Characterization of power system disturbances using hybrid technique of fuzzy expert system and particle swarm optimization

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ABSTRACT

Recognition and categorization of voltage and current distortions in an electrical network is a critical assignment in power systems control and security. This present work introduces a novel hybrid technique for electrical network distortions recognition and categorization using least mean square filter and fuzzy expert system with particle swarm optimization trainer. The idea of least mean square filter collectively with discrete wavelet transform is utilized to estimate important features such as magnitude and slope from the measured voltage or current signals. The discrete wavelet transform is utilized to enable least mean square filter to afford a decent execution; the measured voltage or current signal is sent to the discrete wavelet transform to find the noise present in it and its variance. The noise and its variance are then passed collectively with the measured signal to the least mean square filter. These two features are treated as the fuzzy inputs to the expert system that employs a few standards on the fuzzy inputs to distinguish the category in which the measured signal has a place. In this study, a novel fuzzy expert system based on particle swarm optimization algorithm is presented. To demonstrate the capacity of the presented hybrid method for categorizing the power quality distortions, a point by point computerized simulation and its outcomes including different sorts of power quality occasions are exhibited. The simulation outcomes delineate that the presented hybrid method has the capacity to precisely recognize and categorizing the power quality distortions.

Keywords: discrete wavelet transform, fuzzy expert system, least mean square filter, particle swarm optimization algorithm, power quality, power system disturbances.

INTRODUCTION

A power quality issue is characterized as any distortions in voltage, current or frequency that can prompt an electrical machine damage or breakdown [1]. The across the board utilization of power electronic converters (for example customizable speed control drivers), energy saving lamps and computer hardware (for example data transfer devices & programmable microcontrollers) have prompted a variation in the property of electrical load. The power load is all the while the real reasons and the significant casualties for the power quality issues. Some hypothetical establishments of voltage and current distortions are portrayed in [2,3]. Over the previous years, lots of researches in light of various strategies for examination and classification of power quality distortions have been analysed. Due to their non linear nature, every one of these loads can cause distortions in the voltage or current signals [4]. A vital advance in comprehension and consequently enhancing the quality of electric power is to extricate adequate data about the occasions that reason the power quality problems. The capacity to perform automated power quality information examination and classification is the basic part of power quality investigations.

Short time fourier transform (STFT) is regularly utilized to recognize and describe the power quality distortions in the time frequency space [5]. For dynamic voltage waveforms, STFT does not distinguish the signal flow attribute because of the constraint of constant window step. In any case, STFT is appropriate only for static waveforms where the frequency of the voltage signal does not change with respect to time. Nevertheless, both time and frequency data of the distortion signal can be estimated by utilizing wavelet transform (WT). As a renowned technique for time frequency space representation, the WT is substantially more prominent endorse for investigation of signals with limited transient parts emerging in the signal examination [6,7]. WT also shows a few weaknesses for example, its complex calculation, affectability to noise level, and the reliance of its exactness on the selected parent wavelets [8–12]. In [13–15], S-transform (ST) was presented as a recent successful system for power quality distortions signal handling. The frequency dependant determination of the ST bolster the recognition of high-frequency blasts and shows great frequency determination on the long period signal. ST is an enhanced thought of WT or STFT with the qualities better than WT and STFT. ST has been employed in investigating and identifying some power quality issues.

Utilizing the change in amplitude of the essential segment of supply voltage, Least Mean Square (LMS) filter can be utilized to identify and to investigate voltage occasion [16]. The LMS method is initially presentation by Widrow and Hoff, and it has been broadly utilized as a part of signal processing technology as an adaptive filtering method [17]. The LMS strategy has the advent of straight forwardness in its fundamental structure, computational effectiveness, and lustiness. By method for the power quality analysis, LMS is viewed as reasonable for examining signals with confined driving impulses and oscillations especially for those regularly present in fundamental and low order harmonics. The consequences of LMS rely upon the model of the framework utilized and the appropriate choice of the LMS filter parameters. When the choices of the LMS filter parameters are not appropriate, the rate of convergence of the outcomes will be moderate or the outcomes will vary.

Expert systems have been presented to distinguish, group and analyze power system occasions effectively for a set number of occasions [18–21]. Rules based expert frameworks are profoundly subject to if-then statements. Another disadvantage is that these frameworks are not generally convenient because of the settings that depend for the most part on the designer or administrator of the frameworks for a specific arrangement of occasions. If numerous occasion types or features are examined, the expert framework would turn out to be more confused and dangers of losing selectivity would increment.

In this paper, a novel fuzzy expert system based on the standard particle swarm optimization algorithm (PSO) is proposed for optimizing the membership functions. The PSO has attracted many researchers' sights due to its simplicity and effectiveness. PSO, inspired from bird flocking and fish schooling, is a flexible, robust, population based algorithm [12] that are adopted by many people for various power system problems [13, 14].

Two phases system for distinguishing the power system distortions is proposed. In the principal phase, the measured voltage waveform is gone through discrete wavelet change (DWT) to distinguish its noise [22]. The variance of this noise together with the measured voltage waveform is sent to the LMS filter to improve and accelerate its rate of convergence. In the next phase, the outputs of the LMS filter; the magnitude of the measured voltage waveform and its rate of progress with time (slope), are gone through a PSO based fuzzy expert framework that uses a few standards on them to recognize and order the power quality occasions in the measured waveform. A few computerized simulation outcomes utilizing MATLAB and practical information outcomes are displayed to fulfil and guarantee the capacity of the presented method for characterizing the distortions effectively.

PRESENTED METHODOLOGY

The presented approach is depicted in Fig. 1. The two phases are executed with every voltage signals, (i) calculating an updated esteem of features (magnitude and slope) using LMS filter with the use of DWT, (ii) categorizing the distortions using PSO based fuzzy expert system with the aid of estimated features.

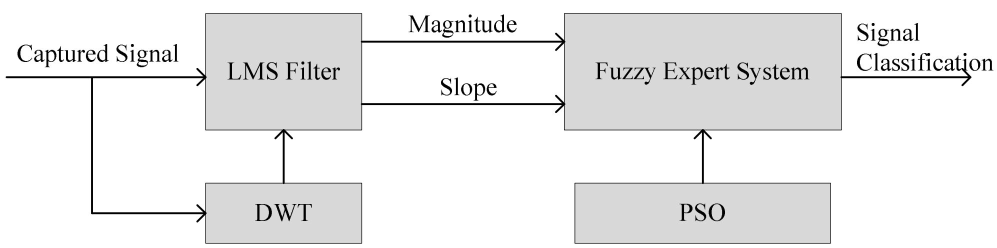

Fig. 1. Structure of the presented method.

Wavelet Transform (WT)

The continuous WT of a signal y(t) is described as [23]:

$$Y_{a,b} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} y(t)\, \psi(\frac{t-b}{a}) dt \quad (1)$$

$$\psi_{a,b} = \frac{1}{\sqrt{|a|}} \psi(\frac{t-b}{a}) \quad (2)$$

where a and b are the time shift and scale respectively, $\psi(t)$ is the mother wavelet and other wavelets are its shifted time and scaled version.

The DWT computations are made for a selected subset of scales and time shift. This strategy is carried by utilizing filters and calculating the details and approximations components. The details (D) are the low scale, high frequency components of the signal. The approximations (A) are the high scale, low frequency components of the signal. The DWT coefficients are calculated as follows,

$$Y_{a,b} = Y_{j,k} \sum_{n \in Z} x[n] g_{j,k}[n] \quad (3)$$

where a = 2j, b = k2j, j ∈ N, k ∈ N. The wavelet filter g plays the role of ψ.

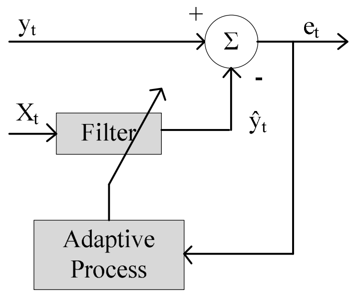

Fig. 2. Least Mean Square Filter.

Least Mean Square Filter (LMS filter)

The LMS method of signal feature extraction is depicted in Fig. 2, where y_t denotes the actual signal, $\hat{y}_t$ denotes the signal estimate and $X_t = [x_{0t}, x_{1t}, \ldots, x_{N-1t}]^T$ is the input vector at the t^{th} instant. The signal can be assessed accurately by the filter with an appropriate esteem of its coefficient W_t, which is computed by reducing the squared of the signal error e_t [24]. Thus the framework gains knowledge from its condition; this is represented as a tuned filter where the filter coefficients are adapted in a recursion manner towards their optimal esteems. At every iteration, the weight vector W_t is calculated as,

$$W_{t+1} = W_t + \mu(-\nabla_t) \tag{4}$$

Where μ is the adaptation parameter, $W_t = [w_{0t}, w_{1t}, \ldots, w_{N-1t}]^T$ is the filter coefficient and ∇_t is the gradient of the error performance surface with respect to filter coefficient, this can be calculated as,

$$\hat{\nabla}_t = -2e_i X_t \tag{5}$$

The recursion (4) is known as the LMS technique and it is initialized by assuming all filter coefficients as zero. First the technique continues by calculating the error signal e_t, then it is employed to calculate the adapted coefficients. This process is executed till the stable conditions are achieved. The stableness of the closed loop network is administered by the parameter μ and it ought to fulfil the following criteria,

$$0 < \mu < \frac{2}{Total\ input\ power} \tag{6}$$

where the total input power pertains to the sum of the mean squared value of the input data. When the adaptation parameter μ is little, the LMS technique consumes huge time to gain knowledge about its input with least mean square error and vice versa. Accordingly, a time changing step sized ordering of μ is desirable for optimal convergence [25].

LMS BASED FEATURE EXTRACTION

The voltage signal of a three phase electrical network can be presented in discrete mode as,

$$\mathrm{V_{a_t}} = \mathrm{V_m}\cos(\omega t\Delta T + \varphi) + \epsilon_{a_t}$$
$$\mathrm{V_{b_t}} = \mathrm{V_m}\cos\left(\omega t\Delta T + \varphi - \frac{2\pi}{3}\right) + \epsilon_{b_t}$$
$$\mathrm{V_{c_t}} = \mathrm{V_m}\cos\left(\omega t\Delta T + \varphi + \frac{2\pi}{3}\right) + \epsilon_{c_t} \tag{7}$$

where V_m is the maximum magnitude of the fundamental component, ϵ_t is the noise present in the voltage signal, t is the sampling time, φ is the phase of fundamental component, and ω is the angular frequency of the voltage signal ($\omega = 2\pi f$, with f being the system frequency). The complex form of signal derived from the three phase voltages is obtained by αβ transform [7] as mentioned as follows,

$$\begin{bmatrix} V_{\alpha_t} \\ V_{\beta_t} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} [V_{a_t} \quad V_{b_t} \quad V_{c_t}]^T \tag{8}$$

A complex voltage V_t can be estimated from (8) as,

$$V_t = V_{\alpha_t} + jV_{\beta_t} \tag{9}$$

The voltage V_t can be formulated as,

$$V_t = Ae^{j(\omega t\Delta T + \varphi)} + \xi_t$$
$$V_t = \hat{V}_t + \xi_t \tag{10}$$

Where A is the magnitude of the complex signal V_t, and ξ_t is its noise component and $\hat{V}_t = Ae^{j(\omega t\Delta T + \varphi)}$.

The voltage can be formulated as,

$$\hat{V}_t = \hat{V}_{t-1}e^{j\omega\Delta T} \tag{11}$$

This formula is used in the proposed feature extraction method and the strategy that explains the extraction procedure is depicted in Fig. 3. The error signal e_t for this situation is calculated as,

$$e_t = V_t - \hat{V}_t \tag{12}$$

where $\hat{V}_t$ is the evaluated esteem of voltage at the t^{th} time. Then

$$\hat{V}_t = W_{t-1}\hat{V}_{t-1} \quad (13)$$

where the weight $W_t = e^{j\hat{\omega}_{t-1}\Delta T}$, $\hat{\omega}$ is the calculated angular frequency. The essentialness of the model is that the input data consists of only one component and the weight vector. The complex LMS method as introduced in [11] is utilised to calculate the state. The method reduces the square of the signal error by recursively changing the complex weight vector W_t at every sampling time as,

$$W_t = W_{t-1} + \mu_t e_t \hat{V}_t^* \quad (14)$$

where * denotes the complex conjugate of the value and μ is the convergence parameter ensuring the stability and convergence rate of the technique.

The step size μ_t is changed as in [24] for good convergence of the LMS technique in the presence of noise. For complex states, the equations can be updated as,

$$\mu_{t+1} = \lambda\mu_t + \gamma p_t p_t^* \quad (15)$$

where p_t denotes the autocorrelation of e_t and e_{t-1} is calculated as

$$P_t = \rho p_{t-1} + (1-\rho)e_t e_{t-1} \quad (16)$$

where ρ is an exponential weighting factor and $0 < \rho < 1$, $0 < \lambda < 1$ and $\gamma > 0$ controlling the speed of convergence. μ_{t+1} is set to μ_{max} or μ_{min} when it goes above or below the upper and lower limits correspondingly. These esteems are selected based on signal statistics described in [13].

The voltage magnitude A_t is instantly calculated at any time sample t from the evaluated esteem of voltage $\hat{V}_t$ as,

$$A_t = |\hat{V}_t|$$

(17)

The slope S_t is calculated as follows,

$$S_t = \frac{(A_t - A_{t-1})}{\nabla T} \quad (18)$$

where A_t and A_{t-1} are the voltage magnitudes at the time interval t and t+1 respectively.

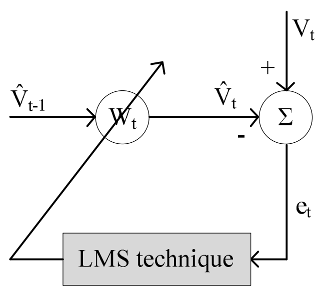

Fig. 3. LMS based feature extraction.

PARTICLE SWARM OPTIMIZATION TRAINER

The particle swarm optimization algorithm, first developed by Kennedy and Eberhart [12], is motivated from the simulation of the behavior of social system. PSO searches for optimal solution in the problem domain via collaborating with individuals within a swarm. Each individual is called particle, which is made of two parts, the position and velocity, and follow two major operations, velocity and position updating rules. Position and velocity represent the candidate solution and step size a particle will advance in next iteration, respectively. For a *n*-dimensional problem and a swarm of *m* particles, the i^{th} particle's position and velocity, is denoted as $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T$ and $v_i = [v_{i1}, v_{i2}, \ldots, v_{in}]^T$, for $i = 1, 2, \ldots, m$, respectively. PSO stores the best position $p_i = [p_{i1}, p_{i2}, \ldots, p_{in}]^T$ it has ever visited in the search space. Also, each particle is considered to have a neighborhood that consists of a number of other particles and its movement is influenced by their best experience, i.e., best positions $p_g = [p_{g1}, p_{g2}, \ldots, p_{gn}]^T$. Here, superscript *T* denotes transpose of matrix/vector. For the inertia type PSO, the operation on position and velocity are expressed as follow,

$$v_{id}^{t+1} = \omega . v_{id}^t + \varphi_1(p_{gd} - x_{id}^t) + \varphi_2(p_{id} - x_{id}^t) \quad (19)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (20)$$

where *t* is the iteration count, ω is the inertia weight, $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$, where c_1 and c_2 are two positive acceleration parameters, called social and cognitive parameter, respectively; r_1 and r_2 both are random numbers uniformly distributed in *(0,1)*, *d* is the index of dimension. According to the definition of neighborhoods, there are two variants of PSO with respect to the number of particles that comprise the neighborhood of a particle. If the whole swarm is considered as the neighborhood of each particle, it is called global variant while in local variant, a smaller neighborhood is used. To distinguish the difference between these two variants, p_g is reserved for global variant while in local variant, p_h is used to replace pg for clarify in this paper.

PSO BASED FUZZY EXPERT SYSTEMS

Fuzzy logic alludes to a logic framework which symbolizes the learning and reasoning in a loose or fuzzy way to reason under uncertain conditions [26]. It is typically fitting to utilize fuzzy logic when a scientific design of a procedure does not exist or exists but rather is excessively troublesome, making it impossible to encode and excessively complex, making it impossible to be assessed sufficiently quickly for continuous operation. Not alike the conventional logic frameworks, it directs at designing the inaccurate methods of logical thinking that acts a basic part in the human capacity to surmise an estimated solution to an inquiry in view of a learning that is inaccurate, inadequate, or not absolutely solid. The exactness of the fuzzy logic control is depends on the learning of human specialists. Consequently, it is just as best as the quality of the rules.

In this work, the fuzzy framework modelled and carried out to execute the classification or categorization operation is a mamdani type fuzzy inference system (FIS) with two input sources (magnitude and slope), ten fuzzy rules and one output. The proposed fuzzy expert system utilizes max-min arrangement, and the centroid of area strategy for defuzzification. To categorize the different voltage distortions, two fuzzy inputs are utilized in the work for fuzzification. The first fuzzy input is voltage magnitude (A) which has five membership functions and is projected as very small magnitude (VSM), small magnitude (SM), normal magnitude (NM), large magnitude (LM), and very large magnitude (VLM). The membership function plot of the fuzzy input magnitude is shown in Fig. 4. The second fuzzy input is slope (A) which has three membership functions and is projected as positive slope (PS), negative slope (NS) and zero slope (ZS). The membership function plot of the fuzzy input slope is shown in Fig. 5.

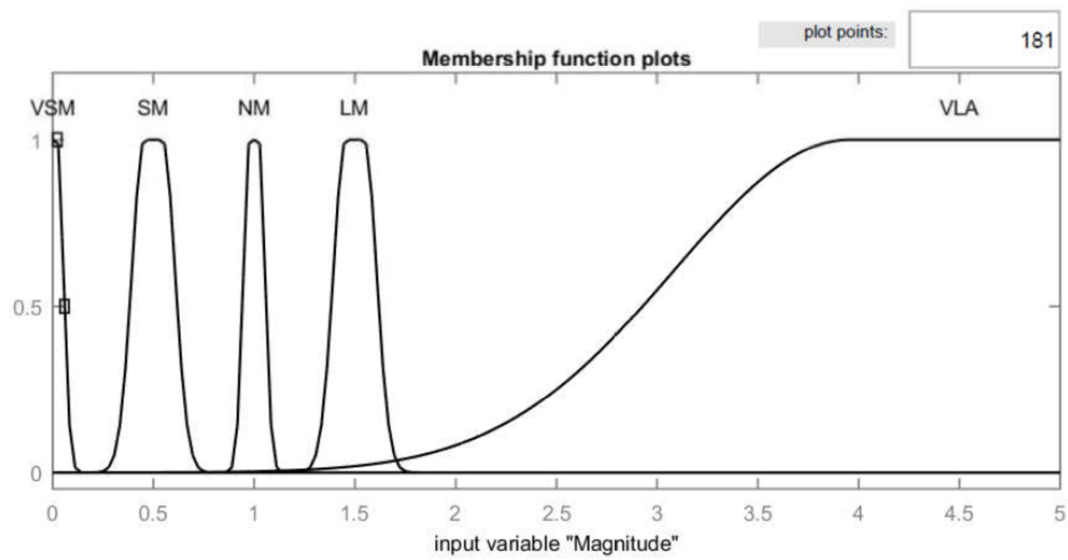

Fig. 4. Magnitude membership functions.

The fuzzy output of the proposed FIS is power quality of the voltage signal which has five membership functions and is projected as normal, sag, swell, outage and surge. In this work, a number between 0 and 3 is assigned for the crisp output of the mamdani type FIS, where Outage = 0, Sag = 0.5, Normal = 1, Swell = 1.5 and Surge = 2. The membership function plot of the fuzzy output is shown in Fig. 6. The ranges of magnitude membership function are estimated based on the definition of each power quality occasion as described in the following section. The slope and fuzzy output membership functions are estimated by training approach.

The set of fuzzy rule are given as follows,

- *If (the magnitude is SM) and (the slope is PS) then (the output is Sag).*
- *If (the magnitude is VSM) and (the slope is PS) then (the output is Outage).*
- *If (the magnitude is LM) and (the slope is PS) then (the output is Swell).*
- *If (the magnitude is VLM) and (the slope is PS) then (the output is Surge).*
- *If (the magnitude is NM) and (the slope is ZS) then (the output is Normal).*
- *If (the magnitude is VSM) and (the slope is ZS) then (the output is Outage).*
- *If (the magnitude is SM) and (the slope is NS) then (the output is Sag).*
- *If (the magnitude is VLM) and (the slope is ZS) then (the output is Surge).*
- *If (the magnitude is LM) and (the slope is NS) then (the output is Swell).*
- *If (the magnitude is VLM) and (the slope is NS) then (the output is Surge).*

In the past rules, the categorization of few power quality occasions such as a voltage sag and swell can be just in view of the magnitude input, but the second input slope in the rules 1 and 7 for a voltage sag; and in the rules 3 and 9 for a voltage swell is utilized to recognize the starting and the end of these occasions, thus these rules are more valuable for both classifying and distinguishing the power quality distortions.

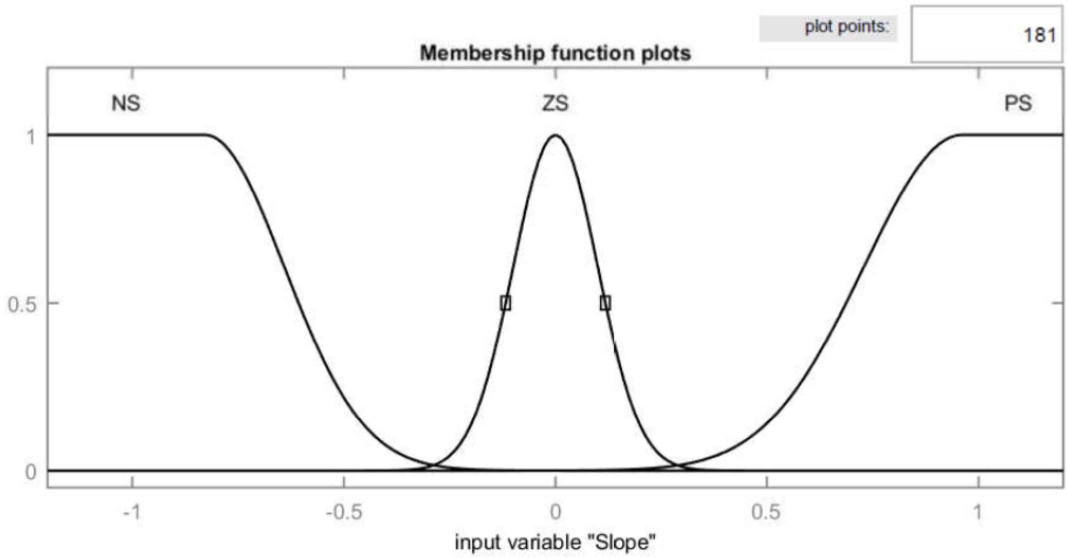

Fig. 5. Slope membership functions

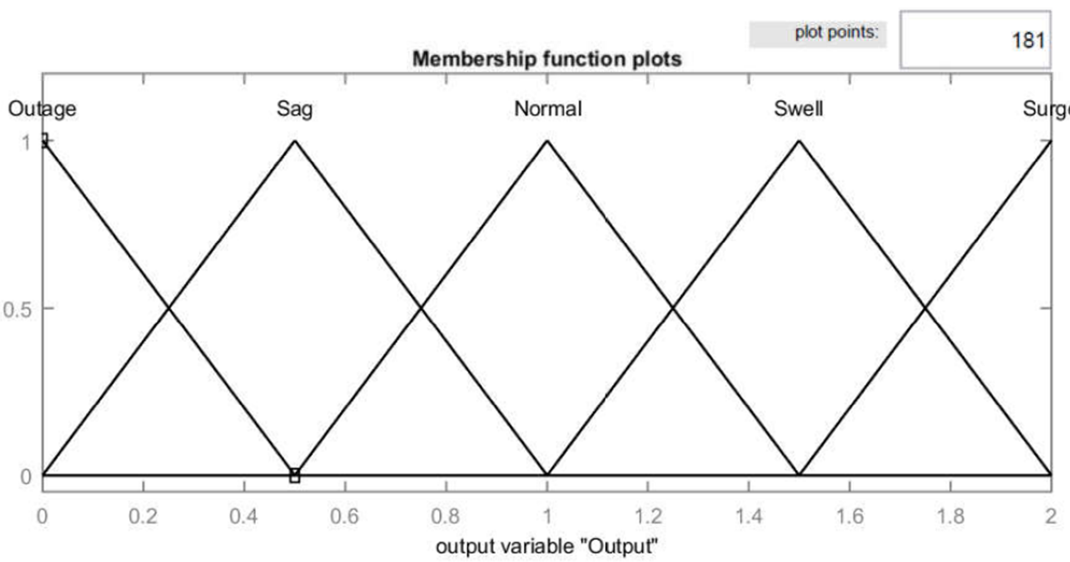

Fig. 6. Output membership functions

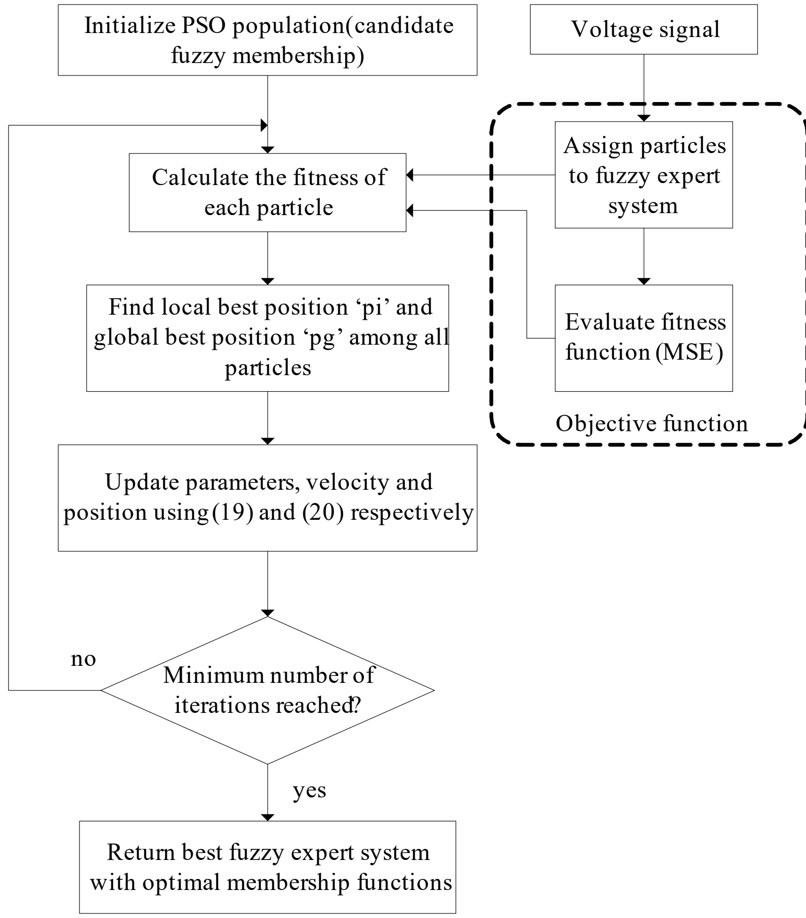

Fig. 6. General steps in training the membership function of Fuzzy expert systems using PSO

SIMULATION RESULTS

In this work, power quality distortions signals are five voltage signal distortions admitting sag, swell, outage, surge and harmonic distortions [27]. These voltage distortions are produced by using MATLAB software as per the simulation test network shown in Fig. 7. The simulation test network comprises of a generator providing the power to the distribution system that contains a short transmission line section and three loads such as normal, heavy, and nonlinear loads at the point of common coupling (PCC). Each generated signal comprises of 25 cycles of a voltage waveform sampled at a rate of 6.4 kHz, which is equal to 128 samples per cycle. The following simulation analyses are proposed to outline the performance and efficiency of the presented method. The heavy and nonlinear loads are interconnected to the network through a circuit.

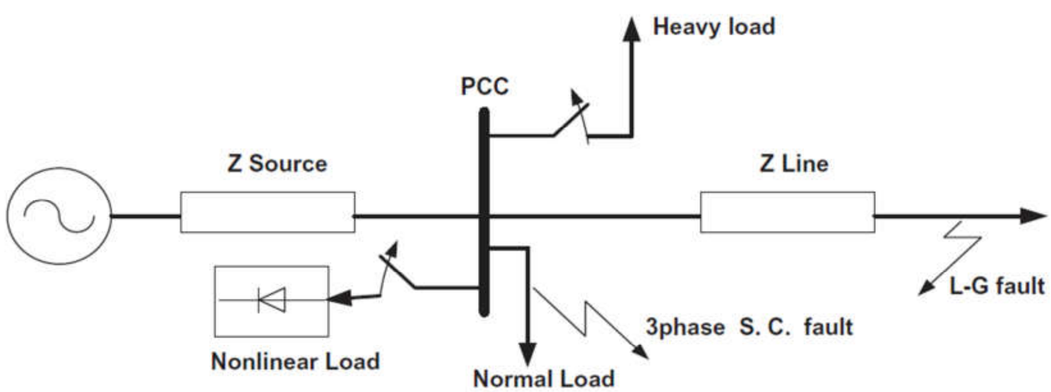

Fig. 7. The system configuration of the model utilized for testing.

Table 1. The classification results of disturbances.

Disturbance Type	SNR 20 db		SNR 30 db		SNR 40 db	
	Method [28]	Proposed Method	Method [28]	Proposed Method	Method [28]	Proposed Method
Outage	92	97	98	100	100	100
Sag	93	98	99	100	100	100
Swell	94	97	99	100	100	100
Surge	92	97	96	98	98	100
Harmonic	90	95	94	99	97	99
Sag with harmonic	93	97	97	98	98	100
Swell with harmonic	92	97	96	98	98	99
Mean accuracy (%)	92.28571429	96.85714286	97	99	98.71428571	99.714286

The tracking error of LMS filter is observed to be under 0.5%. The tracking error depicts the measured voltage magnitude using LMS filter. If the magnitude is assessed with high precision and minimum tracking error, the slope is precisely assessed. Subsequently, the fuzzy inputs (magnitude and slope) are exact. This implies that the fuzzy classifier will give accurate outcomes. For every sort of power system distortions, another 100 case studies were set up by altering the values of all loads (normal, heavy, nonlinear) and altering the starting and the end time instant of every disturbance. The generated signals are mixed with random white noise of zero mean and distinctive ranges of the signal to noise ratio (SNR) (20 db, 30 db and 40 db). In [28], a hybrid strategy utilizing a DWT, kalman filter and fuzzy expert system for the categorization of power quality disturbance was proposed. The simulation outcomes demonstrate that the normal classification accuracies of the proposed PSO based fuzzy expert systems are 96.86%, 99% and 99.71% with SNR 20 dB, 30 dB and 40 dB correspondingly, whereas classification accuracies of the existing strategy [28] are 92.3%, 97% and 98.71% with SNR 20 dB, 30 dB and 40 dB respectively. These analyses show that the presented technique for feature extraction and decision making are effective for the classification. Moreover, the LMS method in the presented classifier gives more precise outcomes than the existing method.

CONCLUSIONS

A novel hybrid classification technique using DWT, LMS filter and PSO based fuzzy expert system is presented in this work for recognizing and classifying the power system distortions. A novel fuzzy expert system based on PSO is proposed to optimize the membership functions. The DWT is utilized to separate the noise of the measured voltage signal. The variance of the noise is given along with the measured voltage signal to the LMS filter to enhance its efficiency and performance. LMS filter is then employed to calculate the magnitude and the slope of the voltage signal that turn into the inputs to the fuzzy logic for categorization of the different voltage distortions. A few case studies have been carried out to evaluate the efficiency and performance of the presented method. The simulation outcomes demonstrate that the presented method has the capability to discover and categorize the power system distortions with good exactness, precise and very less computational time when compared with other existing strategies.

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