A SPECTRAL – NEURO MODELING FOR FAULT LOCATION AND DIAGNOSIS IN DISTRIBUTED POWER SYSTEM

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ABSTRACT

In this paper an approach for the improvement of the neural training error and its improvement for real time system is developed. The approach of learning the neural network is developed using the advanced feature of wavelet transformation approaches and is designed to observe even the minor current variations, which result in variation in the observation result. In this paper a contribution towards the accurate estimation of the current disturbance is developed using DWT learning for a neuro classifier.

Keywords: wavelet spectral data, frequency resolution, fault location, neural network.

1. INTRODUCTION

Current power system [3] demand for clean power has been increasing in the past several years. The reason is mainly due to the increased use of microelectronic processors in various types of equipments such as computer terminals, programmable logic controllers and diagnostic systems. Most of these systems are quite susceptible to disturbances [2] in the supply voltage. The amount of waveform distortion has been found to be more significant nowadays due to the wide applications of nonlinear electronic devices in power apparatus and systems [1]. Without determining the existing levels of power quality, electric utilities cannot adopt suitable strategies to provide a better service. Therefore an efficient approach of justifying these electric power quality disturbances [2] is motivated.

Several research studies regarding the power quality have been conducted. Their aims were often concentrated on the collection of raw data for a further analysis, so that the impacts of various disturbances can be investigated [2]. Sources of such disturbances can be located or further mitigated. However, the amount of acquisition data was often massive in their test cases. Such an abundance of data may be time consuming for the inspection of possible culprits. A more efficient approach is thus required in the power quality assessment. The implementation of the discrete Fourier transform by various algorithms has been constructed as the basis of modern spectral analysis. Such transforms were successfully applied to stationary signals where the properties of signals did not evolve in time. However, for those non-stationary signals any abrupt change may spread over the whole frequency axis. In this situation, the Fourier transform is less efficient in tracking the signal dynamics.

A point-to-point comparison scheme has been proposed to discover the dissimilarities between consecutive cycles. This approach was feasible in detecting certain kinds of disturbances but fail to detect those disturbances that appear periodically. With the introduction of new network topologies and improved training algorithms, neural network technologies have demonstrated their effectiveness in several power system applications [3]. Once the networks have been well trained, the disturbances that correspond to the new scenario can be identified in a very short time. This technique has also been applied in the power system applications. However, it can only be applied to detect a particular type of disturbance.

When encountering different disturbances, the network structure has to be reorganized, plus the training process must be restarted. A method of detecting power quality disturbances based on neural networks and wavelets has been proposed. In this method, the fundamental component is removed using wavelets and the remaining signal corresponding to disturbances is processed and given as input to ANN. However, this method fails to detect voltage sag/swell and also new ANNs have to be developed for different rated load voltages and sampling frequencies. Recently with the emergence of wavelets it has paved a unified framework for signal processing and its applications. Fourier transforms rely on a uniform window for spreaded frequencies. Wavelet transforms can apply various lengths of windows according to the amount of signal frequencies. Characteristics of non- stationary disturbances were found to be more closely monitored by wavelets.

The transient behavior [4, 5] cavities and discontinuities of signals can be all investigated by wavelet transforms. For example, if there is an instantaneous impulse disturbance, which happens at a certain time interval it may contribute to the Fourier transform, but its location on the time axis is lost. However, by wavelets both time and frequency information can be obtained. In other words, the wavelet transform are more local. Instead of transforming a pure 'time domain' in to a pure' frequency domain ', the wavelet transforms find a good compromise in time -

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frequency domain. In this work an algorithm, which overcomes all these difficulties and can accurately detect and classify the disturbances present in the signal is tested. This method is independent of the load voltage and can be easily customized for different sampling frequencies. In this approach, for detecting each disturbance a particular wavelet is used. The method uses wavelet filter banks in an effective way and does multiple filtering to detect the disturbances.

2. FAULT DIAGNOSIS IN POWER SYSTEM

Modern electric power systems have three separate components - generation, transmission and distribution. Electric power is generated at the power generating stations by synchronous alternators that are usually driven either by steam or hydro turbines. Most of the power generation takes place at generating stations that may contain more than one such alternator-turbine combination.

Depending upon the type of fuel used, the generating stations are categorized as thermal, hydro, nuclear etc. Many of these generating stations are remotely located. Hence the electric power generated at any such station has to be transmitted over a long distance to load centers that are usually cities or towns. This is called the power transmission. In fact power transmission towers and transmission lines are very common sights in rural areas. The basic structure of a power system is shown in the figure-1.

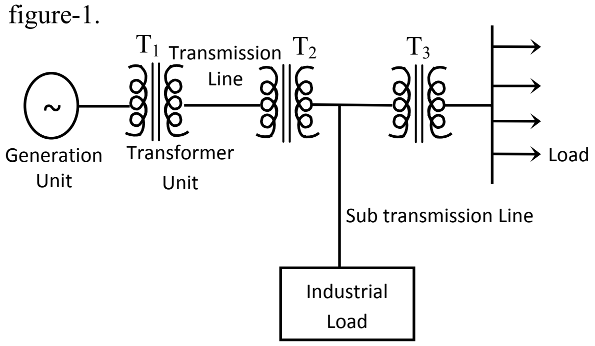

Figure-1. A typical power system.

It contains a generating plant, a transmission system, a sub transmission system and a distribution system. These subsystems are interconnected through transformers T_1, T_2 and T_3. When the power transmission is carried out on such electrical system there are disturbances been observed due to the electrical interfacing devices such as power transformers and switching devices. These disturbances are termed as 'Harmonics'. Harmonics only mean trouble if the power system is not designed to handle them. High harmonic neutral currents are a problem only if the neutral is not properly sized. Current harmonics are not a problem to a transformer if it is derated appropriately. Even some voltage distortion below 8% THD at the point of utilization is acceptable as long as sensitive equipment is not affected.

However, it is always important to be aware of the presence of harmonics and to try to minimize them by purchasing low distortion electronic ballasts and reactors for PWM ASDs. This will not only keep the harmonics in check and improve the power factor in the facility, but will also save energy by reducing losses on power system components. In addition, any time there is a considerable increase of nonlinear loads, it is important to check power system components to prevent problems.

The fundamental idea behind wavelets is to analyze the signal at different scales or resolutions, which is called multi resolution. Wavelets are a class of functions used to localize a given signal in both space and scaling domains. A family of wavelets can be constructed from a mother wavelet. Compared to windowed Fourier analysis, a mother wavelet is stretched or compressed to change the size of the window. In this way, big wavelets give an approximate image of the signal, while smaller and smaller wavelets zoom in on details.

Therefore, wavelets automatically adapt to both the high frequency and the low frequency components of a signal by different sizes of windows. Any small change in the wavelet representation produces a correspondingly small change in the original signal, which means local mistakes do not influence the entire transform. The wavelet transform is suited for non-stationary signals, such as very brief signals and signals with interesting components at different scales. Wavelets are functions generated from one single function ψ, which is called mother wavelet, by dilations and translations

$$\psi_{a,b}(x) = |a|^{-1/2}\,\psi\left(\frac{x-b}{a}\right) \qquad \text{—— (1)}$$

Where ψ must satisfy $\int \psi(x)\,dx = 0$

The basic idea of wavelet transform is to represent any arbitrary function 'f' as a decomposition of the wavelet basis or write 'f' as an integral over a and b of $\psi_{a,b}$.

Let $a = a_0^m, b = nb_0 a_0^m$ with m, n € integers, and $a_0>1, b_0>0$ fixed. Then the wavelet decomposition is

$$f = \sum c_{m,n}(f)\psi_{m,n} \qquad \text{—— (2)}$$

In power analysis, the sampled data are discrete in time. It is required to have discrete representation of time and frequency, which is called the Discrete Wavelet Transform (DWT).

Wavelet Transform (WT) was used to analyze non-stationary signals, i.e., whose frequency response varies in time. Although the time and frequency resolution problems are results of a physical phenomenon and exist regardless of the transform used, it is possible to analyze any signal by using an alternative approach called the

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Multi Resolution Analysis (MRA). MRA analyzes the signal at different frequencies with different resolutions.

MRA are basically designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach is useful especially when the signal considered has high frequency components for short durations and low frequency components for long durations which are basically used in practical applications. The DWT based feature descriptor is designed for the training of neuro controller as a learning feature for making decision for the fault location and diagnosis.

3. SYSTEM DESIGN

The first step of the detection module is to obtain the transmitting voltage and current samples. The current samples are normalized and passed to discrete wavelet transform (DWT) for obtaining frequency resolved coefficients. The fault detection is carried out through the analysis of the current wavelet coefficient energy. In the case of no fault, no data are transferred.

It is well known that the main power quality deviations are caused by short circuits, harmonic distortions, voltage sags and swells etc. In order to correct such problems, it is required, in general that, firstly, they should be detected and identified. Whenever the disturbance lasts for only a few cycles, a simple observation of the waveform in a bus bar may not be enough to recognize that there is a problem or not and more difficult is to identify the sort of the problem. The discrete wavelet transform (DWT) has been applied to analyze the currents during short duration disturbances in the transmission line.

The discrete wavelet transform (DWT) is one of the three forms of wavelet transform. It moves a time domain discretized signal into its corresponding wavelet domain. This is done through a process called "sub-band coding", which is done through digital filter techniques. The Line current signals obtained from the bus bar are applied to the wavelet filters to evaluate the frequency resolution coefficients by passing through high pass filter and low pass filter.

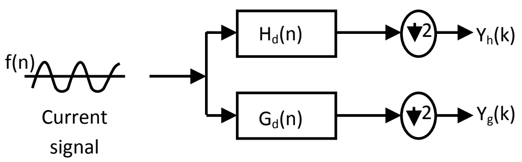

Figure-2. Wavelet decomposition of electrical current pulse.

To filter the given current signal f(n), a convolution of this signal is done at each filtration using a defined filter coefficient h_d and g_d. A recursive multiplication and accumulation operation is performed on the given current signal to obtain the detailed and approximate coefficient as given in equations 3, 4.

$$cA_1(n) = \sum_k f(n).h_d(-k+2n) \tag{3}$$

$$cD_1(n) = \sum_k f(n).g_d(-k+2n) \tag{4}$$

The f(n) signal is passed through a low pass digital filter ($h_d(n)$) and a high pass digital filter ($g_d(n)$). The obtained coefficients are decimated by factor of 2 i.e., half of the signal samples are eliminated.

The DWT operation is performed in two stages. The first consists of the wavelet coefficients determination. These coefficients represent the given signal in the wavelet domain. From these coefficients, the second stage is achieved with the calculation of both the approximated and the detailed version of the original signal, in different levels of resolutions, in the time domain. At the end of the first level of signal decomposition, the resulting vectors $y_h(k)$ and $y_g(k)$ will be, respectively, the level 1 wavelet coefficients of approximation and of detailed wavelet coefficients. The fault detection rules are established by means of the analysis of the current waveforms in time domain and in the first decomposition level of the DWT. This level contains the highest frequency components.

For the implementation of DWT based decomposition following steps are used for the calculation of wavelet coefficient:

Step 1: Evaluation of the wavelet coefficients of the signal under study.

Step 2: Evaluation of the square of the wavelet coefficients found at step 1.

Step 3: Calculation of the distorted signal energy, in each wavelet coefficient level.

The "energy" mentioned above is based on the Parseval's theorem which states that: "the energy that a time domain function contains is equal to the sum of all energy concentrated in the different resolution levels of the corresponding wavelet transformed signal". This can be mathematically expressed as:

$$\sum_{n=1}^{N} |f(n)|^2 = \sum_{n=1}^{N} |a_j(n)|^2 + \sum_{j=1}^{J}\sum_{n=1}^{N} |d_j(n)|^2 \tag{5}$$

Where, f(n): Time domain signal under study
N: Total number of samples of the signal

$\sum_{n=1}^{N} |f(n)|^2$: Total energy of the signal f(n)

$\sum_{n=1}^{N} |a_j(n)|^2$: Total energy concentrated in the level j' of the approximated version of the signal

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$\sum_{j=1}^{J}\sum_{n=1}^{N}\left|d_j(n)\right|^2$: Total energy concentrated in the detailed version of the signal, from levels '1 to j'

The obtained energy value for the given current signal is taken as the feature for training the neural network.

In order to classify faults, a feed forward back propagated neural network architecture is used, which is trained before testing the proposed method. The learning database contains a great variety of faulted scenarios to improve the ANN's generalization capability. By using this strategy, the ANN can classify correctly simulated and real faults in transmission line.

The output of the ANN must indicate which fault type is related to the actual input pattern. Hence, binary coding is used for the ANN's outputs in such a way that a fault is characterized by the presence (1) or absence (0) of one or more phases and of the ground, as shown in the Table-1, where no fault term indicates that the input pattern is not related to a fault. After the ANN learns, the fault classification [6] is carried out through the analysis of each window obtained from windowing process aforementioned. This means that the most identified fault type prevails. By using this strategy, even if the ANN makes a mistake for some windows, the fault classification will be correct anyway.

Table 1: Binary coding of the ANN output

The neural network is passed with the above stated fault outputs with their possible trained fault current wavelet features. On testing, these features are used as knowledge by the neural network for the accurate classification of fault type and their occurrences. For the implementation of the neural network a feed forward back propagation architecture is developed with 30 hidden nodes and with tangential sigmoid function for each hidden node. The training of this network is carried out using Least Mean (LM) algorithm. The network is trained with all the possible input patterns obtained for each fault case, with the minimum and maximum range of input and output. An epoch limit of 800 iterations, probability of error is given as 0.1 with a learning rate of 0.01. The operational model of the suggested approach is as defined below.

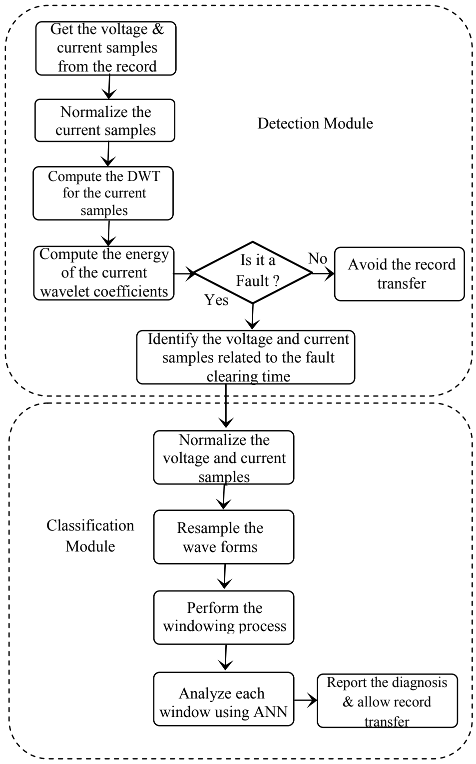

Figure-3. Operational flow chart for detection and classification method.

Fault type	Phase A Output 1	Phase B Output 2	Phase C Output 3	Ground Output 4
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
AC	1	0	1	0
BC	0	1	1	0
ABG	1	1	0	1
ACG	1	0	1	1
BCG	0	1	1	1
ABG	1	1	1	0
Nofault	0	0	0	0

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4. SIMULATION RESULTS

The proposed wavelet and ANN based fault detection and classification architecture is tested on a randomly distributed network as shown below with following specifications.

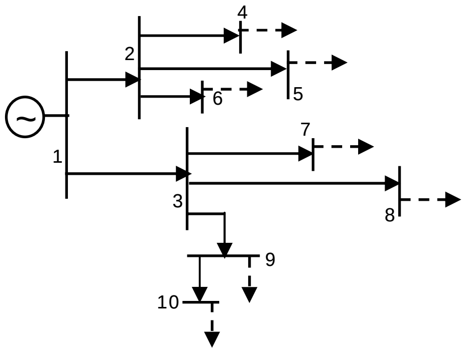


Figure-4. Considered Distributed power system architecture for implementation.

The faults were simulated over a 25MV, 13.2 kV, 100 km transmission line system. The obtained simulation results were as illustrated below.

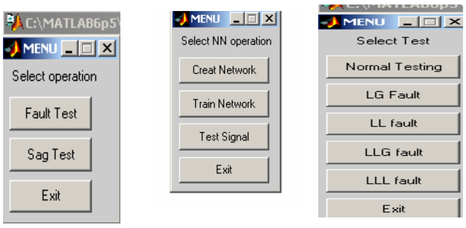


Figure-5. Menu generated for the selection of test operation, NN operation and fault testing conditions.

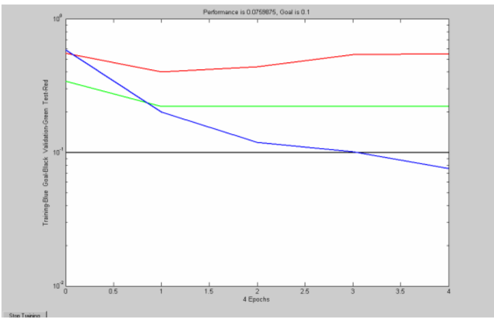


Figure-6. Learning plot for the validation, testing and training for the generated neural network.

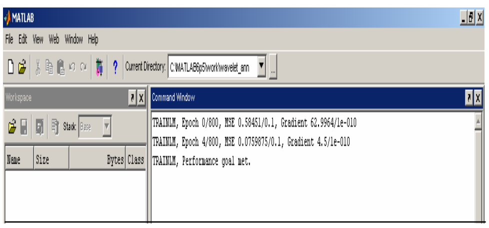


Figure-7. Simulation result showing the training process of the neural network.

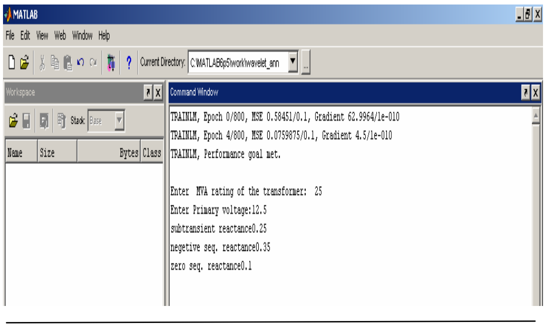


Figure-8. The input test values passed for the simulation of the electrical system.

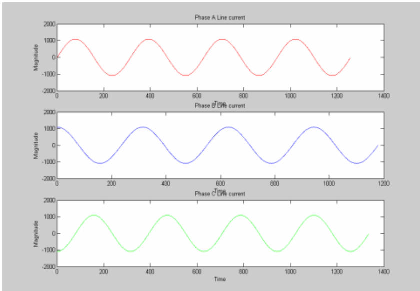
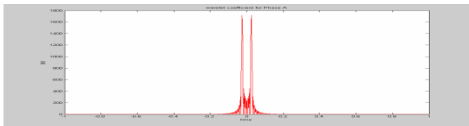


Figure-9. Three line currents generated for transmission.



(b)

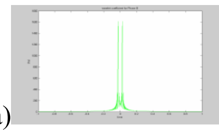
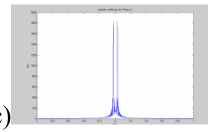
(a)  (c) 

Figure-10 (a),(b),(c). Wavelet coefficients for the three line currents passed.

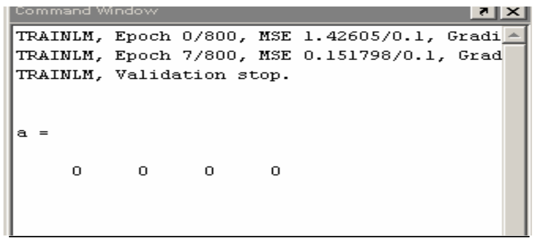


Figure-11. ANN output result for the normal testing.

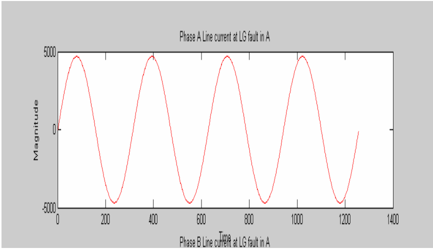


Figure-12. Fault current at phase A for L-G fault.

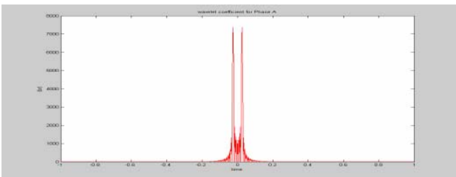


Figure-13. Wavelet coefficient generated for the fault current in line A.

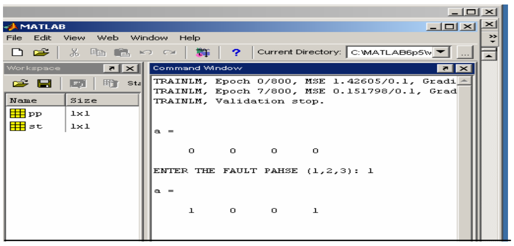


Figure -14. ANN test output for L-G fault in Line A.

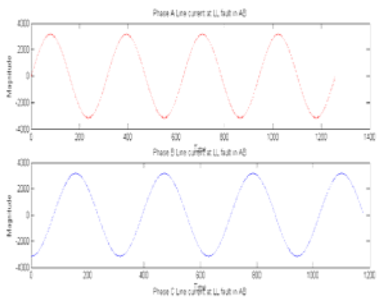


Figure-15. Fault currents generated for L-L fault in line AB.

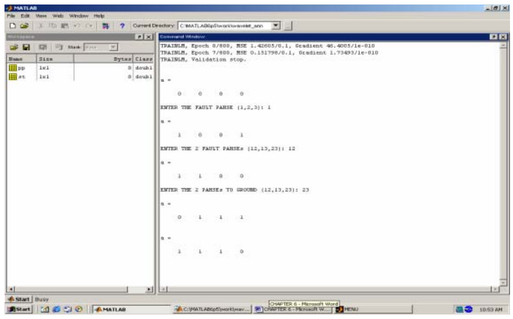


Figure-16. ANN output for L-L-L fault.

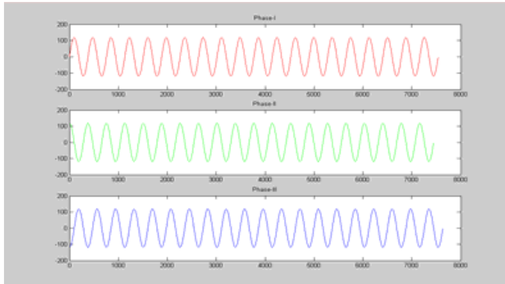


Figure -17. Line current for three phase under sag testing.

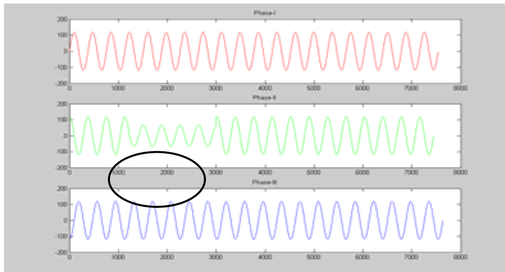


Figure -18. Generated sag current in phase 2.

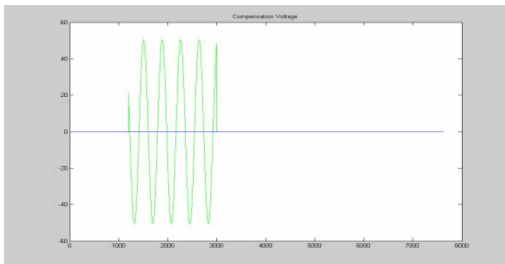


Figure-19. Compensation current generated for sag compensation.

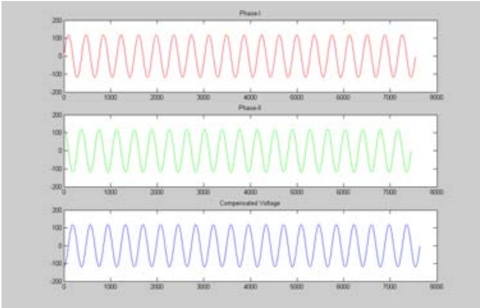


Figure-20.: Compensated current after sag compensation.

5. CONCLUSIONS

By the integration of these two techniques for fault diagnosis it is observed that the developed neural network detects and classifies the fault current accurately under various conditions. The current disturbances were also detected accurately. The algorithm is tested for distributed network with 10 nodes for different fault conditions and the result obtained from the classification unit is observed to be accurate. The proposed detection architecture for fault diagnosis shows accurate detection and classification under various fault conditions, which provides an efficient architecture for the development of fully automated monitoring systems with classification ability in distributed power system.

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