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A NEW APPROACH FOR PATTERN RECOGNITION OF NON-STATIONARY SIGNAL USING FWNN

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ABSTRACT

This paper discusses new approaches in time- time transform and Non-stationary power signals classification using fuzzy wavelet neural networks. The time-time representation is derived from the S-transform, a method of representation of a real time series as a set of complex, time-localized spectra. When integrated over time, the S-transform becomes the Fourier transform of the primary time series. Similarly, when summed over the primary time variable, the TT-transform reverts to the primary time series. TT-transform points to the possibility of filtering and signal to noise improvements in the time domain. In our research work visual localization, detection and classification of Non-stationary power signals problem using TT-transform and automatic Non-stationary power signal classification using FWNN (Fuzzy wavelet Neural Network) have been considered. Time- time analysis and Feature extraction from the Non-stationary power signals is done by TT-transform. In the proposed work pattern recognition of various Non-stationary power signals have been considered using particle swarm optimization technique. This paper also emphasizes the robustness of TT-transform towards noise. The average classification accuracy of the noisy signals due to disturbances in the power network is of the order 92.1.

Keywords: Non-Stationary Power Signals, FWFNN, S-Transform, TT-Transform, Particle Swarm Optimization

I. INTRODUCTION

In electrical power networks, the voltage and current signals exhibit fluctuations in amplitude, phase, and frequency due to the operation of solid-state devices that are prolifically used for power control. The sudden increase and decrease in voltage signal is known as swell and sag, respectively. Apart from these steady state disturbances, transient oscillations are seen in power networks when power electronically controlled capacitors are switched across a node in an electrical power networks. These transients are of large amplitude in comparison to the normal voltage or current signal and exhibit multiple frequencies ranging from 300Hz to 5000Hz In addition to oscillatory transients, impulsive transients, multiple voltage notches due to solid-state converter switching, harmonics and power sinusoids being modulated by low frequency signals are also observed in the electric power networks. To

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distinguish and finding the similarity between Non stationary disturbance signal patterns like voltage sag, voltage swell, oscillatory transients, impulsive transients, multiple voltage notches, in the normal sinusoidal signals of frequency 50Hz or 60Hz, advanced signal processing techniques along with intelligent system approach play a vital role in generating patterns that resembles the nature of the Non stationary disturbances. TT-Transform provides a unified framework for processing distorted power signals. In this paper we present a two dimensional time-time representation of different Non stationary power signals, based upon the S-transform. This is termed the TT-transform. One of the major utilities of the TT-transform is the time-local view, through the scaled windows of the primary time series.

The extracted features (Standard deviation, &Normalized values) have been taken for non- stationary power signal classification using fuzzy wavelet neural networks (FWNN). Fig-1 illustrates the use of popular TT-transform algorithm to extract the features of the Nonstationary power signals. The extracted features are applied to the FWNN classifier for classification.

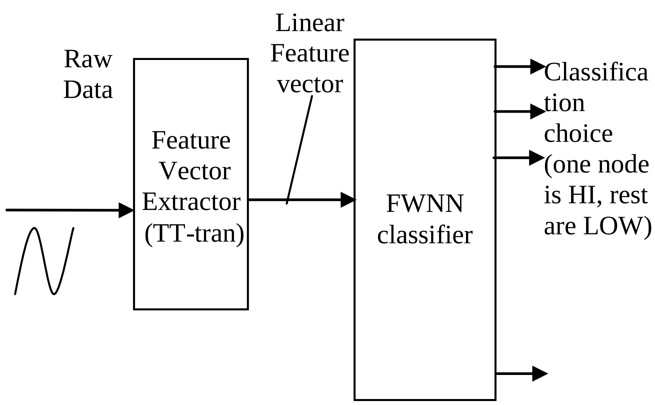

Fig .1 Feature vector approach to

Fuzzy Wavelet neural networks are investigated here for classifying the power signals automatically due to its efficiency in processing power signals. This makes the FWN net implement able for real time application

II. THE TT-TRANSFORM

We define a second time –time distribution, the TT-transform (C. R. Pinnegar and L. Mansinha), obtained from the inverse Fourier transform of the S-transform

$$TT(t,\tau)]=\int_{-\infty}^{\infty} S(t,f)\exp(+2\pi i\, f\,\tau)df. \qquad (1)$$

If TT (t, τ) is considered at all τ but a specific t, the result is a time-local function, conceptually similar to a windowed function. Since a different window has been used to obtain S at each value of f. Therefore

From (3) and (5)

$$\int_{-\infty}^{\infty} TT(t,\tau)dt = h(\tau). \qquad (2)$$

So, like the S-transform, the TT-transform is invertible [2].

The discrete S-Transform and the discrete TT-transform**.** The S-transform $\hat{S}$ may be evaluated by sampling Eq. (2) in frequency because of efficiency in computation:

$$\hat{S}\left[jT,\frac{n}{NT}\right]=\sum_{m=-N/2}^{N/2-1}\hat{H}\left[\frac{m+n}{NT}\right]\exp\left[\frac{2\pi imj}{NT}\right] \qquad (3)$$

The discrete TT-transform $\hat{T}T$ is obtained from the discrete form of (5):

$$\hat{T}T[jT,kT]=\sum_{n=-N/2}^{N/2-1}\hat{S}\left[jT,\frac{n}{NT}\right]\exp\left[\frac{+2\pi ink}{N}\right] \qquad (4)$$

The discrete TT-transform contains edge effects since it is obtained from $\hat{S}$. The invertibility of $\hat{T}T$ is given by

$$\sum_{j=0}^{N-1}\hat{T}T[j,T\,kT]=\hat{h}[kT] \qquad (5)$$

III. FEATURE EXTRACTION

In our research work we have extracted various features like Energy, Standard deviation, Autocorrelation, mean, variance and normalized values from the Non stationary power signals. During feature extraction it is found that the standard deviation and normalized values are the most distinguished features.

Therefore standard deviation and normalized values have been taken for classification of various Non stationary power signals. Non stationary power signal classification has been done with (denoising) and without noise.

IV.SIMULATION RESULTS OF NONSTATIONARY POWER SIGNALS USING TT-TRANSFORM

The proposed techniques are used to analyze the power signal disturbance in a realistic power network simulated by power system block set supported by MATLAB software. The sampling rate for the collection of power quality data is taken to be equal to 3.84 kHz. In our study we have discussed different types of Non stationary power signal problems such as Voltage sag, Voltage swell, Voltage notches, etc with MATLAB software.

The TT output shows the plot of the normalized TT- contour and the absolute value of a given magnitude of change in the time-time co-ordinate system. The various power signal transient tests are conducted on the simple power network to study the performance of the TT-transform.

The following case studies are presented in this paper: From the above simulation results it is quite clear that the TT-transform does excellent detection and visual classification of Non stationary power signals because of superior time-time resolution characteristic. Which are given below.

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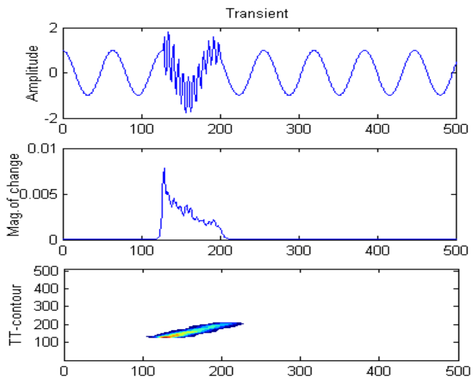
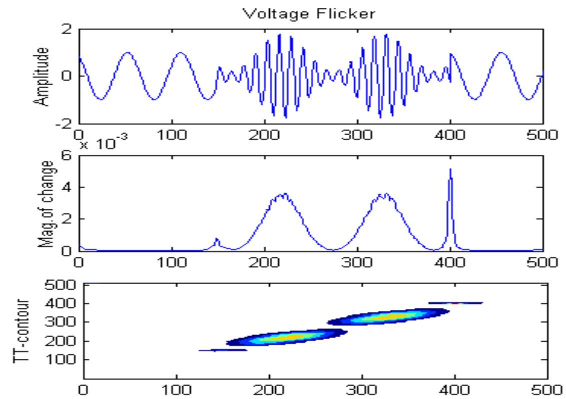


(A)



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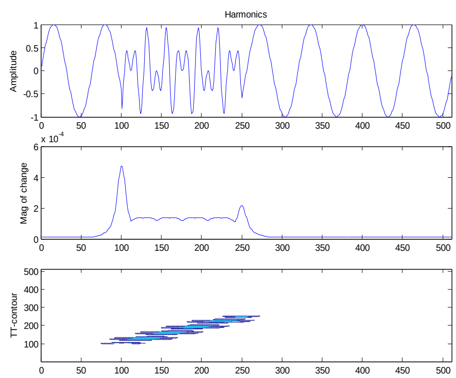

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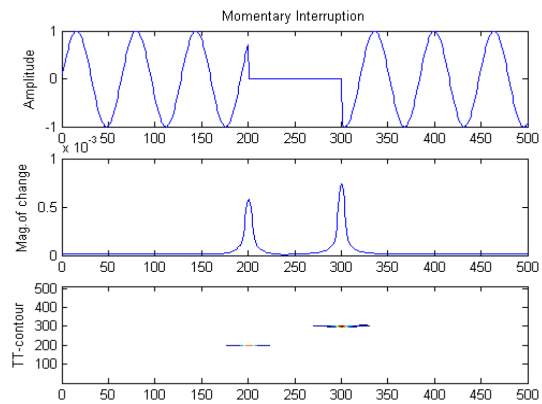

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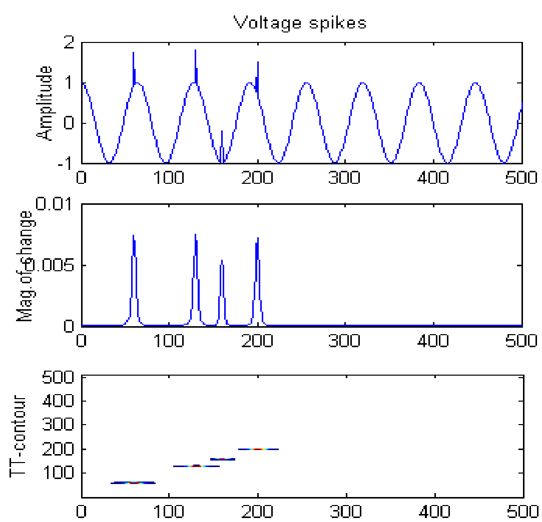

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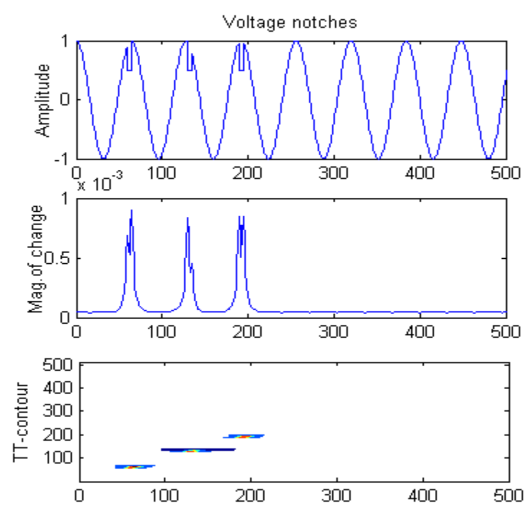

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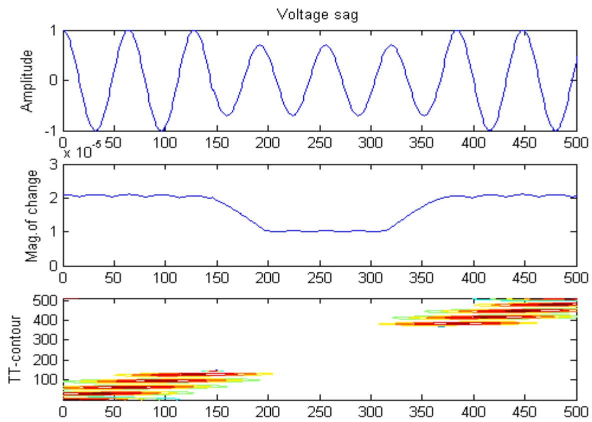


(G)

Fig.2 Oscillatory voltage waveform and TT-transform result.

V. THE PROPOSED FUZZY WAVELET NEURAL NETWORK

The fundamental idea behind wavelets is to analyze according to scale. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. If we look at a signal with a large "window," we would notice gross features. Similarly, We know the Gaussian function is local in both time and frequency domains and is a $C^{\infty}(R)$ function. Therefore, any derivative of the Gaussian function can be used as the basis for a wavelet transform. In our model we have taken first derivative Gaussian wavelet function for pattern recognition of Non stationary power signals. The Gaussian first derivative wavelet, is defined as:

$$\psi(x) = -x\exp\left(-\frac{x^2}{2}\right)$$

Wavelets are well suited for approximating data with sharp discontinuities.

ALGORITHM

LAYER 1 (Fuzzification Layer):

Features like standard deviation, and normalized value of certain disturbances in the power signals such as Voltage sag, Voltage swell, Voltage notches, Harmonic distortion, Sag with harmonic, Swell with harmonic, Voltage chirp and Harmonic distortion with momentary interruption are applied as input to the network. Gaussian membership values of the inputs are found out at their respective nodes using their respective centers and scope. The output of this layer is the sum of the Gaussian MF value of each feature according to the node.

$$I_i(1) = \{x_1, x_2, x_3, \ldots\ldots\ldots\ldots\ldots\ldots x_n\}$$

Where x_1 = Standard deviation

x_2 = Normalization and so on.

$$O_{ii}^{(1)} = \exp(-(I^{(1)} - m_{ij})^2 / (\sigma_{ij}^2))$$

Where m_{ij} = center σ_{ij} = scope

LAYER 2 (Normalization Layer):

The output of layer 1 acts as input to the layer2

$$I_{ij}^{(2)} = O_{ij}^{(1)}$$

The output of layer 2 is obtained by normalizing in the same layer.

The normalized output is given as :

$$O_{ij}^{(2)} = I_{ij}^{(2)} / \sum I_{ij}^{(2)}$$

LAYER 3:
The mother wavelet is given by

$$\psi(t) = -t^* \exp(-t^2 / 2)$$

This simple wavelet function exhibits a great ability to generalize and has a short learning time.
The normalized output of the second layer acts as input for the wavelet bases.

$$I_{ij}^{(3)} = O_{ij}^{(2)}$$

$$O_{ij}^{3} = \psi(I_{ij}^{(3)})$$

LAYER 4 (Output Layer):
Error is calculated by subtracting the output of fourth layer from the desired output. Whenever the characteristic features of any disturbance are given the output node corresponding to that disturbance should have the highest value amongst the all.

$$Error(\varepsilon) = (desired\ output) - (O_{ij}^{(4)})$$

WEIGHT UPDATION USING BACK PROPAGATION

The weights are updated according to the following formula:

$$W_{ji}(t+1) = W_{ji}(t) + \eta \Delta W_{ji}$$

Where η is the learning rate parameter and suitably chosen between [0,1]

To achieve a faster convergence and

$$\Delta w_{ji} = -\delta\varepsilon(n) / \delta W_{ji}$$

$$= -(\partial\varepsilon(n) / \partial e_j(n)) * (\partial e_j(n) / \partial y_j(n)) * (\partial y_j(n) / \partial w_{ji})$$

$$= -e_j(n) * (-1) * I_i^{(1)}$$

$$= I_i^{(1)} * e_j(n)$$

The weights are updated in each iteration and free zed in the last iteration.

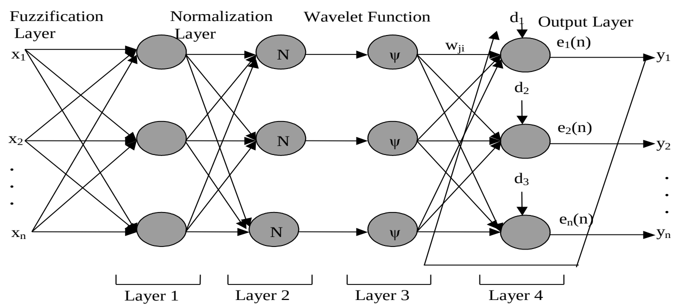


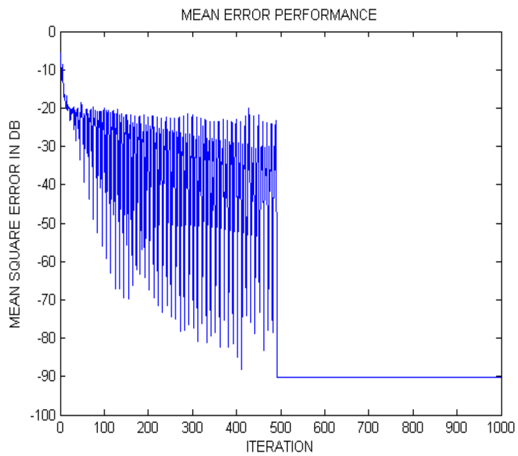
Fig.3 Fuzzy wavelet neural network model

VI. DENOISING PROCESS

After classifying the Non stationary power signals without noise, classification is done by adding a noise of 30 dB SNR to each disturbance and denoising it. The denoising process is adopted, keeping in view of practical implementation because practically we cannot have any signal without being interfered with noise. In general it is found that the noise occurred in power signal is approximately 30 dB SNR. Initially 30 dB white Gaussian noises have been added with each of the power signals. Then TT-transform is taken. Thereafter only 30 dB noises have been taken and TT-transform is found out. Finally TT-transform of 30 dB noise subtracted from the TT-transform of signal with 30 dB noises. In this way denoising process is carried out and feature vectors have been extracted from the de-noised signal. These de-noised feature vectors have been tested in our model for 1000 & 2000 iteration respectively.

VII. DISCUSSIONS

As can be seen from the Tables, the proposed method is doing very well in classifying these ten types of disturbances using the concept of PSO. Even after denoising, the variation of the classification accuracy of the fuzzy wavelet neural network is negligible. This is the result of the TT-transforms robustness towards noise. An interesting point to note is that the classification accuracy of harmonics actually increases with the presence of noise. The mean square error plot in dB and the classification accuracy table is given below for 1000 & 2000 iteration respectively



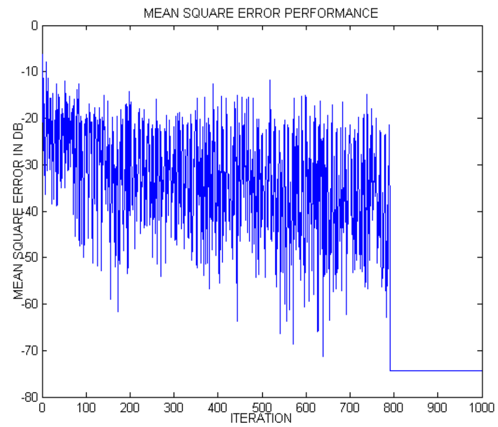


Fig.4 **Fig.5**

Fig.4 Mean square error (dB) plot without noise for 1000 iteration

Fig.5 30 dB de-noised. Mean square error (dB) plots for 1000iteration..

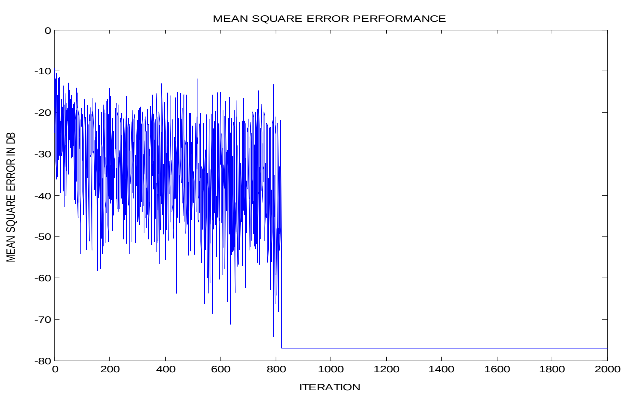


Fig.6 30 dB de-noised. Mean square error (dB) plots for 2000 iteration.

Table:1 Classification accuracy of the network without noise

Epoch	1000	2000
Voltage Sag	100%	100%
Voltage Spike	100%	100%
Voltage Chirp	100%	100%
Oscillatory Transient	100%	100%
Voltage Swell	100%	100%
Voltage Notch	100%	100%
Momentary Interruption	100%	100%
Voltage Flicker with harmonic	99%	99%
Harmonic Distortion	100%	100%
Voltage Sag with harmonic	100%	100%
Average percentage	99.9%	99.9%

Table:2 Classification accuracy of the network after denoising

Epoch	1000	2000
Voltage Sag	92%	98%
Voltage Spike	85%	89%
Voltage Chirp	91%	96%
Oscillatory Transient	82%	79%
Voltage Swell	96%	97%
Voltage Notch	86%	84%
Momentary Interruption	72%	87%
Voltage Flicker with harmonic	80%	96%
Harmonic Distortion	95%	98%
Voltage sag with harmonic	99%	97%
Average percentage	87.8%	92.1%

VIII. CONCLUSION

It is shown that the classification accuracy of the network is very high and is practically invariant even in the presence of noise. The network is quick to train, as only two thousand iteration are needed to give 92.1% classification accuracy. The time-time transform is used in this paper as a powerful analysis tool for detection, localization and classification of Non stationary power signal waveforms. TT-Transform provides a unified framework for processing distorted power signals. The learning curve of the FWNN model appears to have some oscillation at the beginning of learning. This situation reflects the structural change during the early stages of learning. With progressive iterations our model has rapid convergence. The proposed FWNN model requires only one adjustable parameter (weight matrix) and hence converges more quickly than other alternative models. It is successful in achieving faster learning and higher pattern recognition accuracy with fewer parameters in many problems. Thus the FWNN model with feature vector of TT-Transform has a powerful ability to pattern recognition of power signal disturbances using PSO.

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