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Islanding Detection Method Based Artificial Neural Network

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ABSTRACT. *This paper presents a new islanding detection technique based on an artificial neural network (ANN) for a doubly fed induction wind turbine (DFIG). This technique takes advantage of ANN as pattern classifiers. Five different ANN systems are presented in this paper based on various inputs: three phase power, phase voltage, phase current, neutral voltage, and neutral current. An ANN structure is trained for each input, and the comparison between the different structures is presented. Feedforward ANN structures are used for the five systems. Three different learning algorithms are used: backpropagation and two artificial optimization techniques: Genetic Algorithm (GA) and Cuckoo optimization algorithm. For each method in each training technique, the results and the cost function are presented. The comparison of different inputs different algorithms is conducted. MATLAB 2020a is used to simulate the ANN structure and code the training algorithms. A detailed discussion of the input sample rate has also been manipulated to make the computational burden a factor in assessing the performance.*

Keywords: Islanding Detection Method (IDM), Artificial neural network (ANN), Genetic Algorithm, Cuckoo algorithm, optimization, backpropagation, feedforward, distributed energy resources (DER), double fed induction wind turbine (DFIG), micro-grid.

1. Introduction.

Islanding detection is one of the most critical issues considered in any distributed energy resource (DER). Islanding occurs when a part of the distribution system becomes isolated from the main supply. If islanding is detected, the DER should be tripped out. Typically, a DER should be disconnected within 0.1-2 seconds after the loss of the main supply [1-3]. If the islanding is failed to detect, the islanding may lead to power inequality issues and safety issues for machines and humans. Different techniques are presented in the literature for these purposes. These techniques can be broadly divided into remote and local techniques. Remote techniques are associated with islanding detection on the supply side and the local on the DER side. In remote techniques, communication is needed to send a trip signal to the DER when the islanding is detected. Furthermore, Local algorithms divide into passive, active, and hybrid methods.

The main philosophy of the local techniques is based on monitoring the output of the DER and detecting the status of the main supply. This monitoring may base on output power, voltage, frequency, current, etc. If the external source (auxiliary) injects current, power, harmonic…. to the system, in parallel with the monitoring, the technique is called active techniques, otherwise it is called passive technique.

Some of the remote detection techniques presented in the literate are based on the transfer scheme trip and power line signaling scheme. The concept of the transfer trip scheme is based on monitoring all breaker status and sent a trip signal to the DER if the islanding is detected. Supervisory control and data acquisition (SCADA) [4], or wide-area monitoring system (WAMS) [5-6] are used as remote IDM. The signal is continuously generated at the transmission side in the signaling technique, and the DER has a receiver to detect this signal. In these techniques, the islanding status is proved if the DER does not receive any signal [7-9]. A high-frequency impedance estimation-based technique is an example of active detection techniques [10]. In [10], the potential failure mechanism of the f-Q (frequency-reactive power) drifting is analyzed. Then, the researchers proposed a high-frequency transient injection-based islanding detection method. From the results of this paper, the high-frequency temporary injection method is better than the traditional injection method. Another researcher presents a detection method as an example of passive techniques in [11]. In [11], researchers using the Forced Helmholtz Oscillator to the signal at the point of common coupling. The dynamic characteristics of the synchronous generator and signal processing technique are presented in [12]. This paper proposes a hybrid islanding detection method for distribution systems containing synchronous distributed generation (SDG) based on two active and reactive power control loops and a signal processing technique.

Other techniques based on artificial neural network are presented in [13-15]. In [13], the proposed artificial neural network (ANN) employs minimal features of the power system. The performance comparison between stand-alone ANN, ANN- evolutionary programming, and ANN- particle swarm optimization in the form of regression value is performed. In [14], a new composite approach based on wavelet-transform and ANN for islanding detection of distributed generation is presented. The wavelet transform is used to detect events, and then the artificial neural network (ANN) is used to classify islanding and non-islanding events. In [15], the S-transform is used to obtain the frequency spectrum at the terminals of the DER; then, the ANN is used to identify whether the event is islanding. Like other protection functions [16-18], WAMS and machine learning can be used to detect the islanding in the system and send a protection signal to the remote protective relays to prevent any mis operation. Still, it is expensive to apply and need a good communication infrastructure.

This paper is organized as follows: Section II presents the ANN structures and the used learning techniques. Section III offers the proposed ANN structure for the three systems. The simulation results and comparisons are shown in section IV. Then the conclusion is presented in Section V.

2. ANN and Learning Techniques

2.1 Feed-Forward ANN structure ANN is a learning technique used in different areas for different purposes. The very widely used applications of ANN are classification applications. The main structure of the ANN is shown in Figure 1.

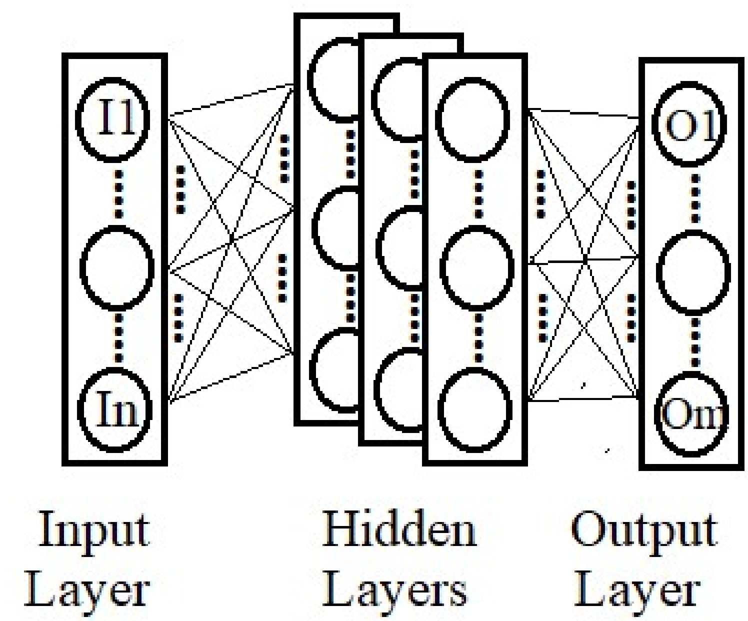


FIGURE 1. General feedforward ANN structure

In general, ANN has three types of layers: an input layer has n neurons, hidden layer(s), and the output layer has m neurons. Where n and m are the number of inputs and outputs, respectively. The number of hidden layers and the neurons in each hidden layer is adjustable. The optimal number of layers needs more information about the problem to identify. For this study, the number of layers and neurons are selected based on experience; then, general formula to determine the number of neurons in each layer is proposed. Each neuron has an activation function, so the neurons' output is a function of the sum of the inputs (net). Different activation functions are available to use. These activation functions may be divided into step, linear, and nonlinear functions in general. Other nonlinear functions are presented in the literature include sigmoid function, hyperbolic tangent function, rectified linear unit function, leaky rectified linear unit function, soft-max function, and switch function. Each of these functions has advantages and disadvantages. The selection of the activation function is based on the application. The sigmoid function is the most common. Each neuron in layer (i) connects with each neuron in layer (i+1) via a weight. The arrows in Figure 1 refer to the weights.

The weights in the structure are defined by the learning technique based on the inputs/outputs samples. The training samples should represent the overall behavior. The output samples are called targets, where the outputs of the neural network are called outputs. The learning techniques are mainly optimization techniques. The cost function of the methods is to minimize the sum of the absolute (square) error between the output and the target. Once the outputs and the targets are very close together, the learning is done. The backpropagation learning technique is very commonly used in this context. The main disadvantage of this algorithm is the highest probability of sticking to a local solution. Based on this concept, any optimization algorithm (hard or soft computational techniques) can be used to solve this optimization problem. In this paper, two soft computational methods: Genetic algorithm (GA) and cuckoo algorithm (CA) and one hard computational technique (backpropagation), are used and then compared.

2.2 Genetic Algorithm.

Genetic algorithm (GA) is one of the very widely used techniques in optimization problems. This algorithm is based on the concept of human gene behavior. Firstly, a considerable population generated randomly has a specific number of randomly proposed solutions. Each solution is called a gene. The behavior of these genes is getting from the cost function (the value of the cost function at a specific solution 'chromosome'). If the problem is to maximize, the chromosomes with the highest values have the best performance and vice versa. From the first iteration, the chromosome which has better performance is selected, then these chromosomes will be mated to get a new population. The mating is similar to human mating, but for variable cross-over, so the latest population performs better than the old one. This procedure will repeat more and more to get the specific cost function. The mutation idea is created to prevent any predicted local solution. In the mutation process, the genes in the chromosomes are changed randomly. This simple step is used to add noise to the signal, which will help the algorithm to go over any local solution.

2.3 Cuckoo Algorithm

This algorithm is inspired by the eggs laying feature of a family of birds called Cuckoo. Like other evolution approaches, Cuckoo start by generation random population. There are two types of population: cuckoo bird and eggs, each Cuckoo has a nest with an arbitrary number of eggs, and each egg refers to a proposed solution. The position of eggs in the nest is organized based on the egg-laying radius (ELR). Cuckoos search for the best area to maximize their eggs' life lengths. After hatching and turning into adult cuckoos, they form societies and communities. Each community has its habitat to live in. The best habitat of all communities will be the next destination for cuckoos in other groups. All groups immigrate to the best current existing area. Each group will be the resident in an area near the best current existing site. An egg-laying radius (ELR) will be calculated regarding the number of eggs each Cuckoo lays and its distance from the current optimized area.

2.4 Backpropagation algorithm

For the first iteration, the weights are selected randomly. Then the output of each neuron is calculated for each input sample. A weight will be modified to decrease the error. So, the weights' effect on the total error is calculated (a partial derivative of the error to the weight i). For all weights, the derivative is added in the first iteration. Then the new weights are used for the next iteration and so on.

3. Proposed ANN Structure.

In this paper, three different systems are designed: Power-based system, voltage-based system, and current-based system. Five different sampling rates are tested: 400 Hz, 800 Hz, 1600 Hz, 3200 Hz, and 6400 Hz (8, 16, 32, and 64 per cycle). A complete cycle is considered as a data window. So, in a 400 Hz sampling, the system has eight inputs and a single output.
The number of layers in each system (400, 800, 1600, 3200, 6400) is selected due to Equation (1). The number of neurons in each hidden layer is defined by Equation (2). These equations are based on experience in the classification application. These equations may be used in other classification applications to identify the optimal number of the layers and neurons.

$$N_{Hidden\ layer} = \log_2 \frac{N_{input}}{N_{output}} - 1 \tag{1}$$

$$N_i = \frac{N_{input}}{N_{output} 2^i} \tag{2}$$

Where, N_i: number of neurons in hidden layer number i. Two biases are added to the structure: input and output biases (independent neurons have constant output '1'). Figure 2 shows the design of the 800 Hz system. Based on previous equations, the number of hidden layers for 16 inputs and one output equals 3. The numbers of neurons are (8, 4, 2) per each layer, respectively. In this example, the number of weights (size of the optimization techniques) = 51. Generally, the number of weights (N_w) is given by Equation (3), where N_h is the number of the hidden layer.

$$N_w = \left(\frac{N_{input}}{N_{output}}\right)^2 * \sum_{i=1}^{i=N_h} \left(\frac{1}{2 * 4^i}\right) + \frac{N_{input}}{2} + N_{output} \tag{3}$$

The sigmoid function is selected as an activation function of all neurons in this paper. In Figure 2, the green cycles refer to inputs, grey cycles refer to the neurons in hidden layers, red cycles refer to the output neuron, and white cycles refer to biases. Each simulation cycle is used as a sample in the training phase, either with the islanding status or non-islanding status. For each data rate, there is a specific number of inputs. In the simulation phase, the algorithm uses several cycles to decide either the system is islanding or not. The number of cycles depends on the sample rates used. The higher the sample rate, the better the accuracy.

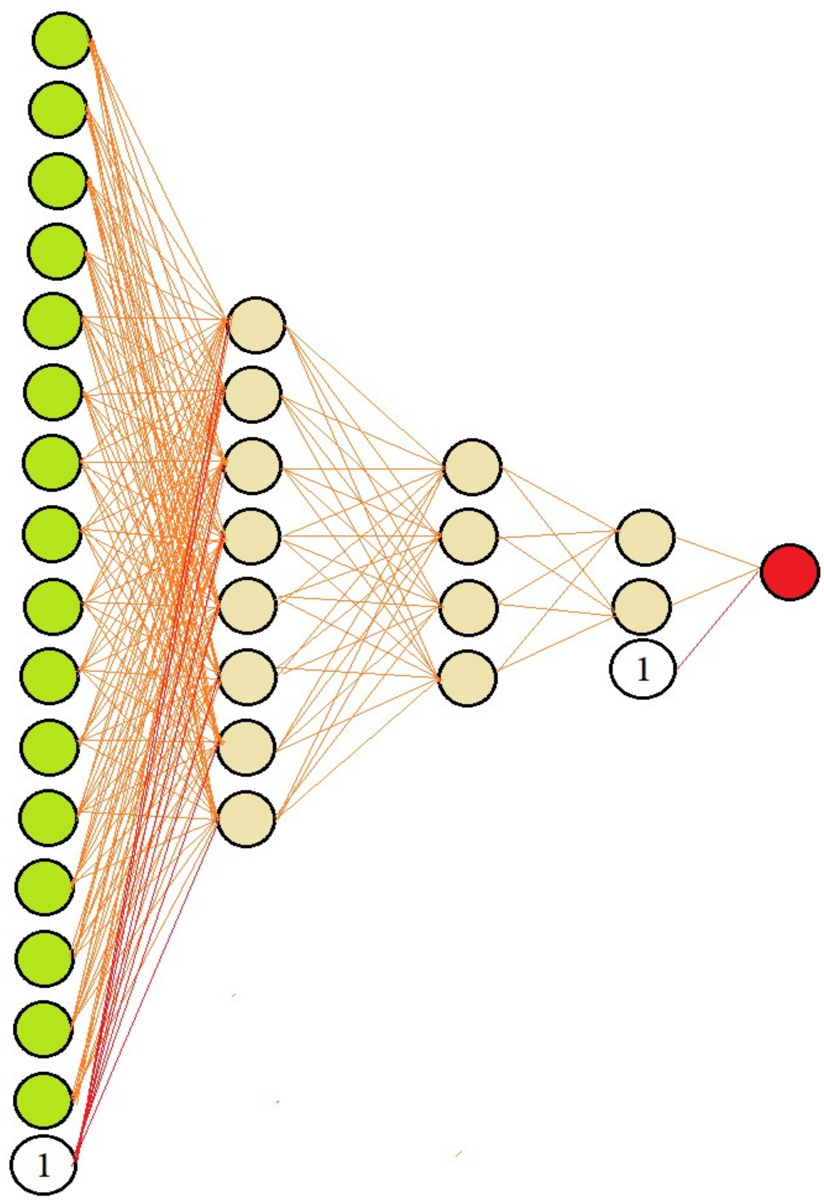


FIGURE 2. ANN structure, for an example of sample rate equal to 800 Hz

4. System Understudy.

Different sample rates are considered in this section: 0.4, 0.8, 1.6, and 3.2 KHz. Figure 3 shows the simulation system. Three scenarios are covered here: increase the load to its double value, decrease load to its half value, and trip main supply. Ten cycles are covered for each scenario (five cycles before the event and five cycles after the event). So for each load level, 30 samples are generated (10 samples for load up event, 10 samples for load down event and 10 for the islanding event). Two data sets are generated at different load levels: test data used in training systems and validation data used in simulation systems. Different load levels are covered from 0.2 Pu to 2 Pu stepped by 0.1 Pu for the training data set and from 0.25 to 1.95 stepped by 0.1 for the validation data set. The size of the test data for the 0.8 kHz system is 600×16. Figure 4 shows the sampling technique. Then these inputs are normalized. Figure 5 shows the Simulink model for the system.

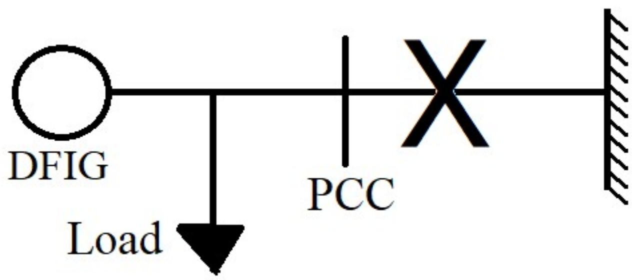
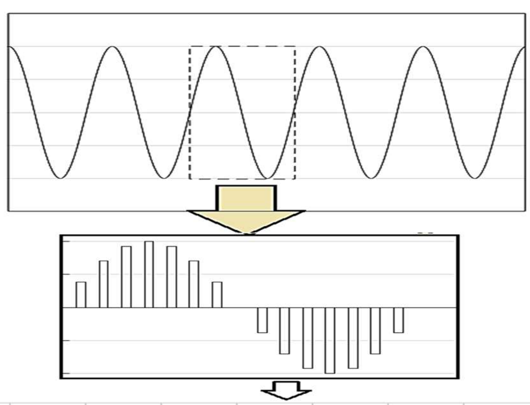


FIGURE 3. System understudy



9	84	3	95	24	7	65	81	62
27	93	43	34	92	5	68	86	35
54	67	38	58	34	53	74	8	51
95	75	76	22	19	77	45	39	40
96	74	79	75	25	93	8	25	7
15	39	18	25	61	12	22	80	23
97	65	48	50	47	56	91	43	12
95	17	44	69	35	46	15	91	18
48	70	64	89	83	1	82	18	23
80	3	70	95	58	33	53	26	41
14	27	75	54	54	16	99	14	4
42	4	27	13	91	79	7	13	90
91	9	67	14	28	31	44	86	94
79	82	65	25	75	52	10	57	49
95	69	16	84	75	16	96	54	48
65	31	11	25	38	60	0	14	33

FIGURE 4. Sampling technique

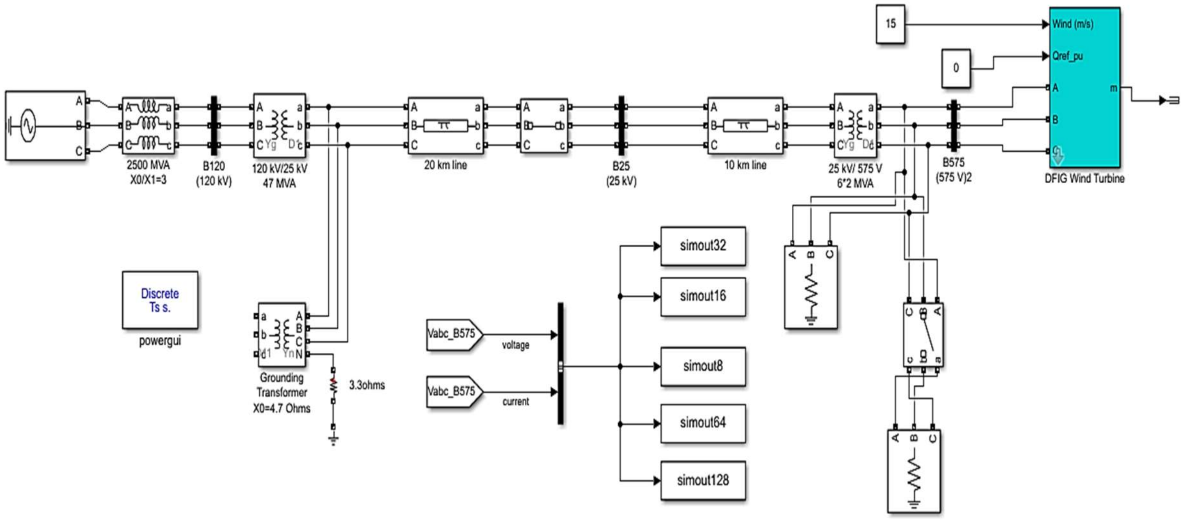


FIGURE 5. Simulink blocks of the system under study

5.Training and Simulation.

The five systems are presented in this section in three different algorithms: backpropagation, Cuckoo, and genetic algorithm. In this section, the test sample is used to train the systems. For each specific load, three scenarios are considered: increase the load, decrease load, trip main supply.

5.1. Backpropagation learning technique.

5.1.1. Phase Voltage-Based ANN classification. The voltage-Based techniques are used to the ANN inputs in this section. The results for the different rates are shown in table 1. In this table, the mean absolute error (AE), maximum absolute error (MAE), computational time (Tc), number of iterations (N), the best performance (BP), the best test performance (BTP), and the best validation performance (BVP) where the performance function is the mean square error. The performance diagram of the tanning data, validation, and test data are shown in figure 6.

TABLE 1: performance of phase voltage-based ANN classification

Parameter/system	400 Hz	800 Hz	1600 Hz	3200 Hz
AE (%)	0.0077	3.2771e-05	0.0036	3.5348e-05
MAE (%)	0.4154	0.0032	0.2371	0.0025
Tc (sec)	7.8993	13.1665	80.7673	2.9896e+03
N	32	42	42	67
BP	6.5521e-08	1.8647e-15	4.0507e-10	1.9343e-13
BVP	4.7966e-07	3.0771e-11	5.5616e-09	1.7872e-11
BTP	4.4202e-10	1.8448e-11	1.9192e-07	1.1457e-13

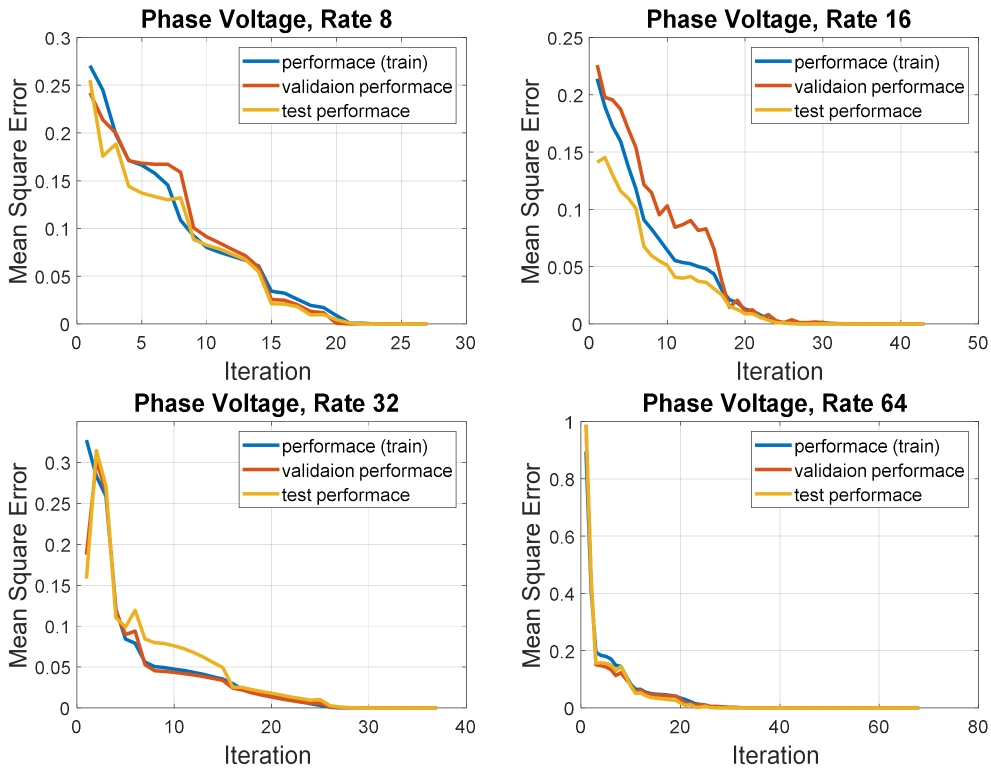


FIGURE 6. Performance values at different sample rates: 8, 16, 32, 64 sample/cycle for phase voltage classification technique.

5.1.2 Neutral voltage-based ANN classification technique. The results of neutral voltage-based techniques are shown in table 2. All training parameters are presented. Figure 7 shows the performance diagrams (mean square error).

TABLE 2: Neutral Voltage-Based ANN Classification

parameter	Rate 8	Rate 16	Rate 32	Rate 64
AE (%)	4.4626	5.8859	3.1438	0.5304
MAE (%)	97.9332	100.1624	99.9997	99.9851
Tc (sec)	8.2904	8.7641	53.5698	985.7196
N	36	18	28	26
BP	0.0175	0.0063	1.0173e-09	2.9969e-10
BVP	0.0605	0.0412	0.0285	0.0298
BTP	0.0276	0.1378	0.1685	4.0495e-10

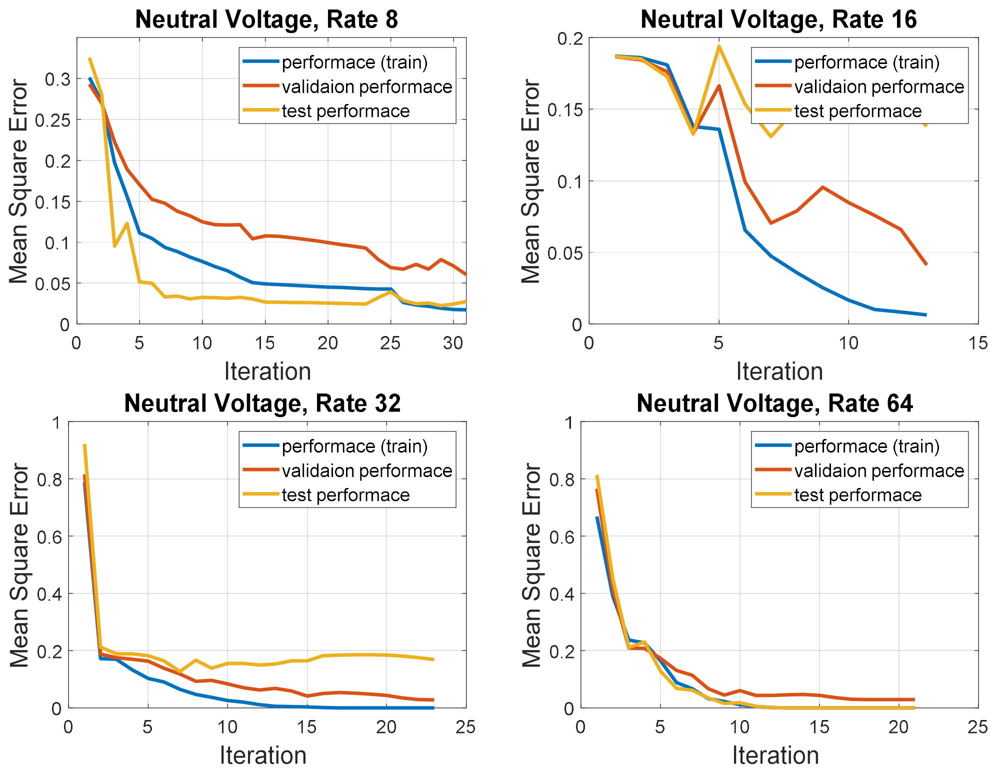


FIGURE 7. Performance values at different sample rates: 8, 16, 32, 64 sample/cycle for neutral voltage-based classification technique.

5.1.3 Phase Current-based ANN classification technique. The results of phase current based techniques are shown in Table 3. All training parameters are presented. Figure 8 shows the performance diagrams (mean square error).

TABLE 3: performance of phase current-based ANN classification technique

Parameter	Rate 8	Rate 16	Rate 32	Rate 64
AE (%)	0.0516	0.0144	0.4164	1.2158e-04
MAE (%)	12.3667	1.8671	100	0.0260
Tc (sec)	13.0758	12.1063	105.2228	1.7868e+03
N	35	36	54	43
BP	7.2882e-14	1.0687e-14	1.5602e-14	1.5435e-14
BVP	7.6036e-11	1.1724e-05	3.1091e-11	1.0475e-11
BTP	4.2482e-04	4.9432e-16	0.0278	4.0495e-10

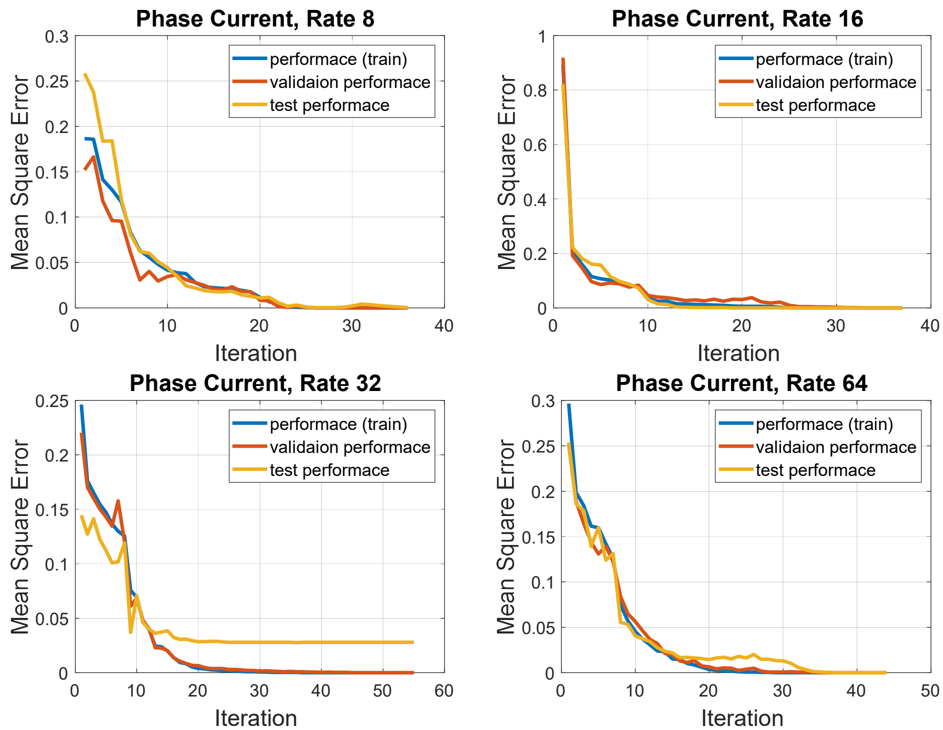


FIGURE 8. Performance values at different sample rates: 8, 16, 32, 64 sample/cycle for phase current-based classification technique.

5.1.4 Neutral Current-based ANN classification technique. The results of neutral current based techniques are shown in Table 4. All training parameters are presented. Figure 9 shows the performance diagrams (mean square error).

TABLE 4: performance of neutral current-based classification technique

parameter	Rate 8	Rate 16	Rate 32	Rate 64
AE (%)	5.7508	3.6738	7.4295	1.6682
MAE (%)	99.9508	100	100	99.9998
Tc (sec)	8.1301	11.7517	26.3722	1.0442e+03
N	25	33	12	27
BP	0.0117	6.9086e-09	0.0059	4.0477e-10
BVP	0.0350	0.0253	0.0853	0.0278
BTP	0.1771	0.1895	0.1533	0.0829

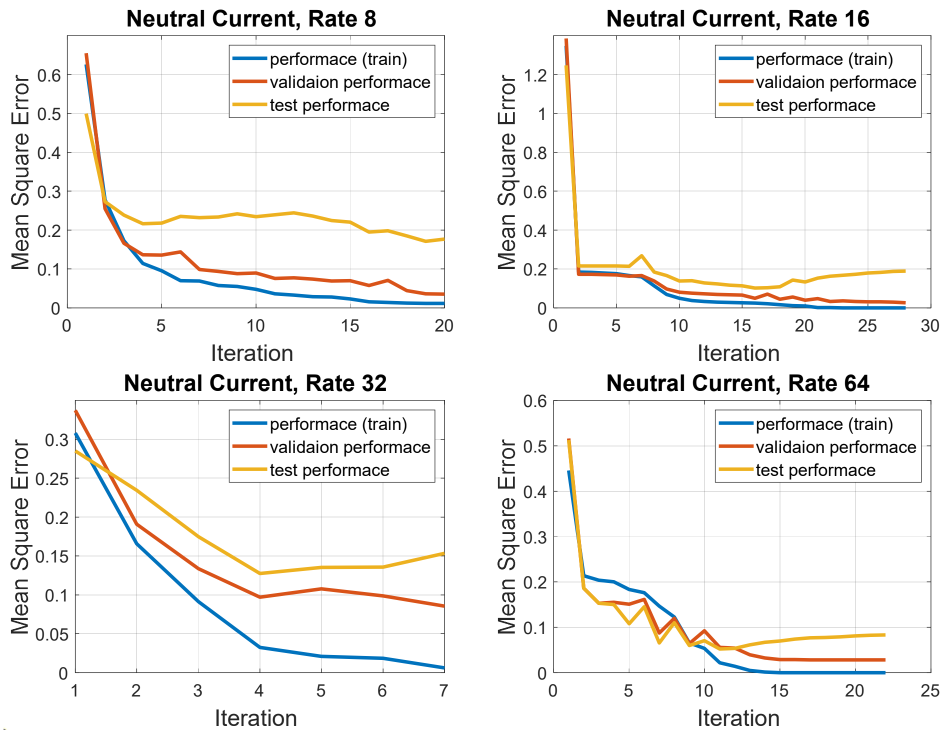


FIGURE 9. Performance diagram at different sample rates: 8, 16, 32, 64 sample/cycle for neutral current-based classification technique.

5.1.5 Power-Based ANN classification technique. The results of the power-based technique are shown in table 5. All training parameters are presented. Figure 10 shows the performance diagrams (mean square error).

TABLE 5: performance of power-based classification technique

Parameter	Rate 8	Rate 16	Rate 32	Rate 64
AE (%)	3.9743e-05	0.0014	0.6151	0.7150
MAE (%)	0.0078	0.3098	99.9563	33.2028
Tc (sec)	8.9601	16.2225	92.0121	2.7580e+03
N	46	58	48	58
BP	7.7913e-14	1.2236e-14	7.9597e-09	5.7312e-05
BVP	7.6225e-17	1.3894e-14	0.0022	0.0038
BTP	1.6947e-10	2.6772e-07	0.0278	6.9807e-04

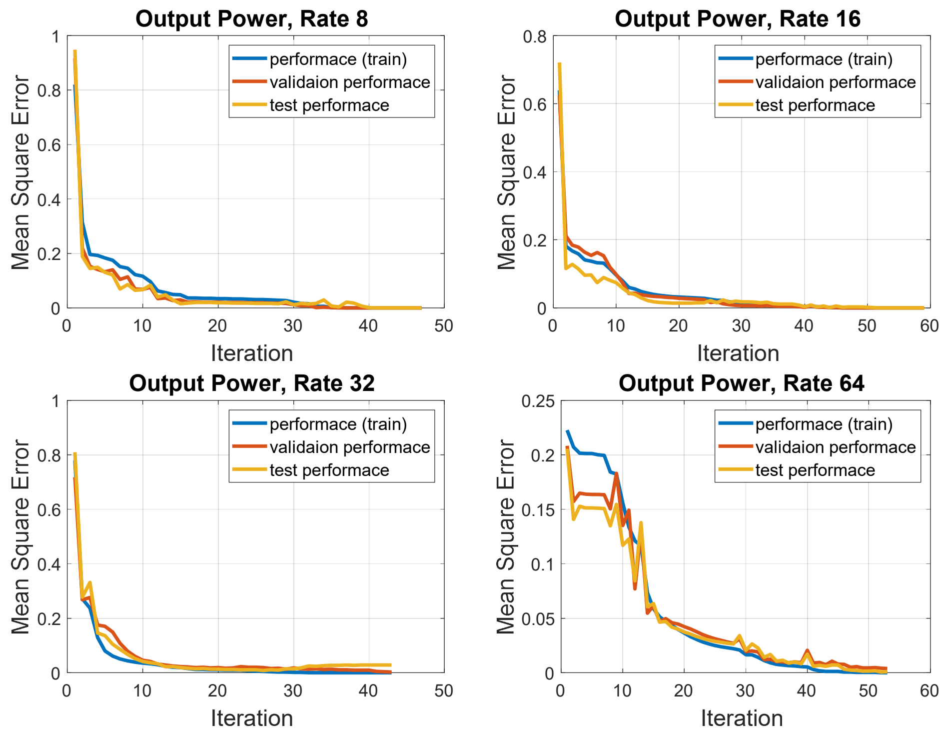


FIGURE 10. Performance diagram at different sample rates: 8, 16, 32, 64 sample/cycle power-based classification technique

5.2 Cuckoo optimization algorithm.

The tables below (Tables 6-9) show the results of rates 8, 16, and 32 sample/ cycle system using Cuckoo Algorithm. Where Va is a phase (A) voltage and Vn is a neutral voltage, Ia: phase (A) current, In: neutral current, and P is the three phase power. From these tables, the better results are shown in three-phase power sampling. The better sampling rate is 32 samples/ cycle.

TABLE 6: results of rate eight samples/cycle

parameter	Va	Vn	Ia	In	p
AE (%)	5.55	21.5145	7.7674	19.9547	1.2625
MAE (%)	5.401	11.8281	3.908	10.5221	1.2502
Tc (sec)	53.05	50.0236	48.21	49.586	48.1732
N	600	600	600	600	600

TABLE 7: results of rate 16 samples/cycle

parameter	Va	Vn	Ia	In	p
AE (%)	3.50335	11.2507	4.3074	22.2548	2.9179
MAE (%)	3.3181	11.2500	2.9891	11.74	2.9151
Tc (sec)	92.36	89.93	90.36	90	90.17
N	600	600	600	600	600

TABLE 8: results of rate 32 samples/cycle

parameter	Va	Vn	Ia	In	p
AE (%)	1.6667	19.066	2.1753	12.0833	0.8333
MAE (%)	1.6667	11.1769	2.0924	12.0833	0.8333
Tc (sec)	268	250	251	250	249
N	600	600	600	600	600

TABLE 9: results of rate 64 samples/cycle

parameter	Va	Vn	Ia	In	p
AE (%)	4.032	14.7198	1.25	22.955	2.0681
MAE (%)	3.7427	13.107	1.25	12.0912	1.6553
Tc (sec)	3053.4	1066.2	1084.6	1078	1142.4
N	2000	800	800	800	800

The figure below (Figure 11) show the cost function (mean square error) using the Cuckoo algorithm for each system.

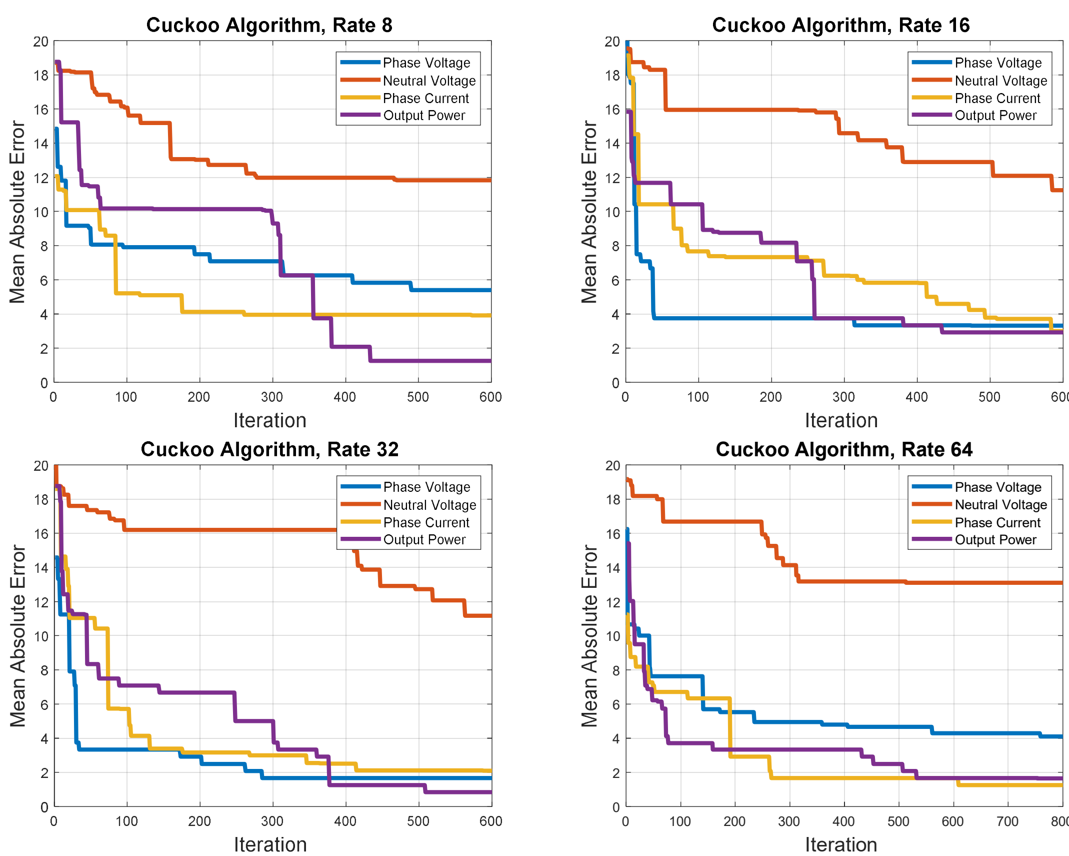


FIGURE 11. The cost function of different systems: phase current, three-phase power, phase voltage, and neutral voltage for 400Hz, 800Hz, 1600Hz, and 3200 Hz system.

5.3 GA Algorithm

The tables below (Tables 10-11) show the results of rates 8, and 16 samples/cycle systems using the GA Algorithm.

Where Va is a phase (A) voltage and Vn is a neutral voltage, Ia phase (A) current, In neutral current, and P is power. From these tables, the better results are shown in three-phase power sampling. The better sampling rate is 16 samples/ cycle.

TABLE 10: results of rate eight samples/cycle system

parameter	Va	Vn	Ia	In	p
AE (%)	5.4310	37.5047	13.4394	28.9243	12.01
MAE (%)	4.94	18.75	6.4282	14.98	8.6894
Tc (sec)	1404	1396	1392	1389	1390
N	1000	1000	1000	1000	1000

TABLE 11: results of rate 16 samples/cycle system

parameter	Va	Vn	Ia	In	p
AE (%)	7.1271	34.5123	1.25	37.5002	2.92
MAE (%)	2.49	17.19	1.25	18.75	2.92
Tc (sec)	2655	2663	2661	2645	2709
N	1000	1000	1000	1000	1000

The figure below (Figure 12) shows the cost function (mean square error) using the GA algorithm for each system.

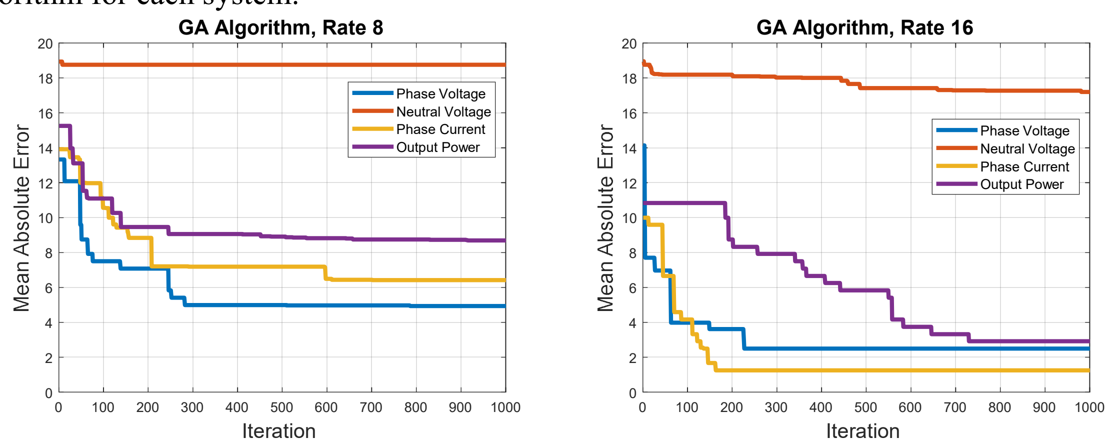


FIGURE 12. The cost function of different systems: phase current, three-phase power, phase voltage, and neutral voltage for 400Hz and 800Hz systems.

6. COMPARISON

In the previous section, five ANN systems are simulated using MATLAB 2020a: phase voltage-based ANN, phase current-based ANN, neutral voltage-based ANN, neutral current-

based ANN, three phase power-based ANN system. Three different learning techniques are used to optimize the ANN: backpropagation and two soft computation optimization techniques: Cuckoo and Genetic algorithms. The objective function of these optimization techniques (cost function) minimizes the sum square error between the target and system output.
This section presents a complete comparison between the learning techniques for the five systems at different sample rates.

Based on section 5, the best system which gives the best performance in learning testing validation is the power-based system using backpropagation technique. The phase voltage-based approach is better than the phase current, phase quantities (voltage and current) are better than neutral quantities, and the results of the phase voltage are very acceptable at different sample rates.

The optimal sample rate in voltage is 64 samples/cycle. More than one cycle may be needed to increase the algorithm accuracy. In table 12, the optimal sample rate and the minimum number of cycles may make a good decision for different systems.

TABLE 12: optimal selection

System	Sample/cycle	Number of cycles
Power	8	4
Phase Voltage	64	6
Phase current	64	8
Neutral voltage	64	13
Neutral current	64	14

The number of cycles in table 12 is based on validation data collected at different load levels. The cuckoo algorithm is better than GA in this context. The computational time of the cuckoo algorithm (or the number of iterations) is lower than GA to get the same accuracy.

Backpropagation techniques are the best in this application. Power-based at rate 16 sample/cycle is the best for the islanding detection. At least four cycles are needed (80 ms for 50 Hz) to make a 100% correct decision. Finally, the cuckoo algorithm solves this problem better than GA.

7. CONCLUSION

In this paper, the ANN-based technique in the islanding detection application is studied. Doubly fed induction generator wind turbine is selected as distributed generators. Different ANN systems are simulated based on various inputs: Phase voltage/current, neutral voltage/current, and three-phase power, different sample rates are considered: 8, 16, 32, and 64 sample/cycle for each system, and three learning algorithms are simulated using MATLAB 2020a: Backpropagation, Genetic Algorithm, and Cuckoo optimization technique.

From the results, the ANN is a very effective method to detect the islanding in the micro-grid. Different inputs may be used to feed the trained ANN system: Power, phase voltage, and phase current, where the neutral quantities (voltage, current) are not able to use in this application. The accuracy of the system depends on the sample rate. The higher the sampling, the better the performance. 16 sample/cycle is enough to detect the islanding within four cycles in the case of power-based input data.

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