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# Optimal Feature Oreinted Classification of One and Merged Disturbances of Power Quality Through Supervised Learning

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***ABSTRACT---The emergence of power quality topic in power systems has gained an increased research interest due to its widespread applicability in different applications. Since the quality of power is devalued due to various disturbances, detection of such disturbances is required. This paper provides refined power quality disturbances classification mechanism which is associated with various compositions like the presence of noise, and accumulation of two or more disturbances. Considering the both linear and non-linear dependencies between PQDs, two optimal feature extraction techniques, Joint Mutual Information as well as Correlation based feature selection, are proposed. These optimal set of features are processed for PQDs classification by employing pair of supervised learning algorithms, Support Vector Machine (SVM) along with Decision Tree (DT). Extensive simulations are conducted over different PQ disturbances at different Signal to Noise Ratio (SNR) levels give away the performance constructiveness of proposed approach. The robustness is derived through the provision of a tradeoff between the computational time and classification accuracy.***

***Keywords—Power Quality Disturbances, Mutual Information, Correlation, SVM, DT, Swell, Sag, Accuracy, Computational Time.***

## I. INTRODUCTION

In recent years, the expanded usage of distributed generations (DG) and sensitive power devices has increased much prominence due to the widespread practice of power electronics in the residential, commercial and industrial sectors. Consequently, both electrical appliances and end users are becoming steadily more bothered about the reliability and quality of electric power. Besides, in this broad electrical market system, arrangement of a diverse quality power and the individual electrovalence procedures are should have been given as a significant support of the consumers. Due to all these aspects such as integration of different devices and accomplishment of new power regeneration techniques, Power Quality Disturbances (PQDs) has turned into a genuine concern in the electrical related appliances [1]. Since the electricity is now a commercial product and the end users expects only the power with high quality. The customer will choose the supplier those who can provide only the electrical energy having better quality that meets the needs of his/her loads. The electric power providers or the utilities need to guarantee that a high caliber of power that they providing is more qualitative and to attract or retain the consumers in the new electrical market system [2].

PQDs can be both stationary and non-stationary in nature and also covers a broad range of frequencies with noticeable variations in the magnitudes [3]. The on-line detection and classification of PQDs is necessary such that the reason for such occurrence can be identified and an appropriate mitigation action can be taken over the disturbance to nullify its effect in the electrical appliances. A functional way to deal with accomplish this objective is to integrate a detection mechanism into the monitoring devices so that the disturbances can be detected, recognized and classified in an automatic manner. This process can be accomplished in a well ordered procedure by distinguishing disturbance, then processing for localization and finally performing the classification of PQDs [4]. To execute this procedure, a device is required which has both the capability of analyzing the power quality events and to classify them too.

This paper comes up with a new PQD detection and classification mechanism to detect various PQDs. Since the detection process is directly and indirectly related with so many aspects such noise presence, accumulation of two or more disturbance events, design of an optimal detection mechanism is typical in nature. Keeping in the mind, this paper proposed a two stage detection mechanism considering two different supervised algorithms with an innovative feature extraction technique to perform power quality disturbances detection.

Rest of the paper is drafted as follows; Section II depicts the literature survey details. The details of proposed feature selection and classification approach are illustrated in section III and section IV respectively. Experimental assessment is described in section V and finally the conclusions and future scope are portrayed in section VI.

## II. LITERATURE SURVEY

Various authors proposed various approaches to develop an automatic PQD detection and classification system to recognize the all PQD signals. In the earlier developed approaches, they considered peak values of PQD signals. Crest factor, energy deviation, instantaneous frequency, power factor and Total Harmonic Distortion (THD) as features of PQD signals and these features are extracted with the help of Parseval's theorem for monitoring or frequency spectrum [5]. Some more methods like Fast Fourier Transform (FFT), Welch Algorithm, Z-Transform (ZT), and Zoom FFT are also popularly used strategies to monitor the electrical parameters [6], [7]. However these are the basic techniques and sometimes they failed in exactly analyzing the electrical parameters of the PQD signal. For example, the FFT cannot inspect the

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characteristics of disturbances in the case of non-stationary nature [7]. The examples of non-stationary signals are Voltage Transients and Voltage Notches.

Next, some more methodologies are created dependent on the time-frequency inspection of PQD signals like Short Time Fourier Transform (STFT), Wavelet Transform (WT) [8-12], and Kalman Filters [13]. However, the primary disadvantage of Wavelet Transform is its inability to find the disturbances in the existance of noise. Hence, a new version of WT is developed, named as S-Transform to improve the detection performance [14]. However, due to the relative fixed size of Gaussian Window, this method cannot provide satisfactory results for all types PQD signals at various time-frequency resolutions. To overcome this problem, a new version of the S-Transform is proposed [15], is more suitable technique to achieve an improved detection performance for all types of disturbance signals at all time-frequency resolution levels. Further with an aim of reduced loss of information of the original signals, an extended S-Transform, Double Resolution S-Transform (DRST) [16] is proposed which improves the robustness in the detection of all disturbances with less computational complexity. The DRST has good localization at either time and frequency resolutions and furthermore have better vigor with less computational complexity. Further to achieve an improved detection performance at all cases, some approaches are proposed by combining the WT and S-Transform [14, 17]. These methods achieved better results in the detection of PQDs but build an unnecessary computation burden over the system.

Likewise, some classification ways are proposed based on soft computing techniques; for instance Artificial Neural Network (ANN) and fuzzy and neuro-fuzzy systems [18]-[22]. ANN is an important technique with simple architecture and also ensures better results even with the noise existence. Multiple strategies are proposed depended on ANN to perform automated detection of PQD detection and classification. However ANN has lot of drawbacks, e.g., training of ANN need a lot of specimens and they come under the local optimum and also have leisured convergence rate. Next, majorly authors moved to Support Vector Machine (SVM) for detection and classification of PQDs [23]-[25]. So many issues like signals with non-linearity, small samples, higher dimensions can be solved by SVMs. Decision Tree is also an important supervised learning algorithm, used by various authors for the purpose of classification of electrical PQDs [26].

Compared with the single classifier algorithms, a combiner classification strategy gives more optimal performance in the detection of PQDs which have both linear and non-linear statistics. Raj Kumar [27] has given a hybrid PQD detection way by combining the ANN in addition to Rule-based Decision Tree to classify the one stage and more than one PQ disturbances. However, this method accomplished S-Transform for feature extraction which has less robustness for time-frequency resolutions. Next, the ANN is combined with C4.5 decision tree [28] to perform the classification of PQDs in smart meters by extracting an optimal feature set in both time and frequency domains. Though the classifiers are best at their performance, the feature extraction introduces an extra complexity due to the multiple set of features extraction. Thinking about these certainties, another methodology is proposed in [29] dependent on the mutual information combined with SVM algorithm at it was observed an optimal results in the case of both noise free and noisy PQDs. However, only a single classifier was accomplished here to perform the classification. Based on the above observations, the performance can be further improved by integrating two classifiers. Subsequently, this paper meant to incorporate two classifiers with the mutual information based feature selection to aim an enhanced classification performance in the PQD detection.

## III. FEATURE SELECTION

The feature selection mechanism proposed here combines the Mutual Information dependent feature selection algorithm with pair of classification algorithms and the details are depicted below.

Feature selection is an significant move in the detection of automatic PQD signals. Here in paper, the feature selection phase gets the mutual information existing between different PQD signals. Since the MI is a non-linear relation, this paper also proposed a correlation dependent feature selection to get the linear relations with a less set of features for every PQD signals. The extracted set of features is of small in size and is more informative and also provides a perfect discrimination between the PQD signals. The primary distinction between the traditional methodologies and the proposed methodologies are delineated as below;

1. The conventional approaches extracted time domain features of PQD signals such as amplitude, energy, peak values, Kurtosis, Root mean square, Harmon mean, Standard Deviation, Difference between maximum and minimum values and entropy are not robust in the presence of external noises. Furthermore, these features are not able determine the statistical relationship between the PQD signals by which there is possibility of information loss. Furthermore, if these features are extracted over an entire signal, it is too complex to differentiate the signals due to the reason that the obtained values are almost nearer.
2. The conventional approaches extracted transform domain features of PQD signals such as total harmonic distortion, magnitude of fundamental signal, magnitudes of 2nd, 3rd, 4th, and 5th harmonics

establishes an additional computational pressure on the detection system. Majorly, the transformed features are extracted by the accomplishment of frequency domain transformation techniques such as FFT, time-frequency domain techniques like WT and ST. All these approaches have their individual drawbacks and are described in section II.

To beat the issues with the two areas, this paper proposed a novel feature extraction



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technique that takes both the linear and non-linear dependencies into account between the PQD signals and the given technique is dependent on the mutual information followed by correlation. A dual feature extraction mechanism is accomplished here to extract the both dependencies. In the beginning, the mutual information dependent approach, joint mutual information dependent feature selection is given to derive the non-linear dependencies among the normal sinusoidal signal and the PQD signals such as voltage sag, voltage swell, oscillatory transient, harmonics, flicker, interruption, Swell plus harmonics, Sag plus harmonics, notch and spike. Next, a correlation based feature extraction strategy is accomplished over only the PQD signals to extract the linear dependencies between them. Here the proposed feature selection strategy assumed that the normal sinusoidal signals are too much deviated from the PQD signals and it is not all linearly related. Furthermore, the PQD signals are linearly related with each other and if that linear relation is extracted properly, then the computational complexity will be reduced greatly.

The recent Flexible Entropy based feature selection mechanism [29] is just based on the non-linear dependencies only but not considered the linear relationships between PQDs. Furthermore, this method is based on the most popular Battiti's MI [30]. Further there are such huge numbers of variations are proposed dependent on MI, for example, MIFS-U [31], mRMR [32], NMIFS [33], MIFS-ND [34] and JMI [35]. In any case, the primary downside of these techniques is class insignificance and over estimation of feature importance. The class irrelevancy is simply defined as the irrelevancy between the selected set of optimal feature and new feature. Due to this irrelevancy, the feature which has to select is evaluated for mutual dependency with the set of already selected features but not with class label. Next, the overestimation of feature significance reveals that the feature which is intensely correlated to one feature is not correlated with other features and constitutes a redundancy. In view of these angles, the proposed feature extraction is outlined as follows;

### *A. Joint Mutual Information Maximization dependent Feature selection (JMIMFS)*

Consider F is the full set of features; S is the subset of features which was so far selected for the Feature set F. Let a feature$f_i$,$f_i \in F - S$, and $f_s \in S$, the m-Joint MI is described as the MI between $f_i$ and the features present in the so far selected feature subset S. The lowest value of m-Joint MI is referred as minimum joint MI, i.e., $\min_{s=1,2,\dots,K} I(f_i, f_s; C)$. A maximum value of joint MI of $f_i$ and the features in the subset S denotes a more relevance to the class label C. Next, a maximum value of joint MI also denote that the m-joint MI of other features, $f_j$, $f_i$ and $f_j \in F - S$ denotes the minimum joint MI between the features $f_j$ and $f_i$ . Basically it signifies that, contrasted to the feature$f_i$, the feature$f_j$, shares less data towards the class label C. According to the above definitions, the element which offers most extreme data is said to be progressively important.

The new model for the FS as indicated by the JMIM is defined as

$$f_{JMIM} = \arg\max_{f_i \in F-S}\left(\min_{f_s \in S}(I(f_i, f_s; C))\right) \quad (1)$$

Where

$$I(f_i, f_s; C) = I(f_s; C) + I\left(f_i; {}^{C}/_{f_s}\right) \quad (2)$$

$$I(f_i, f_s; C) = H(C) - H\left({}^{C}/_{f_i}, f_s\right) \quad (3)$$

$$I(f_i, f_s; C) = [-\sum_{c \in C} p(c) \log(p(c))] - \left[\sum_{c \in C}\sum_{f_i \in F-S}\sum_{f_s \in S} log\left(\frac{p(f_i, f_s, {}^{c}/_{f_s})}{p({}^{f_i}/_{f_s})p({}^{c}/_{f_s})}\right)\right] \quad (4)$$

This method finds the relevant feature subset (size *k)* within the feature space which follows the iterative forward greedy search algorithm. The JMIMFS reduces the almost all redundant features from the PQ signals and preserves only the features which are high informative and contributes to the class. Approximately, the first stage feature selection technique reduces 40% of features from the full set of features.

### *B. Correlation Based Feature Selection (CFS)*

This feature extraction phase is based on the evaluation of Pearson product-moment Correlation Linear Coefficient (PCLC). This measure is quick and precise in measuring the correlation among random linearly dependent variables and the same is insensitive to non-linear correlations also.

Given two PQD signals X and Y, the PCLC (X; Y) or r (X; Y) is measured as,

$$r(X;Y) = \frac{A}{B.\ C} \quad (5)$$

Where

$$A = n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i - \sum_{j=1}^{n} y_j \quad (6)$$

$$B = \sqrt{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{j=1}^{n} x_j\right)^2} \quad (7)$$

$$C = \sqrt{n\sum_{i=1}^{n} y_i^2 - \left(\sum_{j=1}^{n} y_j\right)^2} \quad (8)$$

The value of$r(X;Y)$comes under a definitely closed interval [-1, 1]. A value of -1 or 1 specifies a high correlation between two variables. A worth near zero demonstrates the frail connection between them.

## IV. CLASSIIFCATION APPROACH

In this section, the details of classification algorithms considered for classification are illustrated briefly. The proposed classification approach considered a two stage classification mechanism, one classifier is for normal sinusoidal signal and other is for PQDs. In the first stage, SVM has achieved to differentiate the normal sinusoidal signal from PQDs and decision tree has achieved to differentiate individual PQDs in the second stage. The facts of SVM and Decision tree are summarized in the following subsections;


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### A. Support Vector Machine

Based on the minimization of structural risk, SVM is a supervised learning algorithm for the classification of patterns [36]. Compared to the other supervised learning algorithms like neural networks, fuzzy algorithms, and Bayesian classifier, SVM hasobtained a greater performance in the detection of PQD signals. Due to the accomplishment of sequential management in the SVM algorithm, the detection will be more accurate and it is able to detect even under uneven circumstances. Basically SVM is a binary classifier, i.e., at a time it can classify only two classes. The output of SVM is labeled as 1 and -1. Here one denotes for one class -1 denotes for another class. This paper considered SVM at the first phase to classify the normal sinusoidal signal from PQD signals. The basic working principle of SVM is outlined as follows;

For an n-dimensional input $p_i (i = 1,2,3, \dots, N)$, where N is the number of samples of class A or class B with outputs $o_i = 1$ for class A and $o_i = -1$ for class B. The hyperplane differentiating the two classes is formulated as

$$f(p) = w^T p + b = \sum_{j=1}^{n} w_j p_j + b = 0 \quad (10)$$

Where $w$ is an n-dimensional vector and b is is a parameter. These are the parameters which decide the separating position of hyper plane. An example hyper plane separating class A and class B is given in figure.1.

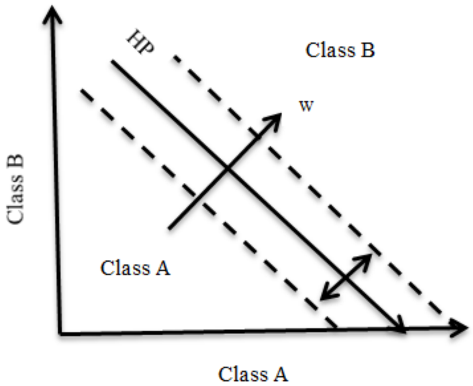


**Figure.1 Hyper plane (HP) of SVM classifier**

The constraints to figure out the hyper plane of two classes are mentioned as $f(p_i) \geq 1$ if $o_i = 1$ and $f(p_i) \geq -1$if $o_i = -1$, thus

$$o_i f(p_i) = o_i \left( \sum_{j=1}^{n} w_j p_j + b \right) \geq +1,$$

$$i = 1,2,3, \dots N \quad (11)$$

Where the geometrical separation is acquired by $\frac{1}{\sqrt{\|w\|}}$. The optimal hyperplane is derived based on the following optimization constraint

$$Minimize\ \frac{1}{2} \frac{1}{\sqrt{\|w\|}} + C \sum_{i=1}^{N} \xi_i \quad (12)$$

Subject to

$$o_i \left( \sum_{j=1}^{n} w_j p_j + b \right) \geq 1 - \xi_i, \quad i = 1,2,3, \dots N$$

$$\xi_i \geq 0 \ \forall \ i \quad (13)$$

Forwardly the optimal bias value is obtained through

$$b^* = -\frac{1}{2} \sum_{SVs} o_i \alpha_i^* (v_1^T p_i + v_2^T p_i) \quad (14)$$

Where $v_1$ and $v_2$ are two random support vectors for class A and class B, respectively. Then the desired function corresponds to

$$f(p) = \sum_{SVs} o_i \alpha_i p_1^T p_i + b^* \quad (15)$$

Based on the above constraint, the undetected signal is classified through

$$p = \begin{cases} Class\ A, & if\ f(p) \geq 0 \\ Class\ B, & if\ f(p) < 0 \end{cases} \quad (16)$$

The PQD signal classification is implemented through the Gaussian radial basis kernel function [37].

### B. Decision tree

Decision trees [36] are the tools that use divide and conquer strategy to learn by induction. The main advantage of the decision tree is its comfort of achievement such that they model compact and highly readable structures, so that the results are easily understandable. Thus, decision tree based classification is achieved in a tree format, being hierarchically structured by a set of intermediate nodes. Decision trees are popularly used in the classification problems dependent on the selection of an attribute which maximizes and fixes the vision of information [38], [39]. Next the attributes are split into various branches in a recursive manner, until the final classification was reached. Mathematically the achievement of decision tree based classification is formulated as follows;

Let $X_i, i = 1,2,3, \dots, N$ number of signals and $x_i, i = 1,2,3, \dots, M$ be the number of samples in every signal, $X_i$, and S be the m-dimensional vector predicted form $\bar{X}$. The primary concern of DT is to predict the S based on the observation of $\bar{X}$. The optimal sized DT is built with respect to the respective optimization constraint

$$\hat{R}(T_{k0}) = \min\{\hat{R}(T_k)\}, \quad k = 1,2,3, \dots, K \quad (17)$$

$$\hat{R}(T) = \sum_{t \in \hat{T}} \{r(t) p(t)\} \quad (18)$$

Where $\hat{R}(T_k)$ = the level of error obtained in the misclassification of a tree $T_k$, $T_{k0}$ = the optimal decision tree through which the misclassification is minimized, T = a binary tree, k = the tree's index number, t = tree node, $r(t)$ = the re-substitution estimation of error obtained in the misclassification of node t, and $p(t)$ = the probability that any case drops into node t.

A simple DT based classification of PQD signals is represented in figure.2.


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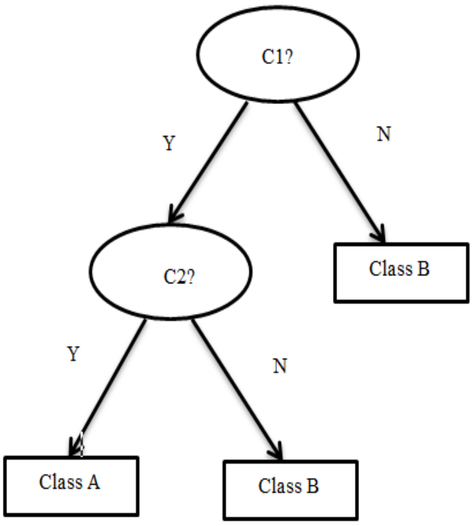


**Figure.2 DT based classification**

## V. EXPERIMENTAL EVALUATION& RESULTS

### *A. Experimental Data*

To simulate the proposed detection and classification system, various PQDs are generated and processed through the detection system. So as to confirm the presentation adequacy of proposed technique in this paper, MATLAB 2015 is embraced to reproduce the PQD sign as indicated by the IEEE standard. One normal sinusoidal signal, eight pure disturbances, namely Swell, Sag, Harmonics, Oscillatory Transient, Notch, Spike, Interruption and Flicker, and fifteen mixed disturbances are considered for experimental evaluation. The details of experimental test signals of single type are represented in table.1. Further these single PQDs are mixed one with other to generate mixed PQDs and the details are represented in table.2.

**Table.1 Test Set of Single Power Quality Disturbances**

| Single PQD | Varying parameters | Total signals |
|---|---|---|
| Normal | t =0:0.0001:0.4 | 10 |
| Swell | T= 0.4,0.5,0.6,…….,3.6 ; $\alpha = 0.1,0.2,0.3,\dots,0.8$ | 33∗8 =264 |
| S ag | T= 0.4, 0.5,0.6,…….,3.6 ; $\alpha = 0.1,0.2,0.3,\dots,0.9$ | 33∗9 =297 |
| F licker | $\alpha = 0.1,0.2;\ \beta = 5,6,7,\dots,20$ | 16∗2 =32 |
| I nterruption | T= 0.4,0.5,0.6,…….,3.6; $\alpha = 0.9$ & 1.0 | 33∗2 =66 |
| O scillatory transient | T= 0.2,0.4,0.6,0.8,1.0,1.2; $f_n = 300,400,\dots,800$ ; $\alpha = 0.1,0.2,0.3,\dots,0.8$ | 6∗8∗6 =288 |
| Harmonics | $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15 | 3∗3∗3=27 |
| Notch | k=0.1,0.2,0.3,0.4 ; $t_1$=0,0.1,0.2,…,0.5; $t_2$=0,0.1,0.2,…,0.5 | 4∗6∗6=144 |
| Spike | k=0.1,0.2,0.3,0.4; $t_1$=0,0.1,0.2,…,0.5; $t_2$=0,0.1,0.2,…,0.5. | 4∗6∗6=144 |

**Table.2 Test set of Mixed Power Quality Disturbances**

| Mixed PQD | Varying parameters | Total signals |
|---|---|---|
| Swell + Flicker | T=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$, $\alpha\_F = 0.1,0.2,\ \beta = 5,6,7,\dots,20$ | 8448 |
| Sag + Flicker | T=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$, $\alpha\_F = 0.1,0.2,\ \beta = 5,6,7,\dots,20$ | 9504 |
| Swell + harmonics | $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$ | 216 |
| Sag + Harmonics | $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$ | 243 |
| Swell + Oscillatory Transient | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$ T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots,800$, | 9504 |
| Sag + Oscillatory Transient | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$, T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots,800$, | 10692 |
| Flicker + Oscillatory Transient | $\alpha\_F = 0.1,0.2,\ \beta = 5,6,7,\dots,20$ T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots,800$, $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, | 9216 |
| Harmonics + Flicker | $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15, $\alpha\_F = 0.1,0.2,\ \beta = 5,6,7,\dots,20$ | 288 |
| Oscillatory Transient + Harmonics | T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots,800$, $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15 | 2592 |
| Swell + Harmonics + Oscillatory Transient | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$, $\alpha_3,\alpha_5,\alpha_7$=0.05, 0.1, 0.15, $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots,800$, | 85536 |


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| | | |
|---|---|---|
| Sag + Harmonics + Oscillatory Transient | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots.,800$, | 96228 |
| Swell + Harmonics + Flicker | T=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, $\alpha\_F = 0.1,0.2$, $\beta = 5,6,7,\dots,20$ | 76032 |
| Sag + Harmonics + Flicker | T=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, $\alpha\_F = 0.1,0.2$, $\beta = 5,6,7,\dots,20$ | 85536 |
| Oscillatory Transient + Harmonics + Flicker | T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots.,800$, $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, $\alpha\_F = 0.1,0.2$, $\beta = 5,6,7,\dots,20$ | 82944 |
| Interruption + Oscillatory Transient + Harmonics | T1=0.4,0.5,0.6,…….,3.6, $\alpha = 0.9$ and 1.0 $\alpha\_OT = 0.1,0.2,0.3,\dots,0.8$, T2=0.2,0.4,0.6,0.8,1.0,1.2, $f_n = 300,400,\dots.,800$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15 | 171072 |
| Swell + Harmonics + Interruption | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.8$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, T2=0.4,0.5,0.6,…….,3.6, $\alpha = 0.9$ and 1.0 | 4752 |
| Sag + Harmonics + Interruption | T1=0.4,0.5,0.6,…….,3.6, $\alpha\_S = 0.1,0.2,0.3,\dots,0.9$, $\alpha_3, \alpha_5, \alpha_7$=0.05, 0.1, 0.15, T2=0.4,0.5,0.6,…….,3.6, $\alpha = 0.9$ and 1.0 | 5346 |

### *B. Results Evaluation*

For the above specified experimental dataset, the simulation is conducted over multiple times with varying noise level and at every simulation; the performance is realized using execution metrics like Accuracy, Detection Rate (DR) or Recall, Precision, F-Measure, False-Positive-Rate (FPR) and Computational time (CT). These execution metrics are measured through the confusion matrix. The basis for these metric evaluations is confusion matrix and it is represented in table.3.

**Table.3. Sample Confusion Matrix**

| | | Predicted | |
|---|---|---|---|
| | | Normal | Disturbance |
| Actual | Normal | TP | FN |
| | Disturbance | FP | TN |

From the obtained TP, TN, FP and FN values the confusion matrix, execution metrics are evaluated and the respective mathematically given as;

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (19)$$

$$Precision = \frac{TP}{TP+FP} \qquad (20)$$

$$Detection\ rate\ or\ Recall = \frac{TP}{TP+FN} \qquad (21)$$

$$False\ Positive\ Rate = 1 - Recall \qquad (22)$$

$$F - Score = \frac{2*Recall*Precision}{Recall+Precision} \qquad (23)$$

Where

TP is True Positives, TN is True Negatives, FP is False Positives and FN is False Negatives.

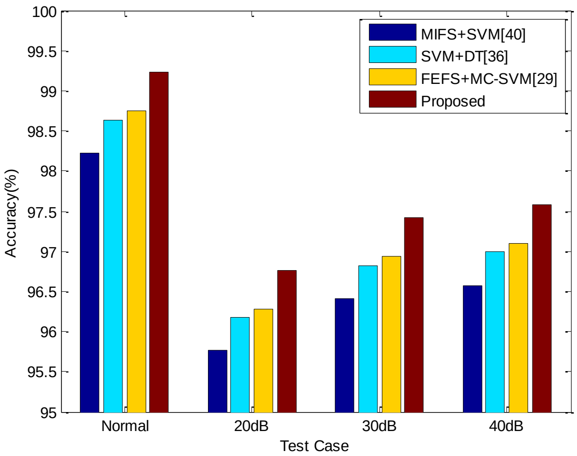


**Figure.3 Average Classification accuracy for varying SNR**

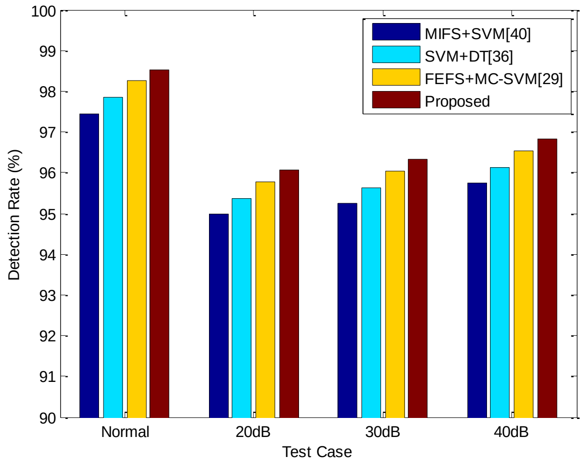


**Figure.4 Average DR for varying SNR**

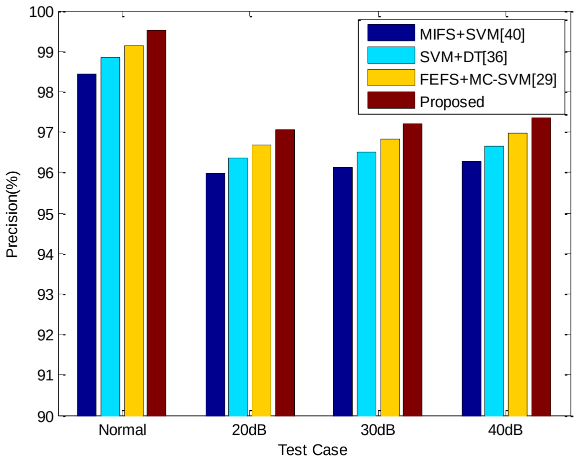


**Figure.5 Average Precision for varying SNR**

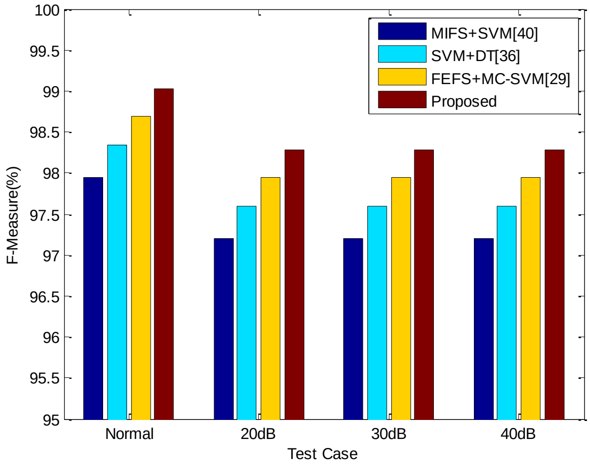


**Figure.6 Average F-Measure for varying SNR**

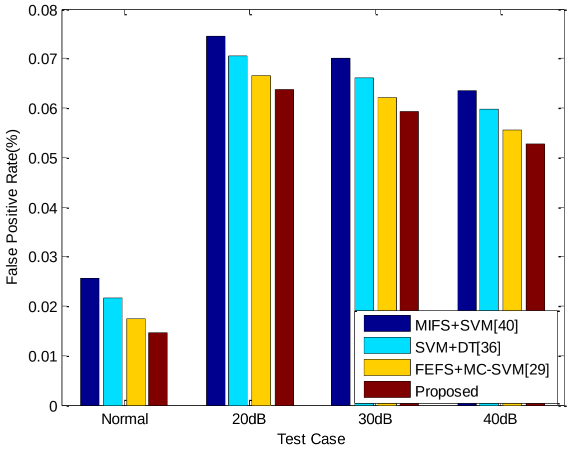


**Figure.7 Average FPR for varying SNR**

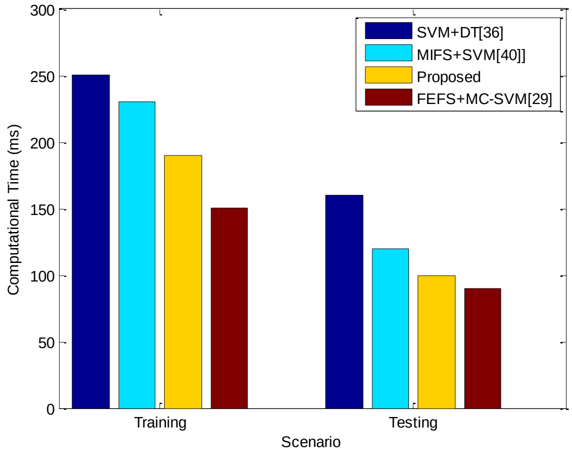


**Figure.8 Average Computational Time (ms) Comparison**

After getting the performance evaluation, the obtained execution metrics such as Accuracy, Detection Rate, Precision, F-Measure and Computational time are represented in figures from 3 to 8 respectively. These metrics are measured according to the formulae specified in the above section. Since the performance is accomplished over varying SNR levels, the above figures denote the average values of all metrics. From figure.3, it is observed that the proposed approach has secured an enhanced classification accuracy when compared to the traditional approaches. As itself the proposed approach is a hybrid mechanism it can detect all possible disturbances more effectively. Furthermore, the proposed approach reduced the features which are more redundant thereby the extracted final set of features is more effective. The final set of features provides a perfect discrimination between the disturbances such that the classifier will classify more easily without any confusion by which the proposed method obtained improved classification accuracy. Further the results depicted in figure.4 represent the details of average detection rate for varying SNR levels.

From figure.4, it is clear that the detection rate is high for normal case and it followed an increasing slope with an increment in the SNR level. For 20db SNR, the DR of proposed approach is observed as 96.02 approximately whereas it is observed as 96.23 and 96.89 at 30dB and 40dB SNRs respectively. Simply it can be demonstrated as the PQD signal with more SNR has more clarity about the type of disturbance. In the existence of noise, the amplitude of PQD signals will change and results a less discrimination between the features set of individual signals. A similar metric, precision for varying SNR levels is represented in figure.5. Further the subsequent metric of DR and Precision, F-Measure is represented in figure.6. The F-measure is simply a harmonic mean of precision and recall and it is directly related to these metrics.

Next, the details of FPR for varying SNRs are represented infigure.7. Here the FPR is measure as the ratio between the number of negatives signals wrongly classified as positive (false positives) and the total number of original disturbance signals (irrespective of classification). Furthermore, the FPR is simple obtained by subtracting the DR form one. Based on this, simply the FPR can be stated as the values remained after the evaluation of DR from total values. Hence, the FPR follows an opposite relation with DR and if the DR is high, the FPR is low and vice versa. The characteristics of FPR (figure.7) are observed to be in the range of 0-0.08 whereas the DR range is 95-99. Besides, the FPR of


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proposed approach is seen as less in all experiments. Since the proposed methodology achieved the Decision tree for the classification of PQDs (both single and numerous) the FPR is less contrasted with the traditional methodologies, MIFS+SVM [40], SVM+DT [36], and FEFS+MC-SVM [29]. Among these approaches, the first one, MIFS+SVM considered mutual information between the PQD signals to extract the optimal feature set and used SVM for classification. But this method just considered MI as a reference criterion for the feature subset selection. To achieve an optimal feature set, the obtained MI required to be normalized further (Related to the FEFS). Based on this aspect, the most recent approach, FEFS+MC-SVM performs normalization over the obtained MI but the redundant features reduced through this method are not selected based on the joint relevancy of different classes. Next, a hybrid PQD detection and classification technique is proposed in [36] with the help of SVM and DT. This method considered HS-transform features extraction but these features are not sufficient to discriminate the PQDs. Based on the inspiration of [36], the proposed approach also considered two algorithms for classification of PQDs and obtained an effective performance in the detection of all possible single and multiple PQDs.

Computational time is one more important factor on which current researchers are mostly focusing. The CT is direct proportional to the dataset size. Besides, size dataset increases, CT also increases and it reduces when the dataset size reduces. In the conventional approaches, most of the research focused to achieve an increased accuracy but not focused much on the time complexity. In the proposed approach and also the conventional approaches (only considered for comparison), the focus was made over the CT also by proposing different feature selection techniques. But they have their own disadvantages while extraction of most optimal set of features through which the all PQD signals can be distinguished in a more discriminate procedure. The proposed strategy has got succeeded in this evaluation and extracts only the most relevant features those are related to all possible classes; hence the CT of proposed approach is less. The obtained results of CT are shown in figure.8. Both the training time and testing time taken in the accomplishment of proposed and conventional approaches are represented in Figure.8. As it can be seen from figure.8, both the training & testing time of proposed approach got better compared to the traditional approaches, MIFS+SVM [40], SVM+DT [36], but it is more when compared to FEFS+MC-SVM [29]. Since the method [29] is considered only one algorithm for classification, the computational time is observed as less. Whereas the other conventional approaches, MIFS+SVM [40] only considered MI and SVM+DT is of two algorithms. These conventional approaches didn't focus over the tradeoff between performance and computational time but this was achieved through the proposed approach.

## VI. CONCLUSION

This paper presented a two stage PQD classification, detection framework focusing towards the provision of tradeoff between the performance and computational time. To increase the performance in the classification of all possible PQD events, this paper approached two supervised learning algorithms, SVM and Decision Tree. As SVM is more effective in the case of binary classification and Decision tree is most prompt method in the detection of tree structured events, this paper considered these two algorithms only to classify the both one and numerous power quality events. Further to reduce the computational time due to these two algorithms, this paper focused over the reduction of redundant features form every PQD signals. Towards the feature extraction, this paper considered both linear and non-linear dependencies through MI and correlation. Simulations are carried over the given approach through various SNRs and the performance s measured through execution metrics like accuracy and computational time and for every test case, the obtained results of given approach outperforms the traditional approach in both the aspects.

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