An Expert System Based on Least Mean Square and Neural Network for Classification of Power System Disturbances

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***Abstract*—** This paper proposes a new solution method for power quality (PQ) classification using least mean square (LMS) and neural network (NN). The proposed hybrid LMS-NN method comprises of LMS based effective feature extractor and PQ classifier based on a multi layer perceptron neural network (MLP-NN). First, the LMS method is employed to estimate the efficient features such as amplitude, slope, and harmonic indication from the measured voltage signals where the developed structure is merely simple. Further, the PQ classification is executed with the aid of MLP-NN. The different voltage signals analyzed for this research work are pure sine, sag, swell, outage, harmonics, sag with harmonics, and swell with harmonics. The performance and efficiency of the presented hybrid LMS-NN classifier is assessed by testing total 1400 voltage samples which are simulated based on PQ disturbance model. The rate of average correct classification is about 96.71 for the different PQ disturbance signals under noise conditions.

Keywords- *feature extraction; least mean square; multi layer perceptron neural network; power disturbance classification; power quality*

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I. INTRODUCTION

Power quality (PQ) evaluation is one of a fundamental segment for watching and controlling the system nature of the huge interconnected power framework, conditioning of high power converters, and synchronization of different power sources related with it. The majority of the synchronization procedures used in sustainable source interconnected power framework relies upon exact power quality estimation [1]. As it is notable, a perfect three-phase ac supply comprises of three-phase voltages that are 120◦ out of phase and have indistinguishable magnitudes. Most importantly, these voltages ought to be sinusoidal and ought to be accessible consistently. Any diversion from these prerequisites is considered as low quality [2]. Low quality of electric power is typically caused by power line unsettling influences, for example, impulses, notches, glitches, momentary interferences, wave flaws, voltage droop/swell, harmonic distortion, and glint, bringing about mis-operation or disappointment of end-utilize hardware [3].

To enhance PQ, the sources and reasons for such unsettling influences must be known before proper moderating moves can be made. A doable way to deal with accomplish this objective is to consolidate identification abilities into observing equipment so occasions of intrigue will be perceived, caught, and ordered consequently. Thus, great execution observing hardware must have capacities which include the location, confinement, and classification of transient occasions. Specifically, when the unsettling influence type has been classified precisely, the PQ specialists can characterize the significant impacts of the disturbance at the load and analyze the source of the unsettling influences with the goal that a proper arrangement can be planned [4]. An essential advance in comprehension and henceforth enhancing the nature of electric power is to extricate adequate data about the occasions that reason the power quality problems. The capacity to perform programmed power quality (PQ) information investigation and characterization is the basic part of power quality examinations. Over the previous years, various papers in light of various strategies for investigation and characterization of power quality disturbances have been analyzed.

Artificial neural network (ANN) systems can provide an effective method to cope with such problems [5-7]. Be that as it may, the intricacy of the classifier framework may rely upon the decision of the ANN structure and the signal features such as amplitude, time, frequency and shape. Thus, a good signal processing strategy must be offer for breaking down power quality related issues. In previous literatures, lots of signal processing methods are employed to extract and examine the features of the power signals. Some examples are wavelet transform [5-7], linear kalman filter [8], fourier transform [9], and S-transform [10].

The major problem of the traditional analyzing methods is that it is not provide sufficient information on the time domain. One technique emerged to overcome the above-mentioned problem is by using wavelet transform whose strength is on handling signals on short time intervals for high frequency components and long time intervals for low frequency components. Hence in this paper, a technique based on least mean square (LMS) is developed to estimate efficient features such as amplitude, slope, and from the measured voltage signal where the developed structure is merely simple and can overcome the existing practical issues in feature extraction process of the power quality assessment. 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 [11]. 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 proposed feature extraction scheme based on LMS algorithm utilizes the three phase AC voltages [12]. In LMS algorithm, a complex signal is formulated from the three phase AC voltages by the Clarke transformation [13]. As the signal in the model is complex, the LMS calculation employed is in complex frame [14]. Be that as it may, such a calculation endures the issue of bad convergence rate as the adjustment step-size is settled. To conquer this, time shifting step size is normally utilized in the standard LMS calculation [15]. Still, the method is sensitive to commotion unsettling influence, noise and disturbance which are normal in a power system environmental condition. Hence, in this paper, a calculation with variable step size, balanced as per the square of the time averaged at the midpoint of gauge of the autocorrelation of successive error samples is utilized [16]. Such a calculation has the advent of better insusceptibility against commotion unsettling influence, noise and disturbance. The execution of the proposed LMS based feature extractor is declared through various illustrations which incorporate information gathered from power grid.

Eventually, the execution correlation between the proposed technique and past literature reports is introduced for a superior validation. The outcome demonstrates that LMS-NN could dissect the PQ signal proficiently. The curiosity displayed in this paper can condense as follows. A standard LMS-based successful feature extraction technique which diminished size of the element vector from the power signal is proposed. Utilizing this technique, the classification exactness rate of the power quality disturbances can be improved by a less demanding disturbance classifier in view of a MLP-NN.

The paper is organized as follow. In Section 2, it is given a preliminary for LMS algorithm. In Section 3, the methodology and the implementation of the proposed LMS based feature extraction is given. In Section 4, classification method used in this study is given. In Section 5, simulation and analysis study is introduced and the classification results are shown. Finally, conclusions are discussed in Section 6.

II. LMS ALGORITHM

The LMS method of signal feature extraction is depicted in Fig. 1, where y_t denotes the actual signal, $\hat{y}_t$ denotes the signal estimate and $X_t = [x_{0t}, x_{1t}, \dots, x_{N-1t}]^T$ is the input vector at the t[th] instant. The signal can be estimated correctly by the filter with a suitable value of its coefficient W_t, which is obtained through minimizing the squared of the error signal e_t [17]. 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,

$$W_{k+1} = W_k + \mu(-\nabla_k) \quad (1)$$

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

$$\hat{\nabla}_k = -2e_k X_k \quad (2)$$

The recursion (1) is called the LMS algorithm and it is initialized by setting all coefficients to zero. Then 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,

$$0 < \mu < \frac{2}{Total\ input\ power} \quad (3)$$

where μ the input power refers to the sum of the mean-square value of the inputs. When μ is little, the LMS technique consumes huge time to learn about its input with minimum mean square error and vice versa. Accordingly, a time changing step sized ordering of μ is desirable for optimal convergence [15].

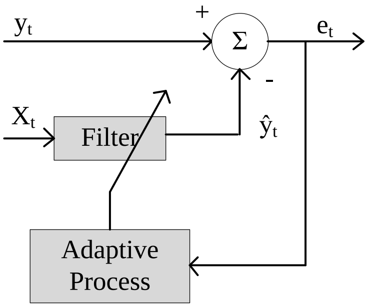

Figure 1. Least Mean Square Filter.

III. LMS BASED FEATURE EXTRACTION

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

$$V_{a_k} = V_m \cos(\omega k\Delta T + \varphi) + \epsilon_{a_k}$$
$$V_{b_k} = V_m \cos\left(\omega k\Delta T + \varphi - \frac{2\pi}{3}\right) + \epsilon_{b_k}$$
$$V_{c_k} = V_m \cos\left(\omega k\Delta T + \varphi + \frac{2\pi}{3}\right) + \epsilon_{c_k} \quad (4)$$

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 (ω = 2πf, with f being the system frequency). The complex form of signal derived from the three phase voltages is obtained by αβ transform [18] as mentioned as follows,

$$\begin{bmatrix} V_{\alpha_k} \\ V_{\beta_k} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} [V_{a_k} \quad V_{b_k} \quad V_{c_k}]^T \quad (5)$$

A complex voltage can be obtained from above as

$$V_k = V_{\alpha_k} + jV_{\beta_k} \quad (6)$$

The voltage V_t can be modeled as

$$V_k = Ae^{j(\omega k\Delta T + \varphi)} + \xi_k$$

$$V_k = \hat{V}_k + \xi_k \quad (7)$$

where A is the amplitude 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 modeled as

$$\widehat{V_k} = \hat{V}_k - 1^{e^{j\omega\Delta T}} \quad (8)$$

This model is utilized in the proposed feature estimation algorithm and the scheme that explains the extraction procedure is depicted in Fig. 2. The error signal e_t for this situation is calculated as,

$$e_k = V_k - \hat{V}_k \quad (9)$$

where $\hat{V}_t$ is the estimated value of voltage at the t[th] time. Then

$$W_k = W_{k-1}\hat{V}_{k-1} \quad (10)$$

where the weight $W_t = e^{j\hat{\omega}_{t-1}\Delta T}$, $\hat{\omega}$ is the estimated angular frequency. The significance of the model is that the input data consists of only one component and the weight vector. The complex LMS method as developed in [15] is applied to estimate 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,

$$W_k = W_{k-1} + \mu_k e_k \hat{V}_k^* \quad (11)$$

where * represents the complex conjugate of the value and μ is the convergence factor controlling the stability and convergence rate of the technique.

The step size μ_t is varied as in [16] for better convergence of the LMS algorithm in the presence of noise. For complex states, the equations can be updated as,

$$\mu_{k+1} = \lambda\mu_k + \gamma p_k p_k^* \quad (12)$$

where p_t represents the autocorrelation of e_t and e_{t-1} is computed as

$$P_k = \rho p_{k-1} + (1-\rho) e_k e_{k-1} \quad (13)$$

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 values are chosen based on signal statistics described in [16].

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

$$A_t = |\hat{V}_t| \quad (14)$$

The slope S_t is calculated as follows,

$$S_t = \frac{(A_t - A_{t-1})}{\nabla T} \quad (15)$$

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

IV. EXPERT SYSTEM BASED ON LMS FILTER AND NEURAL NETWORK

Neural networks (NN) are frameworks that are developed to make utilization of some hierarchical standards taking after those of the human brain [19]. They represent the promising new generation of data processing frameworks. Neural networks are great at tasks, for example, pattern matching and classification, function approximation, optimization and information grouping, while conventional computer systems, as a result of their architecture are ineffective at these errands, particularly pattern matching assignments.

The NN structure is a pattern classification technique attempted to coordinate parts of the LMS filter for the feature extraction and neural network approaches with the characteristic decision abilities for the classification. In this method, after understanding the feature extraction (preprocessing) stage utilizing standard measurable statistical acquired from LMS filter, the classification (processing) stage is executed by utilizing NN structure based multi-layer perceptron with resilient back propagation (RPROP) learning technique. Expert system based on LMS filter and NN is appeared in Fig. 3. The input to the classifier is the time domain disturbance signal, and the output is the sort of the disturbance alongside its corresponding level of conviction.

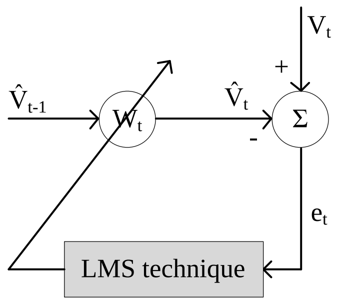

Figure 2. LMS based feature extraction.

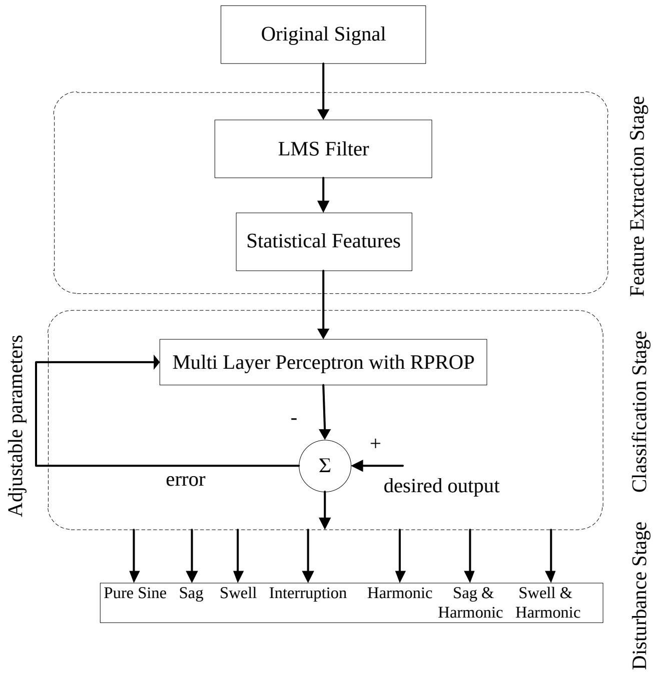

Figure 3. The structure of LMS-NN for PQ disturbance classification.

A. *Classification using neural network*

In the classification stage, the features obtained from the LMS filter are applied as input to NN. The architecture of the NN is the multi layer perceptron (MLP) with RPROP learning algorithm. The output of the classification stage is the types of the disturbances. Neural networks represent the promising new generation of information processing systems. They are good at tasks such as pattern-matching and classification, function approximation, optimization and data clustering, while traditional computers, because of their architecture, are inefficient at these tasks, especially pattern- matching tasks [20]. In this paper, the classification process is realized with NN architecture called as MLP. The MLP networks are artificial neural networks formed of cells simulating the low level functions of neurons. MLP networks are very useful for classification of input signals where the signals cannot be defined mathematically. Further, MLP networks have redundant networking and are very robust, providing a mathematical flexibility not available to algorithms based classifiers [21].

For learning algorithm of MLP network, the RPROP is used. It eliminates the harmful effect of having a small slope at the extreme ends of sigmoid squashing transfer functions. Only the sign of the derivative of the transfer function is used to determine the direction of the weight updates; the magnitude of the derivative has no effect on the weight update. RPROP is generally much faster than the standard back propagation algorithm. It also has the remarkable property of requiring only a modest increase in memory requirements. A detail discussion about this learning algorithm can be found in [22]. The training parameters and the structure of the MLP used in this study are shown in Table 1. They were selected to obtain best performance, after several different experiments, such as the number of hidden layers, the size of the hidden layers, value of the moment constant and learning rate, and type of the activation functions.

TABLE I. MLP ARCHITECTURE AND TRAINING PARAMETERS

Architecture	
The number of layers	3
The number of neuron on the layers	Input: 13, hidden: 10, output: 7
The initial weights and biases	Random
Activation functions	Tangent sigmoid
Training parameters	
Learning rule	RPROP
Learning rate	0.75
Mean-squared error	1E−08

TABLE II. POWER QUALITY DISTURBANCE MODEL

PQ disturbance	Class symbol	Model	Parameters
Pure Sine	S1	$f(t) = \sin(\omega t)$	
Sag	S2	$f(t) = A(1-\alpha(u(t-t1)-u(t-t2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.9$; $T\leq t2 - t1 \leq 9T$
Swell	S3	$f(t) = A(1 + \alpha(u(t-t1) - u(t-t2)))\sin(\omega t)$	$0.1\leq\alpha\leq0.8$; $T\leq t2 - t1 \leq 9T$
Outage	S4	$f(t) = A(1-\alpha(u(t-t1)-u(t-t2)))\sin(\omega t)$	$0.9\leq\alpha\leq1$; $T\leq t2 - t1 \leq 9T$
Harmonic	S5	$f(t) = A(\alpha1 \sin(\omega t) + \alpha3 \sin(3\omega t) + \alpha5 \sin(5\omega t) + \alpha7 \sin(7\omega t))$	$0.05 \leq \alpha3 \leq 0.15$, $0.05 \leq \alpha5 \leq 0.15$, $0.05 \leq \alpha7 \leq 0.15$; $\sum \alpha_i^2 = 1$
Sag with harmonic	S6	$f(t) = A(1-\alpha(u(t-t1)-u(t-t2)))(\alpha1)\sin(\omega t) + \alpha3 \sin(3\omega t) + \alpha5 \sin(5\omega t))$	$0.1 \leq \alpha \leq 0.9$; $T \leq t2 - t1 \leq 9T$, $0.05 \leq \alpha3 \leq 0.15$, $0.05 \leq \alpha5 \leq 0.15$; $\sum \alpha_i^2 = 1$
Swell with harmonic	S7	$f(t) = A(1 + \alpha(u(t-t1)-u(t-t2)))(\alpha1)\sin(\omega t) + \alpha3 \sin(3\omega t) + \alpha5 \sin(5\omega t))$	$0.1 \leq \alpha \leq 0.8$; $T \leq t2 - t1 \leq 9T$, $0.05 \leq \alpha3 \leq 0.15$, $0.05 \leq \alpha5 \leq 0.15$; $\sum \alpha_i^2 = 1$

V. SIMULATION AND ANALYSIS

A. *Data generation*

Data generation by parametric equations for classifiers tests has advantageous in some ways. It was possible to change training and testing signal parameters in a wide range and in a controlled manner. The signals simulated with this way were very close to the real situation. On the other hand, different signals belonging to the same class gave possibility to estimate generalization ability of classifiers based on neural networks [23]. The input data to the LMS-NN based on PQ disturbances classification system was generated based on the model in papers [24]. Seven classes (S1–S7) of different PQ disturbances, named pure sine (normal), sag, swell, outage, harmonics, sag with harmonic and swell with harmonic, were considered [25]. Table 2 gives the signal generation models and their control parameters. 200 cases of each class with different parameters were generated for training and another 200 cases were generated for testing. Both the training and testing signals are sampled at 256 points/cycle and the normal frequency is 50 Hz. Sixteen power frequency cycles which contain the disturbance are used for a total of 4096 points. A set of sample voltage waveforms given in Fig. 4 demonstrate the characteristics of the various PQ disturbances.

B. *Simulation results*

The voltage magnitude and slope are estimated using (14) and (15) at each time samples from the LMS filter and then the 2-dimensional feature sets for training and testing data are constructed. Thus, the dimensions here describe different features resulting from the LMS filter, that is to say, the total size of training data or testing data set is 2×1400, where 2 is the dimension of feature size of each case and 1400 comes from 200 cases per class multiplied by 7 classes. This is the input vector (voltage magnitude and slope) to be classified using MLP-NN. Considering the classification performance of this method, this input vector is applied as the input to the MLP layer of the LMS-NN structure. Classification results are described in terms of a 7×7 confusion matrix. The diagonal elements represent the correctly classified PQ disturbances. The off-diagonal elements represent the misclassified PQ disturbances.

The system can correctly classify 1354 of the 1400 different PQ disturbance signals in the testing set, as shown in Table 3. Hundred percent correct classification rate is obtained for four disturbances signal (S1, S5, S6 and S7). S2, S3 and S4 are classified correctly above 90% mean success rate. This means that the overall success rate is found to be about 96.7142%, when no noise is added to the signal. The reason of the lower classification accuracy of especially S2 and S4 classes comparing to those of other classes is the similar features of the two classes. As shown in Table 2, the minimum amplitude value of S2 class is very close to the maximum amplitude value of S4 class.

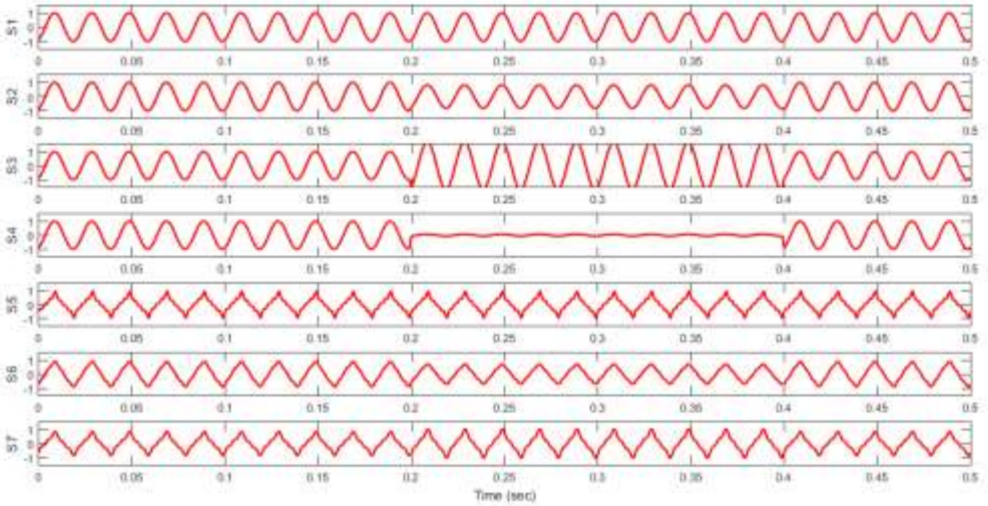

Figure 4. Power quality disturbances (S1: pure sine, S2: voltage sag, S3: voltage swell, S4: outage, S5: harmonic, S6: sag and harmonic, S7: swell and harmonic).

TABLE III. CLASSIFICATION RESULTS OF PROPOSED LMS-NN METHOD

TRUE class	S1	S2	S3	S4	S5	S6	S7	Accuracy (%)
S1	200	0	0	0	0	0	0	100
S2	2	180	0	15	0	3	0	90
S3	2	0	197	0	0	0	1	98.5
S4	1	14	0	177	0	8	0	88.5
S5	0	0	0	0	200	0	0	100
S6	0	0	0	0	0	200	0	100
S7	0	0	0	0	0	0	200	100
				Overall success rate				**96.7142**

TABLE IV. PERFORMANCE COMPARISON IN TERMS OF PERCENTAGE OF CORRECT CLASSIFICATION RESULTS

Class	Proposed method	Reference [25]	Reference [24]	Reference [26]
S1	100	100	100	100
S2	90	88	87	76.5
S3	98.5	96.5	100	97
S4	88.5	85.55	80.5	90
S5	100	100	100	100
S6	100	100	97	71.5
S7	100	100	100	98
Overall	**96.714286**	**95.71**	**94.93**	**90.42**

C. *Performance comparison*

In order to evaluate the effectiveness and feasibility of the proposed method, a comparison in terms of percentage of the classification accuracy between the results of this study and results of classification schema in [24-26] is made and comparatively presented in Table 4. The papers in [24-26] are selected for the comparison because of including the same disturbance types and the same pattern numbers and generating by parametric equations of data for training and testing of the classification stage. As seen from Table 4, the performance of the classification process with the proposed feature extraction method exceeds the performance of the classification process proposed in [24-26].

VI. CONCLUSION

In this paper, a least mean square filter based effective feature extraction method is proposed for the automatic PQ disturbance classification. The disturbance classification schema is performed with multi layer perceptron neural network. It performs a feature extraction and a classification

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algorithm composed of LMS filter and a classifier based on a multilayer perceptron. The performance comparison in terms of the classification accuracy is presented for previous studies. Often, many practical applications, including PQ disturbance classification, require a large computational ability to cope with complexity or real-time limitations. Often traditional computers cannot achieve quickly such ability, or they are too expensive and cannot always be afforded.

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