the first step, features are extracted and in the second step, classification task is performed for islanding detection. Thus, feature selection is one of the important tasks involved in the proposed approach. Different techniques have been proposed [1], [5]–[10]

which work on one of the estimated parameter. Thus, we have derived all possible features such as change in power, change in voltage, rate of change of power, rate of change of voltage, total harmonic distortion (THD) (current), THD (voltage), change in power factor, etc., could be affected by islanding and can be measured locally at the target location.

The derived features [18] are used as inputs to the DT for deciding the most significant features which take part in the decision-making process and the initial classification boundaries. From the DT classification boundaries of the most significant features, trapezoidal fuzzy membership functions are developed and corresponding rule base is formed for classification. But some of the fuzzy MFs are merged depending upon the similarity measure and thus reducing the number of fuzzy MFs. From the reduced fuzzy MFs, a simplified fuzzy rule base is developed for islanding detection.

Sections II–V deal with the system studied, DT transformation to fuzzy rule base, computational results, discussion and conclusions.

II. Studied System and Feature Extraction

The system studied for the proposed method is shown in Fig. 1. The details of the studied system are given as follows. The base power has been chosen as 20 MVA.

- *Generators data*:
  Equivalent System S: rated short-circuit $\mathrm{MVA} = 1000$, $f = 60$ Hz, rated kV $= 69$, $V_{\mathrm{base}} = 69$ kV.
  Generators DG1 and DG2: rated $\mathrm{MVA} = 10$, $f = 60$ Hz, 54 poles, Yn, rated kV $= 13.8$, $V_{\mathrm{base}} = 13.8$ kV, Inertia constant $H = 3.0$ Sec., $R_0 = 0.0025$ pu, $X_0 = 0.113$ pu, $R_1 = 0.001$ pu, $X_1 = 0.15$ pu, $X_d = 1.028$ pu, $X_q = 0.654$ pu, $X'_d = 0.34$ pu, $X'_q = 0.654$ pu, $X''_d = 0.253$ pu, $X''_q = 0.298$ pu, $T'_{d0} = 7.5$ s, $T'_{q0} = 0$ s, $T''_{d0} = 0.07$ s, $T''_{q0} = 0.09$ s.
- *Power Transformers data:*
  Transformer T1: rated $\mathrm{MVA} = 25$, $f = 60$ Hz, rated kV $= 69/13.8$, Dyn1, $V_{\mathrm{base}} = 13.8$ kV, $R_1 = 0.00375$ pu, $X_1 = 0.1$ pu, $R_m = 500$ pu, $X_m = 500$ pu.
- *Transformer T2 and T3*: rated $\mathrm{MVA} = 10$, $f = 60$ Hz, rated kV $= 13.8/13.8$, Ynd1, $V_{\mathrm{base}} = 13.8$ kV, $R_1 = 0.00375$ pu, $X_1 = 0.1$ pu, $R_m = 500$ pu, $X_m = 500$ pu.
- *Transmission lines data*:
  Rated kV $= 13.8$, rated $\mathrm{MVA} = 20$, $V_{\mathrm{base}} = 13.8$ kV, $R_{0L} = 0.0414$ ohms/km), $R_{1L} = 0.0138$ ohms/km, $X_{0L} = 0.0534$ ohms/km, $X_{1L} = 0.0178$ ohms/km$X_{0CL} = 5.1$ nF/km, $X_{1CL} = 17$ nF/km, Line $1 = 20$ km, Line $2 = 10$ km, Line $3 = 10$ km.
- *Normal Loading data*:
  (Rated kV $= 13.8$) $L-1 = 10$ MW, 3.5 MVAR. $L-2 = 5.0$ MW, 2.0 MVAR. $L-3 = 5.0$ MW, 2.0 MVAR. $L-4 = 5.0$ MW, 2.0 MVAR.

The various features are collected at the DR_x with different operating conditions of the network. Normally, the indices are chosen to include all possible sensitive system parameters that could be affected by islanding and that can be measured locally. In the proposed technique, the following 11 features are chosen and defined for any target distributed resource DR_x.

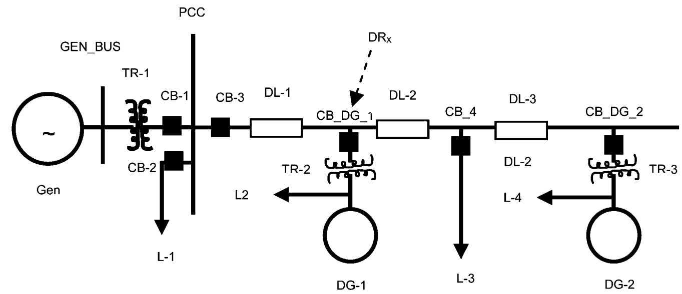

Fig. 1. Power distribution system with multiple DG (distributed generations) interface. The target islanding location is shown at DR_x.

$x_1 = \Delta f$ is the frequency deviation (Hz)

$x_2 = \Delta V$ is the voltage deviation (pu).

$x_3 = (\Delta f/\Delta t)$ is the rate-of-change of frequency (Hz/s).

$x_4 = (\Delta V/\Delta t)$ is the rate-of-change of voltage (pu/s).

$x_5 = (\Delta P/\Delta t)$ is the rate-of-change of the DR_x power (MW/s).

$x_6 = (\Delta f/\Delta P)$ is the rate-of-change of frequency over power (Hz/MW).

$x_7 = CTHD$ is the total harmonic distortion of the current (pu).

$x_8 = VTHD$ is the total harmonic distortion of the voltage (pu).

$x_9 = \Delta pf$ is the power factor deviation under.

$x_{10} = (U \cdot \cos(phi))$ is the absolute value of the phase-voltage times power factor (pu).

$x_{11} = (\Delta (U \cdot \cos(phi))/\Delta t)$ is the gradient of the of the voltage times power factor (pu/s).

The aforementioned features are extracted under different islanding and nonislanding conditions of the network as follows.

1) Condition-1: Tripping of the circuit breaker CB-1 to simulate the condition of islanding of the DG with the PCC bus loads.
2) Condition-2: Tripping of the circuit breaker CB-2 (isolating the PCC bus loads) to simulate disturbances on the DG.
3) Condition-3: Tripping of the circuit breaker CB-3 to simulate the islanding of the DG without the PCC- bus loads.
4) Condition-4: Three-phase fault on the GEN_BUS with instantaneous (1 cycle) fault-clearing time by the CB-1 which, in turn, causes islanding of the DG.
5) Condition-5: Sudden decrease of the loading on the target distributed resource DR_x by 40%.
6) Condition-6: Tripping of the largest distributed resource within the DG other than the target one.

Each condition of these events is simulated under different operating conditions of the DG and power system network. The operating conditions are given as follows.

Normal loading ($\mathrm{Zs} = j0.02$ pu) with normal PCC-bus loading ($P = 0.5$ pu, $Q = 0.175$ pu).

Normal loading ($\mathrm{Zs} = j0.02$ pu) with minimum PCC-bus loading ($P = 0.3$ pu, $Q = 0.105$ pu).

Normal loading ($\mathrm{Zs} = j0.02$ pu) with maximum PCC-bus loading ($P = 0.625$ pu, $Q = 0.22$ pu).

Minimum loading ($\mathrm{Zs} = j0.05$ pu) with normal PCC-bus loading ($P = 0.5$ pu, $Q = 0.175$ pu).
Minimum loading ($\mathrm{Zs} = j0.05$ pu) with minimum PCC-bus loading ($P = 0.3$ pu, $Q = 0.105$ pu).
Minimum loading ($\mathrm{Zs} = j0.05$ pu) with maximum PCC-bus loading ($P = 0.625$ pu, $Q = 0.22$ pu).
Maximum loading ($\mathrm{Zs} = j0.01$ pu) with normal PCC-bus loading ($P = 0.5$ pu, $Q = 0.175$ pu).
Maximum loading ($\mathrm{Zs} = j0.01$ pu) with minimum PCC-bus loading ($P = 0.3$ pu, $Q = 0.105$ pu).
Maximum loading ($\mathrm{Zs} = j0.01$ pu) with maximum PCC-bus loading ($P = 0.625$ pu, $Q = 0.22$ pu).

From the aforementioned conditions, various features are derived and used to train the DT for generating initial classification boundaries to develop the fuzzy rule base for islanding detection.

III. Decision Tree for Initial Classification

DT [11]–[15] is a classifier in high dimensions. Each internal node in the tree tests the value of a predictor while each branch of the tree represents the outcome of a test. The terminating nodes, also referred to as leaf nodes, represent a classification. The number of predictors, used in the classification problem, indicates the dimension of the problem. Associated with each decision (leaf) of the tree is the confidence of the decision. This is simply a measure of the ratio of the particular class to all the classes present in the dataset for that node.

The proposed approach uses the "Insightful Miner" [19] software package for generating DT for classification. Insightful Miner is a powerful, scalable, data mining and analysis workbench that enables organizations to deliver customized predictive intelligence where and how it is needed. Its easy-to-use interface is specifically designed for statisticians and business analysts without specialized programming skills. With Insightful Miner, one can quickly find the answers you need to solve specific business issues and easily communicate your results to colleagues across the organization. As data sets increase in size, traditional data mining tools become less and less efficient for analysis, and in these situations Insightful Miner performs better providing a rich statistical analysis and graphics capability. Thus, this has been chosen for developing DT structure for the proposed study.

The DT analysis is carried out with most splitting setting taking all the extracted features and provides the most significant features which take part in the decision-making process. It is found that though there are 11 features fed to the DT, but finally only three features ($\Delta f/\Delta t, \Delta P/\Delta t, \Delta f$) are used to develop the classification tree as shown in Fig. 2. Thus, DT provides information on the most significant features (3 features) which take part in real decision-making process, leaving rest 8 features redundant. From the classification boundaries of the most significant features resulted from DT, fuzzy membership functions are developed and used in fuzzy rule base for islanding detection.

IV. DT Transformation into the Fuzzy Rule Base

The DT is transformed to a fuzzy rule base by developing the fuzzy membership functions [20] from the partition boundaries of the DT. From the DT boundaries, rectangular MFs are developed for each independent variable. For illustration, consider

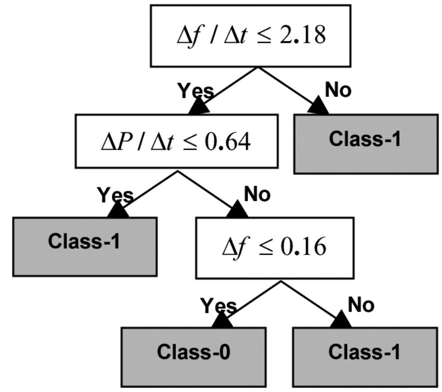

Fig. 2. DT-based islanding detection. Class-1 means islanding and class-0 means nonislanding.

the DT classification boundaries shown in Fig. 3(a). The associated trapezoidal fuzzy MFs [Fig. 3(b) and (c)] are developed for variables X_1 and X_2 as follows:

$$A_1 = \mu\{X_1, [0, 0, a, a]\}$$
$$A_2 = \mu\{X_1, [a, a, c, c]\}$$
$$B_1 = \mu\{X_2, [0, 0, b, b]\}$$
$$B_2 = \mu\{X_2, [b, b, d, d]\}$$

where

$$\mu_j(X_j; a, b, c, d) = \max\left(0, \min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right)\right). \quad (1)$$

From the fuzzy MFs, a simple rule base can be generated for classes 1 and 2 as follows:

If X_1 is A_1 and X_2 is B_1, then Class$-1(C-1)$
If X_1 is A_2 and X_2 is B_2, then Class$-2\,(C-2)$.

From the aforementioned DT-fuzzy transformation technique, the resulting DT output (Fig. 2) is converted to the corresponding fuzzy rule base. The most significant features $\Delta f/\Delta t$, $\Delta P/\Delta t$, Δf are considered as X_1, X_2 and X_3, respectively. Depending upon the values of the above three variables, the classification boundaries are decided for islanding detection. Thus, when X_1 is greater than 2.18, then the class is "1". If X_1 is less than 2.18 and X_2 less than 0.64, then the class "1". If X_2 is greater than 0.64 and X_3 less than 0.1664, then class "0", otherwise class "1". From the DT boundaries, trapezoidal MFs are developed for each variable (X_1, X_2 and X_3). The fuzzy MFs developed for variable X_1 are A_1 and A_2, for X_2 are B_1, B_2, and B_3 for X_3 are C_1, C_2.

Per the above formulations, the rectangular MFs are derived as

$$A_1 = \mu\{X_1, [2.18, 2.18, 34.0, 34.0]\}$$
$$A_2 = \mu\{X_1, [-9.5, -9.5, 2.18, 2.18]\}$$
$$B_1 = \mu\{X_2, [0.64, 0.64, 19.0, 19.0]\}$$
$$B_2 = \mu\{X_2, [-0.5, -0.5, 19.0, 19.0]\}$$
$$B_3 = \mu\{X_2, [-0.5, -0.5, 0.64, 0.64]\}$$
$$C_1 = \mu\{X_3, [0.16, 0.16, 0.6, 0.6]\}$$
$$C_2 = \mu\{X_3, [-0.05, -0.05, 0.16, 0.16]\}.$$

The fuzzy MFs generated from the DT classification boundaries are rectangular in nature. But to further add fuzziness to the membership functions, the rectangular boundaries are skewed to a certain extent by heuristic tuning. The coordinates of the trapezoidal fuzzy MFs are decided after testing on several values around the initial values resulting from DT. Thus, the final fuzzy MFs are

$$\begin{aligned}
A_1 &= \mu\{X_1, [2.18, 2.3, 30.0, 34.0]\}\\
A_2 &= \mu\{X_1, [-9.5, -8.5, 1.95, 2.18]\}\\
B_1 &= \mu\{X_2, [0.64, 0.60, 18.0, 19.0]\}\\
B_2 &= \mu\{X_2, [-0.5, -0.4, 18.0, 19.0]\}\\
B_3 &= \mu\{X_2, [-0.5, -0.4, 0.55, 0.64]\}\\
C_1 &= \mu\{X_3, [0.16, 0.2, 0.5, 0.6]\}\\
C_2 &= \mu\{X_3, [-0.05, -0.03, 0.12, 0.16]\}.
\end{aligned}$$

The corresponding fuzzy rule base is developed for each classification category and given as follows:

$$\begin{aligned}
R1:&\ \text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } B_2, \text{ then Class}-1\\
R2:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_3, \text{ then Class}-1\\
R3:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_1 \text{ and}\\
&\ X_3 \text{ is } C_1, \text{ then Class}-1\\
R4:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_1 \text{ and}\\
&\ X_3 \text{ is } C_2, \text{ then Class}-0.
\end{aligned}$$

In fuzzy rule-based models acquired from numerical data, redundancy may be present in the form of similar fuzzy sets that represent compatible concepts. This results in an unnecessarily complex and less transparent linguistic description of the system. By using a measure of similarity [21], a rule base simplification method is proposed that reduces the number of fuzzy sets in the model. Similar fuzzy sets are merged to create a common fuzzy set to replace them in the rule base. If the redundancy in the model is high, merging similar fuzzy sets might result in equal rules that also can be merged, thereby reducing the number of rules as well.

The similarity measure based on the set-theoretic operations of intersection and union, can be expressed as follows:

$$S(A,B) = \frac{A \cap B}{A \cup B} \tag{2}$$

where $|\cdot|$ denotes the cardinality of a set, and the "$\cap$" and "$\cup$" operators represent the intersection and union, respectively. Rewriting this expression in terms of the membership functions gives

$$S(A,B) = \frac{\sum_{j=1}^{m} [\mu_A(x_j) \wedge \mu_B(x_j)]}{\sum_{j=1}^{m} [\mu_A(x_j) \vee \mu_B(x_j)]} \tag{3}$$

in a discrete universe $X = \{x_j, j = 1, 2, \ldots, m\}$, and "$\wedge$" and "$\vee$" are the minimum and maximum operators, respectively.

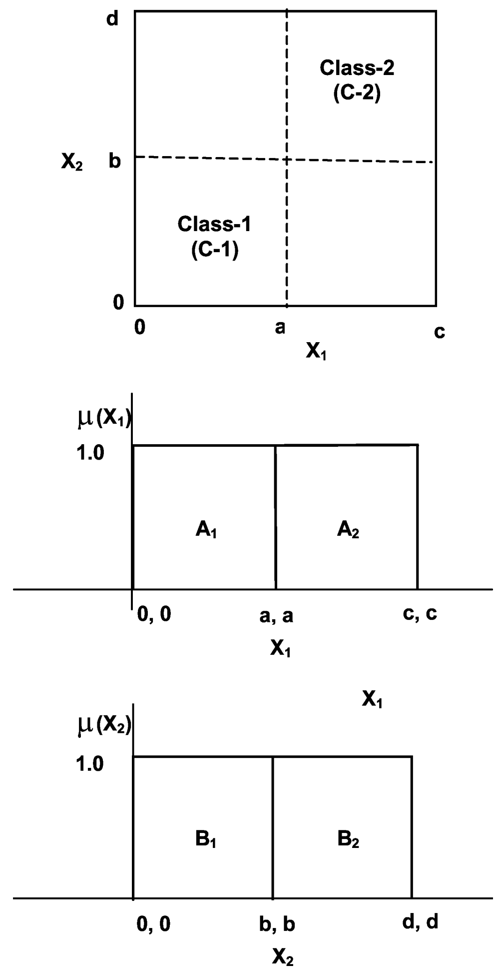

Fig. 3. (a) Decision boundaries of the DT between X_1 and X_2. (b) Fuzzy MF of X_1. (c) Fuzzy MF of X_2.

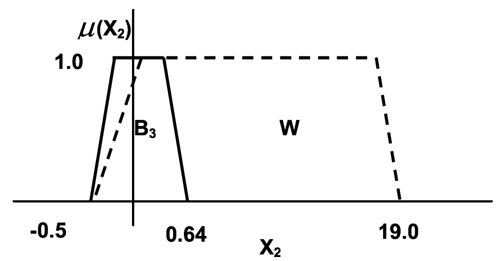

Fig. 4. Fuzzy MFs of X_2 after merging.

Based on the aforementioned criteria, the fuzzy membership function of set "B_1" and "B_2" are merged with a similarity measure of 0.9152 to provide another common fuzzy nembership function $W = \mu\{X_2, [-0.5, 0.1, 18, 19]\}$, shown in Fig. 4.

After merging, there are 6 fuzzy MFs instead of the originally developed 7 MFs. Depending upon the new fuzzy MFs, the rule base is simplified to

$$\begin{aligned}
R1:&\ \text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } W, \text{ then Class}-1\\
R2:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_3, \text{ then Class}-1\\
R3:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } W \text{ and}\\
&\ X_3 \text{ is } C_1, \text{ then Class}-1\\
R4:&\ \text{If } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_1 \text{ and}\\
&\ X_3 \text{ is } C_2, \text{ then Class}-0.
\end{aligned}$$

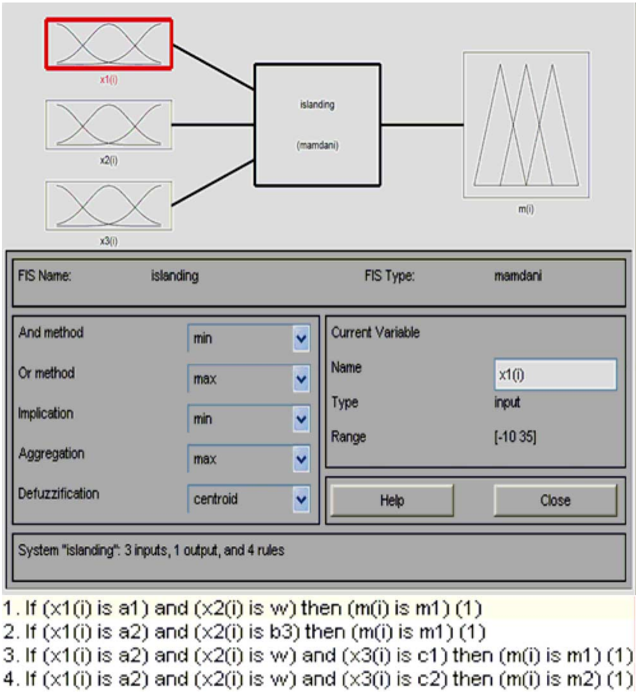

Fig. 5. Fuzzy inference system for islanding detection.

V. Results and Discussion

The details of the fuzzy inference system developed for islanding detection are shown in Fig. 5. The mamdani model with centroid defuzzification is used for implementing the rule base.

Table I provides the test results for different conditions of inputs X_1, X_2, and X_3 for islanding detection. The FIS provides 0.5 for islanding detection and 0 for nonislanding detection. Table II depicts the classification accuracy for data with and without noise. The classification accuracy is 100% on 36 test cases of different conditions for features without noise and with SNR 30 dB. The misdetection and false alarm using only DT is given in bracket (Table III). The misdetection and false alarm conditions for the testing data sets with and without noise have been given in Table III. It is found that there is no misdetection and false alarm in the case of data sets without noise and with SNR 20 dB (Gaussian noise). Only two false alarms are generated in the case of data sets with SNR 20 dB. Thus, the proposed DT initialized fuzzy rule base is found to be accurate and robust for islanding detection. The flowchart for the proposed scheme for islanding detection is given in Fig. 6.

The proposed fuzzy rule base is found to be accurate and robust for islanding detection for wide variations in operating parameters of the distribution network. Although the DT-fuzzy-based approach provides similar results compared to DT only (for our studied database), the fuzzy transformation helps to improve the interpretability of knowledge-based classifiers through its semantics that provide insight in the classifier structure and decision-making process over crisp classifiers. In case of DT only used for the islanding detection task, the scheme is based on an offline decision-making process (a data mining approach) 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 most significant feature and classification boundaries, which are done offline from various derived features. From the DT classification boundaries of the most significant features, fuzzy MFs and the corresponding rule base are formulated for islanding

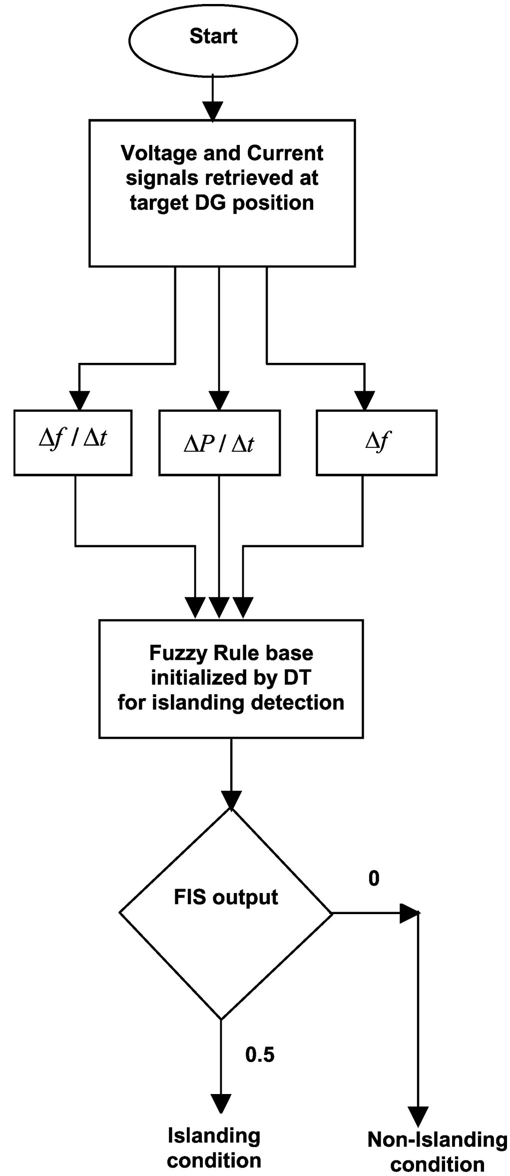

Fig. 6. Flowchart for the proposed fuzzy rule-based scheme for islanding detection.

TABLE I
FIS Output for Different Test Conditions

Sl. No	X_1	X_2	X_3	Actual condition	FIS output
1	11.5	-0.15	0.44	Islanding	0.5
2	-7.5	-0.48	0.09	Islanding	0.5
3	1.9e-5	2.1	1.0e4	Non-Islanding	0
4	1.8e-5	6.0	1.7e-4	Non-Islanding	0
5	3.3	-0.145	-0.014	Islanding	0.5
6	4.6	-0.19	-0.022	Islanding	0.5
7	31	11	-0.048	Islanding	0.5
8	-0.39	4.3	0.0015	Non-Islanding	0
9	-0.35	4.05	0.0017	Non-Islanding	0
10	1.2	6.8	0.03	Non-Islanding	0

TABLE II
CLASSIFICATION RESULTS ON TESTING DATA SETS

Features without noise				
No of cases	Actual Class	Islanding	Non-islanding	Classification Accuracy(%)
18	Islanding	18	0	100
18	Non-islanding	0	18	100
Features with SNR 30 dB				
18	Islanding	18	0	100
18	Non-islanding	0	18	100
Features with SNR 20 dB				
18	Islanding	18	0	100
18	Non-islanding	2	16	88.89

TABLE III
MISDETECTION VERSUS FALSE ALARM

Test data sets	Mis-Detection	False Alarm
36	0 (0)	0 (0)
36 (SNR 30 dB)	0 (0)	0 (0)
36 (SNR 20 dB)	0 (0)	2 (0)

detection. Thus, for final implementation, only three features are derived at the target DG location and directly fed to the fuzzy inference system for islanding detection as shown in Fig. 6.

The proposed fuzzy rule-based classifier is easier to implement for online islanding detection compared to DT only, since DT is an offline data mining algorithm. Also the fuzzy rule base can handle more uncertainties (like noise), which falls on the slope of the fuzzy trapezoidal MFs, compared to the crisp classifiers such as DT having sharp boundaries, with a larger data base. Thus, the superior approximation capabilities of the fuzzy systems over crisp classifiers help to develop the relay to meet the real time application with wide range of uncertainties. The fuzzy MFs can be further tuned to remove redundancy in the model using the real coded genetic algorithm and are being considered for real-time implementation.

VI. CONCLUSION

A DT-initialized fuzzy rule base classifier is proposed for islanding detection. The initial classification model is developed using DT which is a crisp decision tree algorithm. The DT is transformed into a fuzzy rule base by developing fuzzy MFs from the DT classification boundaries. The fuzzy MFs reduction and rule base simplification are performed using similarity measure. The proposed method is tested on data with and without noise and found to provide 100% islanding detection. As the online implementation is easier with a fuzzy rule-based approach, it is thus suitable for developing real time relay for islanding detection in a large power network.

REFERENCES

[1] M. A. Redfern and O. Usta, "A new microprocessor based islanding protection algorithm for dispersed storage and generation units," *IEEE Trans. Power Del.*, vol. 10, no. 3, pp. 1249–1254, Jul. 1995.

[2] T. Funabashi, K. Koyanagi, and R. Yokoyama, "A review of islanding detection methods for distributed resources," in *Proc. IEEE Bologna Power Tech Conf.*, Bologna, Italy, Jun. 23–26, 2003, vol. 2, pp. 23–26.

[3] J. Yin, L. Chang, and C. Diduch, "Recent development in islanding detection for distributed power generation," in *Proc. Large Engineering Systems Conf. Power Engineering*, Jul. 28–30, 2004, pp. 124–128.

[4] S. K. Salman, D. J. King, and G. Weller, "New loss of mains detection algorithm for embedded generation using rate of change of voltage and changes in power factors," in *Proc. Developments in Power System Protection Conf.*, 2001, pp. 82–85.

[5] W. Freitas, Z. Huang, and W. Xu, "A practical method for assessing the effectiveness of vector surge relays for distribute generation applications," *IEEE Trans. Power Del.*, vol. 20, no. 1, pp. 57–63, Jan. 2005.

[6] W. Freitas, W. Xu, C. M. Affonso, and Z. Huang, "Comparative analysis between ROCOF and vector surge relays for distributed generation applications," *IEEE Trans. Power Del.*, vol. 20, no. 2, pt. 2, pp. 1315–1324, Apr. 2005.

[7] G. Hung, C. Chang, and C. Chen, "Automatic phase-shift method for islanding detection of grid-connected photovoltaic inverter," *IEEE Trans. Energy Convers.*, vol. 18, no. 1, pp. 169–173, Mar. 2003.

[8] M. Sumner, B. Patethorpe, D. W. P. Thomas, P. Zanchetta, and M. C. D. Piazza, "A technique for power supply harmonic impedance estimation using a controlled voltage disturbance," *IEEE Trans. Power Electron.*, vol. 17, no. 2, pp. 207–215, Mar. 2002.

[9] J. C. Vieira, W. Freitas, W. Xu, A. Moriduch, and L. Elato, "Performance of frequency relays for distributed generation protection," *IEEE Trans. Power Del.*, vol. 21, no. 3, pp. 1120–1127, Jul. 2006..

[10] J. Yin, C. P. Diduch, and L. Chang, "Islanding detection using proportional power spectral density," *IEEE Trans. Power Del.*, vol. 23, no. 2, pp. 776–784, Apr. 2008.

[11] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees*. New York: Chapman & Hall, 1984.

[12] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Trans. Syst., Man Cybern.*, vol. 21, no. 3, pp. 660–674, Jun. 1991.

[13] H. J. Steadman, E. Silver, J. Monahan, P. S. Apelbaum, P. C. Robbins, E. P. Mulvey, T. Grisso, L. H. Roth, and S. Banks, "A classification tree approach to the development of actuarial violence risk assessment tools," *Law Human Behav.*, vol. 24, pp. 83–100, 2000.

[14] K. R. Hess, M. C. Abbruzzese, R. Lenzi, M. N. Raber, and J. L. Abbruzzese, "Classification and regression tree analysis of 1000 consecutive patients with unknown primary carcinoma," *Clinical Cancer Res.*, vol. 5, pp. 3403–3410, 1999.

[15] G. V. Kass, "An exploratory technique for investigating large quantities of categorical data," *Appl. Statist*, vol. 29, no. 2, pp. 119–127, 1980.

[16] H. Ishibuchi, T. Nakashima, and T. Murata, "Performance evaluation of fuzzy classifier systems for multidimensional pattern classification problems," *IEEE Trans. Syst., Man, Cybern. B*, vol. 29, no. 5, pp. 601–618, Oct. 1999.

[17] Y. Jin, "Fuzzy modeling of high-dimensional systems: Complexity reduction and interpretability improvement," *IEEE Trans. Fuzzy Syst.*, vol. 8, no. 2, pp. 212–221, Apr. 2000.

[18] K. El-Arroudi, G. Joos, I. Kamwa, and D. T. McGillis, "Intelligent-based approach to islanding detection in distributed generation," *IEEE Trans. Power Del.*, vol. 22, no. 2, pp. 828–835, Apr. 2007.

[19] [Online]. Available: http://www.insightful.com

[20] J. Abonye, J. A. Roubos, and F. Szeifert, "Data driven generation of compact, accurate, and linguistically sound fuzzy classifiers based on a decision tree initialization," *Int. J. Approximate Reason.*, vol. 32, pp. 1–21, 2003.

[21] M. Setnes, R. Babuska, and H. R. Lemke, "Similarity measures in fuzzy rule base simplification," *IEEE Trans. Syst., Man, Cybern. B*, vol. 28, no. 3, pp. 376–386, Jun. 1998.

S. R. Samantaray (M'08) received the B.Tech. degree in electrical engineering from UCE Burla, India in 1999 and the Ph.D. degree in power system engineering from the National Institute of Technology (NIT), Rourkela, Orissa, India, in 2007.

Dr. Samantaray was with the TATA Group, working in the area of power systems, industrial automation, and instrumentation for almost four years. Currently, he is Associate Professor in the Department of Electrical Engineering, NIT. He visited the Department of Electrical and Computer Engineering, McGill University, Montreal, QC, Canada, as a Postdoctoral Research Fellow in 2008 and again in 2009. His major research interests include intelligent protection, digital signal processing, soft computing, flexible ac transmission systems, distributed generation, and dynamic security assessment.

Dr. Samantaray is the recipient of the Orissa Bigyana Academy Young Scientist Award in 2007; the Innovative Student Projects Award (doctoral level), Indian National Academy of Engineering, India, in 2008; and the Institute of Engineers, India (IEI) Young Engineers Award in 2009.

Khalil El-Arroudi received the B.Sc. and M.Sc. degrees from Garyounis University, Benghazi, Libya, in 1985 and 1994, respectively, and the Ph.D. degree from McGill University, Montreal, QC, Canada, in 2004.

He is with the General Electricity Co. of Libya (GECOL), first starting as Protection Engineer and then becoming Head of the Eastern System Protection Department in 1992. Currently, he is the Manager of System Protection and Control of the GECOL systems, including generation, transmission, and subtransmission.

Geza Joós (M'82–SM'89–F'06) received the M.Eng. and Ph.D. degrees from McGill University, Montreal, QC, Canada.

Currently, he is a Professor at McGill University, where he has been since 2001. He holds a Canada Research Chair in Power Electronics applied to Power Systems. He is involved in the fundamental and applied research related to the application of high-power electronics to power conversion, including distributed generation and wind energy, and to power systems. He was previously with ABB, the Ecole de Technologie Supérieure, and Concordia University. He is involved on a regular basis in consulting activities in power electronics and power systems.

Dr. Joós is active in a number of IEEE Industry Applications Society committees and in IEEE Power Engineering Society working groups, and in CIGRE working groups. He is a Fellow of the Canadian Academy of Engineering and of the Engineering Institute of Canada.

Innocent Kamwa (S'83–M'88–SM'98–F'05) received the Ph.D. degree in electrical engineering from Laval University, Laval, QC, Canada, in 1988.

Since then, he has been with the Hydro-Quebec Institute/IREQ, Power System Analysis, Operation and Control, Varennes, QC, Canada, where he is currently a Principal Researcher in bulk system dynamic performance. He has been an Associate Professor of Electrical Engineering at Laval University since 1990.

Dr. Kamwa has been active for the last 13 years on the IEEE Electric Machinery committee where as a Working Group Chair and Secretary, he contributed to the latest standards 115 and 1110. A member of CIGRÉ and a registered professional engineer, Dr. Kamwa is a recipient of the 1998 and 2003 IEEE Power Engineering Society Prize Paper Awards and is currently serving on the Adcom of the IEEE System Dynamic Performance Committee.