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Power Quality Disturbances Classification Through Optimal Feature Selective Mechanism

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Abstract: In the Detection and classification of Power Quality Disturbances, feature selection is very important because the more number of features causes more complexity and less number of feature impacts the accuracy. Hence, this paper proposed a new feature selection mechanism called as Flexible Mutual Information based Feature Selection (FMIFS) to represent the Power Quality Disturbances with an effective set of features. FMIFS computes the Mutual Redundancy between PQDs and removes redundant features between them. Once the optimal features are obtained for each PQD, then they are fed to Multi-class Support Vector Machine (MC-SVM) for classification. MC-SVM classifies each PQD based on the feature trained to the system. At experimental analysis, we applied our method on totally 11 types of PQDs for classification and the performance is measured through recall, precision, F1-score, and False Alarm Rate (FAR).

Keywords: Power Quality Disturbances, Mutual Information, Mutual Redundancy, Support Vector Machine, F1-Score.

I. INTRODUCTION

In recent years, due to the rapid growth in the power electronic equipment components, solid state switching devices used in the public sectors and industrial sectors, an increased quality of power is demanded which makes the sensitive equipment more secure from typical power accidents. The quality of electrical supplies has gradually become an important issue for electric utilities and their customers. Since the occurrence of power quality disturbance results a great impact over the equipment, there is a need to design effective power disturbance detection mechanisms by which the safe and economical operations can be preserved more efficiently in the electric systems. Hence, the study and analysis of issues in the power systems is significantly more important for the improvement of power quality. Particularly the exact detection and classification of power quality disturbances is a top priority in this direction and can also support power quality evaluation.

Generally the problems associated with power quality are voltage sag/swell with and without harmonics, interruption, oscillatory transient, pure harmonics, and flicker etc. [1-3] Along with these problems, there exist some more problems, derived based on the deviations in the time, magnitude and frequency characteristics of electrical signals. To detect and classify the power quality disturbances, a complete knowledge about the characteristics of electrical signals is required. So many approaches are developed in earlier to analyze the in depth nature of different electrical signals such that the perfect discrimination between the power quality problems can be obtained. Based on the past studies, the detection and classification of power quality problems is carried out in three phases, (i) preprocessing, (ii) feature extraction and (iii) classification. Feature selection is always the key element among these processes as some essential features may be overlooked and some non-essential features may be inappropriately regarded. Any resulting combination of inappropriate attributes would add to the difficulty of classification when disturbance and noise exist simultaneously. In the feature extraction phase, extracting the optimal feature set is more important by which the classification accuracy increases significantly. But this feature extraction could not result in extra burden over the system. For this purpose, the obtained feature set needs to be optimal and also more

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informative. Further selection of an appropriate classifier also constitutes a major concern in this PQD detection regard.

Towards such aim, this paper proposes a new feature selection mechanism to represent each PQD signal with only few and optimal set of features. The proposed mechanism is called as Flexible Mutual Information based Feature Selection (FMIFS) which consider Mutual Redundancy (MR) between two PQDs to get the optimal features. The MR is evaluated based on the relation between on two aspects; they are (1) feature-to-feature relation and (2) Feature-to-Class relation. Once the optimal feature selection is completed, they are fed to Multi-class Support Vector Machine (MC-SVM) for classification.

Rest of the paper is organized as follows; section II provides the details of related work. The complete details of proposed FMIFS and MC-SVM are explored in section III. The details of simulation experiments and results are explored in section IV and concluding remarks are provided in section V.

II. RELATED WORK

There are several sources of disturbances in any real-time system and it is unquestionably essential to detect and classify the disturbances automatically to improve the quality and reliability of power. Different approaches are proposed in earlier to achieve maximum detection accuracy in the power quality disturbances detection. Based on the objective aimed to achieve, the earlier developed approaches are categorized as feature extraction approaches and classification approaches.

A. Feature Extraction approaches

In this category, the techniques extracts the feature form signals to understand the characteristics of different power quality problems. Different techniques such as wavelet transform (WT), short-time Fourier transform (STFT), Gabor–Winger transform, S-transform (ST) have been applied for detection and classification of PQ disturbances over the past years [4-10]. STFT [4] provides the information about time-frequency characteristics of a disturbance signals, however it has fixed window size which results in the not-efficient representation about the behavior of transient signals. Further the multi-resolution analysis (MRA) [5] and its derivatives are accomplished over the electrical signals to analyze the characteristics of power quality disturbances in the resolution level but it is observed that the performance is quite less in the case of noise affected signals. To overcome this drawbacks, some more techniques like WT [6], [14], S-Transform [7], [8], [13] Kalman filter [9] Gabor-Winger Transform [10], Hilbert Haung Transform (HHT) [11], and Parallel Computing [12] have been proposed for the detection of power quality disturbances in the noisy environments [15]. Wavelet Transform decomposes a the PQD signal into low frequency and high frequency bands through which the more detailed information about the signal disturbance can be revealed. But when the signals are buried under harmonica or noise, Wavelet based methods becomes unreliable. Further the main drawback with WT and its subsequent is the spectral leakage by which the performance of PQD detection system becomes degraded [20].

Hilbert Haung Transform based on empirical mode decomposition is proposed in [16], [17] to analyze the power quality disturbances of the electrical signals by decomposing them into intrinsic mode functions (IMFs). Here the signal is decomposed into IMFs initially and then they are processed for analysis through Hilbert transform. However the HHT cannot reveal the frequency characteristics of the signal followed by resulting in an increased burden. S-Transform is derivative of WT and inherits the STFT and WT since it is considered as the WT with phase correction or STFT with variable sized window. Since the ST [18], [19] has an ability to analyze the signal even under noisy environments, there has been a wide usage is observed in the detection of Power quality disturbances. However, the high computational demand of ST constraints it's application to real time applications. Though all these transform techniques can alleviate the characteristics of power quality problems effectively, considering all the feature results in an unnecessary computational complexity, which was not focused in earlier approaches.

B. Classification Approaches

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In this category, the main objective is to achieve maximum detection accuracy. Different techniques such as Artificial Neural Networks (ANN) [21-23], Fuzzy Logic (FL) [26], Decision Tree (DT) [28], K-nearest Neighbor (K-NN) [25], Support Vector Machine (SVM) [24], and AdaBoost [27] etc. have been applied for detection and classification of PQ disturbances over the past years. Kanirajan et. al., [21] proposed power quality disturbance detection technique by combining wavelet transform with radial basis function neural network (RBFNN). The obtained results are compared with generalized regressive neural network, feed forward neural network, learning vector quantization and probabilistic neural network techniques and it is shown that the accuracy is improved. Adaptive feature extraction technique that combines the EMD and Hilbert Spectral Analysis is combined with probabilistic neural network in [23] to detect the multiple power quality problems.

Further the Moravej et.al., [24] proposed a PQ detection technique based on the support vector machine algorithm based on the inherent characteristics of signals. In [25], a new method is developed based on the K-nearest neighbor classifier by measuring the correlation to detect and classify the transmission line faults. The noise immune S-transform is combined with fuzzy expert system in [26] for assigning a certainty factor for every classification rule thereby to improve the robustness of the PQ detection system in the presence of noise. Another approach for power quality detection is proposed by considering the rule-based S-Transform as a feature extraction and an Adaptive Boost (AdaBoost) as a classifier in [27]. By considering the advantages of ANN and decision tree, a hybrid power quality detection framework is proposed in [28]. This approach is applied on multiple PQ disturbances such as harmonics with swell, sag, interruption and flicker. However all these approaches have their own advantages and disadvantages like some methods are robust for only some power quality problems. For example, the decision tree algorithm achieves better classification accuracy in the case of normal power quality problems but won't work on the harmonics based power quality problems. Similarly the convergence time of neural network related approaches is observed to be high

III. PROPOSED APPROACH

The complete methodology of the developed system is executed in two stages; one is training stage and second is testing stage. The system model is shown in Figure.1.
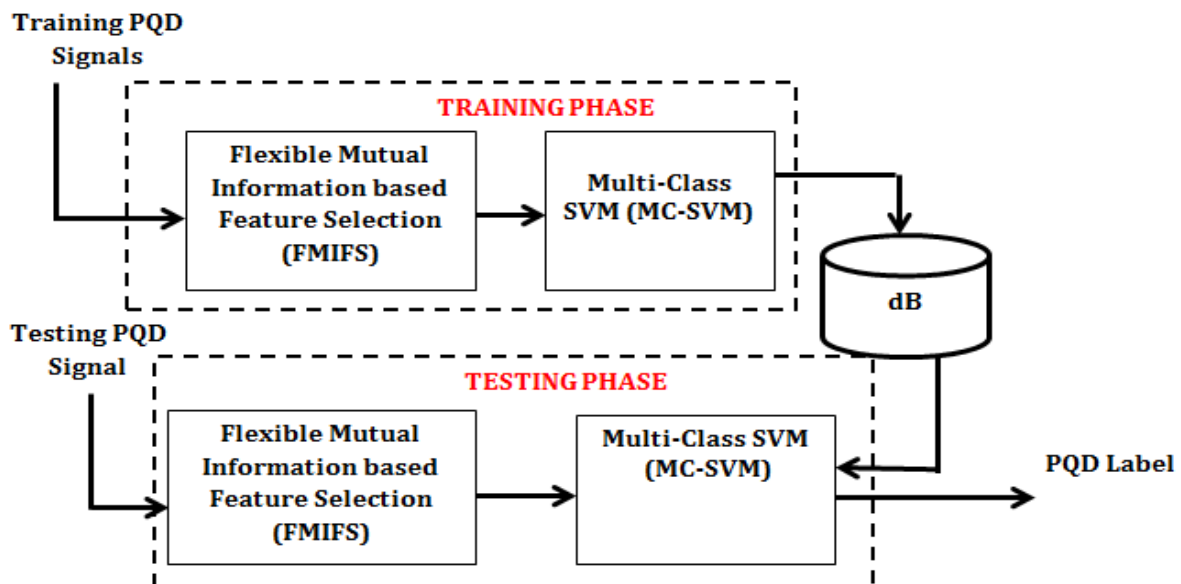

Figure.1 Block diagram of FEFS with MC-SVM based PQD detection

In the training phase, the system is trained with several PQDs such that it can acquire a plenty of knowledge about their characteristics and also can acquire the discrimination capability. In the testing phase, the trained system is subjected to testing process to assess the detection performance. According to figure.4.1, initially, for a given input PQD signal, FMIFS is applied to extract the

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entropy features and then fed to SVM classifier for classification. SVM is a binary classifier and at a time, it can classify only two classes, but our work needs more than two classes. Hence this work accomplished SVM at multiple phases, called as Multi-Class SVM (MC-SVM). At every phase, two classes are detected by SVM classifier. For example, the first mode SVM classifies the input PQD signal into two classes such as normal class and disturbance class. If the signal is classified as disturbance, then it is again fed to second mode SVM. Finally for the classified results, the performance is evaluated with the help of several metrics such as FAR, and Accuracy.

3.1. Feature Selection

Feature Selection has a great importance in the system developed for the PQDs detection. The main intention of a FS is to select an optimal and significant set of features from input PQD thereby the detection system can achieve a better classification results with less computational burden. The feature selection mechanism select only a small set of features from entire signal which results is a reduced feature recount, resulting in a less computational burden. Moreover, the small set of features are more informative and can also provide a discriminative knowledge to the detection system such that the system can classify the PQD signals more effectively, results in an increased accuracy. The feature extraction is accomplished at pre-processing phase. To perform this, a simple study and analysis is required about the characteristics of every PQD signal because, in real time there are so many kinds of PQDs. Purely, the FS mechanism is well-defined as an approach that converts the input PQD from one domain to another domain.

A. Mutual Information based Feature selection (MIFS)

In this contribution, the FS is accomplished through MI. There are so many methods like Euclidean Distance, MI, Distance Distribution Law and Correlation etc., to find the spatial relationships between the signals. Among those methods, MI has a promising solution in which it can measure the dependency estimation of a variable. Moreover, the MI is more proficient in the discovery of linear as well as non-linear dependencies between different aspects of signals. Hence, in this work we have chosen MI for FS process. MI derives the Mutual Relationship between two independent/dependent variables. For a given two statistical variables, a larger value of MI denotes a higher mutual dependency and lower value denotes mutual independency or lower mutual dependency between the variables.

Consider two PQDs A and B as $A = \{a_1, a_2, a_3, \dots, a_n\}$ and $B = \{b_1, b_2, b_3, \dots, b_n\}$, where n denotes the total samples count in both the signals A and B, the MI between A and B is measured as

$$MI(A; B) = H(A) + H(B) - H(A, B) \qquad (1)$$

Where $H(A)$ is the entropy of signal A, $H(B)$ is the entropy of signal B and $H(A, B)$ is the joint entropy. Mathematically the entropy and joint entropy are measured as;

$$H(A) = \sum_{i=1}^{n} p(a_i) \ \log(p(a_i)) \qquad (2)$$

And

$$H(B) = \sum_{i=1}^{n} p(b_i) \ \log(p(b_i)) \qquad (3)$$

And

$$H(A, B) = \sum_{i=1}^{n} \sum_{j=1}^{n} p(a_i, b_j) \ \log\left(p(a_i, b_j)\right) \qquad (4)$$

A simple representation to measure the MI between two variables A and B can be shown as

$$MI(A; B) = \sum_{i=1}^{n} \sum_{j=1}^{n} p(a_i, b_j) \ \log\left(\frac{p(a_i, b_j)}{p(a_i)p(b_j)}\right) \qquad (5)$$

Where $p(a_i)$ and $p(b_j)$ are the marginal density functions of signal A and B respectively, and $p(a_i, b_j)$ is the joint probability density function.

In the FS process, the features are considered as either relevant or redundant. If any feature contributes information about class C, then it is treated as relevant to class C otherwise it is treated as

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redundant. For a give feature f_i and class C, the relevancy or redundancy is measured through $MI(C; f_i)$. In this environment, if we noticed larger values of MI, then the features can be considered as more powerful and contributes more information towards the class. On the other side, if we have noticed that the $MI(C; f_i)$ is zero, then the class C is considered to be independent with feature f_i, thereby the feature f_i is redundant and removed from the feature set.

B. FMIFS

In the algorithm 1, step 4, the factor β signifies the importance of relative MI between the features which are already chosen as relevant to class C and the candidate feature. In this scenario the variations of β are conveyed through two values. If $\beta = 0$, the feature selection process considers only the mutual information with output class. If $\beta = 0$ ($\beta > 0$), the FS measure eliminates particular quantity of data relative to the MI with respect to the features which are already selected. However, assigning an appropriate value for β is a complex and tedious task in the detection and classification of PQDs. To overcome this problem, this work proposes a modified version of MIFS called as FMIFS. This new way of feature selection is a simple extension to the earlier entropy based feature selection and modifies the process at step 4 in algorithm 1. In the new approach, the feature selection process considers the minimum redundancy between the features and the selection process at step 4 is replaced by the equation (6).

$$G_{MI} = \underset{f_i \in F}{\operatorname{argmax}} \left(MI(C; f_i) - \frac{1}{|s|} \sum_{f_s \in S} MR \right) \qquad (6)$$

In the above equation, the new feature selection process considers the minimum redundancy (MR) instead of MI between the features and class. A feature which has maximum MI with class and also has average minimum redundancy is only selected. The MR is obtained as;

$$MR = \frac{MI(f_i; f_s)}{MI(C; f_i)} \qquad (7)$$

Where $f_i \in F$ and $f_s \in S$. In the above equation, $MI(C; f_i)$ denotes the MI between class C and feature f, reveals the significance of feature f with respect to class C. Next, the term $MI(f_i; f_s)$ reveals the MI between already selected feature f_s and feature f_i, reveals the redundancy. If $MI(C; f_i) = 0$, f_i is eliminated without the computation of G_{MI}. If f_i and f_s found to have a high relative dependency between then with respect to $MI(C; f_i)$, f_i gives to the redundancy. Moreover, to decrease the total feature count, a numerical threshold is applied over the G_{MI} in equation (3.6), and the obtained G_{MI} has following two cases;

Case 1: $G_{MI} = 0$. In this case, the candidate feature f_i has no contribution towards class C, thus f_i is eliminated from the feature subset.

Case 1: $G_{MI} \neq 0$. In this case, the candidate feature f_i has some contribution towards class C, thus f_i is added to the feature subset.

In this way, the size of feature set is decreased such that the final feature subset consists of only optimal features and they are trained with reduced computational complexity and CT.
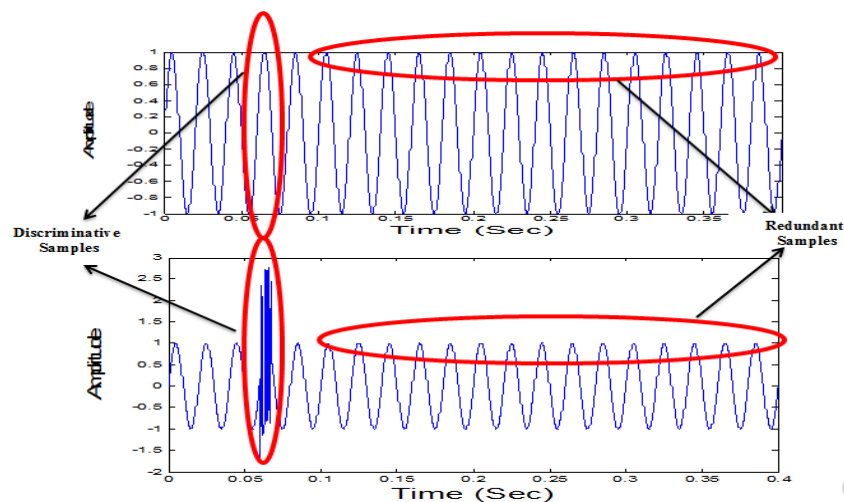
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Figure.2 Example representation of FMIFS based feature extraction

As shown in the above Figure.2, the PQD signals are elapsed with 0.4 sec and they have approximately 4001 samples (noticed during the simulation). Among the 4001 samples, maximum sample convey same information and only few samples convey discriminative information. We have to find those samples only such that the computational burden over the detection and classification system will reduce. Here the main responsibility of FMIFS to fetch that features only. Based on the obtained feature subset S, the more discriminative sample samples are only extracted form PQD signal. From the above figure, we notice that the FMIFS extracts the discriminative Samples and also removes the unnecessary redundant samples. In this work, the FMIFS is applied at both training and testing phases. In the case of testing the discrimination is ensured by finding the mutual entropies between two different PQD signals at a time. In the case of testing, the discrimination is ensured through the mutual redundancy between different samples of same PQD signal.

IV. SIMULATION EXPERIMENTS

This section demonstrates the simulation test details. Initially, the simulation set up formulated to conduct tests is discussed. Next, the details of performance metrics accomplished for simulation are explored. And then the results obtained after the simulation are discussed. Finally the comparative analysis conducted between the proposed model and tradition models is explored to show the effectiveness.

4.1. Simulation setup

To simulate the proposed FMIFS + MC-SVM model, we have used MATLAB software. Initially the PQDs are generated conferring to the mathematical representations depicted Table.2.1. For every class of PQD, number of signals is generated by varying the control parameters. For example, the control parameters for swell signal is α. For a given range constraints of α, it was varied $\alpha = 0.1, 0.2, 0.3, \dots, 0.8$. Further the range constraint of time (T) is 0.4 to 3.6. With an increment of T = 0.1, the total number of possible values can be generated is 33 and for every T values, α is varied. Based on these observations, the total number of possible swell signals can be generated are $33 \times 8 = 264$. Similarly, for every PQD class, number of signals is generated and the signals generated for every class. All these signals are generated by varying their respective control parameters. These signals are divided into two groups, training set and testing set. The total number of signals divided as training and testing signals are represented in Table.1.

Table 4.1 Training and testing set considered for simulation

PQD	Class Label	Total signals	Training Set	Test Set
Normal	C_1	10	7	3

Swell	C_2	264	185	79
Sag	C_3	297	208	89
Flicker	C_4	32	22	10
Interruption	C_5	66	46	20
Oscillatory transient	C_6	288	202	86
Harmonics	C_7	27	19	8
Notch	C_8	144	101	43
Spike	C_9	144	101	43
Swell with harmonics	C_{10}	216	159	57
Sag with Harmonics	C_{11}	241	175	66
Total		**1729**	**1225**	**504**

The entire set of 1729 signals is grouped into two groups namely training and testing. Among the total 1729, 1225 are grouped as training and the remaining 504 are grouped as testing. Under this simulation, we consider two complex PQDs as additional classes; hence the total classes count has become 11, total signals generated has become 1729, total signals used for training are 1225 and total signals used for testing are 504.

4.2. Results

Under the simulation, the proposed approach is simulated for two cases, one is under normal case and other is noisy case. For both cases, the proposed detection system is subjected to the testing with same number of testing signals and the performance is measured individually. In both cases, initially, the detection system is trained with 1225 PQD signals and then tested with 504 signals. In both training phases, initially the PQD signals are subjected to feature selection through FMIMFS. Next, the obtained features are trained in training phase and in the testing phase they are fed to MC-SVM classifier.

a. Case 1: Normal

Under this simulation, the proposed detection system is processed directly with raw signals. After testing, the classified results are formulated into a confusion matrix, as shown in Table.2. Based on the values shown in the confusion matrix, the performance metrics are evaluated and they are formulated in the Table.3.

Table.2 Classification result of testing signals (Confusion matrix)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	**Total**
C_1	**3**	0	0	0	0	0	0	0	0	0	0	3
C_2	0	**76**	0	0	0	0	1	0	0	2	0	79
C_3	0	0	**87**	0	0	0	1	0	0	0	1	89
C_4	0	0	0	**7**	0	1	0	1	1	0	0	10
C_5	0	1	1	0	**17**	0	0	0	0	1	0	20
C_6	1	0	0	1	0	**82**	0	0	1	1	0	86
C_7	0	1	0	0	0	0	**7**	0	0	0	0	8
C_8	0	1	0	1	0	0	0	**40**	1	0	0	43
C_9	0	0	1	0	0	1	0	1	**39**	0	1	43
C_{10}	0	2	0	0	0	0	2	0	0	**53**	0	57
C_{11}	0	0	2	0	0	0	0	1	1	0	**62**	66
Total	4	81	91	9	17	84	11	43	43	57	64	504

Table.3 Performance evaluation metrics under normal simulation

Class	Recall (%)	Precision (%)	F1-Score (%)	FAR (%)
C_1	100.00	75.0000	85.7100	25.0000

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C_2	96.2000	93.8300	95.0000	6.1700
C_3	97.7500	95.6000	96.6700	4.4000
C_4	70.0000	77.7800	73.6800	22.2200
C_5	85.0000	100.00	91.8900	0000
C_6	95.3500	97.6200	96.4700	2.3800
C_7	87.5000	63.6400	73.6800	36.3600
C_8	93.0200	93.0200	93.0200	6.6900
C_9	90.7000	90.7000	90.7000	9.3000
C_{10}	92.9800	92.9800	92.9800	7.0200
C_{11}	93.9400	96.8800	95.3800	3.1300

The performance metrics shown in table 4.3 are measured based on the confusion matrix shown in table.2. In this chapter, along with nine basic PQDs two more PQDs are added at simulation and the performance metrics are measured. The extra added two more PQDs are Swell with Harmonics (C_{10}) and Sag with Harmonics (C_{11}). From the table.3, it can be observed that the maximum recall rate is achieved for Class 1 (Normal – 100%) and minimum is for Class 4 (Flicker - 70%). Next, the maximum precision is observed for Class 5 (Interruption - 100%) and minimum is for Class 7 (Harmonics – 63.6400%). Further, the maximum F1-Score is observed for two classes namely Class 4 (Sag - 96.6700%) and minimum is for two classes Class 4 (Interruption – 73.68%) and class 7 (Harmonics – 73.68%). Finally, the maximum FAR is observed for Class 1 (Harmonics - 36.36%) and minimum is observed for Class 5 (Interruption – 0%).

B. Case 2: Noisy

Under this simulation, the proposed detection system is processed directly with Noisy input Signals. After testing, the classified results are formulated into a confusion matrix, as shown in table.4. Based on the values mentioned in the confusion matrix, the performance metrics are evaluated and they are formulated in the table.5.

Table.4 Classification result of testing signals (Confusion matrix)

Class	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	Total
C_1	**3**	0	0	0	0	0	0	0	0	0	0	3
C_2	0	**74**	1	0	1	0	1	0	0	2	0	79
C_3	0	0	**85**	0	0	0	2	0	0	0	2	89
C_4	0	0	0	**6**	0	2	0	1	1	0	0	10
C_5	0	2	1	1	**15**	0	0	0	0	1	0	20
C_6	1	0	0	2	0	**81**	0	0	1	1	0	86
C_7	0	1	0	0	0	0	**6**	0	0	0	1	8
C_8	0	1	0	1	0	0	0	**39**	2	0	0	43
C_9	0	0	1	0	1	1	0	2	**37**	0	1	43
C_{10}	0	3	0	0	0	0	2	0	0	**50**	2	57
C_{11}	0	2	1	0	0	0	0	1	1	1	**60**	66
Total	4	83	89	10	17	84	11	43	42	55	66	504

Table.5 Performance evaluation metrics under normal simulation

Class	Recall (%)	Precision (%)	F1-Score (%)	FAR
C_1	100.00	75.0000	85.7100	25.0000
C_2	96.2000	93.8300	95.0000	6.1700
C_3	97.7500	95.6000	96.6700	4.4400
C_4	70.0000	77.7800	73.6800	22.2200
C_5	85.0000	100.00	91.8900	0000
C_6	95.3500	97.6200	96.4700	2.3800
C_7	87.5000	63.6400	73.6800	36.3600

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C_8	93.0200	93.0200	93.0200	6.9800
C_9	90.7000	90.7000	90.7000	9.3000
C_{10}	92.9800	92.9800	92.9800	7.0200
C_{11}	93.9400	96.8800	95.3800	3.1300

The performance metrics shown in table.5 are measured based on the confusion matrix shown in table.4. In this chapter, along with nine basic PQDs two more PQDs are added at simulation and the performance metrics are measured. The extra added two more PQDs are Swell with Harmonics (C_{10}) and Sag with harmonics (C_{11}). From the table 4.5, it can be observed that the maximum recall rate is achieved for Class 1 (Normal – 100%) and minimum is for Class 4 (Flicker – 70.0000%). Next, the maximum precision is observed for Class 5 (Interruption - 100%) and minimum is for Class 7 (Harmonics – 63.6400%). Next, the maximum F1-Score is observed for Class 3 (Sag - 96.6700%) and minimum is for Class 7 (Harmonics – 73.6800%). Finally, the maximum FAR is observed for Class 7 (Harmonics – 36.36%) and minimum FAR is observed for Class 6 (Interruption – 0%).

V. CONCLUSION

This paper majorly focused on the removal of redundant features from PQD signal which creates a he computational burden on the classification system. Towards such prospect, FMIFS is proposed which computes the redundancy between PQDs based on the mutual redundancy between them. Since the occurrence of disturbance lays only a few instances, the remaining features are considered as redundant and they are discarded through FMIFS. Once the optimal features are derived for each PQD, they are subjected to MC-SVM for classification. Experimental analysis through 11 types of PQDs proves the superiority of proposed approach.

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