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Research Article

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Power Quality Events Classification using ANN with Hilbert Transform

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***Abstract*—**

With the evolution of Smart Grid, Power Quality issues have become prominent. The urban development involves usage of computers, microprocessor controlled electronic loads and power electronic devices. These devices are the source of power quality disturbances. PQ problems are characterized by the variations in the magnitude and frequency in the system voltages and currents from their nominal values. To decide a control action, a proper classification mechanism is required to classify different PQ events. In this paper we propose a hybrid approach to perform this task. Different Neural topologies namely Cascade Forward Backprop Neural Network (CFBNN), Elman Backprop Neural Network (EBPNN), Feed Forward Backprop Neural Network (FFBPNN), Feed Forward Distributed Time Delay Neural Network (FFDTDNN) , Layer Recurrent Neural Network (LRNN), Nonlinear Autoregressive Exogenous Neural Network (NARX), Radial Basis Function Neural Network (RBFNN) along with the application of Hilbert Transform are employed to classify the PQ events. A meaningful comparison of these neural topologies is presented and it is found that Radial Basis Function Neural Network (RBFNN) is the most efficient topology to perform the classification task. Different levels of Additive White Gaussian Noise (AWGN) are added in the input features to present the comparison of classifiers.

Keywords*— Power Quality (PQ), Artificial Neural Network (ANN), Hilbert Transform, Mean Square Error (MSE), Mean Absolute Error (MAE), Sum of squared Error (SSE), Sum Absolute Error (SAE), Radial Basis Function Neural Network(RBFNN).

I. INTRODUCTION

Power quality is a major key term in power system engineering which affects the flow of power in electrical system. Power quality ideally creates a perfect power supply that is always available, has a pure noise-free sinusoidal wave shape, and is always within voltage and frequency tolerances. Power quality is interrelation of electrical equipment with its electrical power and if there is no production of distortions when power flows through equipments then it is called good power quality. At present scenario, various power electronic devices are used in electrical system. These devices reflect non linear characteristics that are responsible to generate distortions namely Sag, Swell, Harmonic, Interruption, flicker, transient, sag with harmonics, swell with harmonics etc.

These distortions are responsible for the increment of power losses and these affect the performance of the system also. It is needful to eliminate or minimise these distortions to improve the efficiency of power flow.

In recent years, numerous methods have been researched for classification and minimisation of power quality events. A single channel independent component analysis [1] for both single and multiple power quality disturbance classification is employed to separate the power system signal into its independent components which are further classified but the efficiency (maximum efficiency is 97%) wasn't appreciable. A method based on wavelet transform and least square support vector machines [2] has been used that provides good results but includes a lot of computations. Janusz A. Starzyk arranged a self -organising Array System [3] for power quality distortion classification that is based on Wavelet transform. A current differential method [4] is applied through a new Fast Discrete S-Transform which reduces both the computational cost and useless information, but this is primarily used to determine the location of faults at transmission line. S.J. Huang [5] used wavelet packet-enhanced arithmetic coding to compress the distorted signal and classification of signal is accomplished. A de-noising approach [6] is applied to identify transient disturbance in noisy signal. A method based on wavelet transform and fuzzy logic theory [7] is also accounted for classification the classification of PQ disturbance events. In this, the best characteristics of these two methods are applied. Akash saxena et al. [8,9] used wavelet transform for detection of transmission line faults. P.K. Dash et al. [10] used both S -transform and discrete- Wavelet transform together to detect, localize and classify the PQ disturbances.

C.N. Bendhe et al. [11] employed S-transform based modular neural network classifier for the recognition of power quality disturbances. A method based on discrete wavelet transform and linear discriminate analysis [12] is used for classification and detection of faults and this method can be performed for single circuit and double circuit method. In [13], a new approach is determined for detection and classification of non-stationary signals using neural network with S transform.

An effective supervised learning approach is applied for static security assessment of a large power system using support vector machine in [14]. C. F. Drummond and D. Sutanto [15] used Hilbert transform for classification due to its ability to analyze non- stationary signals with better time resolution. In [16], ANN is applied with Hilbert transform by D. Devaraj and R. Sukanesh for their work of PQ events classification for noisy signal.

Hence, a large number of methods have been invented for classification, detection and function approximation of signal. In this work, seven ANN are applied with Hilbert transform for classification of PQ events in input voltage signal. Each ANN is treated with Hilbert transformed signal and data training is performed for further process.

In this paper, power quality disturbance events are classified using ANN with Hilbert transform approach. Statistical values of input signal is used to reduce computational time by supervised learning model and four values of signal namely maximum value, minimum value, entropy value and standard deviation values are used as features of input signal.

II. METHODOLOGY OF CLASSIFICATION

In this work methodology consists following steps:
(i) Generation of distorted voltage signal
(ii)Modification of input signal
(iii)Construction of output class
(iv)Data training by **ANN**
(v)Determination of efficiency of supervised learning model
(vi)Result and Testing

(i)Generation of distorted signal

In this work a random voltage signal is generated and this signal is introduced with seven events namely Sag, Swell, Interruption, Harmonics, Sag with Harmonics, Swell with Harmonics, Flickers. The efficiency ANN for classification degrades when noise is introduced in the signal. In this work, signals are generated and the efficiency of supervised learning model is examined at different levels of noise for classification of signal.

(ii) Modification of input signal

It is required to modify input signal in such a way that the process of classification of PQ events must provide better efficiency with less computation time. In this work, Hilbert transform is used to extract the features of signal and statistical values of each event are determined namely maximum, minimum, standard deviation and entropy values as these values will cover all corresponding values of the event.

An example of input class of Sag disturbance signal is given with its statistical value.

$$v(t)_{sag,} = [max(v(t)_{sag}), min(v(t)_{sag}), std(v(t)_{sag}), shannon(v(t)_{sag})]$$

Each sample of PQ disturbance event has its four values in input signal class and in this work eight PQ disturbance events are introduced in the signal for the classification. Hence the size of modified input signal class matrix will be 4 X 800.

$$v(t)_{input} = [v(t)_{normal}, v(t)_{sag}, v(t)_{swell}, v(t)_{interruption}, v(t)_{harmonics}, v(t)_{flicker}, v(t)_{sag\ with\ harmonics}, v(t)_{swell\ with\ harmonics}]$$

(iii)Construction of output class

The output class is designed such a way that it must contain a definite binary identifier for each event. Hence the number of columns in output class will be equal to the number of columns in input class, so the size of output class in the work is 9 X 800.

(iv)Data training of classifier

It is trained to classifier to recognize the particular PQ event with a definite binary identifier that is related to the output class. The process of training of a neural network involves adjustment of the values of the weights and biases of the network to optimize the network performance. After training if there will be occurrence of any relevant disturbance, the ANN will show the binary identifier for the PQ disturbance event.

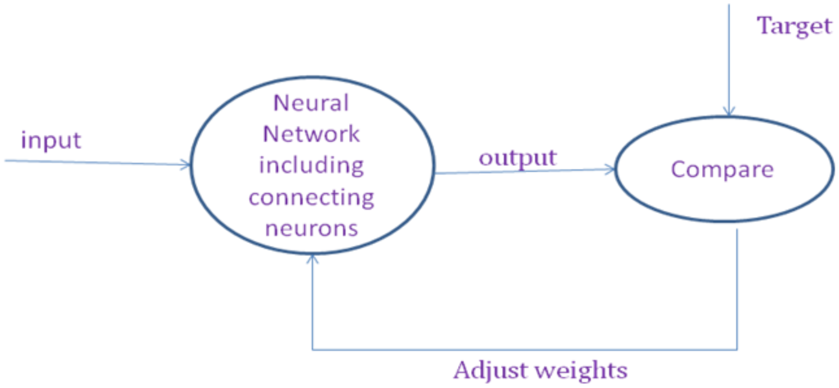

Figure1. Procedure of ANN

(v)Determination of efficiency of supervised learning model

More efficient ANN will provide less error in the process of classification of PQ events. So, it is necessary to determine a suitable ANN topology among these seven topologies of ANN. In this work standard errors are determined to obtain the efficiency of each ANN namely Mean square error(MSE), Mean absolute error (MAE), Sum squared error (SSE), Sum Absolute error (SAE), Root mean square error (RMSE), Confusion and Confusion plot etc.

Case 1: Classification of without noise voltage signal

In this case, test voltage signal (without noise) is taken and its statistical values of Hilbert transformed signal are used to form input features. The voltage signal waveforms of normal signal and modified voltage signal will be different from each other. A comparison of normal PQ disturbance events with their Hilbert transformed signal is presented in figure 2 to figure 9 . It is shown in figures that Hilbert transformed signal is ninety degree phase shifted than the normal signal.

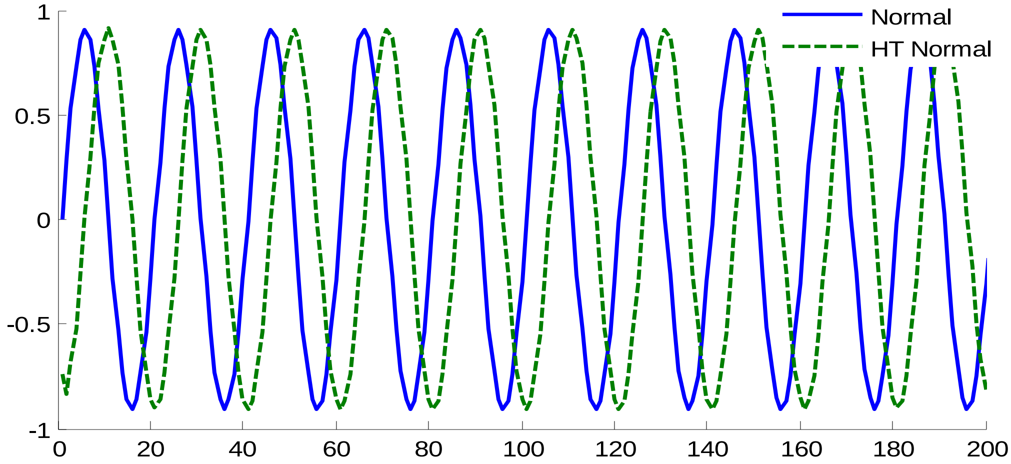

Figure2. Normal signal with Hilbert transformed signal

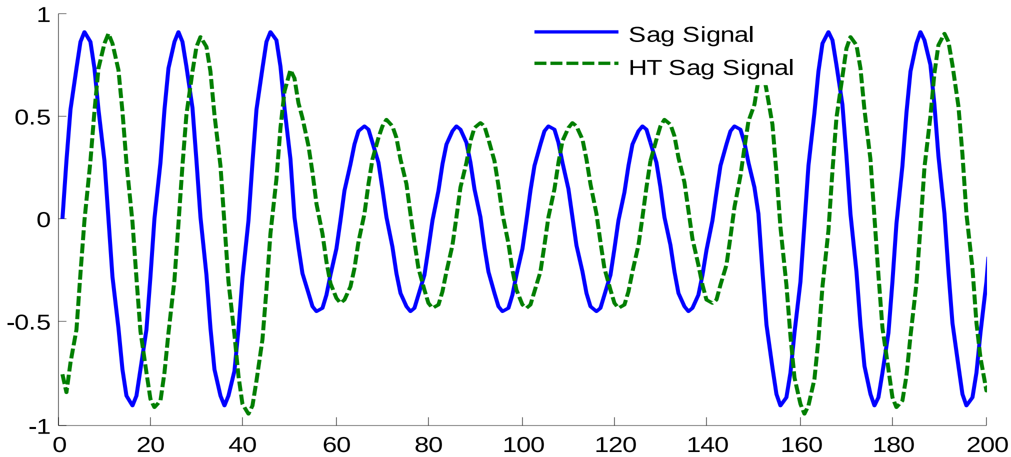

Figure3. Sag signal with Hilbert transformed signal

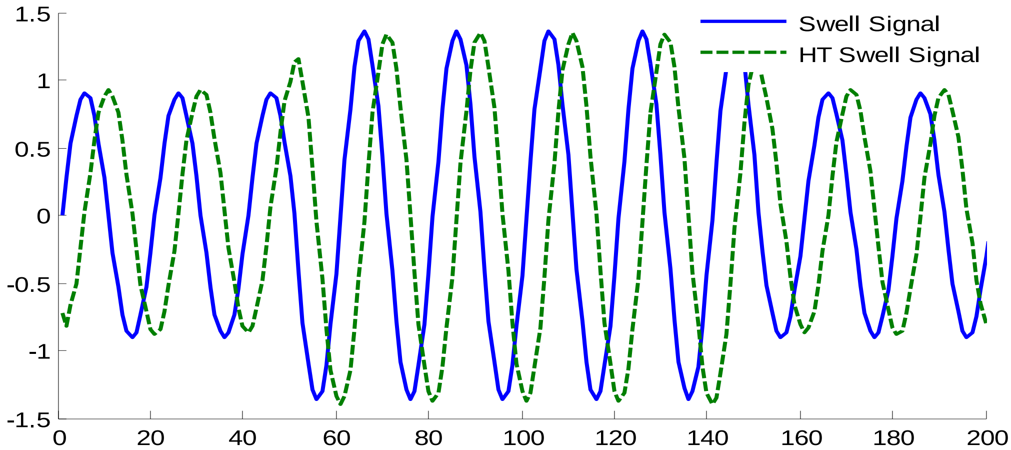

Figure4. Swell signal with Hilbert transformed signal

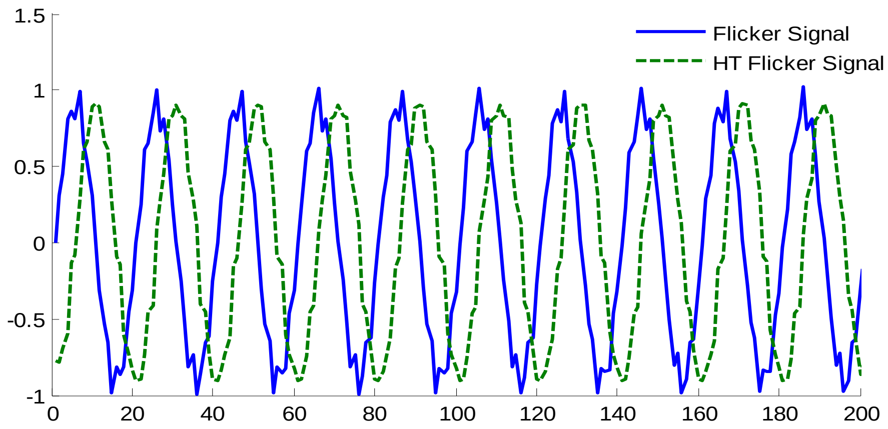

Figure5. Flicker signal with Hilbert transformed signal

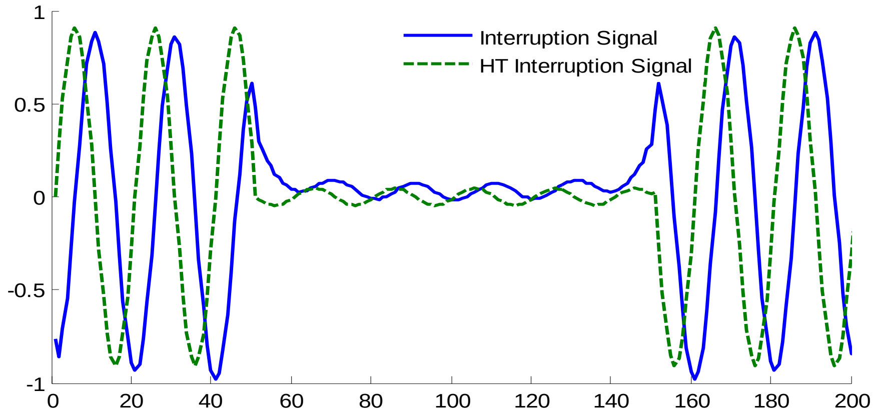

Figure6. Interruption signal with Hilbert transformed signal

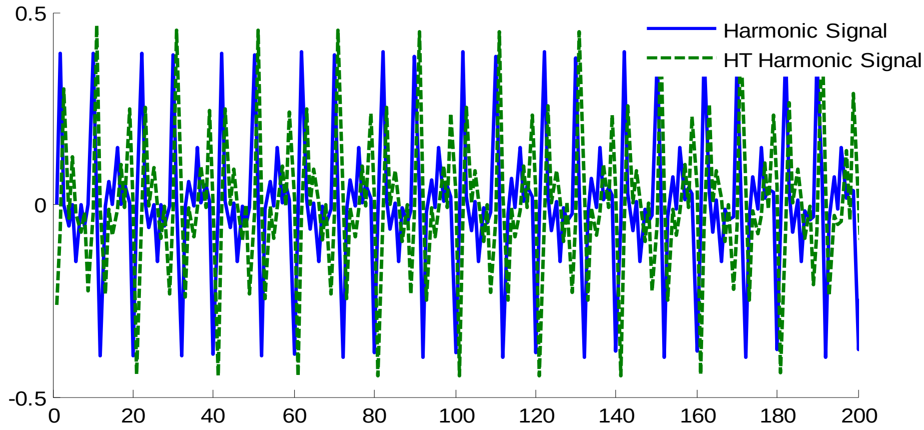

Figure7. Harmonic signal with Hilbert transformed signal

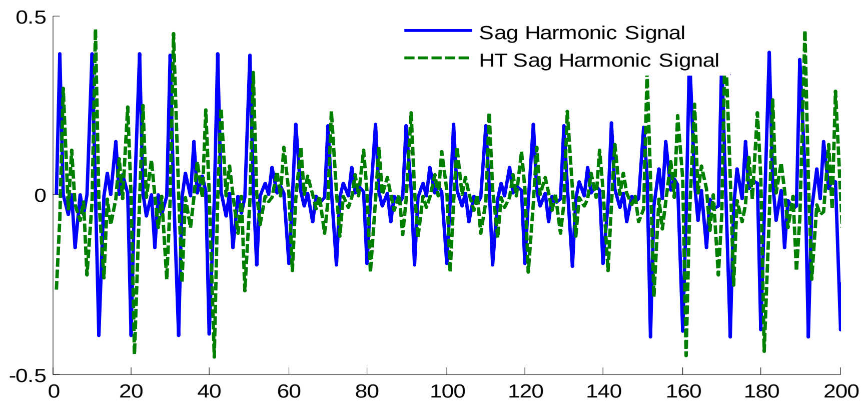

Figure8. Sag Harmonic signal with Hilbert transformed signal

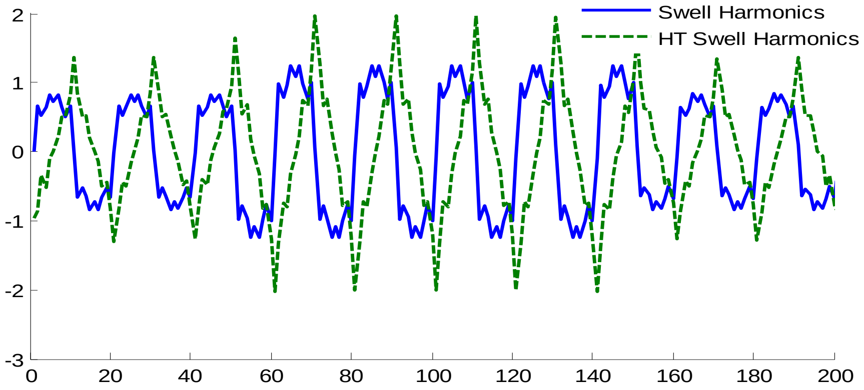

Figure9. Swell Harmonic signal with Hilbert transformed signal

Case 2: Classification of 0.1 db noisy signal

In this case, 0.1 db noise is introduced in the input voltage signal. A comparision of normal voltage signal with 0.1 db noise volage signal is given below in figures 10 to 17.

(a)Normal Signal

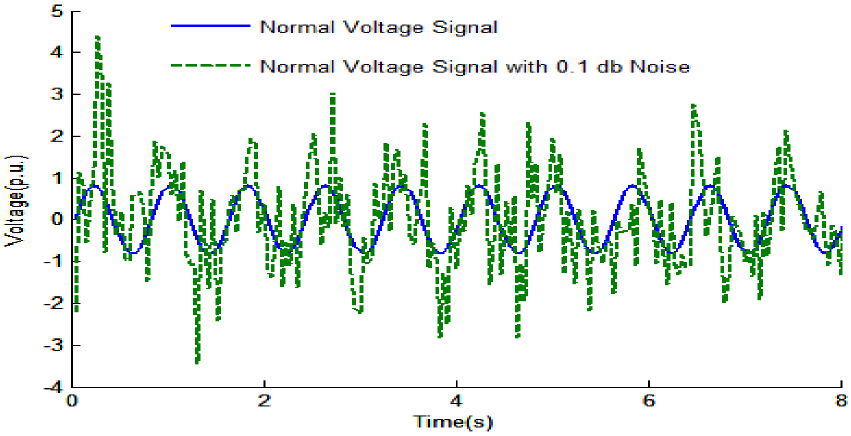

Figure10. Noisy voltage signal with Hilbert transformed signal

(b) Sag Signal

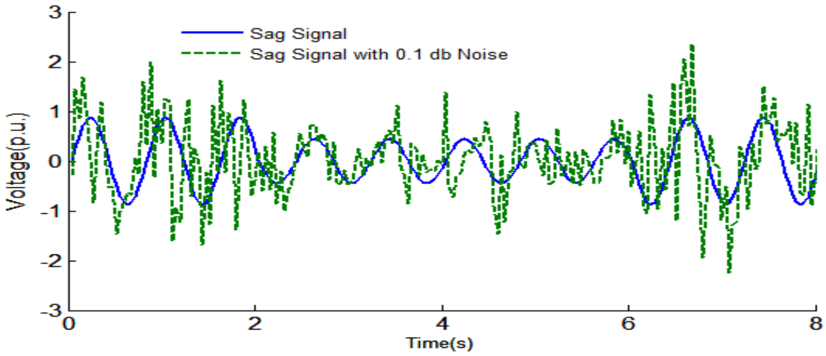

Figure11. Sag signal with Hilbert transformed signal

(c) Swell

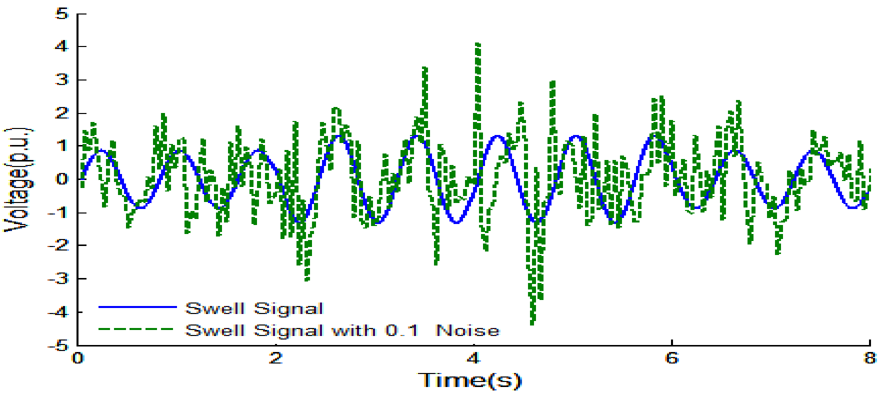

Figure12. Swell signal with Hilbert transformed signal

(d)Interupption

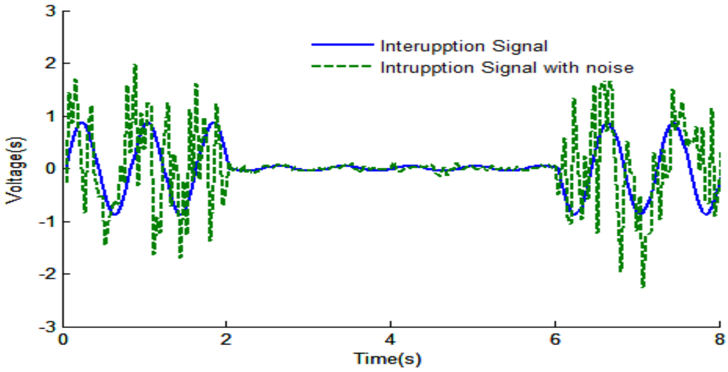

Figure13. Interruption signal with Hilbert transformed signal

(e)Sag Harmonics

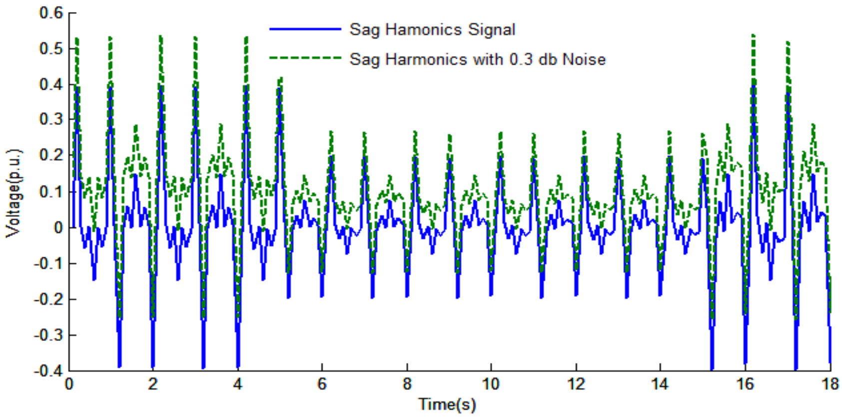

Figure14. Sag harmonic signal with Hilbert transformed signal

(f)Swell Harmonics

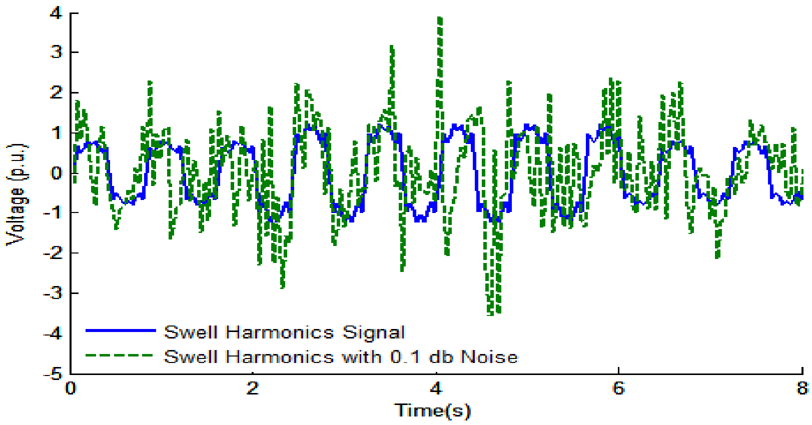

Figure15. Swell harmonic signal with Hilbert transformed signal

(g)Harmonics Signal

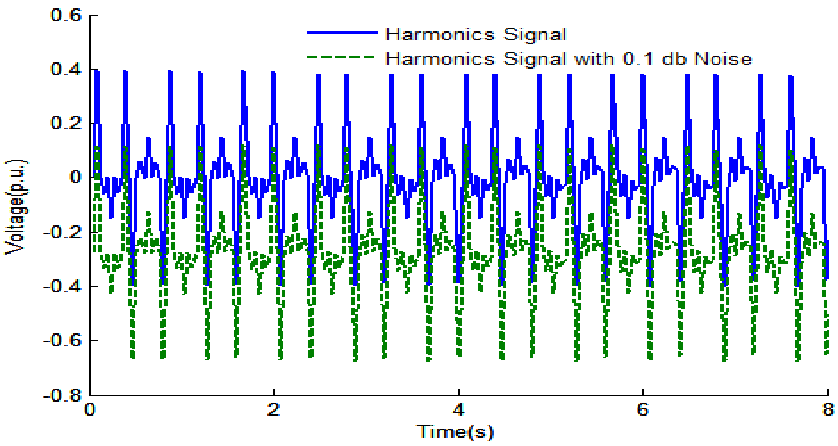

Figure16. Harmonic signal with Hilbert transformed signal

(h)Flicker Signal

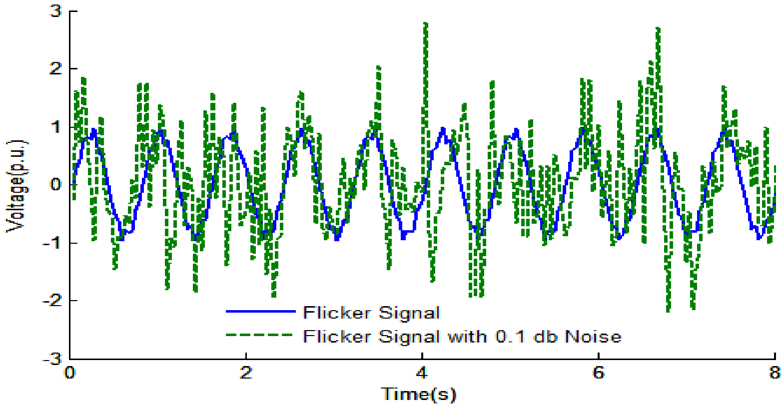

Figure17. Flicker signal with Hilbert transformed signal

III. SIMULATION RESULTS OF CLASSIFICATION ENGINES

This section presents the classification results of various supervised learning engines namely CFBP, EBP, FFBPN, FFDTD, LRNN, NARX and RBEFNN. These supervised learning engines are formed with the help of simulated data. Efficacies of these engines are evaluated with the help of standard error indices. To show the efficacy and robustness of classification engines two cases are simulated. The results of these cases are presented below:

Case 1: Classification of PQ events of without noise voltage signal

Table1. Standard errors and efficiency of different ANNs

Neural Network	MSE	SSE	MAE	RMSE	SAE	CONFUSION	Efficiency (%)
Cascade Forward Backprop	5.50E-03	44.3761	1.23E-02	7.40E-02	99.5629	0.0311	96.9
Elman Backprop	5.40E-03	4.35	0.0113	0.0733	91.2728	0.0333	96.7
Feed-forward backprop	5.60E-03	45.1529	1.18E-02	0.0747	95.722	0.0344	96.6
Feed-forward distributed time delay	6.30E-03	50.8329	1.54E-02	0.0792	124.4085	0.0356	96.4
Layer Recurrent	5.40E-03	43.5095	0.0113	0.0733	91.2954	0.0344	96.6
NARX	5.50E-03	44.4068	4.44E+01	0.074	94.6871	3.44E-02	96.6
Radial Basis (Fewer Neurons)	6.22E-04	5.0393	0.0021	0.0249	17.1497	0.0022	99.8

Table 1 shows the classification results for various PQ events in terms of confusion values and efficiency. It is observed that least error is observed in the case RBEFNN.

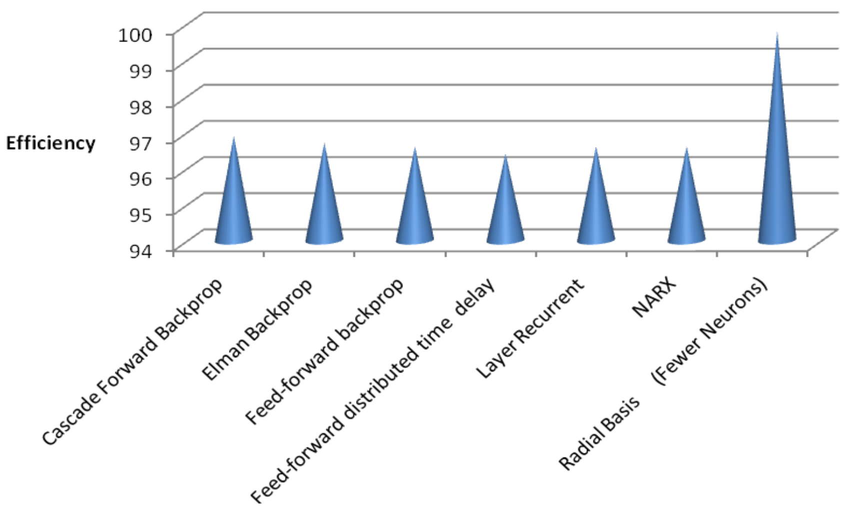

Figure18. Comparision of effeciency of various ANN

RBEFNN proved as a suitable topology as the efficiency of classification is much higher as compared to other topologies.

Case 2: Classification of 0.1 db noisy signal

Table2. Standard errors and efficiency of numerous ANN for 0.1db noise signal.

Neural Network	MSE	SSE	MAE	RMSE	SAE	CONFUSION	Efficiency (%)
Cascade Forward Backprop	3.59E-02	290.5127	7.12E-02	1.89E-01	576.4225	0.2689	73.1
Elman Backprop	4.07E-02	3.30E+02	0.0686	0.2017	555.9209	0.2644	73.6
Feed-forward backprop	3.40E-02	275.7826	6.93E-02	0.1845	561.3017	0.2611	73.9
Feed-forward distributed time delay	3.50E-02	283.6959	6.87E-02	0.1871	556.7514	0.2567	74.3
Layer Recurrent	4.88E-02	395.4085	0.0867	0.2209	702.6454	0.3811	61.9
NARX	3.62E-02	293.348	7.18E-02	0.1903	581.7029	2.62E-01	73.8
Radial Basis (Fewer Neurons)	1.52E-04	1.2337	3.56E-04	0.0123	2.887	0.0011	99.9

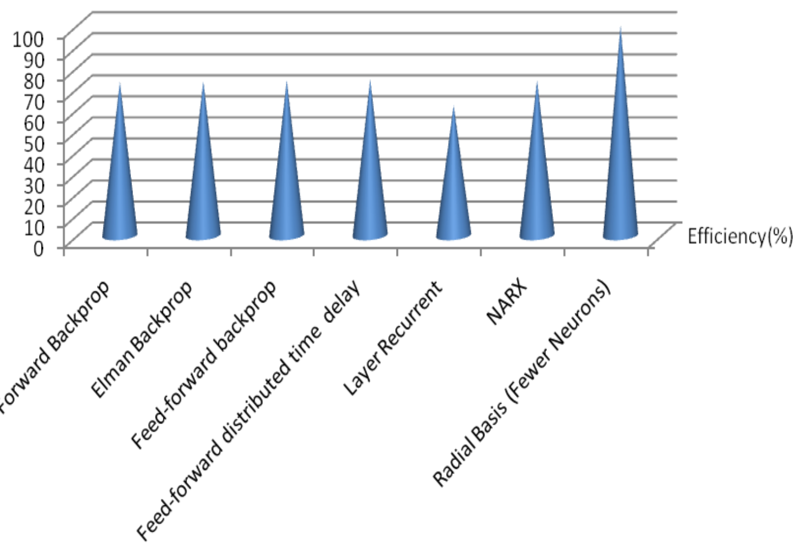

Figure19. Comparision of effeciency of various ANN

From figure 19, it can be observed that RBEFNN gives better results as compared to other ANN topologies in the presence of noise. It is worth to mention here hat classification efficiency of these supervised learning engines reduce in the presence of noise. However, the RBEFNN produces results with superior accuracy. Hence, it is concluded that RBEFNN is the suitable topology for PQ event classification.

CONCLUSION

In the work an effort is made to provide a method to classify the power quality disturbance events using Artificial Neural Network. At completion of whole process following conclusions are obtained.

- The classification of power quality events through ANN provides a very good efficiency. ANN is used here for the classification of power quality disturbance events and it shows a great efficiency comparison to other process.
- The computation time and efficiency of classification can also be increased by feature extraction of input signal. Hilbert transform with statistical approach is good to obtain better efficiency for classification by ANN. In the work Hilbert transform is used for feature extraction and it increases efficiency of supervised learning model up to 99.99 percent for noisy signal also.
- It is shown in the work that among all ANN, Radial Basis (Fewer Neurons) shows maximum efficiency of classification for both normal conditions and noisy conditions. So it is better to use RBF for classification process than other ANN.

This work provides scope to use differ techniques as feature extraction to improve efficiency for different ANN topologies. A scope is available to generate a new ANN with manually obtained parameters that provides better efficiency than obtained efficiency in the work.

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