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# POWER QUALITY DISTURBANCE CLASSIFICATION USING S-TRANSFORM AND FUZZY SYSTEMS ORIENTED BY PSO ALGORITHM

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**Abstract-** In this paper we designated a new method on the basis of s-transform with fuzzy logic and a particle swarm optimization (PSO) algorithm for classification of single and combined power quality (PQ) disturbances. We exploit S-transform to extract features of power quality disturbances and we used the suggested fuzzy system to group power quality events regarding the extracted features. The PSO algorithm serves to precisely show the membership function parameters for the fuzzy systems. We regard the DC offset, noise, spike, interruption, swell, sag, notch, transient, harmonic and flicker as single disturbances. Harmonic with sag, harmonic with sag with transient, harmonic with swell with transient, harmonic with transient, swell with transient and sag with transient are known as combined disturbances for the voltage signal. We studied the suggested approach's power to find these PQ disturbances as well when white Gaussian noise, with various signal to noise ratio (SNR) values, is added to the waveforms. In the simulation results part, it is shown that the suggested method possesses good average rate of accurate identification for various PQ disturbances.

**Keywords:** Power Quality, Disturbances, PSO Algorithm, S-Transform, Classification, Fuzzy System.

## I. INTRODUCTION

Power quality, in recent years, has turned into a very significant issue of electrical power system operation [1] since the use of modern power electronic devices has increased. These devises are very sensitive to voltage disturbances. Disturbances such as voltage sag/swell with and without harmonics, momentary interruption, harmonic distortion, flicker, notch, spike and transients often create waveform distortions, and this leads to problems such as malfunctions, instabilities, short lifetime, and failure of electrical equipments and so on [2].

How to extract features of disturbances from a large number of power signals and how to recognize them automatically are important for further understanding and developing power quality. A lot of researchers have worked on this notion and suggested automation systems. To supervise electrical power quality disturbances, short time discrete Fourier transform (STFT) is used most normally. In order to have a faster method very fast Fourier transform is used in [3]. However, for non-stationary signals, the STFT does not track the signal dynamics appropriately because of the limitations of a fixed window width chosen a priori [4, 5].

As a result, the use of STFT to analyze transient signals comprising both high and low frequency components would not be successful. The wavelet analysis [6-11] shows a windowing technique with different regions to solve the deficiency. Decomposing the signal into time and frequency resolution, it provides a unified methodology to characterize power quality events. Although wavelet multi resolution analysis, which is synthesized with many neural networks, provides efficient classification of power quality (PQ) events, the time-domain featured disturbances such as sags, swells, etc. may not easily be classified [12, 13]. To add to that the defect of wavelet transform is that its ability to detect find noisy conditions is not precise.

S-Transform (ST) is used to extract the feature. It is an extension to the ideas of wavelet transform and it is formed on the grounds of a moving and scalable localizing window and has characteristics above the other transforms. We can recognize S-transform as the "phase correction" of continuous wavelet transform. This transform is able to find the disturbance accurately with the noise present [14]. S-transform is superior to wavelet transform in that it avoids the requirement of testing different families of wavelets to as detect the best one for the correct classification. What more, the decomposition of the disturbance signals at different resolution levels is not required in the S-transform, thereby reducing the memory size and computational overhead [15].

We have suggested a new method that is designated to classify single and combined PQ disturbances using fuzzy system oriented with a PSO algorithm. The fuzzy system is used for classification of PQ disturbances. Optimized values for the parameters of the membership functions of this system are provided by the use of the PSO algorithm. The features which are extracted from the S-transform of the waveforms of the disturbances form the inputs of this system.

The complexity of this input set is prevented by selecting the number and the type of the inputs. whatsmore, the rule base of this system is founded to get at high precision in the classification of single and combined PQ disturbances. It is necessary to notice that all single types of PQ disturbances which are mentioned in second paragraph of this section can be found in the proposed approach.

Harmonic with sag, harmonic with sag with transient, harmonic with swell with transient, harmonic with transient, swell with transient and sag with transient are also recognized as the combined disturbances of the voltage signal. Moreover, to manifest the effectiveness of the suggested method, we examined its sensitivity to noise under various noisy conditions.

## II. S-TRANSFORM

We calculate the discrete version of the S-transform by taking the advantage of the efficiency of the fast Fourier transform (FFT) and the convolution theorem. The discrete Fourier transform of the sampled signal $h(kT)$, $k = 0, 1, \ldots, N$-1 is:

$$H\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=1}^{N-1} h(kT)\mathrm{e}^{-(\frac{j2\pi nk}{N})} \tag{1}$$

and discrete version of the S-transform of is $h(kT)$ obtained as:

$$S\left[kT,\frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right]\mathrm{e}^{\frac{2\pi^2 m^2}{n^2}}\,\mathrm{e}^{\frac{j2\pi nk}{n}}\ ,\ n \neq 0 \tag{2}$$

where $j$, $m$=0, 1, 2… $N$-1, $n$=1, 2… $N$-1 and for $n$=0.

$$S[kT,0] = \frac{1}{N}\sum_{m=0}^{N-1} h\left[\frac{m}{NT}\right] \tag{3}$$

where $T$ is time interval and $N$ is the overall number of samples. The discrete inverse of S-transform is obtained as

$$h[kT] = \sum_{n=0}^{N-1}\left\{\frac{1}{N}\sum_{j=0}^{N-1} S\left[jT,\frac{n}{NT}\right]\right\}\mathrm{e}^{\frac{2n\pi k}{N}} \tag{4}$$

By exploiting the efficiency of the FFT and the convolution theorem, the discrete ST can be calculated quickly. The phase spectrum as wellas the amplitude spectrum is localized by the ST. The S-transform performs multi resolution analysis on a time varying signal as its window width differs inversely with frequency. This allocates high time resolution at high frequency and high frequency resolution at low time. S-transform can be applied effectively because power quality disturbances make the power signal a non-stationary one.

In this paper, we use the ST amplitude matrix (5) to analyze the power disturbances in which the rows are the frequencies and the columns are the time values. The ST amplitude with all frequencies at the same time are displayed in each row and the ST amplitude with time varying from *0* to *N-1* in the same frequency is displayed in each column, where $n$= 0, 1 … $N$/2 -1.

$$A(kT,f) = \left|S\left[kT,\frac{n}{NT}\right]\right| \tag{5}$$

## III. POWER QUALITY ANALYSIS USING ST

Power-quality disturbance signals, in this paper, are ten single disturbances and six complex disturbances, including DC offset, noise, spike, interruption, swell, sag, notch, transient, harmonic, and flicker are recognized as single disturbances and harmonic with sag, harmonic with sag with transient, harmonic with swell with transient, harmonic with transient, swell with transient and sag with transient as combined disturbances. We simulated These signals by using Matlab code and we mixed them random white noise of zero mean having signal to noise ratio (SNR) differing from 40 to 20 dB. In Figures 1 to 17, we can observe the normal signal and above 16 types of power disturbance signals and the time-frequency-amplitude curves generated from their STA, respectively.

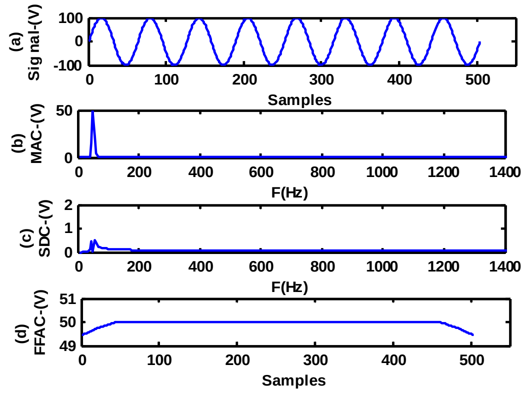


Figure 1. Voltage normal and extracted curves

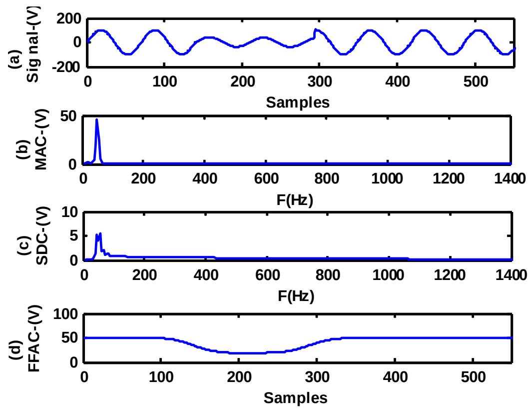


Figure 2. Voltage sag and extracted curves

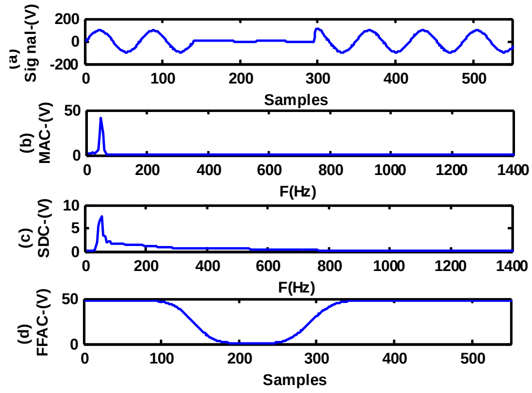


Figure 3. Voltage interruption and extracted curves

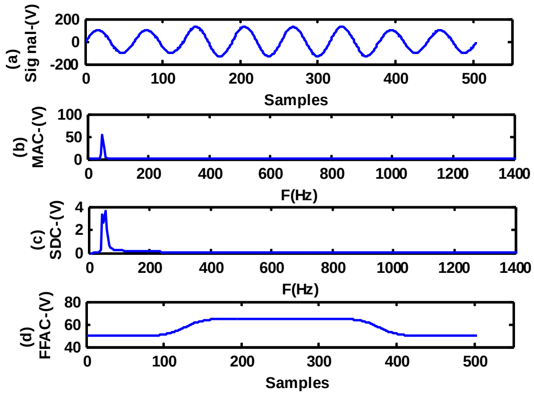


Figure 4. Voltage swell and extracted curves

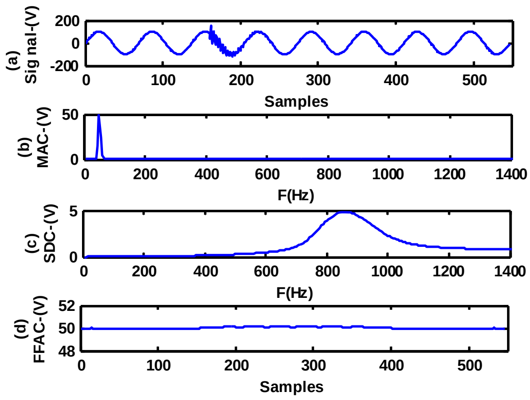


Figure 5. Oscillatory transient and extracted curves

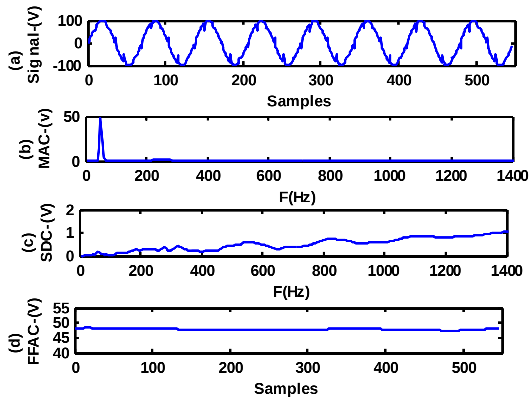


Figure 6. Voltage notch and extracted curves

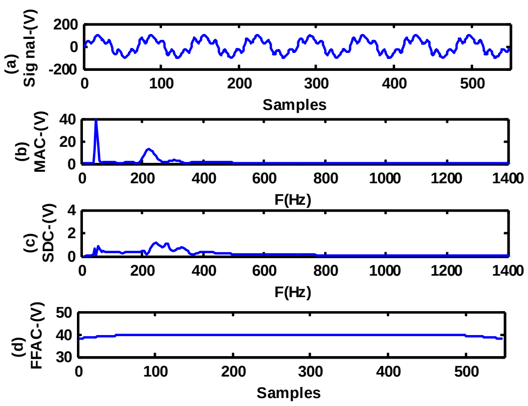


Figure 7. Voltage harmonic and extracted curves

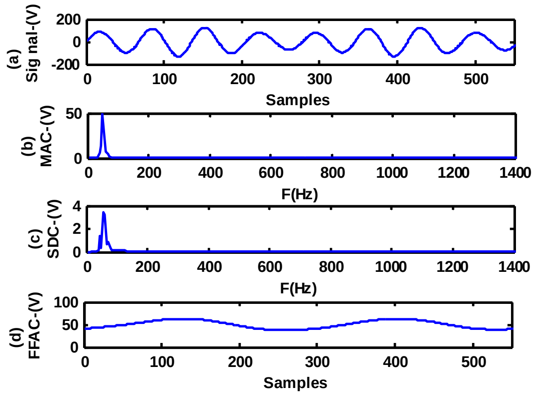


Figure 8. Voltage flicker and extracted curves

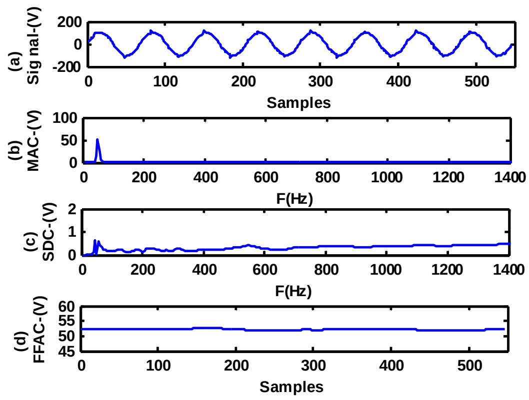


Figure 9. Voltage spike and extracted curves

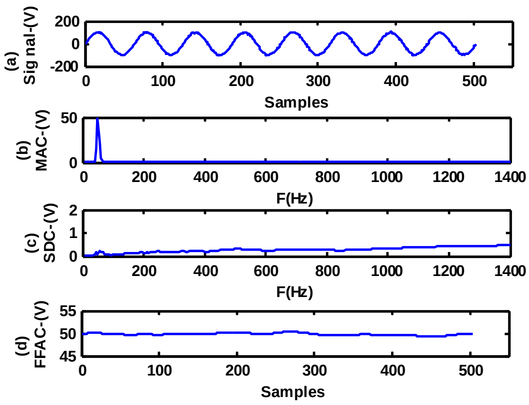


Figure 10. Noise and extracted curves

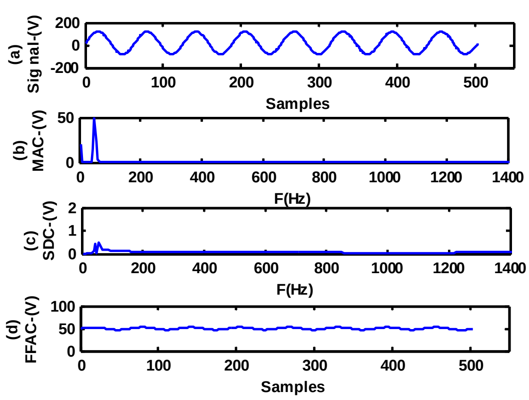


Figure 11. DC offset signal and extracted curves

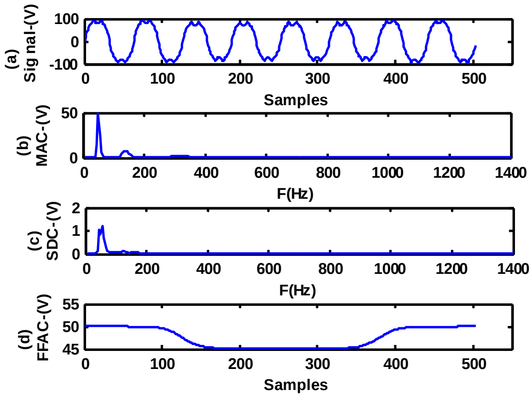


Figure 12. Voltage sag with harmonics and extracted curves

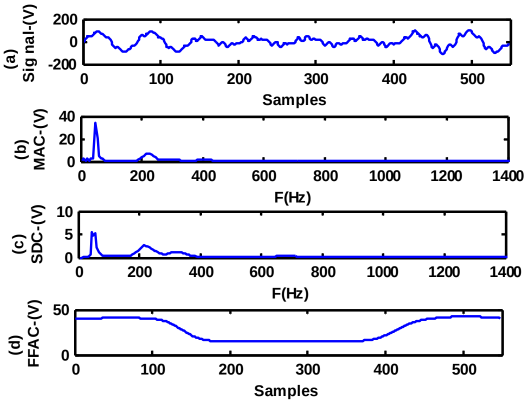


Figure 13. Voltage sag with harmonic with transient and extracted curves

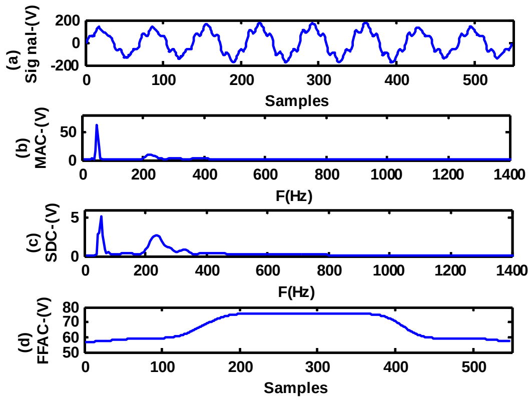


Figure 14. Voltage swell with harmonic with transient and extracted curves

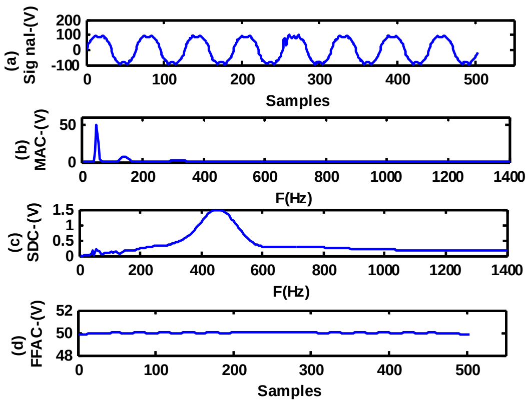


Figure 15. Harmonic with transient and extracted curves

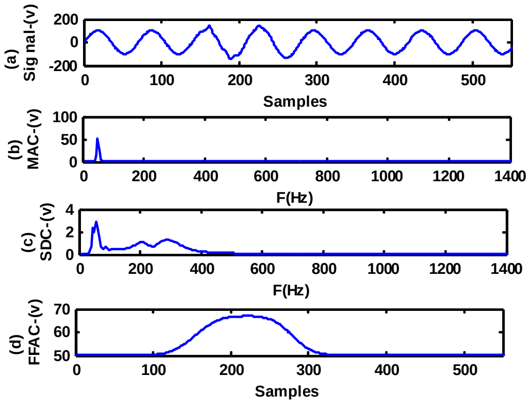


Figure 16. Swell with transient and extracted curves

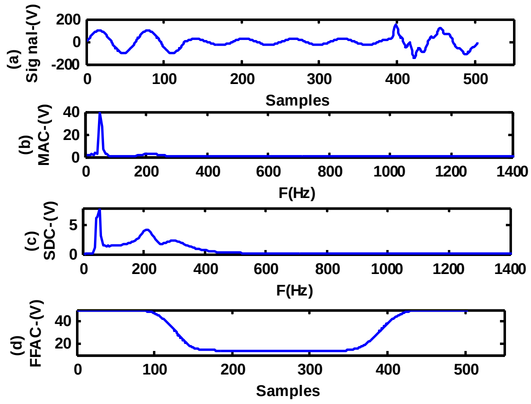


Figure 17. Sag with transient and extracted curves

Figures 2 to 17 (a)-(d) show similar plots as in Figure 1. The normal signal without any disturbance is shown Figure 1 (a). The curve of the sampling disturbance signal is shown in Figures 2 to 17 (a). Figures 2 to 17 (b) are called maximum amplitude curves (MAX-curve), which is frequency versus maximum amplitude by searching rows of STA at every frequency. The disturbance's frequency components and their maximum amplitude are shown in the curve. Where there is a peak on MAC, a frequency component on disturbance signal could be observed.

To lay an example, normal signal includes only one frequency component (50 Hz) and consecutively, there is only one peak on MAC related to this signal. In signal of harmonic, there are two peaks in its related MAC and it shows that there are 2 frequency components in this disturbance signal. Figures 2 to 17 (c) are recognized as the standard deviation curves (STD-curve), which displays frequency versus the standard deviation of STA at every frequency. This curve is the important factor to extract transient features in disturbance signals such as oscillatory transient. To extract this curve, the standard deviation of time values in each frequency in STA-matrix should be counted and be assigned for that frequency. In SDC, related to the oscillatory transient, the frequency which has a peak on this curve is the same as the frequency of transient signal, which is loaded on the primary signal. In other signal where there is a deviation on the amplitude of a frequency component; there is a peak on the same frequency of SDC.

Figures 2 to 17 (d) are called the fundamental frequency amplitude curve (FUND-curve), which shows the STA at the fundamental frequency ($f_1$ =50 Hz). As it is shown in Figure 1 (d) for a normal signal, which does not have disturbance the magnitude of the FUND-curve is a constant value (which is half the maximum amplitude of the normal signal).

### A. Feature Extraction

Recognizing Power quality disturbance is very difficult, because it contains a wide range of disturbance categories and varying degree of irregularities. We outlined the Description of PQ events considered for recognition in Section 3. The time frequency contours are generated the generalized S-transform, which clearly displays the disturbance pattern for visual examination. These contours provide some features that can be exploited by fuzzy logic or neural network-based pattern recognition systems to classify these disturbance frequency regions for amplitude frequency and amplitude time plots. The parameters used for classification in this paper are listed below.

$F_1$: The number of harmonic components in the disturbance signal is brought in this index and it is the same as number of peaks on MAC in Figures 1 (b) to 17 (b).

$F_2$: If there is a peak on SDC in Figures 1 (c) to 17 (c) in the proximity of the fundamental frequency, $F_2$=1, otherwise $F_2$=0. So for signals of sag, swell, interrupt, flicker, harmonic with sag, harmonic with sag with transient, harmonic with swell with transient, swell with transient and sag with transient, $F_2$=1 and for other signals $F_2$=0.

$F_3$: If there is a peak in the proximity of the high frequency on SDC, $F_3$=1 and otherwise $F_3$=0. Into lay an example in Figure 5 (c), we can observe a peak on a frequency higher than fundamental frequency. Consequently, for the signal of oscillatory transient $F_3$=1.

$F_4$: This is the average value of FFAC for each disturbance.

$F_5$: We define this index in order to discriminate sag from interrupt. This index can be derived as follows

$$F_5 = A_{\min} = \min(FFAC) \tag{5}$$

$F_6$: If MAC has value in zero frequency ($f$=0), then $F_6$>1 and otherwise $F_6$=0. For example, in Figure 5 (b) there is a peak on $f$=0. As a result, for a signal having DC component, $F_6$>1 and for other, $F_6$=0. This index can be obtained from (6).

$$F_6 = MAC(f_0) \tag{6}$$

### B. Fuzzy System for Disturbance Classification

Although several researchers have extensively investigated the neural network classifiers for PQ event recognition, the fuzzy logic-based recognition scheme proposes a very simple but accurate classification strategy of the PQ events. The following fuzzy system is provided for classification of the PQ disturbances. Fig.18 pictures the overall structures of this system.

$F_1$, $F_2$, $F_3$, $F_4$, $F_5$ and $F_6$ are input parameters for Fuzzy decision making system. Fuzzy process is in use for Trapezoidal membership functions. Outputs of this system are 'sag', 'swell', 'interrupt', 'oscillatory transient', 'spike', 'notch', 'harmonic', 'flicker', 'noise' and 'DC offset'. Membership functions of all inputs, chosen parameters and the type of membership function can be observed in Table 1. In section 5.1, we presented determination of membership function parameters of this system using the PSO algorithm. Table 2 consists of Fuzzy rules for each disturbance signal. For example 5th rule of this table is as follows:

Based on Rule 5, if ($F_2$ is $F_{22}$ and $F_4$ is $F_{41}$ and $F_5$ is $F_{52}$) then Sag=1 where setting "Sag" to one indicates the occurrence of a sag disturbance, and setting it to zero indicates non-occurrence of a sag disturbance. If only one of the outputs becomes 1, it indicates that there is a single disturbance on the test signal, and having multiple 1 in outputs indicates that there is a combined disturbance on the test signal.

Table 1. The membership function of fuzzy system inputs

| Labels | Range | Membership function labels | Membership function types | Membership function parameters |
|---|---|---|---|---|
| $F_1$ | [0 10] | $F_{11}$ | Trapezoidal | [0.02 0.41 1.78 1.91] |
| | | $F_{12}$ | | [1.68 1.79 8.9 9.30] |
| $F_2$ | [-1 2] | $F_{21}$ | Trapezoidal | [-0.25 -0.17 0.55 0.88] |
| | | $F_{22}$ | | [0.76 0.86 1.66 1.73] |
| $F_3$ | [-1 2] | $F_{31}$ | Trapezoidal | [-0.37 -0.21 0.63 0.78] |
| | | $F_{32}$ | | [0.77 0.85 1.56 1.87] |
| $F_4$ | [0 72] | $F_{41}$ | Trapezoidal | [3.23 7.65 46.36 48.65] |
| | | $F_{42}$ | | [48.02 48.48 49 49.5] |
| | | $F_{43}$ | | [49.2 49.65 50.5 51.02] |
| | | $F_{44}$ | | [50.65 51.21 68.01 70.17] |
| $F_5$ | [0 50] | $F_{51}$ | Trapezoidal | [0 0.11 4.89 5.02] |
| | | $F_{52}$ | | [4.92 5.11 44.95 47.2] |
| $F_6$ | [0 50] | $F_{61}$ | Trapezoidal | [7.43 8.43 46.54 49.74] |

Table 2. The rule base in the fuzzy system

| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | Harm. | Tran. | Int. | Sag | Swell | Spike | Not. | Noise | Flick. | DC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rule 1 | $F_{12}$ | – | – | – | – | – | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Rule 2 | – | – | $F_{32}$ | – | – | – | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Rule 3 | – | $F_{22}$ | – | $F_{41}$ | $F_{51}$ | – | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Rule 4 | – | $F_{22}$ | – | $F_{41}$ | $F_{52}$ | – | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Rule 5 | – | $F_{22}$ | – | $F_{44}$ | – | – | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Rule 6 | – | $F_{21}$ | $F_{31}$ | $F_{44}$ | – | – | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Rule 7 | – | $F_{21}$ | $F_{31}$ | $F_{42}$ | – | – | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Rule 8 | – | $F_{21}$ | $F_{31}$ | $F_{43}$ | – | – | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| Rule 9 | – | $F_{22}$ | – | $F_{42}$ | – | – | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Rule 10 | – | $F_{22}$ | – | $F_{43}$ | – | – | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Rule 11 | – | – | – | – | – | $F_{61}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

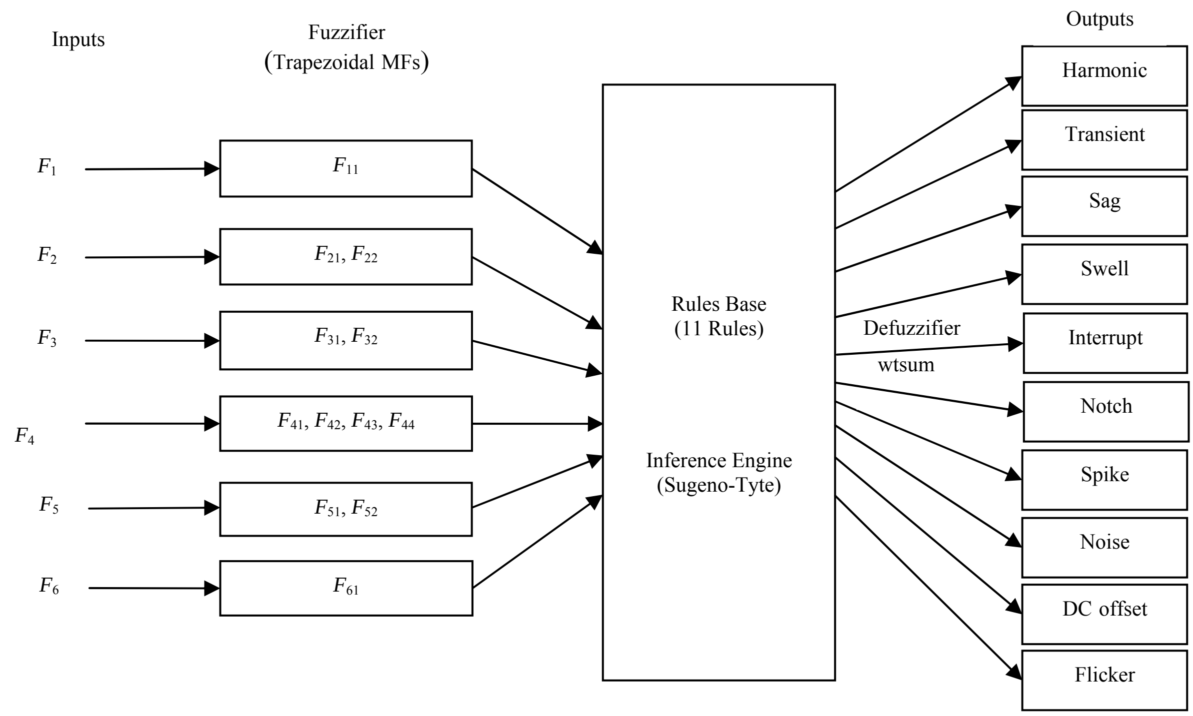


Figure 18. The schematic representation of the fuzzy system for the classification of PQ disturbances

Here, Sugeno is used for fuzzy inference engine; AND is used for rule evaluation, and 'min' is used for the strategy. At the case of having multiple rules for each output, OR is used which has 'max' strategy. Weighted sum (wtsum) methods used for defuzzification process.

### C. PSO Algorithm

Eberhart and Kennedy [16] introduced The PSO algorithm in 1995, which is a kind of group-based evolutionary algorithm. It is similar to other group-based evolutionary algorithms starting with an initial group containing "n" particles (potential solutions to the optimization problem) in a multi-dimensional search space. It is clear that some particles are in better positions than the others. The particles change their positions in this space until they encounter one of the stop-criteria of the algorithm. These criteria can contain reaching an optimal state or ending the number of specific repetitions in the algorithm. For each of iterations, the position of each particle is changed on the grounds of knowing the particle's previous movements and knowing the neighboring particles. In fact, each particle knows its best former position and the best position among all particles. For each of iterations, the velocity vector of the particle is updated according to Equation (7):

$$\bar{v}_i(t+1) = w\bar{v}_i(t) + c_1 r_1 (pbest_i(t) - \bar{x}_i(t)) + \\ + c_2 r_2 (gbest(t) - \bar{x}_i(t)) \tag{7}$$

In this equation, w is the inertia weight factor, $\bar{v}_i(t)$ is the previous velocity of the particle, $\bar{v}_i(t+1)$ is the present velocity of the particle, $c_1$ and $c_2$ are weighting acceleration constants, $pbest_i$ is the best position that a particle of the group has gained till now, and $gbest$ is the best position that a whole group has gained till now. $r_1$ and $r_2$ are random numbers with uniform distribution in the range [0-1] having values produced for each particle in each iteration.

Enough attention should be paid that $w$>0 is a factor controlling the effect of $\bar{v}_i(t)$ in $\bar{v}_i(t+1)$. Also, $c_1$>0 and $c_2$>0 make the particle move toward $\mathrm{Pbest_i}$ and $\mathrm{Gbest}$, respectively. The values of $c_1$ and $c_2$ are normally equal and selected in a way that $c_1+c_2 \leq 4$.

After the updating of its particle's velocity, the particle moves toward its new position $(\bar{x}_i(t+1))$ from its present position $(\bar{x}_i(t))$ by Equation (8):

$$\bar{x}_i(t+1) = \bar{x}_i(t) + \bar{v}_i(t+1) \tag{8}$$

Then, the objective function ($f$) is inspected at the new position of the $i$th particle. If the goal of optimization is the minimization of the objective function, then $pbest_i$ and $gbest$ are updated by Equations (9) and (10), respectively.

$$pbest_i(t+1) = \begin{cases} pbest_i(t) & \text{if } f(pbest_i(t)) \leq f(\bar{x}_i(t+1)) \\ \bar{x}_i(t+1) & \text{if } f(pbest_i(t)) > f(\bar{x}_i(t+1)) \end{cases} \tag{9}$$

$$gbest(t+1) \in \{pbest_1(t+1), \ldots, pbest_n(t+1)\} \mid \\ f(pbest(t+1)) = \min\{f(pbest_1(t+1)), \ldots, f(pbest_n(t+1))\} \tag{10}$$

The term $\bar{v}_i$ in Equation (7) lies in the range of $(-v_{\max}, v_{\max})$ to decrease the possibility that the particle exits from the search space. There are many experiences with PSO; $v_{\max}$ is set at a typical value of 10-20% of $(x_{\max} - x_{\min})$. We should pay attention that if a too high value is chosen for $v_{\max}$, particles may fly past good positions and if $v_{\max}$ is set at too small values, particles may not explore sufficiently beyond local positions [17].

While proper choice of $w$ permits the algorithm to converge to the optimal point in less iteration. In the conventional PSO algorithm, the $w$ factor decreases from the value of 0.9 to 0.4 during the iteration of the algorithm based on the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} k \qquad (11)$$

where $k_{\max}$ is the maximum number of iterations and $k$ is the present iteration number.

### D. The Application of the PSO Algorithm to the Proposed Fuzzy Systems

The PSO algorithm is employed to precisely find out the parameters of the membership functions for the inputs to the suggested fuzzy system. To elaborate on the variation intervals of these parameters, we first have to obtain the variation range for each feature describing the waveform of each type of disturbance. Then by analyzing the variation range of these features, we can determine the variation range of the membership function parameters for each rule. Figure 19 presents the flowchart of the implementation of the PSO algorithm to specify the parameters of the membership functions used to identify each disturbance.

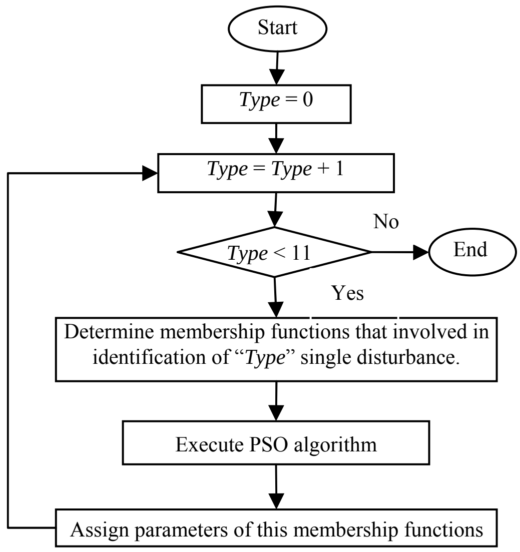


Figure 19. The flowchart of the PSO algorithm to determine the membership function parameters

As shown, the PSO algorithm varies the membership function parameters until the mistake identification rate is minimized for a known collection of waveforms of each single disturbance type (DC offset, noise, spike, interruption, swell, sag, notch, transient, harmonic or flicker).

## V. SIMULATION RESULTS

For this purpose, a 25kV and 100MVA generator is selected to supply a linear load through a 21km feeder and a 25kV/600V transformer. For generating voltage sag, different cases of load to network or short circuit connections are simulated. Swell disturbance is generated by disconnecting different values of loads from the network. Voltage flicker occurred by a variable load instead of linear load of the system. This variable load can produce voltage flicker using a load that absorbs continuously changing currents; like an arc furnace. By changing characteristics of the variable load, different types of flicker signal can be generated. Transient signal is generated by capacitor switching in the beginning of the feeder. By changing the value of the capacitor bank, frequency of the transient disturbance can be varied. Voltage harmonic is generated by a six pulse controlled rectifier as a nonlinear load. Figure 20 shows the simulation diagram of considered test system in Matlab (Simulink) which is used for generating some of test signals in testing stages. Results of performing the proposed method for disturbance signal Classification is shown in Tables 3 and 4 for single and combined disturbances, respectively.

Table 3. Classification results for the single PQ disturbances

| PQ Disturbances | 40dB Noise | 30dB Noise | 20dB Noise |
|---|---|---|---|
| Harmonic | 100% | 98% | 97% |
| Sag | 98% | 95% | 93% |
| Swell | 99% | 98% | 95% |
| Interrupt | 100% | 96% | 93% |
| Transient | 99% | 97% | 95% |
| Spike | 100% | 99% | 94% |
| Notch | 100% | 95% | 91% |
| Flicker | 90% | 88% | 85% |
| Noise | 94% | 90% | 88% |
| DC | 100% | 99% | 96% |
| Ave | 98% | 95.50% | 92.70% |

Table 4. Classification results for the combined PQ disturbances

| PQ Disturbances | 40dB Noise | 30dB Noise | 20dB Noise |
|---|---|---|---|
| Harmonic + Sag | 92% | 91% | 88% |
| Harmonic + Sag + Transient | 91% | 90% | 88% |
| Harmonic + Swell + Transient | 97% | 95% | 90% |
| Sag + Transient | 93% | 90% | 85% |
| Swell + Transient | 95% | 94% | 92% |
| Harmonic + Transient | 100% | 98% | 96% |
| Average | 94.67% | 93.17% | 89.83% |

It can be easily understood from Tables 3 and 4 that the suggested method is a precise and accurate one which can classify almost all single and combined disturbance signals correctly. However, even high levels of noise don't noticeably affect the accuracy of the suggested method. So this can guarantee the usage of this method in all real applications.

## VI. CONCLUSIONS

This paper brings forward a simple and new method for classification of ten typical kinds of single and six combined power-quality disturbances. The generalized S-transform with a variable window as a function of PQ signal frequency is used to produce contours and feature vectors for pattern classifications. A fuzzy system is used in this method to classify the disturbances. Not only can the proposed method classify almost all possible power quality disturbances, but also it has a very precise classification process. Besides, the accuracy of suggested method in noisy environment proves the robustness of the method.

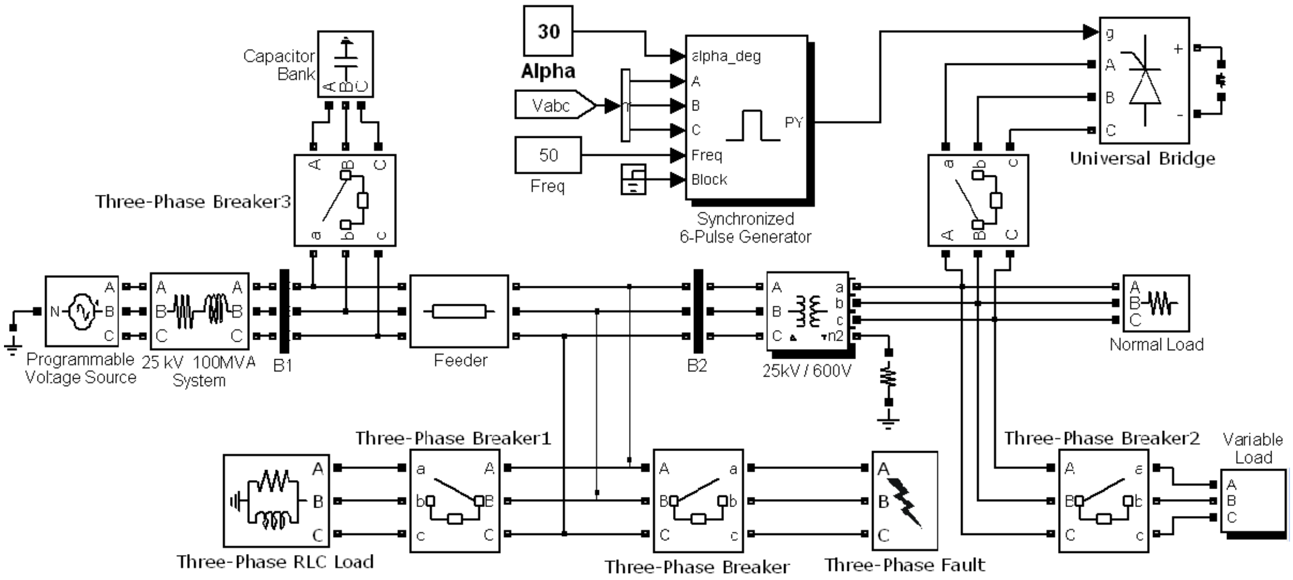


Figure 20. Simulated network to produce disturbance signals

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