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ISLANDING DETECTION IN DISTRIBUTED GENERATION USING FUZZY LOGIC

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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.

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 favourable 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 non detection zone compared to passive approaches. However, the power quality (PQ) of the inverter can be degraded by the perturbation. Different method for islanding detection techniques have been reported in recent years. Some of the papers provide detailed review of islanding detection for DGs in distributed networks. The islanding detection based upon the rate-of-change of power signal , the rate-of-change of voltage and change in power factor , the vector surge technique , the rate-of-change of frequency , the phase-shift method , the harmonic impedance estimation technique 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. 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) 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 non axis 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 partitioning and rule generation on extreme initialization result in complex and no interpretable 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 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.

II. STUDIED SYSTEM AND FEATURE EXTRACTION

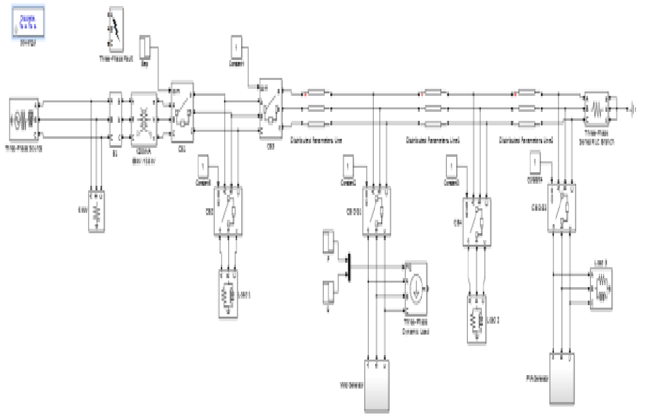

Fig-1 Proposed System

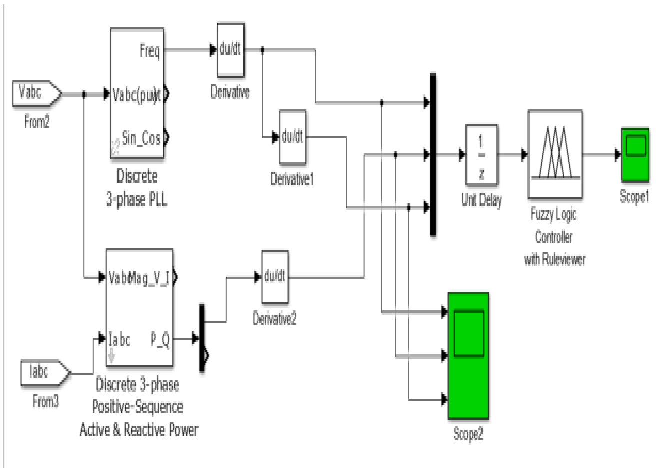

Fig-2 Fuzzy Inference System

- Generator Data: Three phase Source, Rated short circuit= 1000 MVA Phase to phase rms voltage= 69 KVA, Frequency= 60 Hz, X/R ratio 7.
- Transmission lines data ;Rated kV=13.8, rated MVA=20,Vbase =13.8 kV,R0L= 0.0414 ohms/km,R1L=0.0138 ohms/km , X 0L= 0.0534 ohms/km, X1L=0.0178 ohms/km ,X0CL= 5.1 nF/km, X1CL=17 nF/km, Line 1= 20 km, Line 2= 10 km, Line 3= 10 km
- Normal Loading data : (Rated kV=13.8)L-1=10MW,3.5MVAR. L-2=5.0 MW,2.0 MVAR,L-3=1 MW,0.5MVAR, L-4=5.0mMW, 2.0 MVAR.
- DG-1: Wind Generation, 6 DFIG, Rated 2.5MVA/DFIG.
- DG-2: PVA Generator, PV Array Module- Sun Power SPR-305-WHT

The various features are collected at the PCC 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.

The aforementioned features are extracted under different islanding and non islanding 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 by 40%.

6) Condition-6: Tripping of the largest distributed resource within the DG other than the target one.

III. DECISION TREE FOR INITIAL CLASSIFICATION

DT 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” 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 (df/ dt, dP/ dt, df) 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

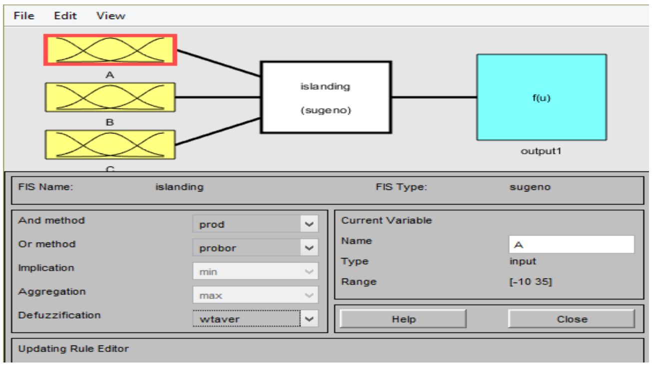

Fig-3 Fuzzy Ruler

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.

$A1 = \mu\{X1,[0,0,a,a]\}$ $A2 = \mu\{X1,[a,a,c,c]\}$ $B1 = \mu\{X2,[0,0,b,b]\}$ $B2 = \mu\{X2,[b,b,d,d]\}$ where $\mu_j(Xj;a,b,c,d) = \max(0,\min(x\text{-}a/b\text{-}a,1,d\text{-}x/d\text{-}c))$ From the fuzzy MFs, a simple rule base can be generated for classes 1 and 2 as follows:

1. If X1 is A1 and X2 is B1 ,then Class-1 (C-1)
2. If X1 is A2 and X2 is B2 ,then Class-1 (C-2)

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

R1: If X1 is A1 and X2 is B2, then Class -1
R2: If X1 is A2 and X2 is B3, then Class -1
R3: If X1 is A2 and X2 is B1 and X3 is C1, then Class -1
R4: If X1 is A2 and X2 is B1 and X3 is C2, then Class -0

V. RESULT AND DISCUSSION

The details of the fuzzy inference system developed for islanding detection are shown in Fig.3. The Sugeno model with weighted average defuzzification is used for implementing the rule base. The FIS provides 0.5 for islanding detection and 0 for non islanding detection as shown in Fig-4. The Sample time is 0.4s and the simulation is set up to create all condition at 0.2s. As per result the islanding is detected at 0.2026s which is quite less than other techniques.

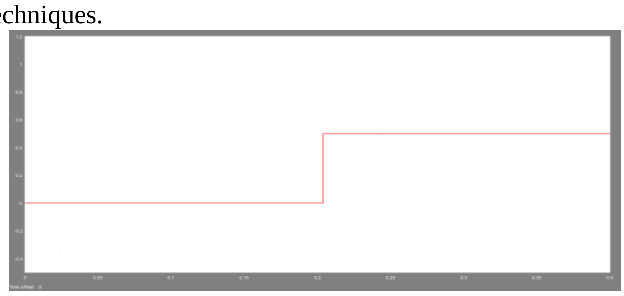

Fig-4 FIS Output

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 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. 5.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.

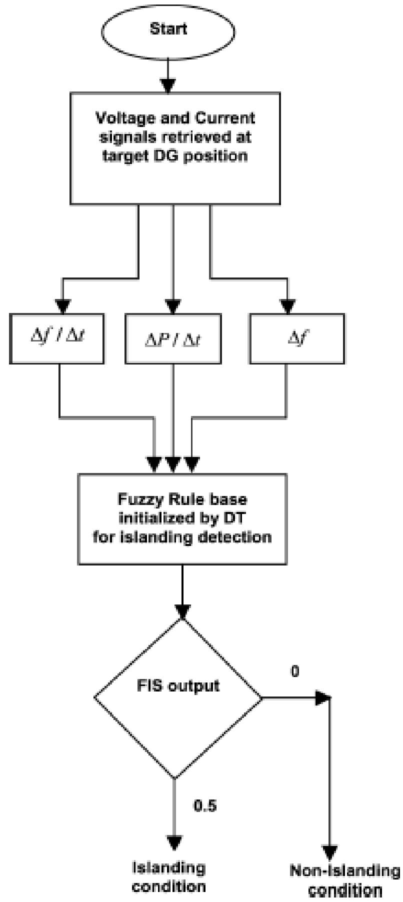

Fig-5 Flowchart for Flowchart for the proposed fuzzy rule-based scheme for islanding detection

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 on- line 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.

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