Classification of The NTEV Signal Problem via the Incorporation of S-Transform Features and Different Types of Neural Network

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***Abstract*—Classification of power quality (PQ) disturbance on the commercial building is one of the most important parts in monitoring, identifying and mitigating of PQ disturbance to avoid misunderstanding the behavior of events. A novel on the Neutral to Earth Voltage (NTEV) classification using S-transform (ST) and different type of neural networks are proposed. The types of a neural network composed of general regression neural network (GRNN), probabilistic neural network (PNN) and radial basis function neural network (RBFNN). NTEV signals are needed to analyse using ST to extract their features that used as an input for the neural network classification. Finally, the GRNN, PNN, and RBFNN are trained and tested using 100 and 150 samples respectively. The performance of GRNN, PNN, and RBFNN are compared in which to identify the best technique in classification the NTEV.**

***Index Terms*—Classification; Power Quality (PQ); Neural Networks; Neutral to Earth Voltage (NTEV); S-transform (ST).**

I. INTRODUCTION

Power Quality (PQ) has become very important issues over the last decade for the detection disturbances on the electrical network and needs a special PQ monitoring in identify and analysing the types of problem. The Neutral to Earth Voltage (NTEV) on the commercial building is one of the issues in PQ monitoring, caused it often exposed the nonlinear load, lightning, poor grounding system, loose neutral cable connection and improper wiring system [1, 2].

In normal condition, according to the regulation IEEE 1695, the magnitude of the NTEV should be below than 10V [1]. However, its' magnitude can increase, and it could pass the permissible threshold. One of the disturbances are harmonic distortion on the system that appears due to most of the electrical appliance uses non-linear load [2, 3]. Another contribution the NTEV rise is the impulsive voltage which generated by the lightning and loose neutral cable connection [4, 5]. According to the problem, a new technique needs to be developed for identifying and classifying the NTEV sources due to the harmonic, lightning and loose neutral cable connection in which to help the engineer to solve the problem with fast and accurately [6].

Proper selection techniques are very important in classifying the NTEV source on the commercial building. An appropriate technique is needed for pre-processing and extract its' features from the system under study. According to the NTEV features that already extracted, it useful for detecting the type of problem on the system using classifier [7].

The signal processing models such as Short Time Fourier Transform (STFT) can be used to extracts the features of the signal. STFT is time-frequency analysis methods that have the capability to handle the various of signals with better operation and efficiency than Fourier Transform (FT).However, these technique are very sensitive to the noise level [8–10]. The S-Transform (ST) is a combination of STFT and WT techniques which is better than STFT and WT. Furthermore, ST is superior technique and capable of processing the signals that have high noise environment. Also, ST uses variable length window.

Neural Network is a popular computational intelligent that often used in PQ due to its' capability in fields of data analysis, identify matching and classification system [11]. In [12], the classification scheme based on the back propagation neural network (BPNN) were used in PQ for identification the disturbance events. However, the problem in BPNN is the selection of the initial weight, a number of hidden layers and efficiency of the learning process in which can affected classification efficiency and accuracy. Furthermore, BPNN uses a lot of times for learning and testing the data. A probability neural network (PNN), general regression neural network (GRNN) and radial basic function neural network (RBFNN) are a simple architecture and can work faster than BPNN [13].

The main contribution of this paper is to classify the NTEV sources at the commercial building, which appears due to the harmonic, lightning and loose neutral termination. The ST is selected as processing signal of NTEV in which to extract its' features for analysing purpose. Moreover, the GRNN, PNN, and RBFNN techniques are utilised for classification the NTEV events. Also, the comparison performances of these techniques have been analysed.

This paper is organized into five (5) sections. The first section has explained the introduction of PQ classification technique. In Section II and Section III described the theory of ST and artificial neural network that used in classification respectively. In Section III is justified the proposed methods that utilised in classification and in Section IV is elaborated the results and discussion. Finally, conclusions are presented in the last section.

II. S-TRANSFORM THEORY

ST is known that the signal will be transformed into time-frequency in which represents a time series signal by uniquely combining the frequency-dependent resolution that contains a complex number spectrum.

ST of signal x(t) can defined as follow [14]:

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau, f)e^{-j2\pi f\tau}dt \tag{1}$$

where: $w(t\text{-}\tau, f)$ = Mother wavelet
$e^{-j2\pi f\tau}$ = Phase factor

Then, the mother wavelet is defined as:

$$\omega(t-\tau, f) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(t-\tau)^2 f^2}{2}} e^{-j2\pi f(t-\tau)} \tag{2}$$

Substituting (2) into (1), the final continuous ST equation becomes:

$$S(\tau, f) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} x(t) e^{\frac{-(t-\tau)^2 f^2}{2}} e^{-j2\pi ft} \tag{3}$$

According to (3), let τ = *kT* and *f* = *n/NT*, the discrete ST is given by:

$$S\left[kT, \frac{n}{NT}\right] = \sum_{m=0}^{m=N-1} X\left[\frac{m+n}{NT}\right] e^{\frac{2n^2m^2}{n^2}} e^{-2\pi mk}, n \neq 0 \tag{4}$$

where: k,m,n = 0, 1, …, N-1
T = Sampling interval
N = Total of sampling point

In this paper, the features from the ST has been extracted to be used as an input for the artificial intelligent classification tools.

The ST shows the results of a signal in a complex-valued matrix that can be divided into rows and columns. The rows of result contain the frequency of the signal at different sampling interval and the columns of result represent the time. Figure 1 shows the type of NTEV features that extracted using ST.

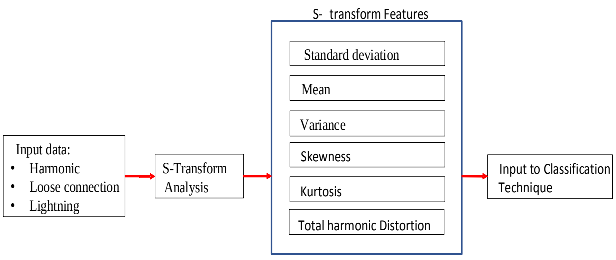

Figure 1: Features extraction module

III. ARTIFICIAL NEURAL NETWORK THEORY

Artificial Neural Network (ANN) is one of the computational models that utilised in machine learning for classifying the problem on the NTEV due to the lightning, loose neutral connection and harmonic. In this paper, ANN is utilised to identify the NTEV problems on the commercial building. In this study, Figure 2 shows the topology structure of ANN, have been developed for the purpose analyse.

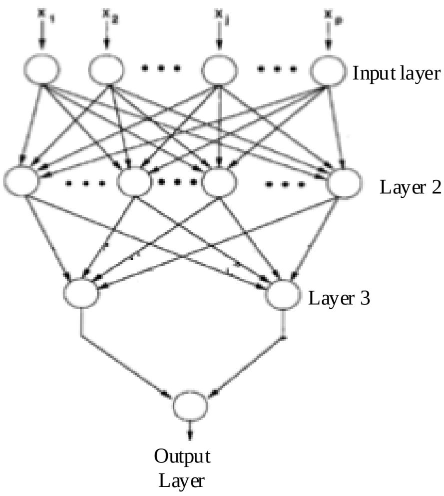

Figure 2: The topology structure of ANN

A. *General Regression Neural Network*

GRNN can be categorised as a probabilistic neural network (PNN) since it works almost similar with PNN. However, GRNN is suitable for prediction where the target variable is continuous. GRNN also use the Gaussian kernel function for training and estimate the sample. The GRNN comprises four layers, which are one input layer, two hidden layers and one output layer.

The first layer is used as sensing in which to detect the distance between the training and testing sample. The output of the first layer is used for the second layer of the Gaussian kernel as followed:

$$D_i^2 = (x - x_i)^2 \tag{5}$$

$$k_i = e^{-\left(\frac{D_i^2}{2\sigma^2}\right)} \tag{6}$$

According to the first and two layers, if the distance between training and testing data is zero, the result of Gaussian kernel become one and its mean the perfect of this training sample. Then, if the distance D_i is small, the result of Gaussian kernel value is big.

For the third layer, the output is divided into two nodes of neuron in which called as numerator and denominator. For the numerator, the Gaussian kernel should be multiplied with the target output.

$$\text{Numerator} = \sum_{i=1}^{N} k_i y_i \tag{7}$$

$$\text{Denominator} = \sum_{i=1}^{N} k_i \tag{8}$$

The output of GRNN, Y(X) is determined through the decision layer divides the value collected in the numerator summation unit by the value in the denominator summation unit.

$$Y(x) = \frac{\text{Numerator}}{\text{Denominator}} \tag{9}$$

B. Probability Neural Network

A PNN is similar with feed forward neural network and uses a statistical algorithm, which called Gaussian kernel in solving the classification problem. Generally, PNN comprises an input layer, a pattern layer, a summation layer, and an output layer [15].

In the first layer, normally used to identify the input and number of neurons. The second layer presents the square of the Euclidean in which the distance between the input and classification vector. In these stages, the number of neurons in pattern layer is equal the sum of training samples as shown in (10). Each neuron comprises one training sample. The output of pattern layer is:

$$\| X - X_{kj} \| = \sum_i (X_i - X_{ki})^2 \tag{10}$$

$$f_{kj}(X) = \exp\left(\frac{\| X - X_{kj} \|}{2\sigma^2}\right) \tag{11}$$

Then, the third layer is summation layer that used to express information on the classification. In this stage, each class only have one summation unit of the pattern layer. Then, n_k is the number of samples point in classification.

$$f_k(X) = \left(\frac{1}{n_k}\right)\sum_{j=1}^{n_k} f_{kj}(X) \tag{12}$$

The fourth layer is the output layer. The output layer is normally used to identify the final of classification result with uses the equation is given:

$$C(X) = Max_k\, f_k(X) \tag{13}$$

C. Radial Basic Function Neural Network

RBFNN is also one of the popular neural networks have been used in classify for many application [16]. The RBFNN is composed of three layers, which are input layer, hidden layer and output layer.

The first layer is used to create the number of neurons that connected to the network. Each neuron represented as one feature of the input layer.

Then, the second layer is a hidden layer. In this stage, each neuron needs to perform the Gaussian kernel. The Gaussian kernel is given by:

$$\phi_j(x) = \exp\left(\frac{-\| x - \mu_j \|^2}{2\sigma_j^2}\right) \tag{14}$$

where: x = Input vector
μ_j = Center of Gaussian function
σ_j = Spread of Gaussian function

The output layer is given by:

$$y_k(x) = \sum_{j=1}^{h} w_{kj}\phi_j(x) \tag{15}$$

where: w_{kj} = Weight

IV. PROPOSED METHOD

Figure 3 illustrates a one-line diagram of commercial building modelling that utilised for recorded the NTEV data. The NTEV data is analysed using ST in which to extracts its' features that used in ANN classification techniques. According to the ST, the signal of NTEV is divided into sample per cycle in which to reduce the time of ST processing and it a good way for extracts the feature of samples.

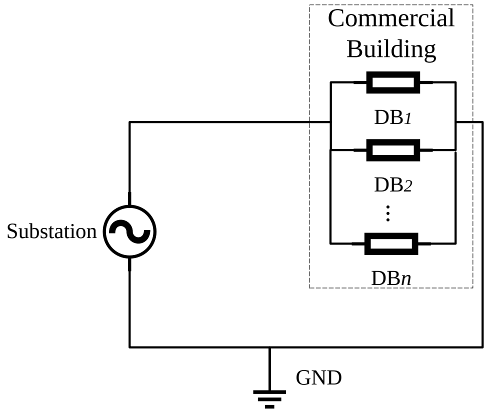

Figure 3: Commercial building modelling

Figure 4 shows an example of NTEV signal that separated into samples per cycle. Only three samples per signal of NTEV were extracted and utilised for ST analysis. For example, sample 1, sample 2 and sample 3 represent the loose neutral connection, harmonic, and lightning strike on the commercial building respectively.

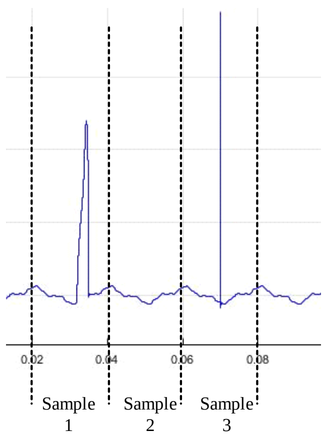

Figure 4: Recorded NTEV data from commercial building modelling

The result of ST in $M \times N$ matrix with complex elements, in which called S matrix. To analyse the transform waveforms, absolute the complex S matrix results as shown in Equation (16):

$$Y_{ij} = abs(S(\tau, f)) \tag{16}$$

Then, based on the mathematical formulation, the first feature that extracts from ST and used as an input of GRNN, PNN, and RBFNN are using the standard deviation and described as follow [17]:

$$\sigma = \sum_{j=1}^{N} \left[\frac{1}{M-1} \sum_{i=1}^{M} (Y_{ij} - \bar{Y}_j)^2 \right]^{1/2} \tag{17}$$

The second and third features are using mean and variance. The formula of mean and variance are shown in (18) and (19) respectively.

$$\bar{Y} = \mu = \sum_{i=1}^{N} \frac{1}{M} \sum_{j=1}^{M} Y_{ij} \tag{18}$$

$$\sigma^2 = \sum_{j=1}^{N} \left[\frac{1}{M-1} \sum_{i=1}^{M} (Y_{ij} - \bar{Y}_j)^2 \right] \tag{19}$$

Then, skewness is fourth feature that defined as [18]:

$$s = \sum_{i=1}^{N} \left(\frac{\frac{1}{M} \sum_{j=1}^{M} (Y_{ij} - \bar{Y}_j)^3}{\left(\left(\frac{1}{M-1} \sum_{j=1}^{M} (Y_{ij} - \bar{Y}_j)^2 \right)^{1/2} \right)^3} \right) \tag{20}$$

The fifth feature which is using the kurtosis and it formula is given by [19]:

$$k = \sum_{i=1}^{N} \left(\frac{\frac{1}{M} \sum_{j=1}^{M} (Y_{ij} - \bar{Y}_j)^4}{\left(\frac{1}{M-1} \sum_{j=1}^{M} (Y_{ij} - \bar{Y}_j)^2 \right)^2} \right) \tag{21}$$

And the last feature is using total harmonic distortion, is given by [20]:

$$THD = \sum_{i=1}^{N} \frac{\left(\sum_{j=2}^{M} Y_{ij}^2 \right)^{1/2}}{Y_{ij=1}} \tag{22}$$

V. Analysis Results

The NTEVs were carried out to generate the data for training and testing on different type of NTEV source.

For the GRNN, PNN and RBFNN implementation, 100 data utilised for training which is consists three condition events, while 150 different data have been used for testing purpose. The results obtained from the GRNN, PNN, and RBFNN in classifying the lightning, loose neutral cable connection and harmonic are presented as in Figure 5. The performance of GRNN, PNN, and RBFNN in classifying the NTEV have been evaluated. The events of NTEV are classified as 1 for harmonic, 2 for loose and 3 for lightning.

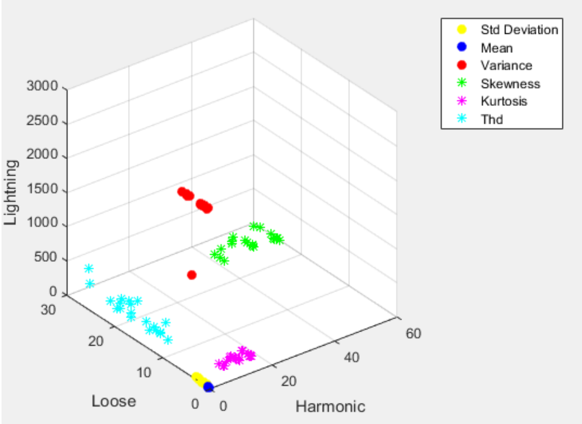

Figure 5: Scatter plot of input features

Figure 6 shows the confusion matrix result for training samples using GRNN, PNN, and RBFNN. According to the figure, 34 data for class 1, 33 data for class 2 and 33 data for class 3 arecorrect in training the samples. And the result of training is successful 100%.

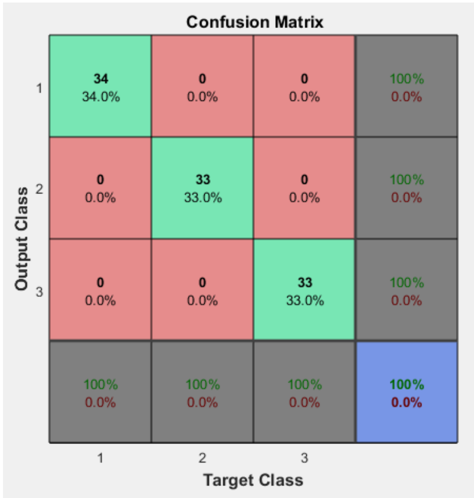

Figure 6: The training result of confusion matrix for GRNN, PNN, and RBFNN

The confusion matrix results for the testing samples by using GRNN, PNN, and RBFNN are shown in Figures 7, 8, and 9 respectively. The result by using the GRNN shows that 49, 51, and 50 numbers of samples correct in classification as class 1, class 2, and class 3 respectively. This corresponds to 32.7%, 34%, and 33.3% accuracy from all 150 samples. For the PNN, the result shows 49, 2, and 10 number of samples correct from all 150 samples in classification as class 1, class 2 and class 3 respectively. The correspond are 32.7%, 1.7%, and 6.7% of all NTEV samples. The RBFNN shows the result of testing are 2, 51, and 2 number of samples correct in classification. Its' correspond to 1.3%, 34%, and 1.3% accuracy for class 1, class 2 and class 3 respectively.The GRNN shows a better performance compared than PNN and RBFNN during classify the harmonic, loose connection and lightning. This is due to the result of each class show that the GRNN is higher than the others neural networks.

Overall result shows, the GRNN produce the best result on classifying the source with 100% accuracy as compare to PNN and RBFNN which produce the accuracy of 40.7% and 36.7%, respectively.

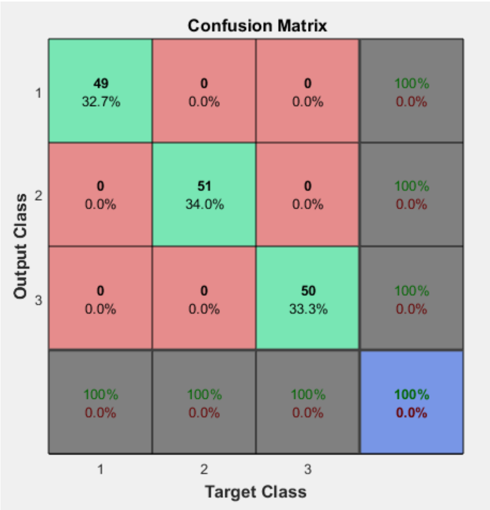

Figure 7: Result of confusion matrix for GRNN

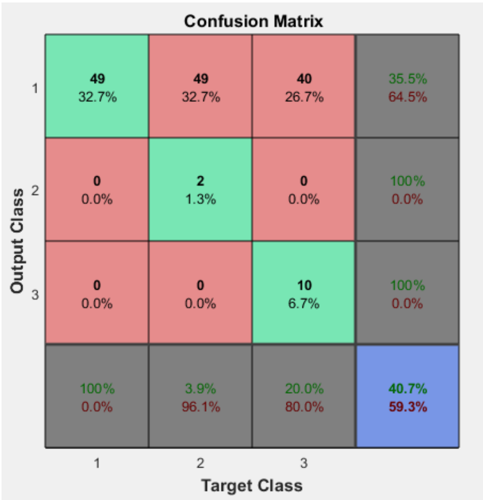

Figure 8: Result of confusion matrix for PNN

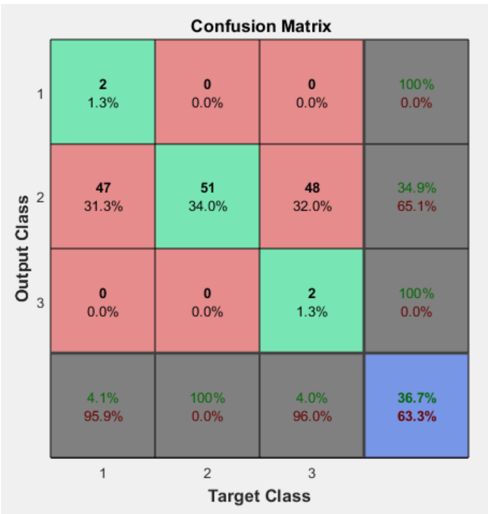

Figure 9: Result of confusion matrix for RBFNN

A. *Performance of GRNN, PNN, and RBFNN with Different Spread, σ*

Table 1 shows the performance of three neural networks in classifying the NTEV with using the different spreads are discussed. According to the table shows that the result of GRNN are maintained 100% even the values of spread are changed. For the PNN and RBFNN, the results show the accuracies values vary when tested with the different spread values. The percentage of PNN and RBFNN are increased when the spread values change. Furthermore, the GRNN has maintained the result 100% compare than PNN and RBFNN. For the PNN, the resultant increase slightly fast than RBFNN during the values of spread changed.

Overall of result shows that the GRNN is more precise rather than PNN and RBFNN.

Table 1
The Accuracies (%) of Neural Networks for a Different Spread Test

SPREAD	GRNN	PNN	RBFNN
σ = 0.001	100.0	35.3	36.7
σ = 0.010	100.0	35.3	36.7
σ = 0.100	100.0	40.7	36.7
σ = 0.500	100.0	45.3	36.0
σ = 1.000	100.0	46.7	36.0
σ = 1.600	100.0	48.0	36.0
σ = 2.000	100.0	48.0	38.0

VI. Conclusion

The strategy to classify the NTEV problem on the commercial building due to the lightning, loose, and harmonic has been presented. The proposed strategy uses ST for analysis the signal, in which to extracts the NTEV feature that can be used as an input classification for GRNN, PNN, and RBFNN. According to the test results show that the GRNN is more accurate rather than PNN and RBFNN.

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