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Electric Power Quality Disturbance Classification Using Self-Adapting Artificial Neural Networks

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Abstract

The issue of power quality is now recognised as an essential feature of a successful electric power system. This is mainly due to the rapid increase of loads, which generate noise and, at the same time, are sensitive to the noise present in the supply system. As a result, power quality monitoring has become an important issue in modern power systems.

This paper presents a technique for classifying electrical power quality disturbance events. The technique is based on a novel Self-Adapting Artificial Neural Network (SAANN), which has the unique capability of adapting to new disturbance features.

In the proposed technique, distinctive feature vectors from disturbance events captured are extracted using Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT). The feature vectors are then fed to two SAANN based classifiers, which classify the captured events into different categories of power quality disturbances. The proposed technique is tested using a number of disturbance events and results are presented.

1. Introduction

In a typical power quality monitoring system, the voltage and/or current waveforms at certain buses are recorded and then analysed to identify known power quality disturbance signatures[1,2]. If the process of power quality monitoring is fully automated, it will enable the utilities to respond more effectively to customer complaints.

Many of the techniques proposed in the literature are designed to reflect the knowledge and experience of an engineer for disturbance classification by using artificial intelligence in the form of Artificial Neural Networks (ANNs), Fuzzy logic, etc [3-5]. These techniques use feature vectors derived from the captured waveforms to classify the disturbances, as shown in Figure (1). However, the main problem seen with these techniques is that they are not able to adapt to new types of disturbances.

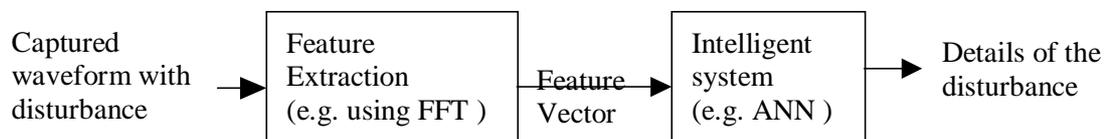


Figure (1)

Block diagram of a typical disturbance classification system

One of the approaches that have been investigated is to use an unsupervised ANN, such as Self-Organising Map (SOM) for disturbance classification [3]. The advantage of SOM is that, it tries to identify significant patterns in the disturbance feature vectors and assign them to different disturbance classes [6,7]. This is done based on a similarity criterion. However, there are no straightforward techniques for determining the best structure of a SOM. In some cases, a number of neurones in the SOM may be redundant after the learning process, whereas in other cases it may not be enough to classify the

entire set of feature vectors. In case of power quality disturbance classification, this will affect the correct classification, as the features of different disturbance classes vary when new types of disturbance sources are added to the system. Therefore, a neural network with a flexible structure is required for this purpose.

An ideal power quality disturbance classification scheme should be able to classify presently known disturbances as well as be able to adapt to new features of disturbances. In addition, it should be able to improve its existing ‘knowledge’ while it is in operation. The Self-Adapting Artificial Neural Network (SAANN) based technique proposed in this paper provide these features.

2. The Self Adapting Artificial Neural Network (SAANN)

Basically, the structure of the proposed SAANN is similar to that of a SOM. It has an input layer and a competitive layer consisting of several nodes referred to as neurones, as shown in Figure (2). A distinctive feature vector (**FV**) representing an event to be classified is fed into the input layer and the competitive layer assigns the feature vectors to different disturbance classes, $C_1, C_2 \dots C_j$.

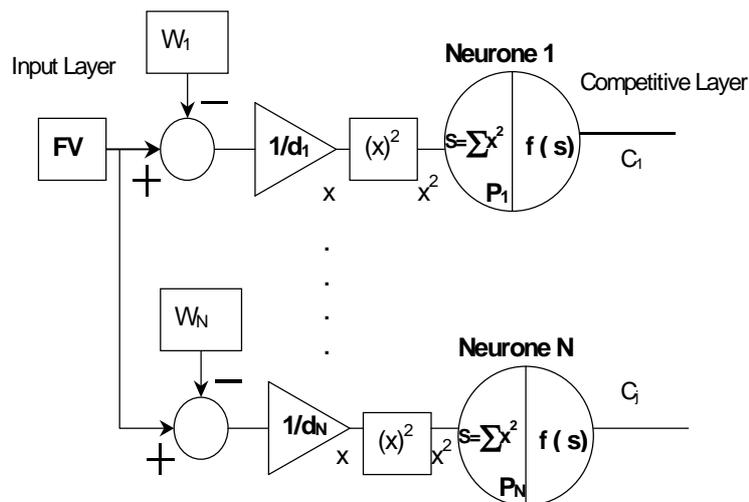


Figure (2)
Structure of the SAANN

During the learning process of the SAANN, each of these neurones is selected to represent a group of feature vectors (**FV**) belonging to a particular disturbance class and having similar features. However, it should be noted that a particular disturbance class might have one or more neurones associated with it depending on its features. The weight vector $\mathbf{W} = [w_1, w_2, \dots, w_N]$ at the input of each neurone has a dimension that is equal to the dimension of **FV**. It contains the mean value of a group of feature vectors represented by the corresponding neurone. Therefore, weight vector $\mathbf{W}^{(G)}$, of a certain feature vector group (**G**) with N_G feature vectors, could be obtained by calculating the mean value of all the feature vectors in that group, as given by equation (1).

$$\mathbf{W}^{(G)} = \frac{\sum_{n=1}^{N_G} \mathbf{FV}_n^{(G)}}{N_G} \quad (1)$$

In the proposed SAANN, in addition to \mathbf{W} , another vector referred to as deviation vector $\mathbf{D} = [d_1, d_2, \dots, d_N]$ is introduced for each neurone. It contains information about how particular groups of feature vectors are scattered around its centre value. The deviation vector \mathbf{D} is calculated using equation (2).

$$\mathbf{D}^{(G)} = \sqrt{\frac{\sum_{n=1}^{N_G} |\mathbf{FV}_n^{(G)} - \mathbf{W}^{(G)}|^2}{N_G}} \quad (2)$$

Each neurone of the SAANN also has a counter $\mathbf{P} = [p_1, p_2, \dots, p_N]$, which contains the number of feature vectors represented by the corresponding neurone. One of the main differences between the SAANN and other ANNs is that it does not have any neurones initially. Neurones are added during the learning process of the SAANN by looking for similar groups of feature vectors. Each time a feature vector **FV** is fed to the SAANN, a parameter denoted by $C^{(n)}$ is calculated using equation (3), which

represents the closeness of FV to all the weight vectors $[W^{(n)}, n=1,2,\dots,N]$ of the existing neurones in the SAANN,

$$C^{(n)} = f \left(\sqrt{\sum_{j=1}^M \left[\frac{(FV(j) - W^{(n)}(j))^2}{D^{(n)}(j)} \right]} \right) \quad (3)$$

where $f(x) = e^{-x}$.

The maximum value of C ($C^{(\max)}$) is compared with a threshold α . If $C^{(\max)} \leq \alpha$, it means that all the feature vector groups represented by the neurones in SAANN are distant from FV. In other words, FV does not fit into any of the existing feature vector groups. In such case, a new neurone is added to the system.

If $C^{(\max)} > \alpha$, the corresponding neurone is referred to as the winner neurone and the input feature vector could be classified into the disturbance associated with the winner neurone. In addition, FV is added to the group of feature vectors represented by the winner neurone. This is done by adjusting the corresponding weight vector $W^{(G)}$ and the deviation vector $D^{(G)}$ of the winner neurone.

A flow chart to illustrate the above algorithm is shown in Figure (3).

During the learning process, some of the neurones may become redundant. That is, the group of feature vectors represented by these neurones is better represented by another close neurone. In such a case a neurone merging procedure is used to combine closely related neurones and eliminate the redundant neurones.

In the neurone merging process, the weight vectors of each neurone are fed to the SAANN and the corresponding values for $C^{(n)}$ are calculated. By finding the maximum value of $C^{(n)}$, the corresponding closest pair of neurones are identified and replaced with a new neurone combining the properties of both neurones.

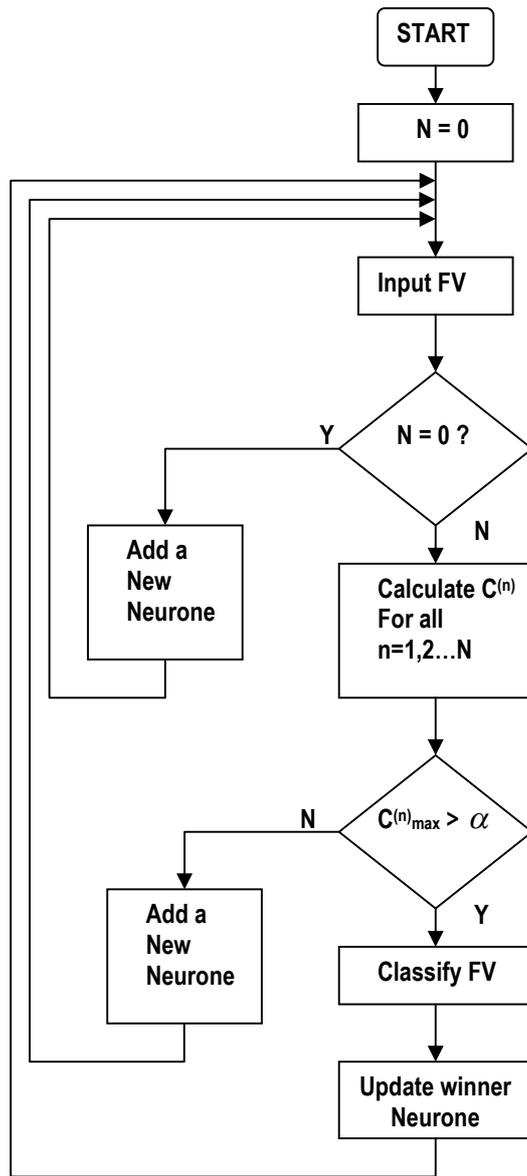


Figure (3)

A flow chart of the SAANN algorithm

3. Disturbance classification using SAANNs

3.1. Pre-processing of disturbance signals

The captured waveform is first processed using a suitable technique to distinguish steady-state events from transition events. The steady-state event is that where the incoming signal waveform does not change during a predefined time period (typically 1

minute). Examples of such event are harmonic distortion, under voltage, over voltage, etc. The normal operating condition with no disturbances is obviously considered as a steady-state event. Other events are termed as transition events where the signal waveform is different from one cycle to another. Examples of transition events are transients, voltage sags and swells. In order to classify these events, distinctive feature vectors from each disturbance event waveforms have to be extracted.

For steady-state events, the frequency components of the signal are sufficient to describe the event uniquely. Therefore, a steady-state event is represented by the magnitudes of its Fourier coefficients, which are calculated using the Fast Fourier Transform (FFT) [8]. A feature vector of 2 elements is extracted, which contains the magnitude of the fundamental frequency component as one element and the sum of energy in all other frequency components as the other element.

In case of transition events, the frequency components of the signal vary within one cycle period. Therefore, the Discrete Wavelet transform (DWT) is used for extracting features from waveforms captured during transition events [9,10]. The DWT transforms a signal from the time domain into a time-frequency domain, where both the frequency components of the signal and their variation with the time are obtained. In the proposed technique, a feature vector with 63 elements (calculated using the DWT) is implemented.

3.2. Training of the SAANN

The SAANN, unlike other neural networks, always learn and adapt itself to new environments. When it is initially installed in a power system, it will classify most of the events as unclassified. At this stage, the operator should give the classes of events to the SAANN. With more and more disturbances experienced, the SAANN eventually

learns to classify events correctly and its overall classification accuracy increases. In this learning method, the classifier takes a long time to achieve an acceptable accuracy level. Therefore, before installing the classifier on a real power system, it is desirable that the SAANN be trained using some known disturbance signals selected from each disturbance class. This will make the classification task easier than starting from zero level. In addition, this will minimise the effect of frequency of occurrence of a certain disturbance type on the accuracy of that type. Also, it will prevent the network 'forgetting' the features of a type that occurs infrequently.

Training data need not necessarily be real disturbance signals, as they only provide a basis to start with. Once the classifier is connected to a real system, it adapts itself to the real data. So there is always room for improving the performance. The neurones trained using simulation data will be always updated using the real event data. If there are any real feature vectors which considerably differ from the simulated feature vectors, the SAANN automatically adds new neurones to cope with such events. Using this method, the classification task becomes easier than starting from zero level.

In the work presented in this paper, two SAANNs (SAANN-1 and SAANN-2) are trained for classifying steady-state events and transition events, respectively. For SAANN-1, 25 feature vectors are used from each disturbance class. In addition, 100 feature vectors are used to represent harmonic distortion. In order to train SAANN-2, 50 feature vectors from each disturbance class are used. In case of oscillatory transients, 100 feature vectors are used. The feature vectors are continuously presented to the corresponding SAANN until the number of neurones converges to a constant value.

4. Results and Discussion

The proposed feature extraction technique is applied to waveforms recorded during different types of disturbance events such as impulsive transient, oscillatory transient, etc. Figure (4) and Figure (5) show the time-domain waveforms captured and the corresponding feature vector in the form of a scalogram during an impulsive transient event and oscillatory transient event, respectively. The darkness of a cell in the scalogram represents the energy of the signal in a particular frequency range and a particular time period.

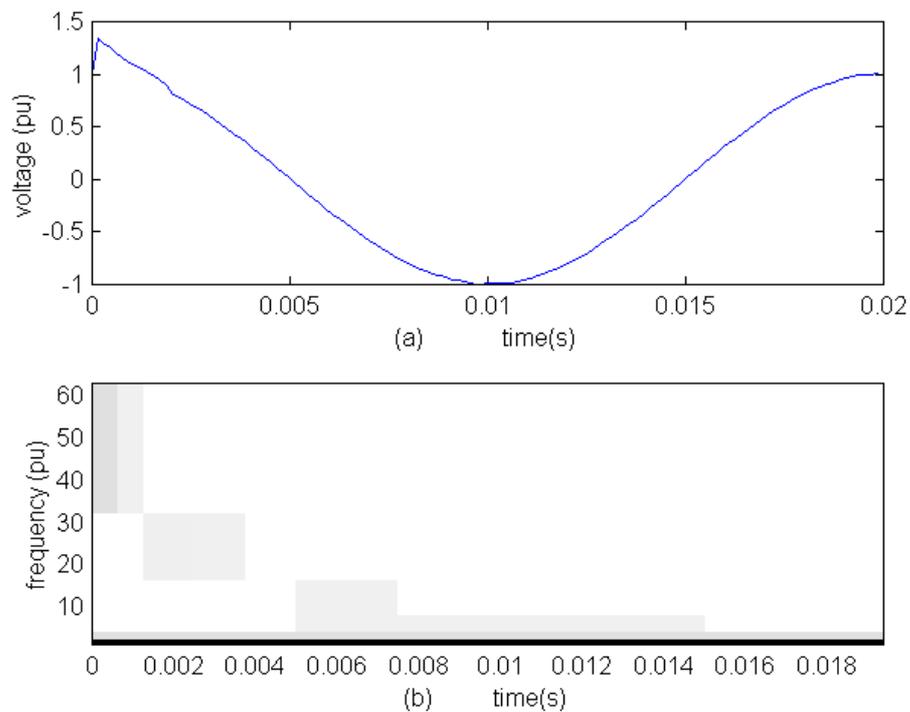


Figure (4)

Captured voltage waveform during an impulsive transient and its corresponding scalogram

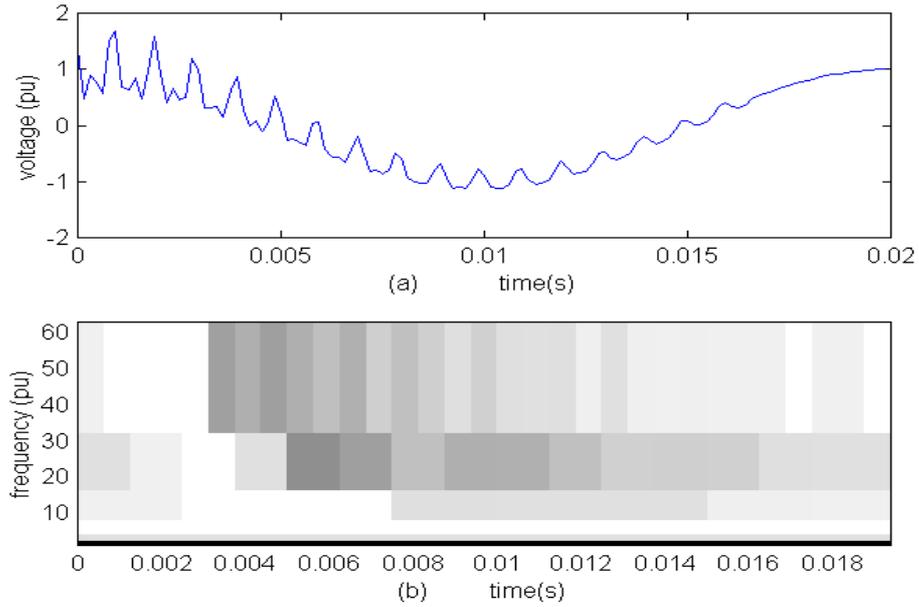


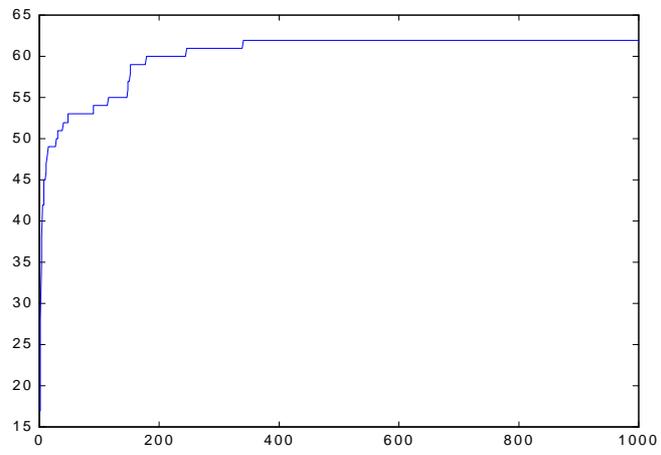
Figure (5)

Captured voltage waveform during an oscillatory transient and its corresponding scalogram

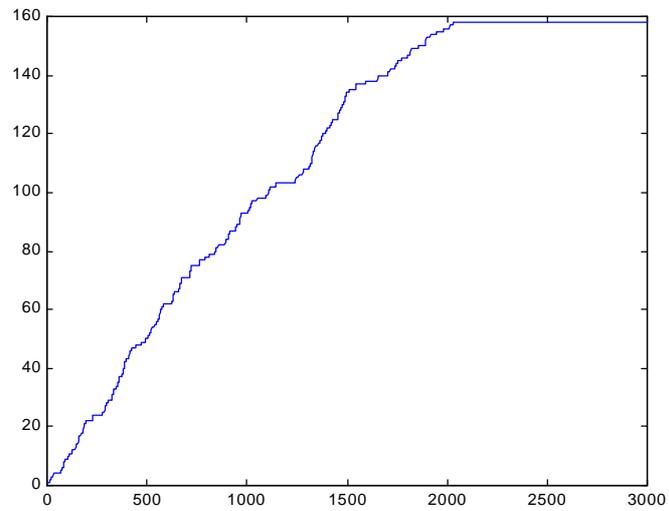
The SAANNs are trained using a number of feature vectors collected during various disturbance events. The variation of number of neurones in SAANN-1 and SAANN-2 with each iteration of the learning process is shown in Figure 6(a) and 6(b), respectively. It can be seen that, during the early stage of the learning process, neurones are added to the network at a higher rate as compared to the later stage where the number converges to a constant value.

After the number of neurones converges to a constant value, a neurone merging algorithm is applied to eliminate the redundant neurones. In the proposed work, the sizes of the SAANN-1 and SAANN-2 were reduced from 62 to 59 neurones and 158 to 90 neurones, respectively.

Both SAANN-1 and SAANN-2 have been tested using data sets, obtained from both experimental tests and computer simulation. The percentage classification accuracy obtained from SAANN-1 and SAANN-2 are listed in Table 1 and Table 2, respectively.



(a). SAANN-1



(b). SAANN-2

Figure (6)

Variation of number of neurones during the learning process

Type	(%) accuracy (before merging)	(%) accuracy (after merging)
Normal condition	88	88
Supply interruption	80	80
Under voltage	88	88
Over voltage	100	100
Supply interruption	97	97
Over all accuracy	93	93

Table 1: Classification accuracy of SAANN-1

Type	(%) accuracy (before merging)	(%) accuracy (after merging)
Impulsive transients	100	98
Oscillatory transients	96	94
Voltage swell	98	94
Voltage sag	98	96
Supply interruption	100	100
Over all accuracy	98	96

Table 2: Classification accuracy of SAANN-2

The results obtained show that the overall classification accuracy is 98% and 93% for transition event and steady-state events, respectively. This is comparable with the percentage accuracy of the techniques proposed by Ghosh and Lubkeman [3] (95%), Damrala, et al [4] (>70%). However, it was observed that 2.5% and 1.33% events are unclassified in steady-state and transition events, respectively. New neurones can be added to the SAANN in case of unclassified events increasing the classification accuracy further. It should be noted that some events have similar classification accuracy which is due to the fact that such events have similar distribution in the feature

space. Also, it is not only the number of feature vectors that determine the accuracy of classification but also the characteristics of these vectors that make them distinctive.

The results also show that removing the redundant neurone does not have any effect on the classification accuracy for steady-state event classification. In case of transition event classification, the overall accuracy is reduced from 98% to 96%. However, considering the large number of neurones removed from the SAANN (43%), this reduction in accuracy is insignificant.

5. Conclusions

A disturbance classification technique employing new SAANNs has been developed and is described in this paper. Unlike other neural networks, the SAANN always learn and adapt itself to new environments. This makes the classification accuracy of the SAANN dependent upon the frequency of occurrence of a certain event. However, this problem can be overcome if the SAANN is trained using known disturbance signals selected from each disturbance type before installing the classifier on a real system. The advantage of the SAANN is that training data need not be real disturbance signals, as they only provide a basis to start with. Once the classifier is connected to a real system, it adapts itself to the real data.

The features associated with power quality disturbances vary from time to time as new types of disturbance sources may be added to the power system. The proposed technique has the capability of adapting to new disturbance features by its self-growing technique. In addition, it learns the statistical properties of known disturbances by self-tuning the weight vectors with every input disturbance. This makes the proposed SAANN technique ideally suited for power quality disturbance classification.

6. Refernces

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Block diagram of a typical disturbance classification system

Figure (2)

Structure of the SAANN

Figure (3)

A flow chart of the SAANN algorithm

Figure (4)

Captured voltage waveform during an impulsive transient and its corresponding scalogram

Figure (5)

Captured voltage waveform during an oscillatory transient and its corresponding scalogram

Figure (6)

Variation of number of neurones during the learning process

Table 1

Classification accuracy of SAANN-1

Table 2

Classification accuracy of SAANN-2