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Discrimination of Power Quality Distorted Signals Based on Time-frequency Analysis and Probabilistic Neural Network

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Due to extensive utilization of sensitive devices, power quality issue has become more important than before. So, accurate recognition and classification of Power Quality Distorted Signals (PQDSs) is an essential task in the power systems. In this paper two well-known time-frequency analyzers i.e. Multi Resolution Analysis (MRA) and Generalized S-Transfrm (GST) are applied simultaneously for extracting of some potential features. In order to choose the best subset features, Orthogonal Forward Selection (OFS) is used. OFS can rank features based on their severability. Probabilistic Neural Network (PNN) is considered as a powerful classifier core for discrimination of dominant selected features. Extensive samples of PQDSs are simulated to evaluate the performance of the suggested detection scheme. Also, sensitivity of the proposed method has been investigated under different noisy conditions. At last the obtained results are compared with the accuracies of some reported methods of previous researches.

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1. INTRODUCTION

The PQ problem can be interpreted as voltage quality. Consumers expect to be supplied with pure signals. Any deformation from pure sinusoidal wave shape can be considered as a disturbance. These distorted signals can affect the proper operation of sensitive electronic devices. So monitoring of PQ is an essential task to evaluate the performance of power systems. Before any corrective solution, the type of PQD should be specified by a robust detection scheme. Despite of many detection studies in the field of PQD, new methods are required for enhancement of accuracy of detection schemes. There are many types of PQD such as: sag, swell, interruption, harmonics and flicker. Each type of PQD has different wave shapes and some of them may happen simultaneously like swell with harmonics. Thus accurate detection of PQDS has become complicated somewhat [1-3].

Many detection schemes have been proposed based on signal processing of PQD. Fast Fourier Transform (FFT) can analyze signals in frequency domain. It yields both magnitude and phase of each component of signal [2]. Since PQDS are non-stationary, FFT can not be very effective as time-frequency analyzer tools can. Wavelet Transform (WT) is a popular signal analyzer which can decompose signal into approximation and details levels. This transform uses different filters namely wavelet function in order to separate low frequency components (approximation level) from high frequency ones (details levels) [4-6].

S-transform (ST) is a powerful signal analyzer that contains both characteristics of WT and Short Term Fourier Transform (STFT), simultaneously. It calculates the magnitude and phase of each component for specified instance. So, complete visualization of the signal is obtained [7-13].

In order to distinguish extracted features, some classifiers have been applied such as: Artificial Neural Network (ANN) [9], Probabilistic Neural Networks (PNN) [13], decision tree [12] and fuzzy systems [11 , 14, 15].

In spite of many published papers in the field of detection of PQD, few of them have used feature selection methods for reduction of training feature

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vectors. By elimination of redundant data, the computational burden decreases and generalization capability of classifier core increases, noticeably [16, 17].

In this paper, a new scheme is presented for detection of PQD based on pattern recognition. The proposed scheme is realized from three main steps: feature extraction, feature selection and classification of selected features. Two powerful signal analyzers i.e. WT and GST process disturbed signals in both time and frequency domains. Some potential features are extracted in this step. In the second step dominant features are selected. So the dimension of input matrix is reduced and learning capability of classifier is increased. In the third step, dominant selected features are classified by PNN. The PNN has more simple structure as compared to ANN. Only one parameter i.e. smoothing factor should be determined in PNN while ANN with complex structure has many different parameters that should be determined by trial and error.

The most important novelties of proposed method are as follows:

1. Using two powerful signal analyzer tools i.e. GST and WT for extraction of potential features.
2. Applying OFS method for ranking of extracted features in order to eliminate redundant features.
3. Choosing of PNN as classifier core with simple structure without any computational burden for training process.
4. Simultaneous events such as sag with harmonics and swell with harmonics have been considered.
5. Sensitivity of the proposed method is evaluated in the noisy conditions.

The rest of the paper is divided into sections as follows: in section 2, some preliminary definitions, including descriptions and ideas of the GST, MRA and OFS are introduced. Then, concepts of PNN is employed in this paper, are given. In section 3, feature extraction, selection and classification methods used in this study are presented. In section 4, simulation and analysis studies are presented and the classification results and performance comparison of proposed scheme are shown. Finally, conclusions are given in section 5.

2. PRELIMINARIES

2. 1. Feature Extraction Methods

2. 1. 1. Generalized S Transform (GST) The standard S Transform (ST) was firstly suggested by R. G. Stockwellin 1996[18] based on the combination of Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) [11, 18]. In GST, a hyperbolic window is replaced by Gaussian window of standard ST for improvement of time-frequency resolution [18]. Gaussian hyperbolic window is used to provide better time and frequency resolutions at low and high frequencies unlike the standard ST which uses the Gaussian window. So, GST as compared to standard ST has higher computational accuracy. In applications which require simultaneous identification time-frequency signatures of different distorted voltages, it may be beneficial to use a window having frequency dependent asymmetry. The shape of hyperbolic window changes from an asymmetric to the symmetric one, when frequency increases. Thus, at low frequency, time resolution is improved and for high frequency a symmetric window yields better frequency resolution.
The discrete version of the GST of the signal samples *h(t)* is calculated as:

$$S(n,j)=\sum_{m=0}^{N-1} H(m+n).W(m,n)exp\left(i2\pi mj\right) \tag{1}$$

where N is the total number of samples and the indices n, m, j are n=0,1,…,N-1, m=0,1,…,N-1, and j=0,1,…,N-1.
Small modification of the Gaussian window has been suggested for better performance [18]. That $W(m,n)$ denotes the Fourier transform of the hyperbolic window given below is used.

$$W(m,n)=\frac{2|f|}{\sqrt{2\pi\left(\gamma_{hy}+\mu_{hy}\right)}}.\exp\left(\frac{-f^2Z^2}{2n^2}\right) \tag{2}$$

Frequency, forward taper parameter and backward taper parameter, are symbolized by f, γ_{hy}, μ_{hy}, respectively. At $f=0$, Gaussian window is very asymmetrical, but when f increases, the shape of it converges towards that symmetrical Gaussian window given in Equation (2) for different values of γ_{hy} and μ_{hy} and with $\varphi_{hy}^2=1$.

$$Z=\frac{\gamma_{hy}+\mu_{hy}}{2\gamma_{hy}\mu_{hy}}t+\frac{\gamma_{hy}-\mu_{hy}}{2\gamma_{hy}\mu_{hy}}(\sqrt{t^2+\varphi_{hy}}) \tag{3}$$

In the above expression $0\le\gamma_{hy}\le\mu_{hy}$ and $H(m+n)$ is the frequency shifted discrete Fourier transform H(m), where

$$H(m)=\frac{1}{N}\sum_{m=0}^{N-1} h(k)\exp(-i2\pi nk) \tag{4}$$

The output of GST is an N×Mmatrix called S-matrix whose rows pertain to frequency and columns pertain to time. From the GST matrix, Time Frequency (TF-contour), Time Maximum Amplitude (TmA) and Frequency Maximum Amplitude (FmA) plots, can be obtained which obviously show the disturbance model for visual inspection. TF-contour is a complete visualization of S-matrix. This is frequency versus time of S-matrix. TmA is maximum amplitude versus time by searching columns of S-matrix at every frequency, and FmA, which is maximum amplitude versus frequency by searching rows of S-matrix at every time [18]. Figure 1 illustrates a complex type of PQDSs i.e. sag with harmonic as well as above mentioned extracted plot i.e. TF, TmA and FmA contours.

2. 1. 2. Multi Resolution Analysis (MRA) Discrete Wavelet Transform (DWT) is calculated separately for different segments of the time-domain signal at different frequenciesresulting in Multi Resolution Analysis (MRA).MRA and Quadrature Mirror Filters (QMF) are alsoimportant for evaluating the wavelet decomposition. In multi resolution formulation, asingle event is decomposed into several signals which have specified harmonic components. A QMF consists of twofilters. One gives the approximation (low pass filter), while the other gives details (high -passfilter). These filters are related to each other in such a way as to be able to perfectlyreconstruct a signal from the decomposed components [6]. In this strategy, the approximation sub-signal $s_j(t)$ and the detail sub-signal $D_j(t)$, which correspond to the components of signal $x(t)$ at different scales, areformulated as follows [6]:

$$S_J(t) = \sum_k s_{J,K}\phi_{J,K}(t) J, K \in I \tag{5}$$

$$D_J(t) = \sum_k d_{j,K}\Psi_{j,K}(t) j, K \in I \tag{6}$$

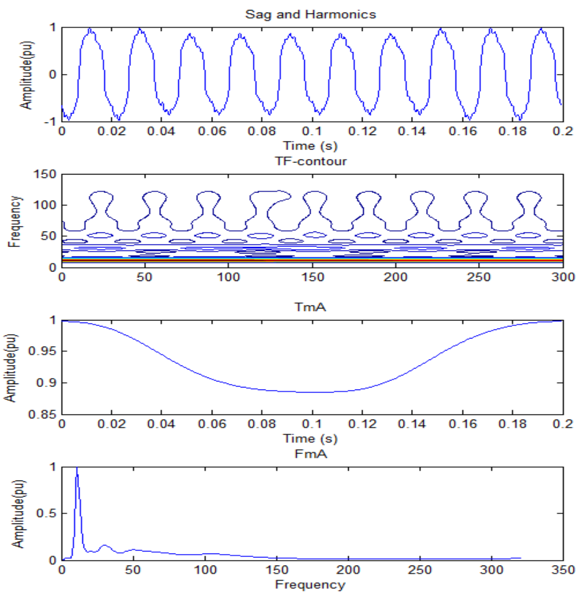

Figure 1. Voltage sag & harmonics

The $D_j(t)$ contents approximate frequency bound of $[f_s/2^{j+1} - f_s/2^j]$ Hz and the $S_J(t)$ contents approximate frequency bound of $[0 - f_s/2^{J+1}]$ Hz, f_s is the sampling frequency. Therefore, the better scales of $D_j(t)$ mainly capture the detail (high-frequency) feature of $x(t)$, while the larger scales of $D_j(t)$ and $S_j(t)$ mainly reveal the whole-view (low-frequency) feature of $x(t)$. After that, the original signal $x(t)$ can be recovered in terms of these sub-signals with diverse resolutions as follow:

$$x(t) \approx S_J(t) + D_J(t) + D_{J-1}(t) + \dots + D_1(t) \tag{7}$$

2. 2. Feature Ranking Method

2. 2. 1. Orthogonal Forward Selection (OFS) One of the fundamental procedures in the linear algebra is Gram–Schmidt (GS) orthogonalization [19] that applies the QR decomposition of a matrix into two factorization $X = QR$. The overview can state that orthogonal basis presents optimal option to perform calculations of the twist vector spaces (finite and infinite dimensional spaces). So, willingness and efforts has always been in this regard that basis set by different methods, such as the GS lead them to orthogonal basis. To achieve an orthonormal basis for an inner product space (or pre-Hilbert space), the GS algorithm is applied to build an orthogonal basis. GS method is a formulation for the orthonormalization of a linearly independent set. Suppose N samples $x(1)$, $x(2)$, …, $x(N)$ are available, and each sample is represented by an n-dimensional vector $x(k) = [x_1(k), x_2(k), \dots, x_n(k)]^T$. Feature vector x_i and feature matrix X are defined as $x_i = [x_i(1), x_i(2), \dots, x_i(N)^T]$

$$X = [x_1, x_2, \dots, x_n] = \begin{bmatrix} x_1(1) & x_2(1) & \dots & x_n(1) \\ x_1(2) & x_2(2) & \dots & x_n(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(N) & x_2(N) & \dots & x_n(N) \end{bmatrix} \tag{8}$$

The feature matrix Xcan be decomposed as:

$$X = QR \tag{9}$$

One of the important methods for solving equations is application of QR decomposition matrices. QR decomposition states that if there is an Xmatrix where $X \in \mathbb{R}^{n*n}$, there exists an orthogonal matrix Q and an upper triangular matrix R such that Equation (9), is the most important result of this orthonormalization. In the GS orthogonal decomposition, the orthogonal matrix Q is built using the following method:

$$q_1 = x_1 \tag{10}$$

$$q_i = x_i - \sum_{j=1}^{i-1} \alpha_{ji} q_j \tag{11}$$

where q_i is the new feature vector in the orthogonal space and

$$\alpha_{ji} = \begin{cases} \dfrac{q_{jx_i}^T}{q_{jq_i}^T}, \ forj = 1, 2, \ldots, i-1 \\ 1, \ forj = i. \end{cases} \tag{12}$$

Equation (9) employs a mapping from space X to space Q: $Q = R^1 X$, and the feature vector q_i (i = 1, 2, …, n) can be explained as sample allocation in the direction of feature q_k in the orthogonal space. For selection of independent features and obtaining decorrelate features, the orthogonal procedure is necessary. The quality of features array can be evaluated based on their abilities in satisfying the classes separability criteria. A significant criteria to calculate severability class which is proposed such as the Mahalanobis distance compute. In orthogonal space, scattering matrix (covariance) σ_{ij}, is a diagonal matrix and the Mahalanobis distanceis easy to calculate.

The average class severability measure can be employed as feature array evaluation criterion for multiclass problem; where L is the number of classes. The average class severability evaluation in the direction of q_k is defined as:

$$J_k = \frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} \frac{(m_{ki} - m_{kj})^2}{\sigma_{kij}^2} \tag{13}$$

where m_i is the mean vector of data samples in class i.We obtain

$$J = \sum_{k=1}^{n} J_k . \tag{14}$$

Equation (14) indicates that the average evaluation of classes severability (sum of average separability evaluate) is entity directions in the orthogonal space. By applying the orthogonal method, the features space is decorrelated, therefore independent features can be evaluated and selected [20]. In fact, the Equation (14) determines rank of features.

The process of forward feature selection in this method begins with a void subset and then in each step the feature that has high priority is added to current subset. Then, the accuracy is calculated. This process is repeated until all features are selected. The subset which maximizes the classification accuracy is selected as the best answer.

2. 3. Classifier

2. 3. 1. Probabilistic Neural Networks (PNN)

Today neural networks are employed as a general approximation utensil for creating non-linear model by input-output data. TheProbabilistic Neural Network (PNN) is a type of neural network. It has a simple and definite structure. It has four layers: input, pattern, summation, and decision layers. No training process is needed for learning the network.PNN is suitable for automatic pattern identification and nonlinear mapping assessment of probabilities of class [21]. The most imperative advantages of PNN classifier include fast training process, an intrinsic parallel structure, no local minima problem and training examples can be attached or eliminated without widespread retraining.

The PNN is a classifier type that contents the Baye's strategy and Parzen window concept of multivariate probability assesses for achieving the Probability Density Function (PDF). The PNN construction is created by four layers; input, pattern, summation, and output layers. The nodes of input layer are the set of measurements. The second layer contains the Gaussian functions structured using the given set of data as centers. The third layer employs an average operation of the outputs from the second layer for each class. The fourth layer achieves a decision, choosing the largest value. Getting a pattern from the input layer, the neuron x_{ij} of the pattern layer calculates its output by formulation as follow [21]:

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{d/2}\gamma^d} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2\gamma^2} \right] \tag{15}$$

where d indicates the dimension of the pattern vector x , γ is the smoothing parameter and x_{ij} is the neuron vector. The neurons of third layer calculate the maximum likelihood of pattern x being classified into C_i by summarizing and averaging the output of all neurons that join the same class:

$$P_i(x) = \frac{1}{(2\pi)^{d/2}\gamma^d} \frac{1}{N_i} \sum_{j=1}^{N_i} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2\gamma^2} \right] \tag{16}$$

where N_i denotes the total number of samples in class C_i. In the decision layer, the pattern x in accordance with the Bayes's decision rule based on the output of all the summation layer neurons is:

$$\hat{C}(x) = \max \ \arg\{P_i(x)\} \qquad i = 1,2,...,m \tag{17}$$

where $\hat{C}(x)$ denotes the evaluated class of the pattern x

and $m$is the total number of classes in the training samples.

3. PROPOSED DETECTION SCHEME

The aim of the material presented in this paper is to introduce a new machine learning-based feature ranking scheme for discrimination of PQDSs. The proposed scheme is implemented on a central computer and recorded data. The normalized three phase voltage waveforms were presented to the suggested method in a sequential procedure.

The proposed method is realized through three serial stages as shown in Figure 2. Generally, feature extraction and feature selection are essential steps in order to enhance the performance of pattern recognition system. In the first stage, some useful features are extracted using two powerful time-frequency analysis tools i.e. MRA and GST. The second step selects the most important features from whole extracted features of the first step. Third stage is the classification step, which assigns a cluster label to the PQDSs.

3. 1. The Feature Extraction Stage Feature extraction is the most important part of the intelligent system as pattern recognition scheme. In the literature, many signal processing techniques have been applied for analyzing PQDSs. Some examples are fast Fourier transform method, fractal-based method, ST method, time–frequency ambiguity plane method, short time power and correlation transform method and wavelet transform method [1-3].

In this paper an integrated method for feature extraction using MRA and GST is introduced. Appropriate features are extracted by spectral data and statistical indicators of MRA andGSToutputs. One of the important characteristics of the selected features is their severability for different disturbances.The GST is used in detection of PQDSs calculating S-matrix and TF-contour, TmA-plot and FmA-plot and some extracted features based on spectral data and statistical indicators.The obtained features vector of the PQD signal from the S-matrix is shown in Figure 3.The most used mother wavelet in PQ diagnosis is the Daubechies wavelet with a four-coefficient filter (db4) [6].

Figure 2. Flowchart of the proposed classification algorithm

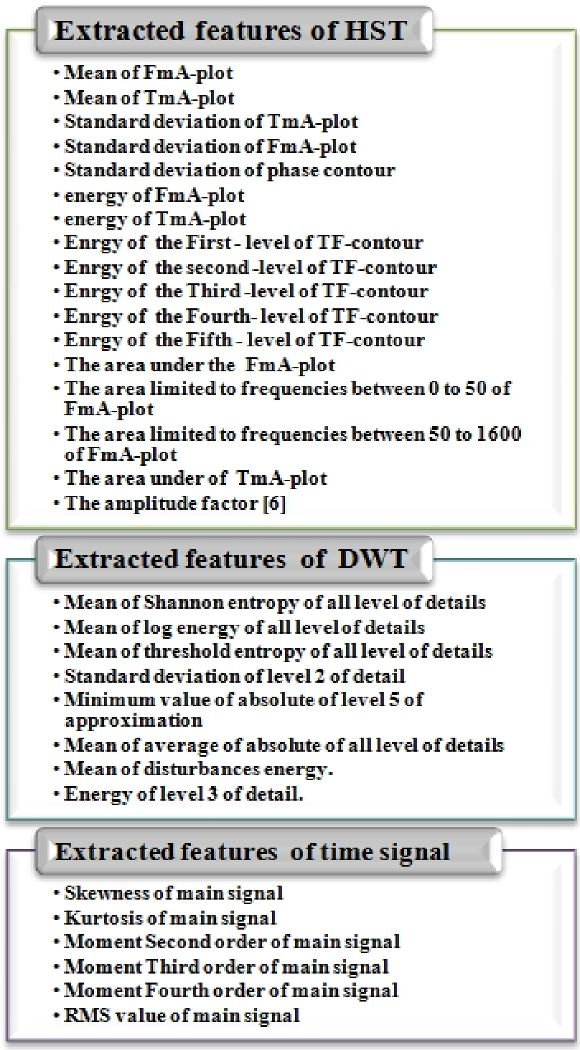

Figure 3. Extracted features for discrimination scheme

Therefore, in this article, the mother wavelet db4 is used. Eight statistical features are extracted from the coefficients of different bands generated using MRA.Moreover, a number of features based on time waveform distortion that statistical indicators are applied on them are extracted.

In this study, some statistical methods such as mean, standard deviation, skewness, kurtosis, RMS (root-mean-square), area, energy, shannon-entropy, log-entropy, threshold-entropy and moment presented in Figure 3have been used as the features extractors. 31 time-frequencystatistical features of PQDSs are extracted using these extractors.

3. 2. Feature Selection Finding a subset of features from a large collection is a challenging problem in the field of pattern recognition scheme.Feature selection as a significant component for the design of intelligent systems based on pattern recognition techniques, should be considered [9]. This stage is very critical because if the selected features are not separable, even the best classifiers cannot yield acceptable results [16].

In this paper, we apply an efficient feature selection method for reduction of required data and increasing the interpretability of features for classifiers. This main stage has been neglected in the most researches in the field of recognition of PQ events.The GS algorithm is considered as one of the most successful methods among the existing relevance-based feature ranking algorithms, due to its simplicity and effectiveness.

At first, OFS as a ranking method with high capability in the detection of useless data is used for ranking of the priority of features. Then forward selection is used according to the rank of the features and the best subset features are selected according to the classification accuracy.

The benefits of applying this orthogonal feature selection method are that it de-correlates the original features so that we can choose them independently. Also, worthless features in the GS space can be connected back to the same number of variables in the original feature space that constructs it appropriate for feature selection [20].

3. 3. The Classification Stage In this stage, selected features obtained from preprocessing stages (i.e. feature extraction and feature selection stages) are used for training of well-known ANN classifier i.e. PNN.

4. SIMULATION AND RESULTS

4. 1. Data Generation In order to get the needed data in this paper, nine types of PQDSs are simulated using the parametric equations in MATLAB environment.To evaluate the classification accuracy of the proposed scheme for PQDSs classification task, distorted signals including pure sine wave, sag, swell, interruption, transient, harmonics, sag with harmonic and swell with harmonic are used in this study. Some works [4, 8, 12] have used parametric equation with variation range of parameters for data generation. In each cycle 64 points are sampled and since the fundamental frequency of power system is 50 Hz, the sampling frequency equals to 3.2 kHz. Ten power frequency cycles which contain the disturbance are used for a total of 640 points.

4. 2. Numerical Results The performance of the proposed method is evaluated by calculating the classification error. In real power systems, signals are usually contaminated with noise. For considering the effect of noise, additive white Gaussian noise (AWGN) is commonly used. So, in order to analyze the performance of the proposed method in different noise environments, white Gaussian noise, with different signals to noise ratio of 40, 30 and 20 dB are employed. Since the variation range of selected features is different, the training and testing data must be normalized. In this study, the features are normalized between -1 to 1. After the training process, 100 samples of unseen data for each disturbance are used for validation of the proposed detection scheme. The obtained results of the feature selection process, including rank of extracted feature are used for training of classifier. Then, PNN classifier is trained with training set and then is tested with unseen data. After training system, it can be used as a powerful tool for identifying disturbances. In the process of test, disturbances are entered to the detection system that had not been used previously. System tests with disturbances which are unknown, shows power of versatility of the system.

The highest accuracies have been obtained by using 22 features for a noiseless signal, 24 features for the signals with 40 dB noise, 22 featuresfor the signals with 30 dB noise and 18 features for the signals with 20 dB noise. Table 1 shows appropriate numbers of selected features and their accuracy for different noisy conditions.

4. 3. Comparison with Published Papers In order to evaluate the effectiveness and feasibility of the proposed method, the obtained classification accuracy of this study are compared with the results of other articles in Table 2. As can be seen from Table 2, the proposed scheme has the best detection accuracy in noisy environment as compared to other researches.

The overall classification accuracy of this study is the best result among other papers.The obtained results in noisy conditions show that the proposed method is robust against different noise levels.

TABLE 1. Percentage of correct classification results of proposed method under different noise condition

Signal	output	classifier
		PNN
Noiseless	Accuracy	97.44
	Number of features	22
40 db	Accuracy	96.44
	Number of features	24
30 db	Accuracy	97.44
	Number of features	22
20 db	Accuracy	96.88
	Number of features	18

TABLE 2. Performance comparison in terms of percentage of correct classification results

PQ studies		Classification accuracy (%)		
References	**Proposed method**	**30db**	**20db**	**Overall**
[21]	WT- RVM	-	96.33	96.33
[19]	WNN-MLP	91.85	89.92	91.8
[4]	ST-FUZZY	96.5	75	90.26
This paper	GST-MRA-OFS-PNN	97.44	96.88	97.05

5. CONCLUSION

In this paper a hybrid intelligent scheme for detection of PQDs has been presented based on the combination of time-frequency and machine learning tools.GST and MRA have been applied as powerful signal analyzers for extraction of features. Then OFS as an efficient feature selection method chooses the best subset feature. Then thePNN is considered as an efficient classifier core for discrimination of dominant selected features.The sensitivity of the proposed scheme under different noisy conditions has also been examined. Comparative results indicate that the proposed discrimination scheme is robust and it has higher classification accuracy with regard to some approaches in the field of PQD detection.High classification accuracy and non sensitivity to noisy conditions show the versatility and reliability of this PQ detection scheme for practical applications in power system.

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GeneralizedS Transform

چکیده

گسترش استفاده از تجهیزات حساس، اهمیت کیفیت توان را افزایش داده است. بنابراین تشخیص و دسته بندی اغتشاشات کیفیت توان یکی از ضروریات در سیستم‌های قدرت امروزی است. یکی از مسائل ارزشمند در آنالیز کیفیت توان، تشخیص اغتشاشات با روشی موثر می‌باشد. در این مقاله، روشی موثر و ترکیبی برای استخراج ویژگی بر اساس ترکیب تبدیل S تعمیمی و تحلیل چند طیفی ارائه شده است. همچنین، روش پیشنهادی به کیفیت ویژگی‌های انتخابی و انتخاب بهترین ترکیب از آنها با کمترین ابعاد، توجه ویژه نموده است. در این مقاله، روشیجدید، بنام OFSبرای انتخابویژگی، بکارگرفته شده و همچنین از ساختار طبقه‌بندی کننده مشهور شبکه عصبی احتمالاتی استفاده شده است. طیف وسیعی از اغتشاشات برای توجیه پذیری سیستم پیشنهادی شبیه سازی شده است. حساسیت روش پیشنهادی تحت شرایط مختلف نویزی با سطوح مختلف سیگنال همراه با نویز بررسی شده است. همچنین با مقایسه نتایج این مقاله با نتایج مقالات دیگر، کارامدی روش پیشنهادی مورد بررسی قرار گرفته است.

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