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Characterization of acoustic signals due to surface discharges on H.V. glass insulators using wavelet radial basis function neural networks

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ABSTRACT

A hybrid model incorporating wavelet and radial basis function neural network is presented which is used to detect, identify and characterize the acoustic signals due to surface discharge activity and hence differentiate abnormal operating conditions from the normal ones. The tests were carried out on cleaned and polluted high voltage glass insulators by using surface tracking and erosion test procedure of international electrotechnical commission 60587. A laboratory experiment was conducted by preparing the prototypes of the discharges. This study suggests a feature extraction and classification algorithm for surface discharge classification, which when combined together reduced the dimensionality of the feature space to a manageable dimension, by "marrying" the wavelet to radial basis function neural network very high levels of classification are achieved. Wavelet signal treatment toolbox is used to recover the surface discharge acoustic signals by eliminating the noisy portion and to reduce the dimension of the feature input vector. A radial basis function neural network classifier was used to classify the surface discharge and assess the suitability of this feature vector in classification. This learning method is proved to be effective by applying the wavelet radial basis function neural network in the classification of surface discharge fault data set. The test results show that the proposed approach is efficient and reliable.

1. Introduction

Atmospheric elements when accumulated on insulator's surface, form a layer of pollutant over time. The dielectric properties of the insulator does not diminish significantly, due to the pollutant layer especially when the layer is dry, but due to high humidity, light rain and even fog, it gets wet, and generates a leakage current resulting in a flashover which eventually leads to a disaster in service reliability [1,2].

The acoustic technology for target detection has developed very rapidly in the past few years. So strong tools are required, such as signal processing and feature extraction for the detection of such a condition [3,4]. Several researchers successfully used a method of acoustic detection for studying the characteristics of electrical discharges on insulators [5,6]. Many techniques on signal analysis have been used such as Fourier transform, wavelet transform (WT) as well as neural network in order to characterize and classify the electrical discharge signals [7,8]. But no work has been done up to now on the combined effect of wavelet transform with radial basis function neural network for characterization of surface discharge (SD).

Wavelet transform (WT) has been successfully employed in various fields of chemistry for signal processing and shape optimization for improving the quality characteristics of the products. A lot of research have been done regarding WT, employed mainly for signal processing in various fields of analytical chemistry, including flow injection analysis (FIA), high-performance liquid chromatography (HPLC), capillary electrophoresis (CE), infrared spectrometry (IR), ultraviolet–visible spectrometry (UV–vis), mass spectrometry (MS), nuclear magnetic resonance spectrometry (NMR), electroanalytical chemistry, and X-ray diffraction [9,10].

Some researchers developed the immune algorithm part of the neural network to optimize machining parameters for milling operations. A new hybrid optimization approach was developed by hybridizing the immune algorithm with hill climbing local search algorithm to maximize total profit rate in milling operations [11,12].

Among different structures of artificial neural networks (ANNs), the multilayer perceptron with the error-back-propagation training algorithm called backpropagation network (BPN) is the most popular one. However, due to its multilayered structure and the greedy nature of the back-propagation algorithm, the training process often settles in the undesirable local minima of error surface

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or converges slowly. Recently radial basis function neural networks (RBF-NNs) have been found to be very attractive for many problems. An important property of the RBF-NNs is that they form a unifying link among many different research fields such as function approximation, regularization, noisy interpolation, pattern recognition, and medicine. The increasing popularity of the RBF-NNs is partly due to their simple topological structure, their locally tuned neurons, and their ability to have a fast learning algorithm in comparison with other multilayer feed forward neural networks [13].

In some applications, electrical surface discharge detection methods are not very effective, typically as a result of excessive interfering signal [14,15]. Acoustic method has been used which has advantages over electrical surface discharge detection methods in that they are immune and non-invasive to electromagnetic noise. For the signal analysis, wavelet signal processing was used to de-noise the surface discharge acoustic signal by discarding the noise [16–18].

Furthermore, gating techniques were used to raise the efficiency of surface discharge acoustic signal extraction. Time and frequency measurements were considered in both domains. Acoustic signals are familiar by their dominating features that are frequency, phase and amplitude in which, key to many signal analysis solutions is the frequency feature.

Ortho-normal basis function local in time can be provided by wavelet transforms. The beauty of WT is that it can nearly give a signal without distortion. The WT can also provide a multi-resolution concept, which is used in signal processing, identification of acoustic signals, numerical analysis and weak signal detection.

This work describes and portrays the great capabilities of WT to extract unique features from the signal of the SD which when combined with radial basis function neural network (RBF-NN) gives high classification accuracy.

The organization of this paper is as follows. In Section 2, the concept of WT applied for SD detection is described first. Although there are many types of ANNs, we focus our study on the commonly seen feedforward network, namely, RBF-NN. A brief introduction to RBF-NN is also given in Section 3. Section 4 reports the experimental setup obtained by developing a model to detect the SD acoustic signals. The feature extraction and the feature vector from the normalized inputs is been generated in Section 5. The analysis of results and discussions are given in Section 6. Section 7 presents some comparison with other related works and the conclusion is made in Section 8.

2. The wavelet transform

The acoustic signals have some non-linear characteristics due to the surface discharge and that makes some difficulties to deal with because of nonlinear and the random like behavior of system. The problem of non-linearity of the acoustic signal is overcome by using wavelet transform which is a strong tool for feature picking-up. It is equivalent to filters. Details (d_n) are produce by high pass filters and approximations (a_n) are produced by low-pass filters. Due to the multidimensional characters which the wavelets possess, there are able to adjust their scale to the nature of the signal features [19]. It can zoom in or zoom out the required details just like a microscope.

Furthermore, wavelets can decompose a signal to give dilations and translations parameters, so the information in the signal is presented by these parameters in the form of frequencies. The matlab wavelet toolbox is used to verify the algorithm where discrete wavelet transform (DWT) is used to analyze the signals. The coefficients are generated and the features from the signal are extracted. Wavelet is a good tool to analyze the non-linear signals as it represents the features both in time and frequency domains [20,21]. The WT analyses the non-periodic surface discharge signal and adopts the principle of linking of frequency scales. Generally the DWT is used for this mission.

The equation for non-static signal for a DWT is shown below [22,23].

$$f(t)=\sum_{k} c_{j0,k}\phi_{j0,k}(t)+\sum_{j>j0}\sum_{k} w_{j,k}2^{j/2}\psi(2^{j}t-k) \tag{1}$$

where ψ is the Mother wavelet function, j is the Dilation or level index, k is the Translation or scaling index, $\phi_{j0,k}$ is the scaling function of the coarse scale coefficients, and $C_{j0,k}$, $W_{j,k}$ is the scaling function of detail (fine) coefficients.

One of the capabilities of DWT is that, it produces details to show high frequency information and approximations to show low frequency information. The most suitable mother wavelet for detecting SD acoustic signals is the Daubechies (Db) wavelets transform, which is capable of detecting short duration, fast decaying, high frequency and low amplitude signals. The decomposition process in the WT consists of many numbers of filters from Db2 to Db44, so the most promising number depends upon how they minimize the aliasing. Basically in the first stage the captured signal is divided in to two of the frequency bandwidth, which is then passed to high pass and low pass filters [24]. After that the output signal from the low pass filter is further subdivided into two of the frequency bandwidth and sent to the following stage [25]. This procedure continues until the predetermined number of levels is reached. The output of the final stage represents the same captured signal but at different frequency bands [26,27]. The suitable selection of mother wavelet depends on the application. Among the various de-noising techniques, from the point of view of the de-noising effect and the computing time the DWT method is the most suitable.

Finally, the Daubechies wavelet is the most appropriate for treating SD [28,29]. In this study, the adaptability of the Daubechies wavelets of orders 2 has been evaluated, and results have shown the superiority. It is befitting to select a suitable number of breakup levels based on the nature of the signal. Based on acoustic signal features, it is seen that six levels of decomposition is the best choice, because it has described the SD acoustic signal in a more mindful and symptomatic way. This decision is mainly due to the low frequency band (approximation), which is the most valuable part of the acoustic signal [30].

3. Radial basis fuction networks

Radial basis function (RBF) networks have certain advantages over other types of ANNs and have been widely applied in many science and engineering fields. It is a three layered feed-forward and fully connected network. The output layer has no nonlinearly and the connections of the output layer are only weighted, the connections from the input to the hidden layer are not weighted. It is a feed-forward network with a single layer of hidden units, called radial basis functions (RBFs). RBF outputs show the maximum value at its center point and decrease its output value as the input leaves the center. Typically, the Gaussian function is used for the activation function. The RBF network is constructed with three layers: input layer, hidden layer and output layer. In input layer, the number of neurons is the same with the number of input dimension. In the case of Gaussian function, this value represents measure in the quality of the match between the input vector and location of the center in the input space. Each hidden node therefore, can be considered as a local detector in the input data space [31,32].

One of the unique features of Radial basis networks is that they can be represented by simple functions. They could cope to any type of model linear or nonlinear and to any network single layer or multi-layer. An RBF-NN is said to be nonlinear if there exists more than one hidden layer or if the basis functions can move or change the size. The activation function of a hidden unit is predicted by the distance between the input vector and a prototype vector [33].

$$z_k(\vec{x}) = \sum_{j-1}^{M} w_{kj}\phi(\vec{x}) + w_{k0} \equiv \sum_{j=0}^{M} w_{kj}\phi_j(\vec{x}) \tag{2}$$

where $\vec{x}$ is the input vector, ϕ_j is the activation of one of the RBFs, w_{kj} is the weight of each RBF, M is the number of RBFs, and z_k is the output (linear sum of radial basis function).

In a 3-layer RBF-NN, conversion from the input room to the hidden room uses a nonlinear function and linear transformation take place between the hidden and the output layer. The hidden units used in radial basis functions usually take the form of [33]:

$$\phi_j(\|\vec{x} - \vec{\mu_j}\|) \tag{3}$$

The distance between the input vector x and a vector μ_j of the function usually depends on Euclidean distance.

$$\|\vec{x} - \vec{\mu}\|^2 = \sum_i (x_i - \mu_{ji})^2 \tag{4}$$

The most ordinary form of basis function used is the Gaussian function.

$$\phi_j(\vec{x}) = \exp\left(-\frac{\|\vec{x} - \vec{\mu}\|^2}{2\sigma_j^2}\right) \tag{5}$$

$\vec{\mu}$ and σ_j^2 are the jth center vector and the width parameter, respectively. A hidden neuron is more susceptible to data points near its center. This sensitivity may be adjusted by tuning the width σ, larger width leads to less sensitivity. For a given input vector, typically only a few number of hidden units will have notable activations [34]. RBF neural networks can design complicated mappings compared to multilayer perceptron. In addition RBF-NN has two layer weights only and a simple learning algorithm, that makes it very fast in training speed compared to multilayer perceptron.

MATLAB provides two commands that can be used to design RBF neural network. Newrb and newrbe. Newrb adds neurons step by step until the goal is hit, with long training time and a little error, while newrbe very quickly designs a network with zero error [35,36]. For the training process the following steps should be fulfilled:

a. The hidden layer's number of neurons.
b. The coordinates of the center of RBF function.
c. The radius (spread) of each RBF function in each dimension.

4. Experimental setup

The test set-up consists of two main parts; the circuit loop (AC source, transformer, connections and insulator), the measurement and acquisition system (earth resistor, wide band antennas and high resolution digital oscilloscope, model Tektronixs TDS55000B series). Fig. 1 shows the experimental set-up for generating surface discharge as well as detecting the consequent acoustic signal of surface discharge. The test was designed based on the international electro-technical commission (IEC) 60587 standard test procedures. A point to plane electrodes configuration was used and mounted at the top and bottom side of the glass insulator surface. The surface discharges were generated across the electrodes by applying high voltage stress across them.

The glass insulator was fixed on a wooden base and the electrodes were fixed by some arrangement on the insulator. A series of experiments were performed on H.V. glass insulator, which are extensively used in transmission lines. Before tests, the insulator surface was cleaned by washing with isopropylic alcohol and rinsing with distilled water, in order to remove any trace of dirt and grease. To reproduce saline pollution typical of coastal areas, the insulators were sprayed with a solution, consisting of NaCl and distilled water, with different degrees of salinity (from 10 g/l NaCl to 30 g/l NaCl). A peristaltic pump was used to continuously deliver the electrolyte at a fixed flow-rate of 0.60 ml/min. Eight layers of filter paper were used between the top electrode and the sample, which act as an electrolyte reservoir to ensure proper flow of electrolyte along the insulating material surface. The contaminant must flow from the quill hole at the bottom of the top electrode and should not squirt out of the side or top of the filter paper. The specimen was adjusted so that the electrolyte ran down as near as possible to the centerline of the specimen.

An ultra sound detector (USD) with a parabolic antenna was used to detect the acoustic signals resulted from the surface discharge activity and was placed at a suitable position from the specimen. The USD was then connected to a digital oscilloscope to capture and record the acoustic signals. The recorded signals were then processed using MATLAB plateform. Many trials were done using the experiment setup and the most logical data was finalized.

Four test conditions were conducted in the laboratory including first condition in which the insulator was kept clean, second condition in which the insulator was lightly contaminated by a layer of NaCl solution (10 g/l), third condition in which the insulator was medium contaminated by a layer of NaCl solution (20 g/l) and fourth condition in which the insulator was heavily contaminated by a layer of NaCl solution (30 g/l). In the first condition the insulator was kept clean and the result is shown in Fig. 2(a). This signal is been processed by using wavelet analysis to remove the noise. It can clearly been seen from the black in colour signal that the clean insulator has no or very small surface discharge activity. So this pattern could be considered to be the reference, default pattern or the target to RBF-NN. Fig. 2(b)–(d) shows the second condition, the third condition and the fourth condition and its de-noise signals respectively.

5. Feature extraction

The wavelet transform is well suited in identifying sharp edge transitions. The decomposition of a signal using the wavelet bases has an inherent adaptation to the signals spatial characteristics. In this work, the SD signals that were collected in the experimental process were processed using the DWT to obtain a feature vector that will be used in the next stage of classification. The approach of using the DWT to extract a feature vector, apart from utilising the properties of the transform itself in representing the signal, has the advantage that it can be combined with sensitivity improvement and noise rejection in a single step. The DWT due to its time frequency localisation, unlike the Fourier transform where all time information about the signal is lost, is able to successfully handle such randomly occuring of SDs [37,38].

5.1. Processing the data

1. The goal of preprocessing is to reduce the number of parameters to face the challenge of "curse of dimensionality".
2. The preprocessing has a huge impact on performances of neural networks.
3. The unwanted field noise and all the interference is filtered off, which massages the data to unique features.

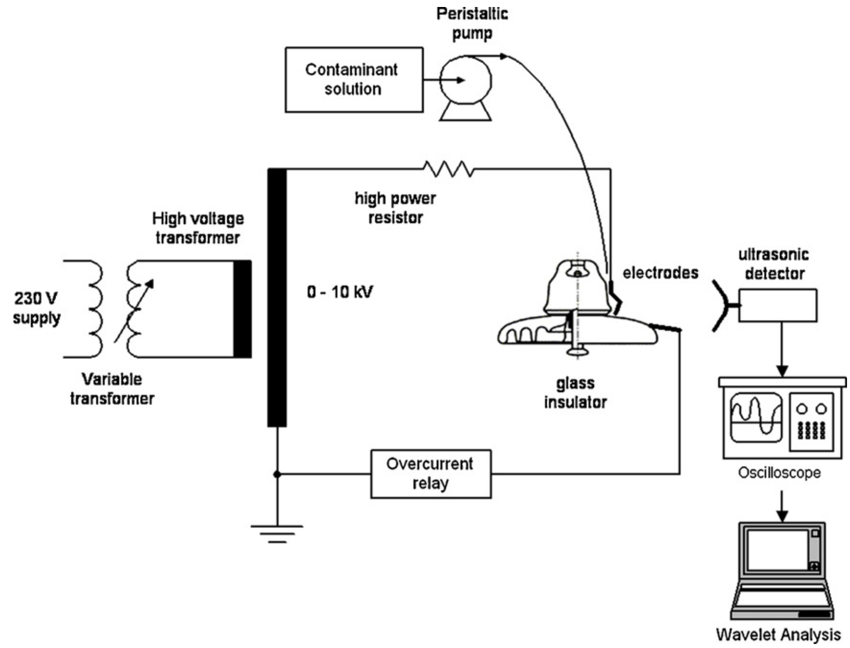

Fig. 1. Experimental setup for surface discharge detection.

5.2. Decomposition of surface discharge signals

In this work the feature vector is obtained by applying wavelet transform. For a single decomposition the number of coefficients produced by Db2 is 7 that is 1 approximation coefficient and 6 detailed coefficients. This approximation coefficient that is low frequency component is further decomposed into approximation and detailed coefficients. In using the DWT certain features of the signal that is not immediately obvious in the time domain become more apparent through this multi scale differential operator. The features selected to represent the most important part of the data are as follows.

Mean η, standard deviation σ, normalized skewness γ and normalized kurtosis k, at each decomposition node, were used as a finger-print for SD and as an input to the classifier. The mean η, the standard deviation σ, the normalized skewness γ and the

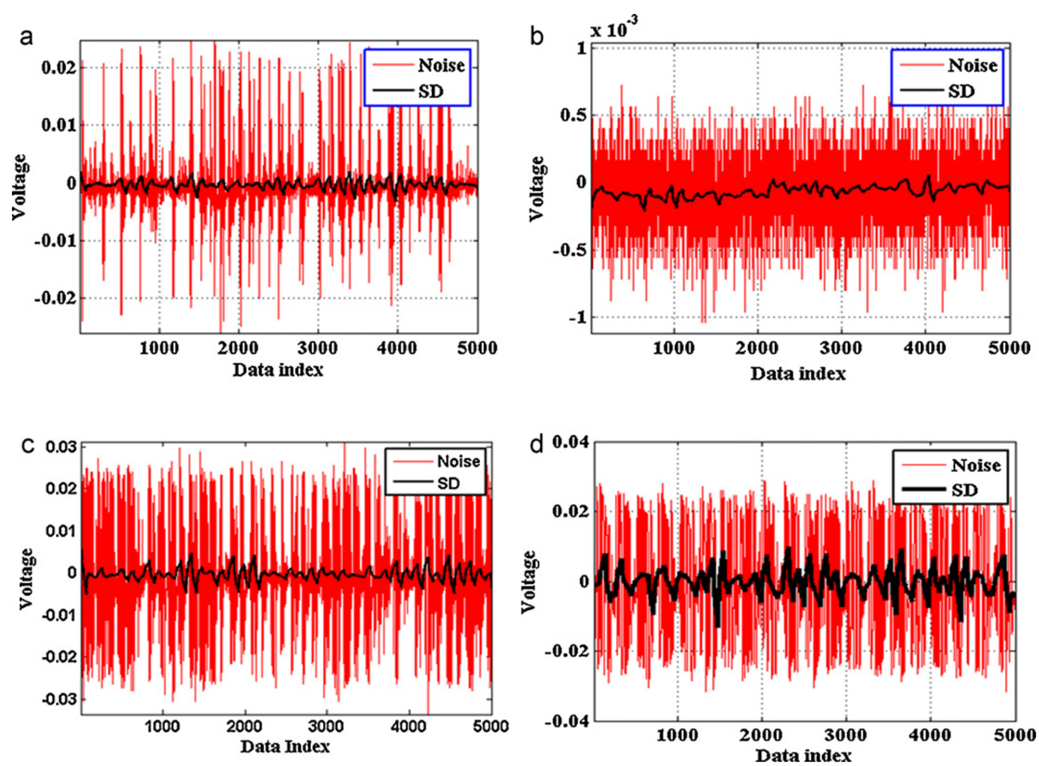

Fig. 2. Captured and the de-noised signal of (a) the clean insulator (b) the lightly contaminated insulator (c) the medium contaminated insulator (d) the heavily contaminated insulator.

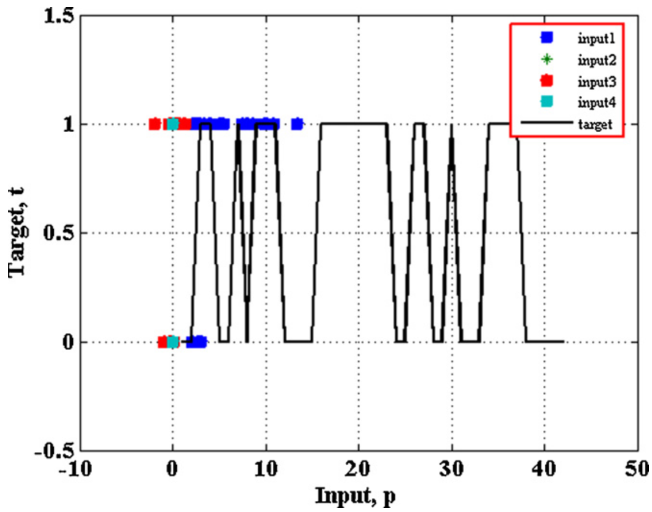

Fig. 3. The inputs overlapping the target.

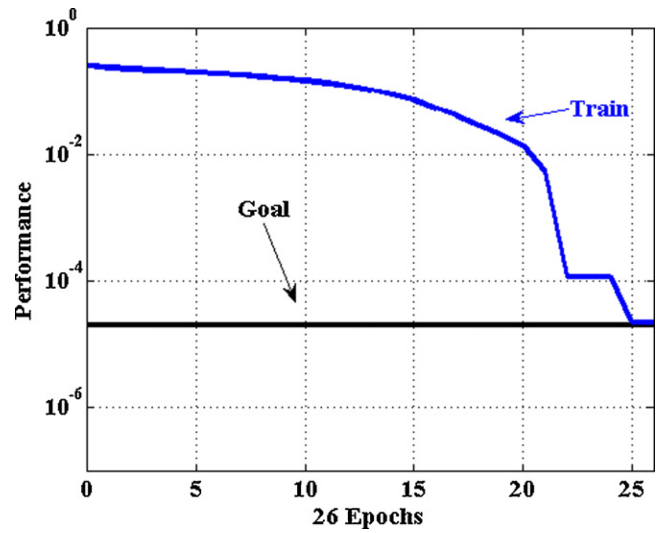

Fig. 4. The training performance.

normalized kurtosis k, were estimated from the following equations [37]:

$$\eta = \frac{1}{N}\sum_{n=1}^{N}(x[n]) \tag{6}$$

$$\sigma = \left(\frac{1}{N}\sum_{n=1}^{N}(x[n]-\eta)^2\right)^{1/2} \tag{7}$$

$$\gamma = \frac{1}{N\sigma^3}\sum_{n=1}^{N}(x[n]-\eta)^4 \tag{8}$$

$$k = \frac{1}{N\sigma^4}\sum_{n=1}^{N}(x(n)-\eta)^4 \tag{9}$$

where $x[n]$ is the wavelet coefficent at postive n and N is the total number of wavelet coefficients used at each scale. By taking 6-detailed coefficients and 1-approixmation coefficients from the wavelet analysis for the 4-conditions mentioned in Section 5, we will have the feature vector which uses four descriptors for each scale, therefore a feature vector of dimensions was needed to represent the data. So the feature vector is of dimension 42×4, i.e. 21 samples for the 3-contaminated conditions and other 21 samples for the clean condition that totally gives us 42 dimensional vector each having 4-features. These coefficients are used to train the RBF neural network, so that it should discriminate SD activity from normal operating conditions.

6. Results and discussion

The four inputs shown in Fig. 3 are the main features of the surface discharge which are kurtosis, mean, standard deviation and skewness extrated by using wavelet transform technique. The target vector consists of two classes that are as follows.

The first class is denoted by (0) which shows no or very small SD activity. The second class is denoted by (1) whichs shows high SD activity. The normalized inputs and targets vectors are randomly divided into two sets, 60% of the vectors are used to train the network, 20% of the vectors are used to validate how well the network generalized. Finally, the last 20% of the vectors provide an independent test of network generalization to data that the network has never seen. By training the RBF-NN with the normalized inputs we can see the result in Fig. 3 which shows us a very perfect overlapping which means that the neural network had recognized the inputs with a 100% accuracy.

Training performance nearly hit the goal in 25 epochs only as could be seen in Fig. 4 giving a very good performance, The stopping conditions of RBF-NN were set to a minimum error of 0.0002 or maximum iteration of 10000. The error during training process in Fig. 5 was acceptable and very low, where it started with a very high value and during the training process reached an average value of 0.0038 within 40 iterations. The computational time was 0.0795 s, this is the ability of WRBF-NN to have a very fast learning algorithm.

Mean squared error (mse) is a network performance function. It measures the network's performance according to the mean of squared errors. The unique feature of WRBF-NN is depicted in Fig. 6 which shows that the mean squared error (mse) required only 22 neurons to attain zero value, this is the beauty of combining the WT with RBF-NN wavelet radial basis function neural network (WRBF-NN).

Testing the WRBF-NN by unseen data shows high classification accuracy which is clearly seen in Fig. 7. The four features of the data is accumulated at (1) which means this data refers to discharge activity.

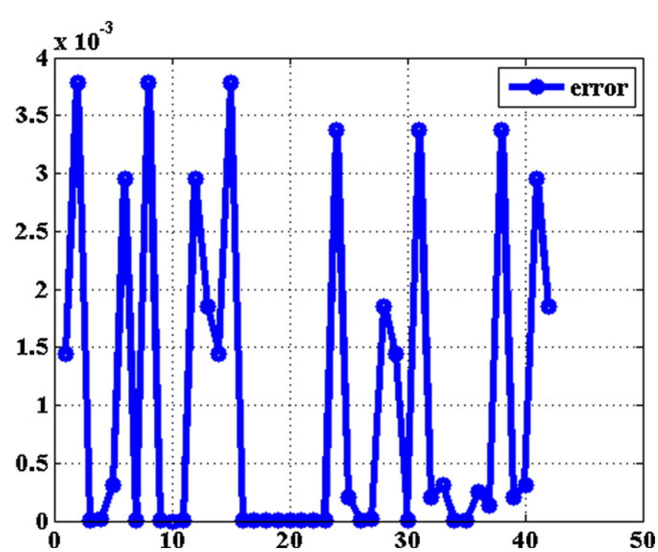

Fig. 5. The error between the output and the target.

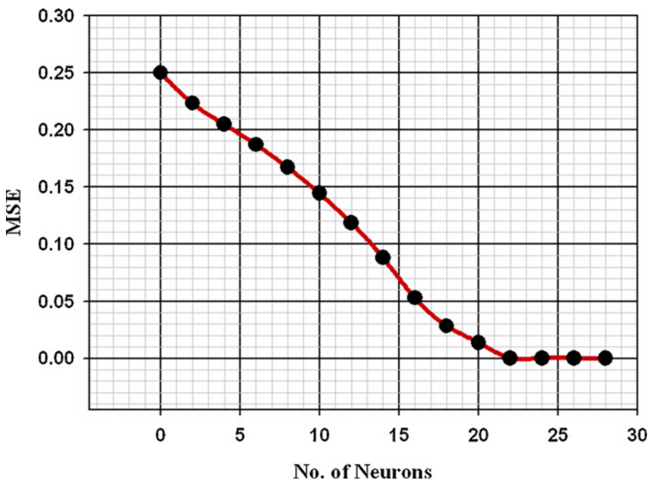

Fig. 6. The mean square error.

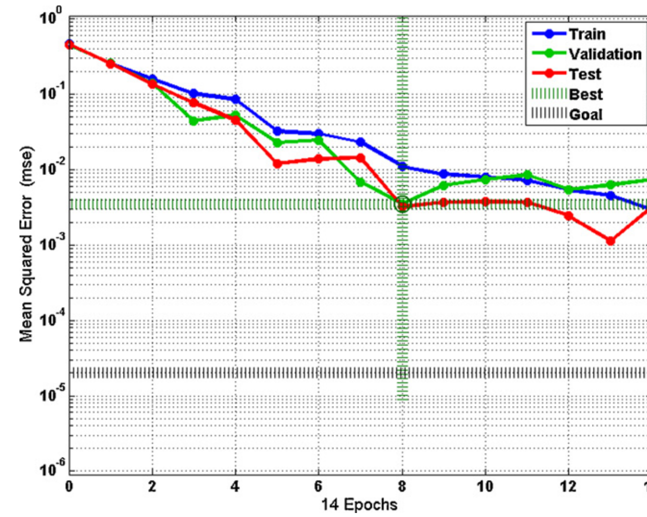

Fig. 8. The training performance.

7. Comparison with other research works

In order to check the reliability of the proposed WRBF-NN the model is been compared with the previous works conducted and mentioned in the literature review. The same SD dataset is been used to compare with the Wavelet feed forward back-propagation neural network (WFFBP-NN).

The plot in Fig. 8 has three lines, because the normalized inputs and targets vectors are randomly divided into three sets. 60% of the vectors are used to train the network, 20% of the vectors are used to validate how well the network generalized. Finally, the last 20% of the vectors provide an independent test of network generalization to data that the network has never seen. Training on the training vectors continues as long the training reduces the network's error on the validation vectors. After the network memorizes the training set (at the expense of generalizing more poorly), training is stopped. This technique automatically avoids the problem of overfitting, which plagues many optimization and learning algorithms. By training the WFFB-NN with the normalized inputs we can see the result which shows us training performance did not reach the goal perfectly. The best validation performance was 0.00351 at epoch 8, this means that the neural network had recognized the inputs with approximately 95% accuracy. The result here is reasonable, because the test set error and the validation set error have similar characteristics, and it does not appear that any significant overfitting has occurred. The error during training process in Fig. 9 was acceptable, which attained 0.38 in 38 iterations. The target vector consists of two classes that are designated as: the first class is denoted by (0) which shows no or very small SD activity. The second class is denoted by (1) which shows high SD activity. Testing the WFFB-NN is shown in Fig. 10 where the 4-inputs are the features of the SD activity, hence most of the data is accumulated at 1 that means high discharge activity can be found and a small SD activity can be seen at 0. It is worth noting that the Convergence Time was 0.61039 s, this is the drawback of FFB-NN, an updating algorithm usually causes the training process to converge slowly. Compared with the WRBF-NN, it can update the parameters, at the same time it does not need the previous updating values. Therefore, the proposed WRBF-NN can achieve numerical convergence and is faster than WFFB-NN in the training process. In addition to that FFB-NN applies a global searching method, while RBF-NN applies a local searching mechanism. It is found that global searching may easily be trapped in the local minimum, therefore, this manner makes the estimation errors in the FFB-NN model difficult to be minimized under the same system parameters as that in RBF-NN. For RBF-NN. On the other hand, designing a radial basis network often takes much less time than training a WFFB-NN, and can sometimes result in fewer neurons.

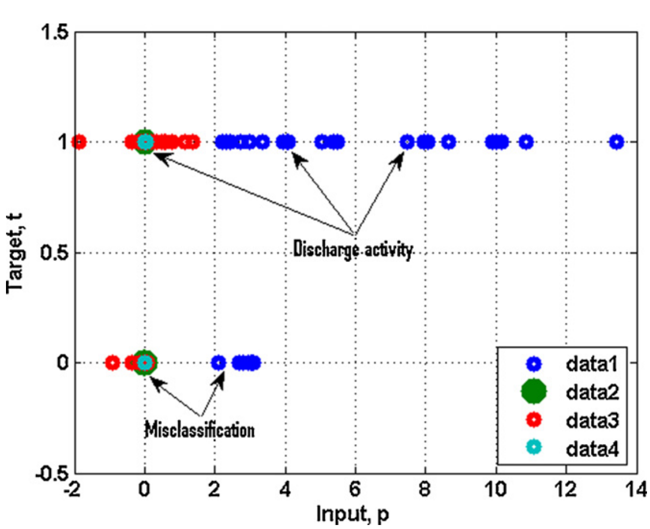

Fig. 7. Testing the input data.

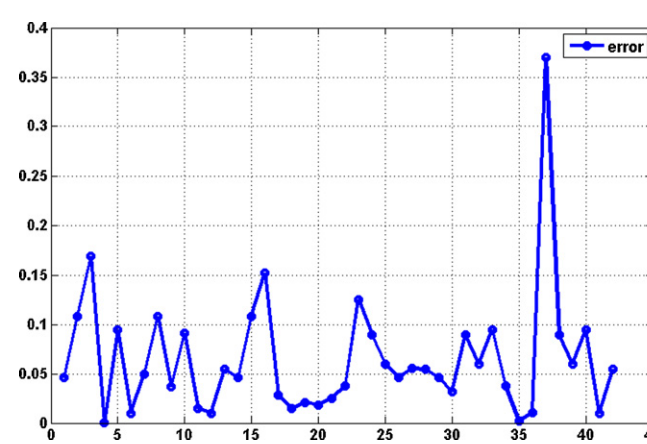

Fig. 9. The training error.

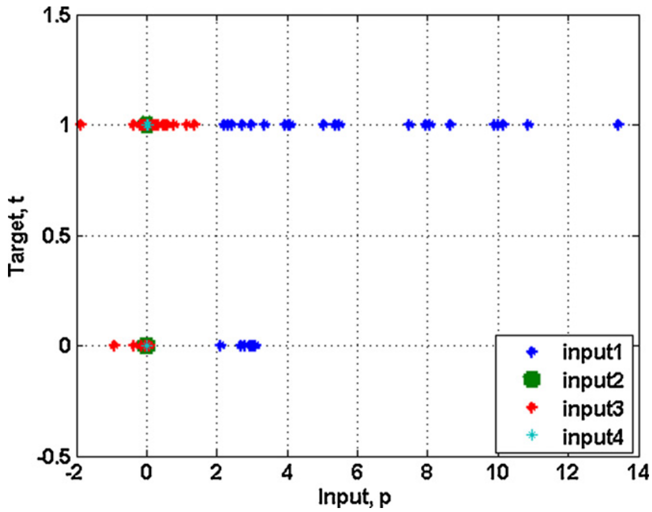

Fig. 10. Testing of WFFB-NN by unseen data.

8. Conclusion

It is an inflate to say that we will introduce as many analysis algorithms as there are signals. Signals are so complex and rich that a single analysis method cannot handle them all. Having done all these analysis we can conclude that acoustic detection of surface discharge is possible by observing the results which are quite good, explainable and logistical. The proposed hybrid model has proved to characterize the SD activity with a high degree of integrity which is attributed to the combined effect of the WT and RBF-NN. The high rate of classification acquired by the RBF-NN is due to the preprocessing of data by the WT.

The model is quite versatile for a wide range of applications in the field of power system analyses. Due to the preprocessing of the data by using wavelet transform gave the RBF-NN high rate of classification accuracy. This shows the beauty of wavelet transform especially when combined in one unit with RBF-NN. As future work four types of partial discharges will be generated in a high voltage laboratory, namely corona discharge in air, floating discharge in oil, internal discharge in oil and surface discharge in air, at different applied voltages will be recorded and a feature vector will be extracted by using wavelet transform which will be used to train the RBF-NN.

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