IEEE Power and Energy Technology Systems Journal

Received 20 February 2017; revised 23 December 2017; accepted 31 January 2018.
Date of publication 13 March 2018; date of current version 22 June 2018.

Digital Object Identifier 10.1109/JPETS.2018.2805894

Smart Distributed Generation Systems Using Artificial Neural Network-Based Event Classification

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ABSTRACT Distributed generation (DG) sources have become an integral part of today's decentralized power systems. However, current DG systems are mostly passive and do not provide intelligent information to help detect power quality issues. In this paper, a novel and intelligent event classification scheme is proposed to provide the DG systems with real-time decision making capabilities. The proposed technique has the ability to provide information to help maintain the quality and reliability of the DG systems under various disturbances or operating conditions. This event classification technique was developed using artificial neural networks (ANNs) with a pre-defined set of local input parameters. The algorithm is implemented using four parallel ANNs that were designed to operate under a majority vote fusion algorithm representing the final classification output. A total of 310 event cases were generated to test the performance of the proposed technique. Simulation results showed that events were accurately classified within 10 cycles of their occurrences while achieving a 96.21% average classification accuracy.

INDEX TERMS Event classification, smart grid, distributed generation, artificial neural networks, majority vote.

I. INTRODUCTION

Conventional electrical power grids consist of large centralized power plants that generate and transfer large amounts of power via long distance transmission lines which presents several operational challenges. The growing demand for electricity has also led to considerable transmission and distribution losses in the system. In addition, the power grid is highly vulnerable to contingencies ranging from severe weather to faults caused by falling trees on power lines [1]. Furthermore, the polluting nature of the fossil-fuel powered generation plants has led to strict regulations on the construction of new power plants. Fortunately, the majority of these issues that are due to the centralized nature of the power grid can be mitigated by integrating distributed generation units within the grid. Any decentralized electrical power source connected to the grid at the distribution level is called a distributed generation (DG) [2]–[4]. Since DGs are generally installed at the consumers' end, they tend to supply part of the local demand and thereby reduce the load on the centralized system including transmission. The small size and the decentralized nature of DG systems render them very reliable since the failure of a small unit can be easily compensated by the remaining units. Furthermore, a considerable portion of DGs is renewable sources such as solar, wind, and fuel cells [5]. Therefore, DG systems are environmentally friendly and can help meet sustainability goals such as the US's Executive Order 13693 [6].

The inherent benefits of DG systems have led to a steady rise in their utilization at the distribution level. A significant portion of DG systems is owned and operated independently by industries, universities, and homeowners [7]. Within the structure of a traditional power system, the main components of the system, such as power generation, power transmission, power distribution, and loads, are considered to be quite independent processes [8]. However, with the increase in DG penetration and active energy resources such as dynamic loads, energy storage, and plug-in hybrid vehicles, the complexity of managing the grid increases significantly since the complexity of the transmission network is combined with the distribution network level [8]. In this case, it becomes

TABLE 1. Comparative analysis of existing event classification techniques.

Reference	Feature Extraction	Classifier	Accuracy
Zhao [21]	S-transform	Decision Tree	95%
Uyar [22]	S-transform	ANN	96.5%
Haibo [14]	Wavelet Transform	ANN	88%
Ekici [15]	Wavelet Transform	SVM	97%
Wang [16]	Wavelet Transform	GA	94%
Cesar [17]	Wavelet Transform	SVM	98%
		ANN	96%
Chandel [18]	Wavelet Transform	ANN	98%
Reaz [19]	Discrete Wavelet Transform	ANN-FL combo	98.19%
Samantaray [20]	S-transform	DT, FL, GA	97%
Eristi [12]	Wavelet Transform	SVM	98.51%
		ANN	97.02%
Ray [13]	S-transform	MPNN	98%
		SVM	98%
		LS-SVM	98.33%
Valtierra-Rodriguez [11]	Fourier Transform	Dual Neural Networks	96%

necessary to incorporate intelligence within the DGs to make them smart and help maintain the overall system stability. Current research on smart DG systems mainly deals with autonomous voltage or frequency regulation and the optimum use of renewable DG systems [9]. There is little research effort towards the implementation of an event classification feature into DG systems. Furthermore, existing research addressing event classification techniques are mainly focused on maintaining constant voltage and frequency in order to prevent damage or shut down of essential electrical equipment [10]. Therefore, extensive monitoring and data acquisition systems are needed to capture event data during power system disturbances. This data is then processed to extract features from local parameters to automate the process of identification and classification of different power quality variations such as voltage sag, swell, harmonics, frequency oscillations, etc. A general structure of such technique is shown in Fig. 1.

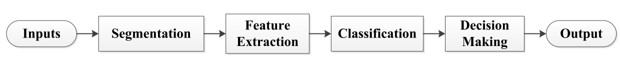

FIGURE 1. General principle of existing event classification techniques.

Most of the classification techniques presented in the literature generally use time domain voltage and current waveforms to perform the classification. After the occurrence of an event, features, that can accurately represent the characteristics of the event, are extracted from the input parameters to be used for classification. The most commonly used feature extraction techniques are Fourier transform [11], wavelet transform [12]–[19] and S-transform [13], [20]–[22]. The extracted features are then used as inputs for the classification algorithm. Machine learning algorithms such as Decision Trees (DT) [20], artificial neural networks (ANN) [12], [14], [17], [18], [22], support vector machines (SVM) [12], [13], [15], [17], genetic algorithm (GA) [16], [20], least-squared SVM (LS-SVM), modular probabilistic neural network (MPNN) [13], and fuzzy logic (FL) [19], [20] have been used as classifiers. Even though these techniques were able to classify the variation in the system's power quality, they were not able to identify the root cause of these variations. In addition, these classification techniques were only tested using systems with conventional generation sources. Table 1 summarizes the different classification techniques presented in the literature including feature extraction techniques and classification accuracies.

In this paper, the proposed DG event classification differs from other existing techniques by adding decentralized intelligence capabilities into the DG sources within the power system. Also, this proposed technique can identify the root cause of a wide range of events which have a substantial impact on the operation of grid-connected DG systems. Such classification can help develop a clear understanding of the operating requirements needed to mitigate the impact of such events on the power system. The technique monitors and logs data for a certain combination of local parameters which are then used as the input to a set of ANNs trained to classify these events. Every ANN is trained using values obtained from only a single local system parameter. The classification outputs of all the ANNs are combined using a majority vote fusion algorithm to generate the final classification decision. The proposed technique was optimized to reduce the computational complexity while maintaining high classification accuracy. The performance of the technique was also validated using a 10-fold cross-validation of a large dataset of local events.

The rest of the paper is organized as follows. In Section II, the proposed approach is presented. In Section III, the simulation model is discussed along with the results. The paper concludes with a summary of the findings in Section IV.

II. PROPOSED CLASSIFICATION TECHNIQUE

The proposed technique is designed to classify power system events according to their root cause by monitoring a set of local parameters using a network of ANN classifiers combined with a majority vote fusion algorithm. Local power system events, such as islanding, faults, load switching, capacitor switching, and loss of parallel feeder have their own signature on the measured electrical parameters at the DG point of common coupling (PCC). When recording DG electrical parameters for various events, distinct waveform patterns can be observed. Fig. 2-a illustrates the characteristic difference in the voltage waveforms for different types of events over a period of 10 cycles. As shown, each event exhibits a distinct pattern. On the other hand, events of the same type exhibit high characteristic correlation as illustrated in Fig. 2-b which shows the root mean square (RMS) voltage waveforms for 3-phase faults of different magnitudes.

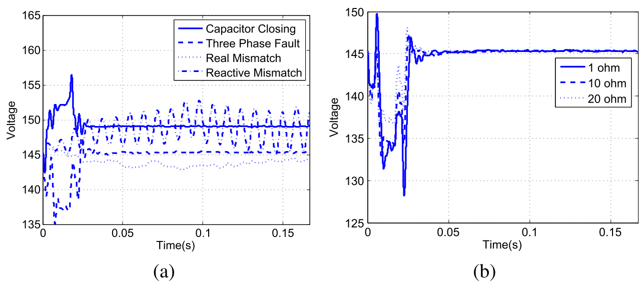

FIGURE 2. Voltage waveforms for (a) different type of events (b) 3-phase events.

Although the differences are visible in the waveform patterns, there is no definite model to distinguish between these different events. Therefore, a suitable machine learning technique can be used to classify the various events by observing the pattern in selected parameters at the PCC.

A. ARTIFICIAL NEURAL NETWORK MODEL

Feed-forward Artificial Neural Networks are used for pattern recognition since they possess the ability to learn from complex non-linear input-output relationships and to adapt to the given data [23].

Fig. 3 illustrates the general structure of a layer of neurons. The input vector I consists of inputs I_1 through I_k. Each element of this vector is associated with a neuron through the weight matrix W with $r \times k$ elements, where r is the number of neurons in the layer. For the i-th neuron, all the weighted inputs are added together with the bias b_i to obtain the total sum (n_i). n_i is then passed through a transfer function to obtain the output (a_i). The relationship between the final output of the neuron (a_i) and the set of inputs (I_j) is modeled by:

$$a_i = f\left(\underbrace{\sum_{j=1}^{k}\left[W_{i,j}I_j\right] + b_i}_{n_i}\right) \quad (1)$$

At the beginning of the ANN training, the weights and biases are randomly initialized. After each iteration,

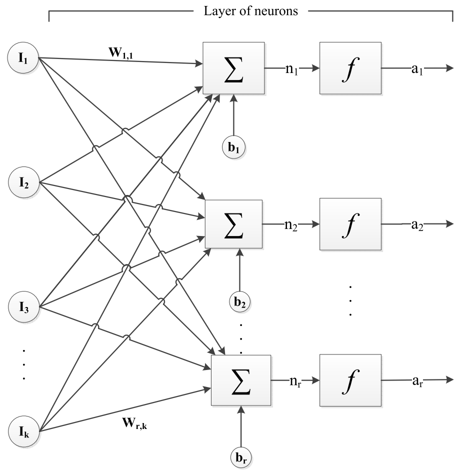

FIGURE 3. A layer of neurons in an Artificial Neural Network.

the ANN training algorithm will slowly converge the values of the weights and biases until the network response matches the desired response. This is generally achieved by adjusting the weight matrix to minimize the error function. The error function is dependent on the classification error. The weights are adjusted according to the derivative of the error function with respect to the individual weights to guarantee a minimum error. The transfer function serves the purpose of normalizing the input data because most training algorithms are sensitive to the actual scale of the data.

Initially, in this study, a single ANN classifier with 8 input parameters was utilized. However, due to the curse of dimensionality, the classifier was complex and required more training which also resulted in relatively poor classification [24]–[26]. Therefore, we proposed a solution for this problem by using a fused network of single input simple ANN classifiers to improve the classifier performance.

B. MAJORITY VOTE BASED MULTIPLE CLASSIFIER SYSTEM MODEL

The proposed technique utilizes multiple Feed-Forward ANN (FF-ANN) classifiers combined with a majority vote fusion algorithm. The input for each classifier represents a specific local DG power parameter such as voltage, rate of change of voltage, frequency, voltage total harmonic distortion, etc. This approach simplifies the classification process by decomposing the multi-input single classifier into a set of simpler single-input classifiers with its inputs distributed over this set of classifiers. This multi-classifier system will exploit the difference in how these local parameters react to different events to enhance the accuracy and the reliability of the overall classification system. i.e., if some parameters fail to accurately classify the event, then the overall system might still be able to accurately classify it using the majority voting fusion algorithm. Fig. 4 illustrates the proposed configuration of the classifier ensemble using the majority vote fusion.

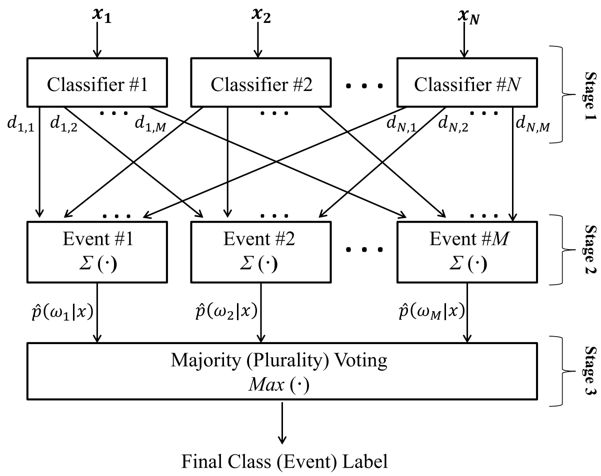

FIGURE 4. Proposed Feed-Forward ANN classifiers combined with a majority vote fusion algorithm.

The proposed system consists of three stages. Stage 1 represents the individual parameter classification process, where local parameters (features) vector x_k defined in the feature space $\Re^n$ is fed to N parallel classifiers. These classifiers are composed of Feed-Forward ANNs with different optimized structure using the same training algorithm. Each classifier in the ensemble is trained to classify M events. Each classifier has M binary classifier outputs each output representing a specific event. The classifiers' outputs are binary vectors ($d_{i,j}$), i.e. $d_{i,j} \in [0, 1]$, where $i = 1, 2, \ldots, N$ represents the classifier number and $j = 1, 2, \ldots, M$ represents the class or event number. In stage 2, the majority voting is used as the fusion algorithm to combine the different classifiers' outputs for each event. This is used to estimate the posterior probability for each event ω_j as follows:

$$\widehat{p}\left(\omega_j|x\right) = \frac{\sum\left(d_{1,i}, d_{2,i}, \ldots, d_{N,i}\right)}{M} \tag{2}$$

In stage 3, the final event classification ω_k is determined. The final classification is basically the event with the maximum posterior probability modeled as follows:

$$assign\ \ x \rightarrow \omega_k \quad if \quad \widehat{p}\left(\omega_k|x\right) > \widehat{p}\left(\omega_l|x\right) \tag{3}$$

In the case of a tie, the final classification of events is based on their historical classification record. The tiebreaker is basically the event that was most recently classified.

To analytically validate that using the majority voting as a fusion algorithm will improve the classification accuracy of a system of classifiers, a simplified parallel classifier model was used and compared to the model under consideration. This simplified model is assumed to have only 2 classes (events) to be classified using an odd number of base classifiers to form an ensemble. The base classifier posterior error probabilities (P_s) are assumed to be equal. In addition, it was also assumed that all the base classifiers have an uncorrelated or negatively correlated mutual error.

The ensemble classification probability of error (P_E) model for a system of classifiers with a majority voting fusion algorithm used to classify two events ($N = 2$) using an odd number of base classifiers M is given as follows:

$$P_E = \sum_{j=(M+1)/2}^{M} \binom{M}{j} \left(P_S\right)^j \left(1 - P_S\right)^{M-j} \tag{4}$$

Fig. 5 highlights the performance of the system in terms of the ensemble classification probability of error (P_E) as a function of the base classifier probability and the number of classifiers.

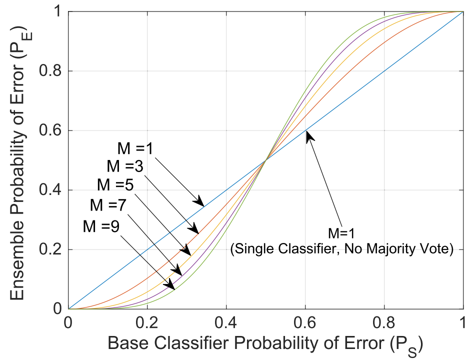

FIGURE 5. Classification probability of error of a parallel system of classifiers combined with a majority vote fusion algorithm versus the base classifier probability of error.

As depicted in Fig. 5, the system of classifiers using majority voting fusion algorithm can improve the overall system classification accuracy as more classifiers are added compared to a single classifier (M = 1) provided that $P_s < 0.5$. However, if $P_s > 0.5$, then the ensemble classification probability of error will increase as more classifiers are added which defeats the purpose of using such a system.

In this paper, the proposed classification model is more complex than the model used to derive the ensemble probability of error. First, the proposed model uses 8 events instead of 2 which complicates the permutations of accurate majority voting. Second, it also uses classifiers that are relatively correlated with different base classifiers' posterior error probabilities. In such a case, the derivation of a closed-form expression to model the ensemble probability of error is more involved. More details regarding majority voting fusion algorithms can be found in [27] and [28].

C. PROPOSED MODEL IMPLEMENTATION

The implementation of the proposed DG event classification method consisted of three principal steps: 1) parameter selection, 2) feature extraction and model construction, and 3) optimization. In the parameter selection step, the local current and voltage waveforms are measured and a set of parameters, affected by the DG events, are derived using these waveforms. In this paper, 8 different input parameters were used which are among the most popular parameters already used in islanding detection techniques [29], [30]. These input parameters are voltage, the rate of change of voltage, voltage total harmonic distortion, current total harmonic distortion, frequency, the rate of change of frequency, power factor, and the rate of change of power factor as listed in Table 2.

TABLE 2. Parameters selected for event classification.

Parameter	Symbol
Voltage amplitude in pu	V_{pu}
Rate of change of voltage	$\frac{dV}{dt}$
Voltage total harmonic distortion	THD_V
Current total harmonic distortion	THD_I
Frequency in Hz	f
Rate of change of frequency	$\frac{df}{dt}$
Power factor	PF
Rate of change of power factor	$\frac{dPF}{dt}$

In the feature extraction step, each input sample represents the mean over one cycle for a specific parameter. For each parameter, a combination of 10 consecutive cycles mean values was used as an input to a moving window. The size of the moving window directly proportional to the amount of information provided to the classifier and inversely proportional to how fast the classification is generated. In this study, the moving window size of 10 cycles was selected, through intensive investigation, to provide the best performance within a reasonable time delay of 166ms which is much lower than the islanding detection delay limit mandated by IEEE Std 1547 [31]. A separate data matrix for each parameter was constructed as depicted in Table 3. In the data matrix, any given column represents the moving window of a specific parameter for a period of 10 cycles. The various event classes are represented in different columns in the matrix. Since a set of 10 average values were recorded for each event, then $m = 10$ while N represents the total number of sample sets of the various events used. A subset matrix for each parameter was assigned as an input to a specific neural network for training and validation.

TABLE 3. Organization of input matrix to neural networks.

$Mean_{11}$	$Mean_{12}$	$Mean_{13}$	.....	$Mean_{1N}$
$Mean_{21}$	$Mean_{22}$	$Mean_{23}$	.....	$Mean_{2N}$
$Mean_{31}$	$Mean_{32}$	$Mean_{33}$	.....	$Mean_{3N}$
....	....	....	....	....
$Mean_{m1}$	$Mean_{m2}$	$Mean_{m3}$	.....	$Mean_{mN}$

Instead of using all the parameters as inputs to one large ANN, a separate and simpler ANN was allocated for each parameter. This approach simplified the design of the classifier, improved its performance, and facilitated its optimization. In the model construction and optimization stage, the neural networks were trained using the MATLAB's Neural Network Toolbox. The pattern recognition feature of this toolbox was used for constructing the feed-forward network. The transfer functions selected for the hidden and output layers were the tan-sigmoid and softmax function respectively. This combination of transfer functions is widely used for pattern recognition applications [32]. The scaled conjugate gradient training algorithm was used because of its fast convergence, memory efficiency, and suitability for large complex systems [33]. Table 4 lists the benefits for selecting these specific ANN hidden and output layer transfer functions and training algorithm.

TABLE 4. ANN transfer function and training algorithm selection.

Design Parameter	Selection Choice	Selection Reasons
Transfer functions	Tan-sigmoid (hidden layer) Softmax (output layer)	- Normalize inputs - Highly differentiable
Training algorithm	Scaled conjugate gradient	- Fast training - Memory efficient - Suitable for complex problems

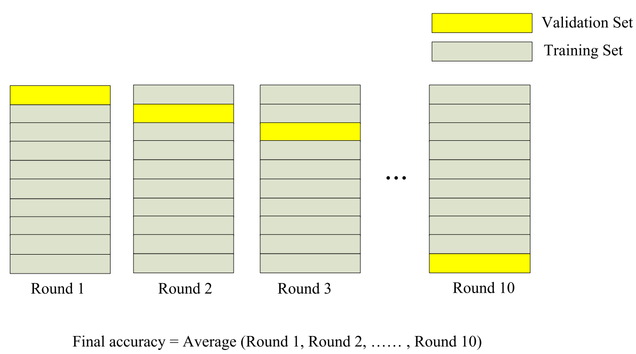

FIGURE 6. Concept of 10 fold cross-validation.

The 10-fold cross-validation method was used to train and validate each neural network. The concept of 10-fold cross-validation is illustrated in Fig. 6. In this method, the dataset was randomly divided into 10 subsets containing equal numbers of the various types of events. Nine of these subsets are then used to train the network and the validation was conducted using the remaining subset. This process was repeated 10 times and the average classification accuracy was recorded as the performance index.

The number of neurons in the hidden layer of each network was varied between 1 to 20 and the cross-validation method was used to optimize the number of neurons in the hidden layers. This optimization process was based on the criteria of minimizing the misclassification rate while maintaining reasonably simple neural networks.

After the optimization of each neural network, the outputs of these networks were arranged in a vector form and the majority vote output was used to generate the final classification. This approach was shown to provide more accurate and robust results compared to using one large neural network.

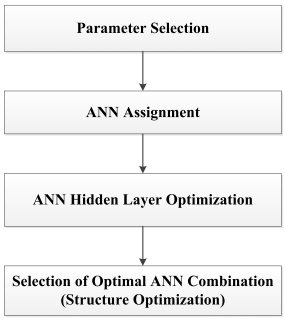

FIGURE 7. ANN structure design process for the DG event classification system.

This structure of parallel ANNs facilitated the process of optimizing the classification performance of the ensemble by removing the low-performing ANNs and their associated parameters. Recursively, the ANNs having the lowest accuracy were eliminated and the updated classification performance was recorded. The optimal structure was obtained when further elimination led to a decrease in the classification performance. Fig. 7 summarizes the ANN structure design process for the proposed DG event classification system.

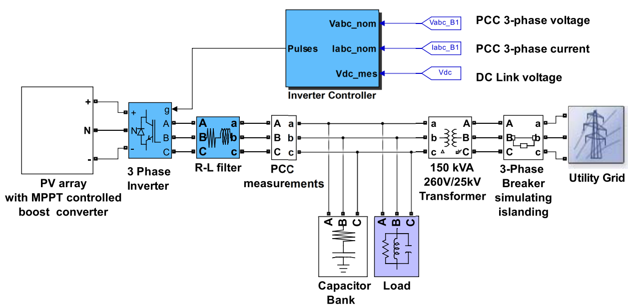

FIGURE 8. Simulation model of a grid-connected PV system.

III. SIMULATION MODEL AND RESULTS

The performance of the proposed event classification technique was verified using a MATLAB Simulink model of a grid-connected photovoltaic (PV) array as shown in Fig. 8. The PV array generated 100.7 kW at an irradiance of 1000 W/m^2 and a temperature of 25^{o}C. It was connected to the grid via a DC-DC boost converter and a 3-phase inverter designed to output AC power at unity power factor ($PF = 1$). The switching duty cycle of the DC-DC boost converter was optimized using a Maximum Power Point Tracking (MPPT) controller with Incremental Conductance and Integral Regulator technique. The RMS of the inverter output voltage was set to 260V and was connected to the 25 kV utility grid via a 100 kVA transformer. The grid had a short circuit capacity of 2500 MVA and an X/R ratio of 7. A 10 kVAR capacitor bank was connected near the utility side to provide reactive support to the load. A total of 310 events were simulated for training and testing of the different ANNs. The distribution of the input samples of various types of events is provided in Table 5.

TABLE 5. Simulated cases for DG event classification

Event	Parameter Range	No. of Events
Real Power Mismatch (Islanding)	-50% to +50% mismatch	30
Reactive Power Mismatch (Islanding)	-10% to +10% mismatch	30
Three-Phase Faults	1-60Ω fault resistance	30
Line-to-Line Faults	1-60Ω fault resistance	30
Single-Phase Faults	1-60Ω fault resistance	30
Load Closing Events	1-100 MVA load	30
Load Opening Events	1-100 MVA load	30
Capacitor Closing Events	250-3000 kVAR capacitor	30
Capacitor Opening Events	250-3000 kVAR capacitor	30
Loss of Parallel Feeder	1500-3500 MVA_{sc} infinite bus	30
Normal Operation	50% to 150% of DG capacity	10

For uniform distribution, each event had 30 samples. In addition, 10 sample cases of grid-connected normal operation were included in the input data for the classifier to operate in real-time. The 10-fold cross-validation was used to evaluate the average performance of the ANNs. Each subset of data in the folds had an equal distribution of the various types of events to avoid any bias in the training and testing.

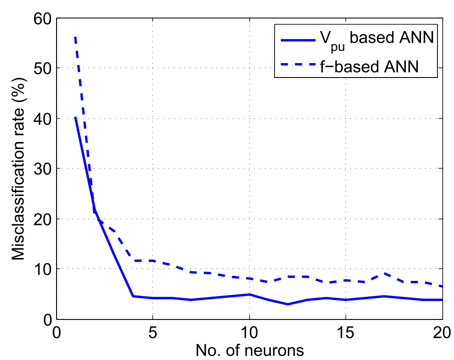

FIGURE 9. Change of misclassification rate for two different ANNs.

Initially, 8 parameters were used as inputs to 8 different ANNs (one ANN per parameter). These parameters were the normalized voltage (V_{pu}), frequency (f), frequency deviation ($\frac{df}{dt}$), voltage deviation ($\frac{dV}{dt}$), voltage total harmonic distortion (THD_V), current total harmonic distortion (THD_I), power factor (PF), and power factor deviation ($\frac{dPF}{dt}$). Fig. 9 depicts the change in the misclassification rate of two different ANNs (using V_{pu} and f as input parameters) as a function of the number of neurons in the hidden layer. The misclassification rate illustrated in the figure represents the average value after 10-fold cross-validation. It can be observed that the misclassification rate decreases drastically as the number of neurons starts increasing and then converges as the number of neurons continues to increase. To heuristically optimize the size of the hidden layer, the selection of the number of neurons for each ANN was based on the lowest misclassification rate observed. Table 6 lists the optimal number of neurons and the corresponding classification accuracy for each ANN. The events classified are listed in Table 7.

TABLE 6. Optimized classification performance of various ANNs

Input Parameter	Optimal Number of Neurons (n)	Optimized Accuracy
V_{pu}	12	95.80%
f	20	92.14%
$\frac{df}{dt}$	16	90.91%
$\frac{dV}{dt}$	17	84.64%
THD_V	7	83.37%
THD_I	20	77.67%
PF	15	67.59%
$\frac{dPF}{dt}$	4	64.27%

TABLE 7. The set of classified events.

Event Number	Event Description
1	Capacitor closing
2	Capacitor opening
3	Line to line fault
4	Load closing
5	Load opening
6	Loss of parallel feeder
7	Islanding condition with reactive mismatch
8	Islanding condition with real mismatch
9	Single line to ground fault
10	Three-phase fault
11	Normal operation

TABLE 8. Classification accuracy in the majority vote for different combinations of ANNs.

No. of Parameters Used	Majority Vote Accuracy
8	96.16%
7	96.84%
6	96.84%
5	96.87%
4	96.21%
3	94.78%

Based on Table 6, the lowest performing ANNs were eliminated one at a time and the classification performance of the majority vote was observed at each step to optimize the event classification technique. Table 8 lists the classification performance at each step of the optimization process. It was observed that the optimal combination of performance and computational simplicity was achieved with the combination of 4 parameters: the normalized voltage (V_{pu}), frequency (f), frequency deviation ($\frac{df}{dt}$) and voltage deviation ($\frac{dV}{dt}$). This combination has a very high classification

TABLE 9. Sensitivity and specificity for each event.

Event	Accuracy	Sensitivity	Specificity
Reactive mismatch	95.6%	95.00%	99.01%
Capacitor switching	99.35%	99.53%	99.07%
Real mismatch	77.33%	77.96%	99.55%
Line to line fault	99.10%	99.13%	99.96%
Load switching	99.50%	99.58%	99.83%
Loss of parallel feeder	100%	100%	99.98%
Single line to ground fault	99.86%	99.76%	99.52%
3-phase fault	94.4%	94.36%	99.98%

accuracy of 96.21% with a variance of 0.48%. Each ANN has only one hidden layer and one output layer. The number of neurons in each hidden layer varied because they were selected according to their individual optimal performance. The number of neurons in each output layer is the same and is equal to the number of classes. The sensitivity and specificity of the model with 4 parametric ANNs with respect to each type of event are listed in Table 9. For a given event, the sensitivity indicates the percentage of correct identification of that event (i.e., avoiding false negatives) while the specificity indicates the percentage of correct rejection of that event (i.e., avoiding false positives). It can be observed that for all events, except the real power mismatch events, the sensitivity and specificity values exceeded 94%. This indicates that all these events were classified accurately most of the time. As for real power mismatch events, the sensitivity was less than 80% indicating that false negatives were relatively higher than all other events. In other words, the classifier didn't always detect real power mismatch events, which could be the subject of future work.

IV. CONCLUSION

In this paper, a novel event classification technique for smart DG systems is proposed. The proposed event classification technique is able to detect and classify local events which have a considerable impact on the safety and operation of DG systems. The technique is implemented using the pattern recognition feature of ANNs. Four parallel ANNs are used for classification. Each neural network is optimally designed to classify events based on a specific local parameter. The output of each neural network is arranged in a vector form and the majority vote of the four ANN classifiers is selected as the final classification output. A total of 310 sample cases of islanded and grid-connected events have been generated to test the performance of the technique. The accuracy of the proposed event classification technique has been verified using 10-fold cross-validation. The technique classifies the event within 10 cycles of event occurrence with a 96.21% average classification accuracy. The implementation of this classification feature in distributed generation systems can help the system operator to develop a clear understanding of the operating requirements to mitigate the effects of such events. Furthermore, this technique is able to classify an islanding event according to the type of mismatch within the island. This added capability can help the system operators make informed actions to react to such events after islanding. To the best of the authors' knowledge, incorporating such an event classification feature into DG systems has not been investigated before. In this study, individual occurrence of events was investigated due to the low probability of two or more events coinciding. However, this case could be further investigated in a future work.

REFERENCES

[1] P. Hines, J. Apt, and S. Talukdar, "Large blackouts in North America: Historical trends and policy implications," *Energy Policy*, vol. 37, no. 12, pp. 5249–5259, Dec. 2009.

[2] A. A. Bayod-Rújula, "Future development of the electricity systems with distributed generation," *Energy*, vol. 34, no. 3, pp. 377–383, 2009.

[3] B. Guha, R. J. Haddad, and Y. Kalaani, "A novel passive islanding detection technique for converter-based distributed generation systems," in *Proc. IEEE PES Conf. Innov. Smart Grid Technol. (ISGT)*, Feb. 2015, pp. 1–5.

[4] B. Guha, R. J. Haddad, and Y. Kalaani, "Anti-islanding techniques for inverter-based distributed generation systems—A survey," in *Proc. IEEE SoutheastCon*, Apr. 2015, pp. 1–9.

[5] (2014). *Renewables 2014 Global Status Report*. [Online]. Available: http://www.ren21.net/Portals/0/documents/Resources/GSR/2014/GSR2014_full%20report_low%20res.pdf

[6] (Mar. 2015). *U.S. Executive Order 13693*. [Online]. Available: https://www.fedcenter.gov/programs/eo13693/

[7] S. Kihm and J. Kramer, "Third-party distributed generation issues and challenges for policymakers," Energy Center Wisconsin, Madison, WI, USA, Tech. Rep. ECW 273-1, 2014.

[8] P. Järventausta, S. Repo, A. Rautiainen, and J. Partanen, "Smart grid power system control in distributed generation environment," *Annu. Rev. Control*, vol. 34, no. 2, pp. 277–286, Dec. 2010.

[9] M. Gujar, A. Datta, and P. Mohanty, "Smart mini grid: An innovative distributed generation based energy system," in *Proc. IEEE Innov. Smart Grid Technol.-Asia (ISGT Asia)*, Nov. 2013, pp. 1–5.

[10] O. P. Mahela, A. G. Shaik, and N. Gupta, "A critical review of detection and classification of power quality events," *Renew. Sustain. Energy Rev.*, vol. 41, pp. 495–505, Jan. 2015.

[11] M. Valtierra-Rodriguez, R. de Jesus Romero-Troncoso, R. A. Osornio-Rios, and A. Garcia-Perez, "Detection and classification of single and combined power quality disturbances using neural networks," *IEEE Trans. Ind. Electron.*, vol. 61, no. 5, pp. 2473–2482, May 2014.

[12] H. Eristi and Y. Demir, "Automatic classification of power quality events and disturbances using wavelet transform and support vector machines," *IET Generat., Transmiss., Distrib.*, vol. 6, no. 10, pp. 968–976, Oct. 2012.

[13] P. K. Ray, S. R. Mohanty, and N. Kishor, "Classification of power quality disturbances due to environmental characteristics in distributed generation system," *IEEE Trans. Sustain. Energy*, vol. 4, no. 2, pp. 302–313, Apr. 2013.

[14] H. He and J. A. Starzyk, "A self-organizing learning array system for power quality classification based on wavelet transform," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 286–295, Jan. 2006.

[15] S. Ekici, "Classification of power system disturbances using support vector machines," *Expert Syst. Appl.*, vol. 36, no. 6, pp. 9859–9868, Aug. 2009.

[16] M.-H. Wang and Y.-F. Tseng, "A novel analytic method of power quality using extension genetic algorithm and wavelet transform," *Expert Syst. Appl.*, vol. 38, no. 10, pp. 12491–12496, Sep. 2011.

[17] D. G. Cesar, V. G. Valdomiro, and O. P. Gabriel, "Automatic power quality disturbances detection and classification based on discrete wavelet transform and artificial intelligence," in *Proc. IEEE PES Transmiss. Distrib. Conf. Expo., Latin Amer.*, Aug. 2006, pp. 1–6.

[18] A. K. Chandel, G. Guleria, and R. Chandel, "Classification of power quality problems using wavelet based artificial neural network," in *Proc. Transmiss. Distrib. Conf. Expo.*, Apr. 2008, pp. 1–5.

[19] M. B. I. Reaz, F. Choong, M. S. Sulaiman, F. Mohd-Yasin, and M. Kamada, "Expert system for power quality disturbance classifier," *IEEE Trans. Power Del.*, vol. 22, no. 3, pp. 1979–1988, Jul. 2007.

[20] S. R. Samantaray, "Decision tree-initialised fuzzy rule-based approach for power quality events classification," *IET Generat., Transmiss., Distrib.*, vol. 4, no. 4, pp. 530–537, Apr. 2010.

[21] F. Zhao and R. Yang, "Power-quality disturbance recognition using S-transform," *IEEE Trans. Power Del.*, vol. 22, no. 2, pp. 944–950, Apr. 2007.

[22] M. Uyar, S. Yildirim, and M. T. Gencoglu, "An expert system based on S-transform and neural network for automatic classification of power quality disturbances," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 5962–5975, Apr. 2009.

[23] J. K. Basu, D. Bhattacharyya, and T.-H. Kim, "Use of artificial neural network in pattern recognition," *Int. J. Softw. Eng. Appl.*, vol. 4, no. 2, pp. 1–12, 2010.

[24] R. Bellman, *Dynamic Programming* (Rand Corporation Research Study). Princeton, NJ, USA: Princeton Univ. Press, 1957.

[25] G. Hughes, "On the mean accuracy of statistical pattern recognizers," *IEEE Trans. Inf. Theory*, vol. 14, no. 1, pp. 55–63, Jan. 1968.

[26] T. M. Cover, "Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition," *IEEE Trans. Electron. Comput.*, vol. EC-14, no. 3, pp. 326–334, Jun. 1965.

[27] L. K. Hansen and P. Salamon, "Neural network ensembles," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12, no. 10, pp. 993–1001, Oct. 1990.

[28] M. F. Hassan and I. Abdel-Qader, "Performance analysis of majority vote combiner for multiple classifier systems," in *Proc. IEEE 14th Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2015, pp. 89–95.

[29] W. Bower and M. Ropp, "Evaluation of islanding detection methods for utility-interactive inverters in photovoltaic systems," Sandia Nat. Lab., Tech. Albuquerque, NM, USA, Tech. Rep. SAND2002-3591, 2002.

[30] B. Guha, R. J. Haddad, and Y. Kalaani, "Voltage ripple-based passive islanding detection technique for grid-connected photovoltaic inverters," *IEEE Power Energy Technol. Syst. J.*, vol. 3, no. 4, pp. 143–154, Dec. 2016.

[31] *IEEE Standard for Interconnecting Distributed Resources With Electric Power Systems*, IEEE Standard 1547.2-2008, Apr. 2009, pp. 1–217.

[32] I. S. Isa, S. Omar, Z. Saad, and M. K. Osman, "Performance comparison of different multilayer perceptron network activation functions in automated weather classification," in *Proc. 4th Asia Int. Conf. Math./Anal. Modeling Comput. Simulation*, May 2010, pp. 71–75.

[33] M. F. Møller, "A scaled conjugate gradient algorithm for fast supervised learning," *Neural Netw.*, vol. 6, no. 4, pp. 525–533, Nov. 1993.

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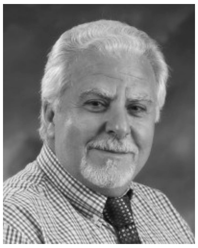

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