Islanding Detection of Distribution Generator in Microgrid System

Sumit Rajendra Gotmare[1] Prof. Chetan M. Bobade[2]
[1]PG Student [2]Head of Department
[1,2]Department of Electrical Engineering
[1,2]G.H.Raisoni University, Amravati, India

Abstract— Distributed Generation (DG,) is a new source which is used in distribution systems. DGs are connected directly by distribution system operators or indirectly by customers. The DGs usually are connected near the consumer load centers. The high use of DGs leads to improvement of power quality, improvement of voltage profile, a decrease of losses. Due to the increasing need to distributed energy resources in power systems, their problems should be studied. One of the main problems of distributed energy resources is unplanned islanding. The unplanned islanding has some dangers to the power systems and the repairman which are works with the incorrect devices. The proposed method is based on wavelet transform and a new classifier named as Artificial Neural Network (ANN) and Support Vector Machine (SVM). The proposed method is implemented on a 14 IEEE bus grid in MATLAB/SIMULINK software. The results show the high accuracy of islanding detection of the proposed method. In this paper, five generator as wind turbine is assumed as a distributed resource. At last, comparison of ANN and SVM are compared and finally conclusion provide for best classifier for islanding detection for distributed generator system.

Keywords: Microgrid System, MATLAB/SIMULINK

I. Introduction

Distributed Generation (DG,) is a new source which is used in distribution systems. DGs are connected directly by distribution system operators or indirectly by customers. The DGs usually are connected near the consumer load centers. The high use of DGs leads to improvement of power quality, improvement of voltage profile, a decrease of losses.

In another hand, the reduction of fossil energies and environmental issues forces the countries to use the distributed energy resources (DER). The main DERs which are used in the world are wind energy, solar energy, fuel cells, and micro-turbines. The islanding detection of DERs when is connected to a distribution system is a vital problem. The islanding detection methods are divided into four main categories names Remote methods, local methods, signal processing methods and intelligent classifiers based methods.

Local methods are divided into two subcategories named active and passive. In passive local methods, the islanding status is detected based on assessing and monitoring of voltage or current waveforms of DG connection point. When the difference between the demand and generation in the distribution system is low, the islanding detection of distribution system with passive methods became difficult. The situation in which the islanding detection methods cannot detect the islanding status correctly is defined as None Detection Zone (NDZ) of each method.

The passive methods have big NDZs, so, the researchers suggest the active methods. In active methods, a voluntary disturbance is applied to the network, and the network response is assessed. The active methods have no NDZ, but the methods are so complicated and have undesirable effects on the power quality of the power system. In another hand, the passive methods are so simple and have no effect on the power quality of the network.

A passive method is presented which has been used adaptive identifier method for estimating of the frequency deviation of the point of common coupling (PCC) link as a target signal that can detect the islanding condition with near-zero active power imbalance.

Main advantage of the adaptive identifier method over other signal estimation methods is its small sampling window. The utility circuit breaker current has been measured at the grid side, and the islanding condition has been detected based on a feature extracted from the measured signal before the utility circuit breaker opening. Discrete wavelet transform has been used to extract the features of the measured current, and then, the artificial neural network has been trained in order to detect the islanding conditions based on the extracted features. A new islanding detection method based on the chaos theory that can detect the islanding condition with near-zero active power mismatch has been introduced. The method has been used the modified frequency of the point of common coupling (PCC) link as an input signal of forced Helmholtz oscillator. The obvious change between chaotic and normal motions in the forced

Helmholtz oscillator is its main advantage over other oscillators. The W-transform and S-transform have been used to extract the negative sequence voltage during an islanding event. The energy content and standard deviation of the S-transform contour has been clearly shown in detecting islanding events and disturbance because of load rejection. The ANNs have been combined with Wavelet, which is capable of decomposing the signals into different frequency bands. The features have been then trained using the ANN model to identify the islanding condition. The approach can detect islanding conditions with a high degree of accuracy and high-quality factor of load performance.

II. Proposed Methodology

Figure 1 shows the generalized block diagram of proposed islanding detection of distributed generator system. A 14 bus IEEE standard system is design in MATLAB simulink modeling software. In this system, there are five distributed generator are connected at different bus bars. Islanding moments is generated at each generator using circuit breaker simulation time adjustment.

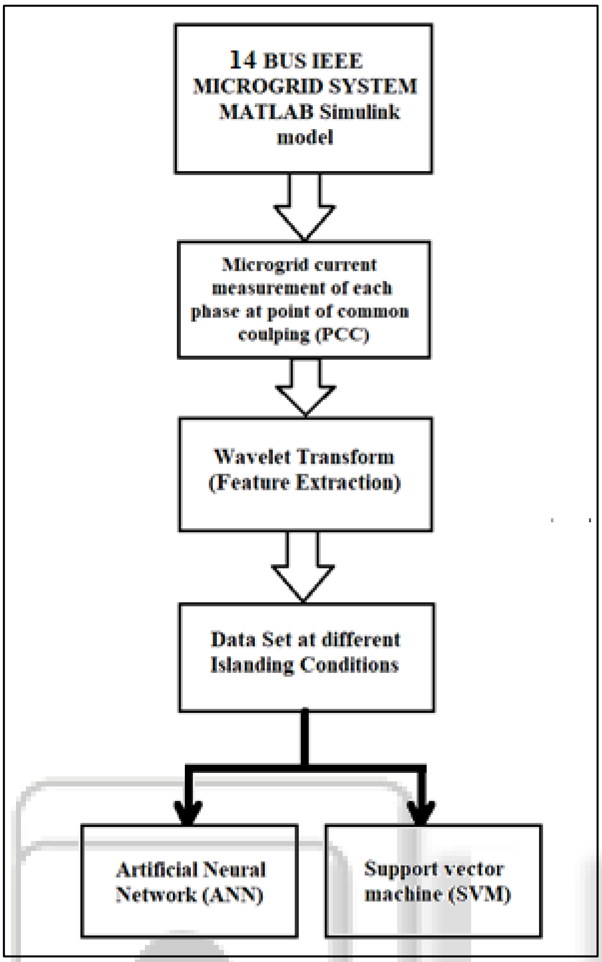

Fig. 1: Generalized block diagram of proposed approach

Then three phase current of IEEE bus system is measured at bus bar 7 which is common bus bar for 14 Bus system model. That measured current is send to wavelet multi-resolution analysis (MRA) based system. Then features extract after MRA send to spectral energy calibration subsystem for calibration of spectral energy of current signal which measured at bus bar 7.

This spectral energy is calibrated for three phase current for different islanding conditions at different distribution generation system. That calibrated spectral energy data is then utilized for training of Artificial Neural Network (ANN) and Support vector Machine (SVM).

III. MATLAB SIMULATION MODEL

A. Complete simulation model

Figure 2 shows the complete matlab simulink model of proposed approach in which IEEE 14 bus subsystem, Wavelet transform subsystem model is design for taking the reading during different islanding condition.

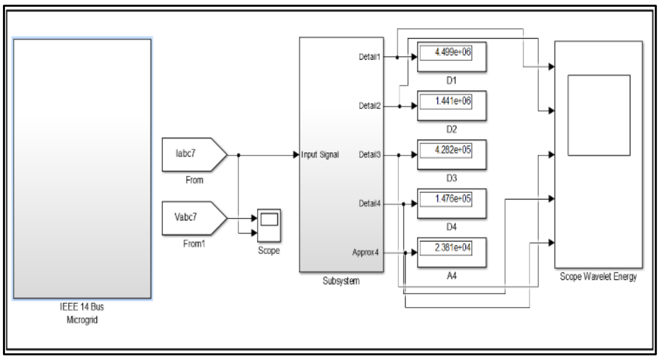

Fig. 2: MATLAB Simulink model of complete system

B. IEEE 14 Bus Subsystem

Figure 3 shows the complete IEEE 14 bus subsystem model. The transmission line connected in between each bus bar and transmission line resistance, inductance and capacitance shown in table 1. There are five generator are connected at bus bar 1, 2, 3, 6, and 8 while RL loads are connected at remaining bus for system. Table 2 shows the bus bar generator and load data for IEEE 14 bus system.

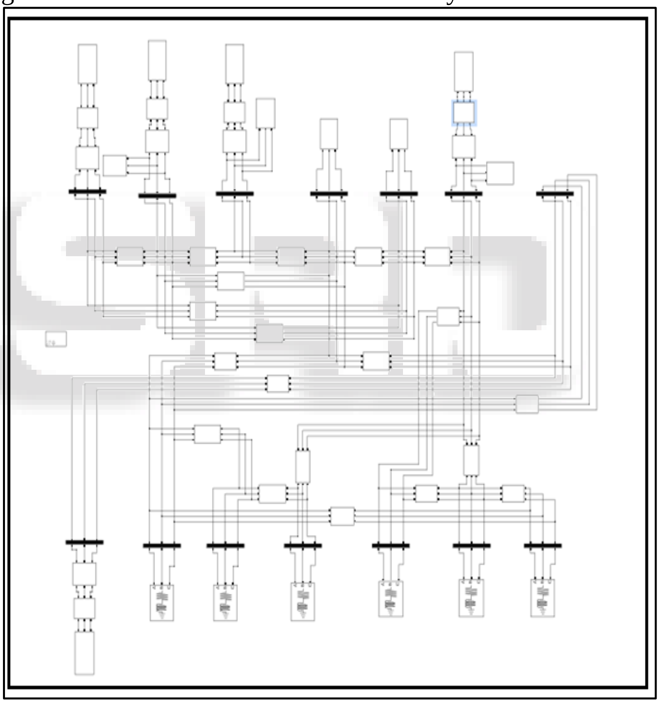

Fig. 3: MATLAB simulation of IEEE 14 Bus subsystem model

Line Number	From Bus	To Bus	Line impedance (pu) Resistance (pu)	Line impedance (pu) Inductance (pu)	MVA Rating
1	1	2	0.01938	0.05917	120
2	1	5	0.05403	0.22304	65
3	2	3	0.04699	0.19797	36
4	2	4	0.05811	0.17632	65
5	2	5	0.05695	0.17388	50
6	3	4	0.06701	0.17103	65
7	4	5	0.01335	0.04211	45
8	4	7	0	0.20912	55
9	4	9	0	0.55618	32
10	5	6	0	0.25202	45
11	6	11	0.09498	0.1989	18

12	6	12	0.12291	0.25581	32
13	6	13	0.06615	0.13027	32
14	7	8	0	0.17615	32
15	7	9	0	0.11001	32
16	9	10	0.03181	0.0845	32
17	9	14	0.12711	0.27038	32
18	10	11	0.08205	0.19207	12
19	12	13	0.22092	0.19988	12
20	13	14	0.17093	0.34802	12

Table 1: IEEE 14 Bus System Matalb Simulation Transmission Line Data

Bus bar No	Bus voltage (pu)		Generation (pu)		Load	
	Magnitude (pu)	Phase difference (pu)	Real power (MW)	Reactive Power (MVAR)	Real power (MW)	Reactive power (MVAR)
1	1.060	0	114.17	-16.9	0	0
2	1.045	0	40	0	21.7	12.7
3	1.010	0	0	0	94.2	19.1
4	1	0	0	0	47.8	-3.9
5	1	0	0	0	7.6	1.6
6	1	0	0	0	11.2	7.5
7	1	0	0	0	0	0
8	1	0	0	0	0	0
9	1	0	0	0	29.5	16.6
10	1	0	0	0	9	4.8
11	1	0	0	0	3.5	1.8
12	1	0	0	0	6.1	1.6
13	1	0	0	0	13.8	4.8
14	1	0	0	0	14.9	5
1	1.060	0	114.17	-16.9	0	0
2	1.045	0	40	0	21.7	12.7
3	1.010	0	0	0	94.2	19.1
4	1	0	0	0	47.8	-3.9
5	1	0	0	0	7.6	1.6

Table 2: IEEE 14 Bus System Bus Bar and Generator Data for MATLAB Simulink Model

C. *Wavelet Transform subsystem*

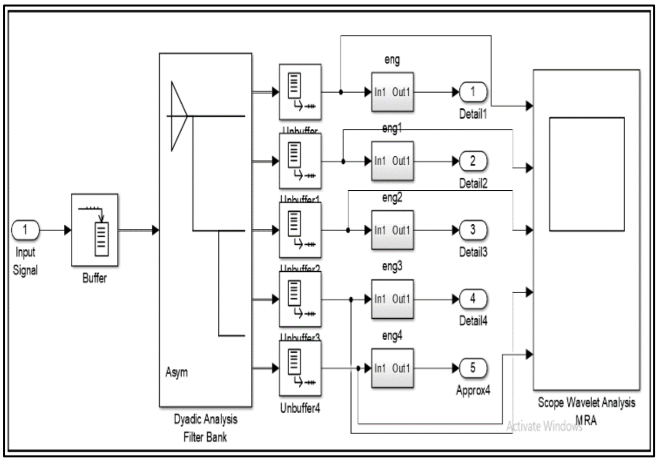

Fig. 4: MATLAB simulink model of wavelet transform and spectral energy calibration subsystem model

Figure 4 shows the wavelet multi resolution analysis subsystem with spectral energy calibration subsystem shown in figure 5. The total four level use for multi-resolution analysis using Daubechies 2 (Db2) mother wavelet. Input for mother wavelet is input three phase current measured at bus bar 7 of IEEE system while output is wavelet features of Detail D1 to D4 and Approximation A4 at level 4. Then after spectral energy of D1 to D4 and A4 are calibrated using spectral energy calibration subsystem connected at each signal shown in figure 5.

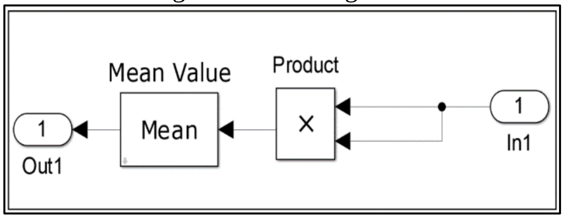

Fig. 5: Spectral Energy calibration subsystem MATLAB simulink model

D. *ANN Subsystem model*

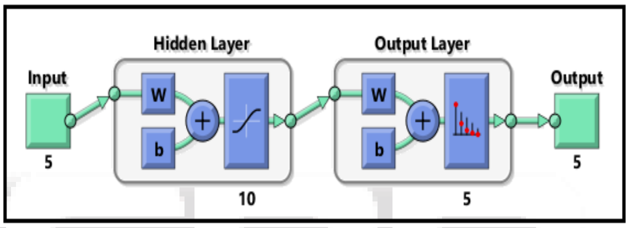

Fig. 6: ANN configuration for islanding classification

Figure 6 shows the Generalized structure of Artificial Neural Network in which there are total 10 number of neurons in hidden layer while 5 neurons in output layer. Total number of inputs and outputs are 5 and 5 respectively. Inputs are calibrated spectral energy of Details D1 to D4 and Approximation A4 while outputs are five generator location for islanding detection.

IV. SIMULATION RESULTS

A. *Three phase voltage and current measurement*

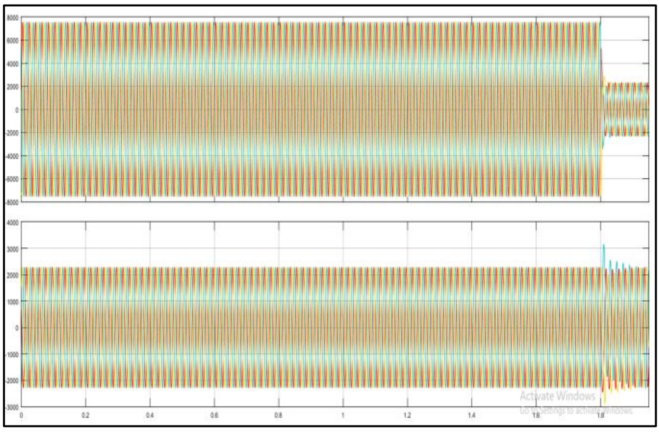

Fig. 7: Three phase voltage and current of IEEE 14 bus system when islanding occurs at generator 5 at 1.8 sec time

Figure 7 Shows three phase voltage and current measured at bus bar 7 of IEEE 14 bus microgrid system during islanding occurs at generator 5 at 1.8 sec simulation time. Upper axis shows the three phase voltage which drop from 1.8 second but not zero because of islanding occurs at generator 5 while current of system also drops from 1.8 sec simulation time.

B. Wavelet Spectral energy calibration

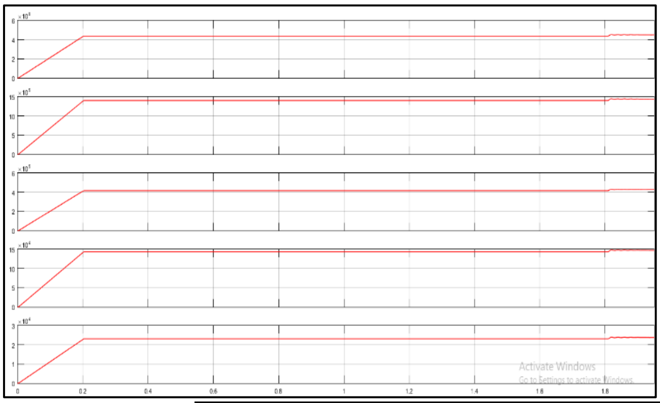

Fig. 8: Wavelet spectral energy of multi resolution analysis signals detail D1 to D4 and Approximation A4 signal of three phase current when islanding occurs at generator 5 at 1.8 sec

Figure 8 shows the wavelet spectral energy calibration of Detail D1 to D4 and Approximation A4 signal after wavelet multi-resolution analysis of three phase current of IEEE 14 bus microgrid system. This figure shows the spectral energy during islanding occurs at generator 5 at 1.8 second simulation time.

C. Data set for Islanding Detections

Table III shows the input data set for ANN and SVM for classification of different islanding detection at different generator which is target of input data shown in table IV.

Gen No	Time of islanding	D1	D2	D3	D4	A4
1	0.2	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	0.4	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	0.6	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	1	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	1.2	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	1.5	2.43E+06	7.80E+05	2.32E+05	8.00E+04	1.29E+04
1	1.8	2.51E+06	8.03E+05	2.39E+04	8.24E+04	1.33E+04
2	0.2	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	0.4	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	0.6	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	1	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	1.2	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	1.5	3.84E+05	1.23E+05	3.66E+04	1.26E+04	2031
2	1.8	1.54E+06	4.94E+05	1.47E+05	5.08E+04	8214
3	0.2	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	0.4	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	0.6	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	1	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	1.2	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	1.5	3.83E+05	1.23E+04	3.65E+04	1.26E+04	2026
3	1.8	1.55E+06	4.95E+05	1.48E+05	5.09E+04	8241
4	0.2	2.16E+05	6.91E+04	2.05E+04	7088	1140

Table 3: Input Training Data Set For Classification of Islanding Event Detection

Case No	Gen 1 Isn	Gen 2 Isn	Gen 3 Isn	Gen 4 Isn	Gen 4 Isn
1	1	0	0	0	0
2	1	0	0	0	0
3	1	0	0	0	0
4	1	0	0	0	0
5	1	0	0	0	0
6	1	0	0	0	0
7	1	0	0	0	0
8	0	1	0	0	0
9	0	1	0	0	0
10	0	1	0	0	0
11	0	1	0	0	0
12	0	1	0	0	0
13	0	1	0	0	0
14	0	1	0	0	0
15	0	0	1	0	0

16	0	0	1	0	0
17	0	0	1	0	0
18	0	0	1	0	0
19	0	0	1	0	0
20	0	0	1	0	0
21	0	0	1	0	0
22	0	0	0	1	0

Table 4: Target Training Data Set For Classification of Islanding Event at Various Generator Location

D. Artificial Neural Network (ANN) Results

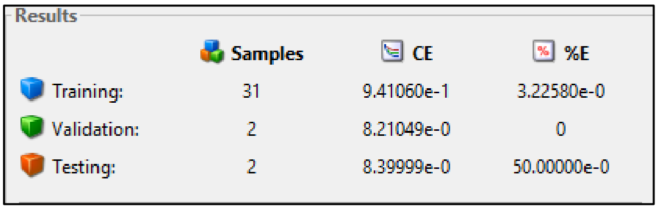

Fig. 9: Training results after training of ANN

Figure 9 shows, for training of ANN, total 35 data sample was utilized out of which 31 data set i.e. 90% data utilized for training. For validation and testing 5% dataset was utilize i.e. 2 sample data set. Also MSE (Mean square error) for all data set was 0.50 % after successful training of ANN.

Figure 10 shows that 94.3 % data are perfectly classify the different islanding detection and 5.7% data not classify properly i.e. ANN not confused for classification. It means that for remaining 5.7 % data set neural network was in confusion state for classify islanding detection i.e. not confused for training of data.

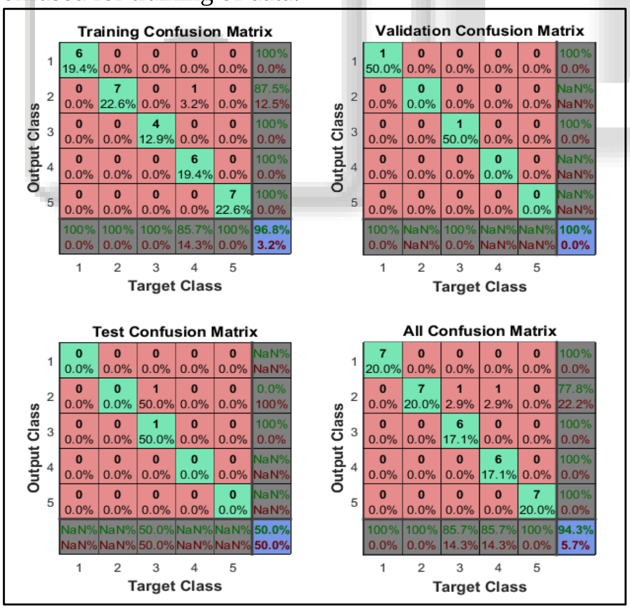

Fig. 10: Confusion matrix of ANN after training

E. Support Vector machine (SVM) Approach

Figure 11 shows the support vector machine (SVM) input and target data set selection subsystem. In which columns 1 to 5 consider as predictor i.e. inputs while column 6 data is selected as response of SVM. While columns 1 to 5 consist of spectral energy of Details D 1 to D4 and Approximation A4 while column 6 consist of classes of different islanding of generator.

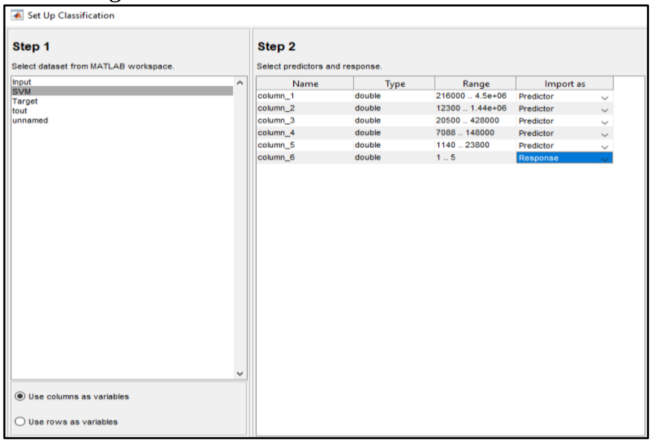

Fig. 11: SVM designing window in MATLAB simulink

Figure 12 shows the support vector machine data set prediction subsystem window in matlab simulink. It is observed that 74.3 % data set is classified by the linear support vector machine tool for different arc zone classification as well as normal condition i.e. without arc conditions.

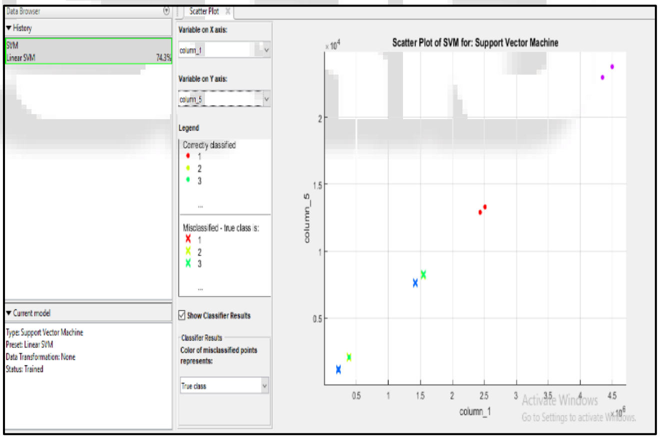

Fig. 12: SVM results after training between input D1 and output as islanding generator number

V. Conclusion

The proposed method is based on wavelet transform and a new classifier named as Artificial Neural Network (ANN) and Support Vector Machine (SVM). The proposed method is implemented on a 14 IEEE bus grid in MATLAB/SIMULINK software. The results show the high accuracy of islanding detection of the proposed method. In this paper, five generator as wind turbine is assumed as a distributed resource. This method implemented for classify or detection of islanding of generator in IEEE 14 bus system.

In this paper we were classify the islanding generator number using ANN and SVM classifier. It is observed that ANN classify the event of islanding upto 94.3% while SVM classify the event of islanding of generator upto 74.3%. Hence it is clear that ANN provide best classification results for detection of islanding generator number event.

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