mathematics

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A Hybrid Approach Based on Principal Component Analysis for Power Quality Event Classification Using Support Vector Machines

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Citation: Saxena, A.; Alshamrani, A.M.; Alrasheedi, A.F.; Alnowibet, K.A.; Mohamed, A.W. A Hybrid Approach Based on Principal Component Analysis for Power Quality Event Classification Using Support Vector Machines. *Mathematics* **2022**, *10*, 2780. https://doi.org/10.3390/math10152780

Academic Editors: Shujin Laima, Yong Cao, Xiaowei Jin and Hehe Ren

Received: 25 June 2022
Accepted: 28 July 2022
Published: 5 August 2022

Abstract: Power quality has emerged as a sincere denominator in the planning and operation of a power system. Various events affect the quality of power at the distribution end of the system. Detection of these events has been a major thrust area in the last decade. This paper presents the application of Support Vector Machine (SVM) in classifying the power quality events. Well-known signal processing techniques, namely Hilbert transform and Wavelet transform, are employed to extract the potential features from the observation sets of voltages. Supervised architecture consisting of SVM has been constructed by tuning the parameters of SVM by various algorithms. It has been observed that Augmented Crow Search Algorithm (ACSA) yields the best accuracy compared to other contemporary optimizers. Further, Principal Component Analysis (PCA) is employed to choose the most significant features from the available features. On the basis of PCA, three different models of tuned SVMs are constructed. Comparative analysis of these three models, along with recently published approaches, is exhibited. Results are validated by the statistical one-way analysis of variance (ANOVA) method. It is observed that SVM, which contains attributes from both signal-processing techniques, gives satisfactory results.

Keywords: power quality; harmonics; Support Vector Machine (SVM); Augmented Crow Search Algorithm (ACSA)

MSC: 68T01; 68T05; 68T07; 68T09; 68T20; 68T30

1. Introduction

In recent years, increasing demands and a competitive business environment have put a heavy burden on grid utilities. With modern power electronic devices, Power Quality (PQ) has become a major concern. In PQ problems, the deviation of voltage and current is observed from the ideal waveforms. Ideal voltage/current waveforms are sinusoidal signals of constant frequency and constant amplitudes [1]. Researchers have come forward with new approaches, designs, and hypotheses to improve the quality of power. Improvement of the quality refers to three common approaches namely identification, determination, and removal of the above said deviations from the voltage/current signals. Electromagnetic transients are the root cause of the PQ problems. These transients are occurred due to switching actions, lightning strokes, fault clearing mechanisms obtained by fuses, capacitor bank operation and end-user equipment switching [2]. Moreover the major causes of degradation in PQ are voltage sag, swell, flicker, notch, transients and harmonics [3–15]. PQ events recognition is an important issue for the development of the subsequent generation. This recognition can be done in two folds: firstly the employment of signal processing techniques like Wavelet transform [5,9,12,13] Discrete Fourier Transform (DFT) [4], Fast Fourier Transform (FFT) [5], Kalman filtering [3] and S-transforms [6–8,11] to extract few representative disturbance signals and secondly to use a supervised learning based paradigm for classification of the disturbances. Signal processing techniques are used for the separation of the disturbed signals into their frequency components. These processed frequency components with statistical attributes are characterized as features for classification. Traditionally Fourier transforms (FTs) are considered a powerful tool to analyze the frequency content of the signals. However, FTs are not efficient to extract the transient information from non-stationary signals [2]. Moreover, the non-stationary nature of PQ events also presents difficulty in the detection of disturbance waveforms. Recently, a Wavelet transform approach is applied by Yong et al. [9]. In this approach, one v/s and multiclass SVMs were employed. A three-stage algorithm namely preprocessing, feature extraction, and classification was employed in work [9]. Optimal feature selection by using k means aripori algorithm is performed in [13]. In the nine-level multiresolution analyses, Wavelet transform coefficients were obtained and a feature of having 90 dimensions is extracted from the signal data. SVM is used as a binary classifier to classify different events. Although Wavelet transforms are an efficient technique for feature extraction in the time and frequency domain, yet the excessive computation, vulnerability to the noise levels and dependency of the accuracy on the choice of mother wavelet make it less efficient for this recognition to be carried out. Another important methodology to detect PQ events is S-transform. Recently Biswal et al. [10] employed S-transform to extract the features from the disturbance signals by using a decision tree methodology. However, the decision tree methodology and several decision steps of the optimization algorithm caused time delay in classification. Short-Time Fourier Transform (STFT) was also employed in some approaches [4,5]. The quality of STFT is to divide the full time intervals into segments. However, the fixed window width of STFT is a significant limitation. The high-frequency signals, with multiple occurrences, pose a difficulty to detection. Recently, an interesting study of harmonic estimation with the application of a modified version of ACSA has been done in reference [16]. Till now various supervised learning models have been applied for the recognition of the PQ problems by researchers. These are namely Feed Forward Neural Network (FFNN), Radial Basis Function Neural Network (RBFNN) [15], Fuzzy classifiers [4,14], Modular Neural Networks [8], Probabilistic Neural Network [6] and Support Vector machines (SVMs) [9,10,12,13,17–20]. In some approaches Fuzzy classifiers are used along with Wavelet transforms [14], in which fuzzy classifier is advocated as a crisp classifier. The problem with fuzzy approaches is that there are no certain boundaries and a clear mathematical relationship between dependent and independent variables. For this reason, in many real classification problems, these approaches are not able to classify the events in an efficient manner. In the past, various approaches related to a single signal processing technique are observed and analyzed for PQ event classification problems. However, the combination of different signal processing techniques and statistical attributes of those remains unexplored. Further the reference [21], reports the application of optimized Bayesian convolutional neural networks for the classification of PQ events. The application of Variational Mode Decomposition and deep learning classifier (simple feed-forward neural network) has been employed for the classification of PQ events under the presence of distributed generation sources [22]. A Grey wolf Optimizer (GWO) based Extreme Learning Machine approach has been reported in reference [23]. The reference [24] reports the application of Discrete Wavelet Transform (DWT) on PQ data along with starting current data to identify the broken rotor bar and bearing fault in induction motors with a neural network for detection. A combined application of chirp mode pursuit and Grasshopper Optimization Algorithm has been reported in reference [25]. Real-time PQ analysis is conducted in reference [26].

The approaches pertaining to SVMs often employs optimization algorithms for tuning hyperparameters. As a parameter, tuning of the support vector machine always plays a critical role in the performance of classification accuracy. A hybrid algorithm-based approach has been proposed in reference to the identification of fault diagnosis of rotating machinery. The authors employed a hybrid algorithm called GWO and Sine Cosine Algorithm [27]. The GWO-based approach has been employed in the work for tuning the hyperparameter for the classification task [28]. In view of the above, the following literature review and objectives are formed for this work:

- To analyze two well-known signal processing techniques namely Hilbert and Wavelet transform for the PQ event classification problem.
- To perform the seven-level Multi-Resolution Analysis, in order to obtain the detailed and approximation coefficients of Wavelet transforms.
- To perform optimization with the help of a recently published advanced metaheuristic algorithm for hype parameter tuning of SVM and present a comparative analysis.
- To perform Principal Component Analysis (PCA) for choosing the efficient input features from the given 9 features.
- To build different modules of Support Vector Machines (SVMs) with the permutations of different efficient input features and present a comparison between these different modules on the basis of standard error indices.
- To test the efficacy of the proposed module by the statistical ANOVA test.

The remaining paper is organized as follows, In Section 2, system description along with preliminaries of PQ is discussed. The details of Hilbert and Wavelet transform are given in Section 3. Basics of SVM and tuning results are given in Section 4. In Section 5 PCA is discussed, following to this, results and conclusions are presented in Sections 6 and 7, respectively.

2. Materials and Methods

PQ disturbance classification is a potential area of research during the last decade. This section presents basic details for framing classification engine for PQ events.

2.1. Power Quality Events

PQ events are broadly classified into three categories namely short-term duration variations, e.g., sag, swell, interruptions [1]. Time durations of these events vary from a few cycles (5 cycles) to a minute. The second important category is the long duration, which consists of sustained interruptions, under voltage and overvoltages over a long time. The third category is transients. Description of the events along with the pictorial representation is exhibited in Table 1 and Figure 1 [29].

Table 1. Classification of power quality events.

S. No.	Categories	Duration	Voltage Magnitude
1.	Normal	-	Fundamental values
2.	Sag	Short term (up to 1 min)	0.1–0.9 p.u.
3.	Swell	Short term (up to 1 min)	1.1–1.4 p.u.
4.	Harmonic	Steady state THD > 5	
5.	Transients	<50 ns	0–4 p.u.

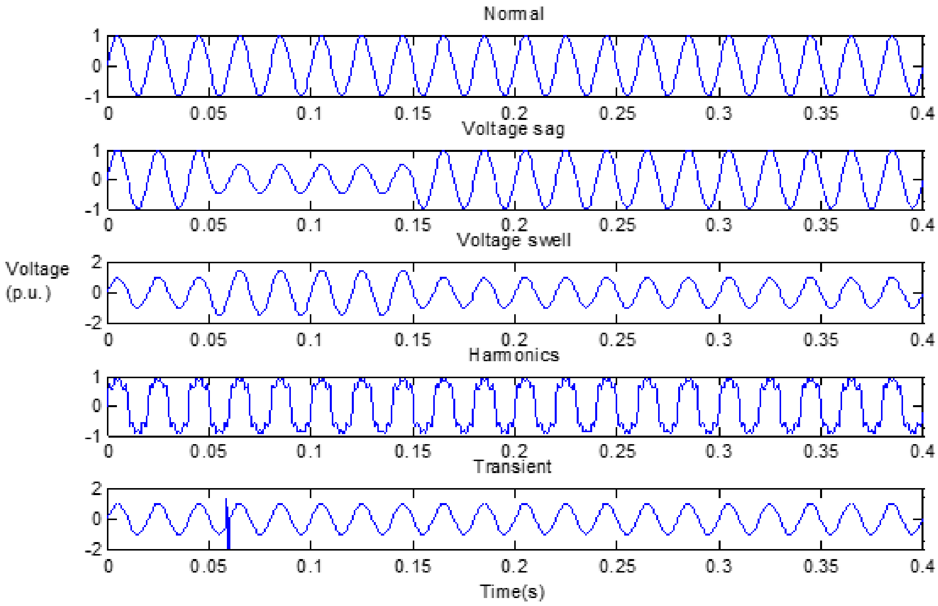


Figure 1. Different Power Quality Events.

2.2. *System Description*

To simulate this work a simple test network along with a laboratory setup, is shown in Figures 2 and 3. A three-phase power system (400 volts (line to line), 50 Hz) with a 100 km long transmission network terminated by an RL load of 10 ohms, 0.005 Henry is considered and simulated in Matlab Environment.

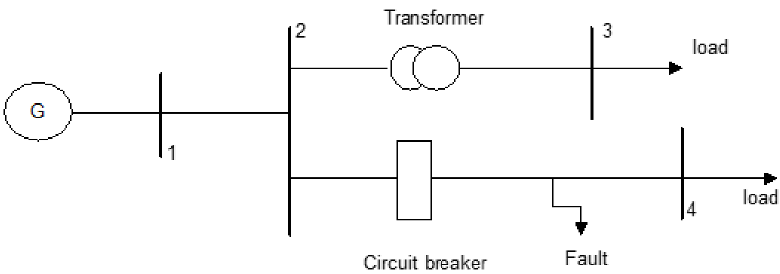


Figure 2. Test System.

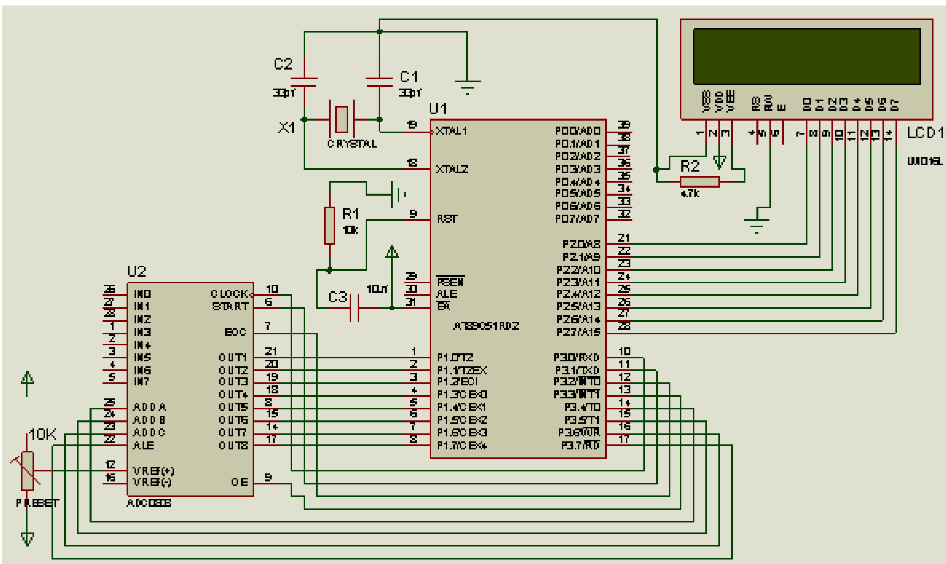


Figure 3. Laboratory Testing Module.

To analyze the system voltages, a potential transformer is employed with an Analog to Digital Converter IC-ADC 0808/0809. This chip is employed to convert analog signals into digital signals. This IC is an 8-bit IC; input three-phase voltages are given on input channels 0–2. The 8051 (Philips) P89V51RD2 microcontroller is the main processing unit for calculating the Hilbert and Wavelet transforms. The unit analyzes the output voltages along with the statistical attributes of features (standard deviations, mean, max, min, and norm values).

A seven-level Multi-Resolution Analysis (MRA) is processed for Wavelet transforms. The detailed coefficients window is shown in Figure 4a–d. Further, the digital to analog conversion is done with the help of DAC to show the status of waveforms. The responses under different operating conditions are analyzed by the controller and used for validation of the results of SVMs. The program for the micro-controller is written in C language. Liquid Crystal Display (LCD) 16 $\times$ 2 is used to display the results. In the first row, the initial five digits represent the target classes for all voltages. Target classes are shown in Table 2.

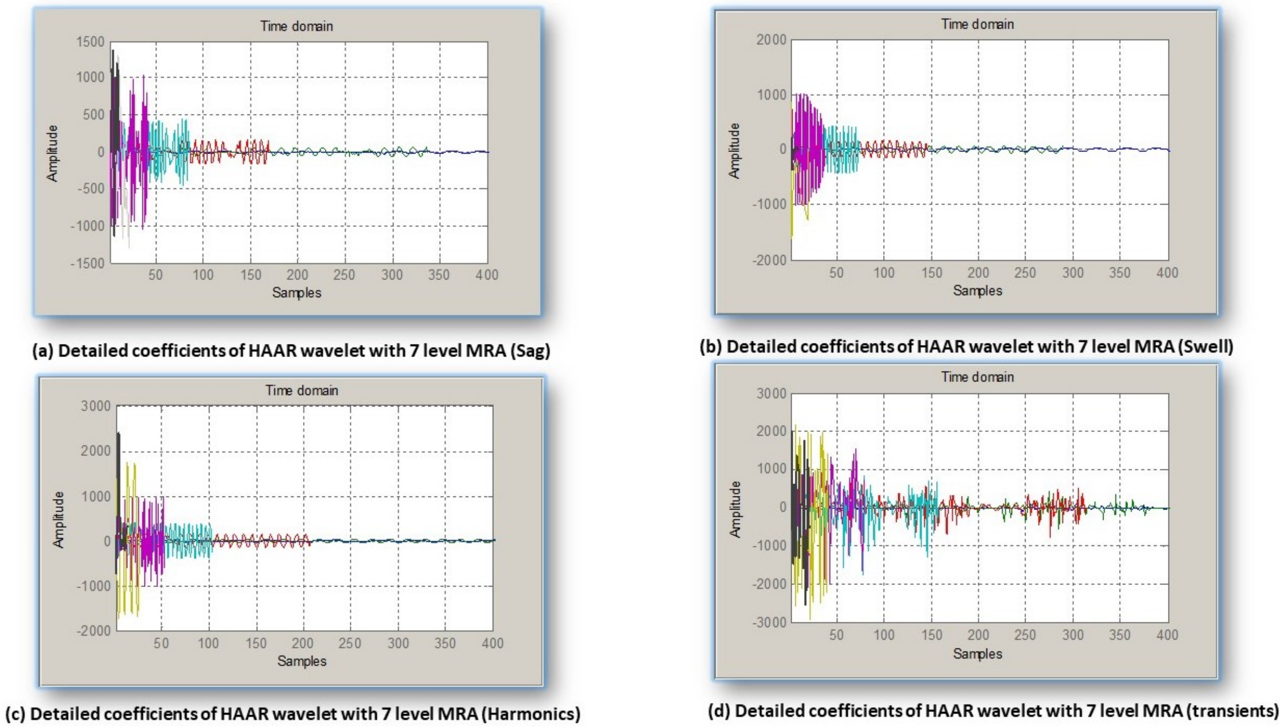


Figure 4. Analysis of detailed coefficients of HAAR Wavelet with different PQ events.

Table 2. Binary Classification for PQ event detection.

Sag	1	0	0	0	0
Swell	0	1	0	0	0
Normal	0	0	1	0	0
Transients	0	0	0	1	0
Harmonics	0	0	0	0	1

3. Signal Processing Techniques

In PQ events identification problems, the employment of an effective signal processing technique to extract significant features from the signals is the fulcrum of the module. In this section preliminaries pertaining to Wavelet and Hilbert transforms signal processing techniques are presented.

3.1. Wavelet Transform

In past, Wavelet transform shows the extraordinary capability to extract features in terms of detailed and approximate coefficients belonging to different event types. In reference [11], the coefficients associated with different levels along with statistical attributes of the coefficients are employed to train the neural networks. However, this procedure has a large number of input features according to different levels and incurs a heavy computational burden. Choice of mother Wavelet is also a critical issue in the Wavelet transforms. In this work "Haar" Wavelet is chosen for the feature extraction. "Haar" Wavelet is the simplest possible Wavelet and can be utilized for the analysis of signals with sudden transitions. A seven-level MRA is performed to extract detail and approximate coefficients. The detail and approximate coefficients alone are impractical to apply as inputs to the classifier. Hence, for each decomposition level, feature extraction methods are implemented. The energy at the decomposition level is given by the following equations:

$$E_i = \sum_{l=1}^{n} |D_{il}|^2 \quad i = 1, 2, \ldots, 7 \tag{1}$$

$$K_i = \sum_{l=1}^{n} |A_{il}|^2 \tag{2}$$

l is the decomposition level and n is the number of coefficients of detail or approximations at each decomposition level. Statistical attributes namely maximum, minimum, norm, mean values, and standard deviations of these coefficients at different decomposition levels are taken as the features. Figure 4a–d presents Detailed coefficients in a single window analyzer cumulatively for five events respectively. From this figure, it is empirical to judge that for complex events and with different multiple data sets, achieving higher classification rates from these features is a daunting task to perform. Windows for different events have been shown in Figure 4; it is empirical to judge that a clear distinction can be done by this transformation.

3.2. Hilbert Transform

Hilbert transform is a mathematical tool for the generation of an analytical signal from a real signal. It is obtained by convolving the real signal $g(t)$ with the function$(1/\pi t)$.

$$gH(t) = g(t)\left(\frac{1}{\pi t}\right) = \frac{1}{\pi}\int_{-\infty}^{\infty} g\left(\frac{\alpha}{t-\alpha}\right) d\alpha \tag{3}$$

A complex signal xc(k) consists of the original signal as a real part, and its Hilbert transform as an imaginary part. In this paper, the imaginary part of the complex voltage signal is captured for different types of events, and the statistical attributes are calculated of the transformed signals. Different statistical attributes of the Hilbert transform are employed as input features to SVM. Different statistical attributes for different events are shown in Figure 5. It is empirical to judge that for the events like sag, swell harmonics and transient this feature can be the source of important information to train the classifier. From Figures 4 and 5, it is judged that in many cases the performance of the classifier is based on the datasets.

Since no significant variations are observed in mean values, the following analysis will not include the mean of the signals as a potential feature. To compete with the pattern recognition-based classifiers, a hybrid approach, which employs features from both signal-processing techniques is more fruitful for such real problems. The motivation for this work hails from here only.

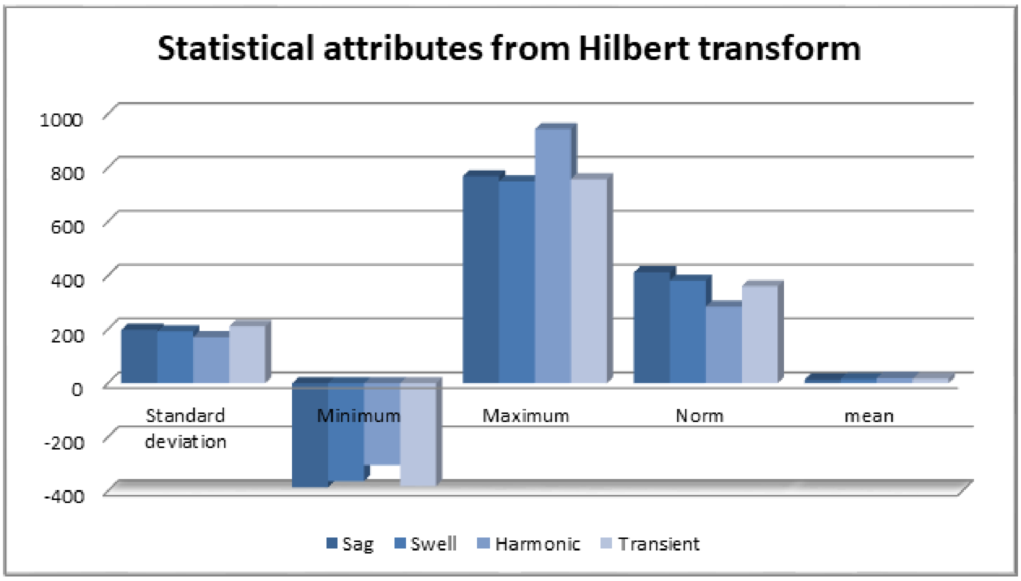


Figure 5. Values of different statistical attributes of Hilbert transforms for different events.

4. Support Vector Machines

In recent years, the applications of SVM in classification problems have increased due to its capability in the segregation of datasets by the best hyperplane. SVMs are applied for classification of PQ events [9,10,12,13,17–20], multi-dimensional data classification [17], classification of microarrays [18], wind speed prediction [19], voltage stability monitoring [20] and many more. The popularity of SVM is rising with every passing day because it can handle large feature space. Also, a large feature space cannot hinder the classification accuracy. In the case of other classifiers, the input feature space dimension is a very crucial design parameter [9].

Due to this virtue of SVM, its employment is a primary reason for large classification problems. SVM utilizes various kernel functions to transfer the input space of data to nonlinear high-dimensional data. A sparse prediction function is generated by choosing a selected number of points; these points are Support Vectors (SVs). SVMs possess two main features such as structural risk minimization and a tradeoff between empirical error and model complexity [19].

Let the n-dimensional inputs Xi (i = 1, 2, 3, . . . , m), where m is the number of samples belonging to class 1 and class 2. Associated labels are $K_{(i)}$ = 1 and $K_{(i)} = -1$. SVM is an inherently two-class separator, hence, the linear hyperplane that separates the data can be determined by the following equation:

$$f(z) = W^T z + d = \sum_{k=1}^{n} W_k z_k + d \tag{4}$$

where W is an n-dimensional vector and d is scalar. These two parameters determine the location of the hyperplane. The constraints are $f(z) \geq 1$ if $K_{(i)} \geq 1$ and $f(z) \leq 1$ if $K_{(i)} \leq -1$. The separating data plane that generates the maximum distance between the nearest data and the plane, is called the optimal separating hyperplane. Geometric margin $\|w\|^{-2}$ and insensitive loss function ε are the most important parameters in SVM design. Let the error between predicted results and targets be visualized by ε, that is

$$|y - f(z)| = \left\{ \frac{0}{|y - f(z) - \varepsilon|} \frac{|y - f(z)| \leqslant \varepsilon}{|y - f(z)| \succ \varepsilon} \right\} \tag{5}$$

The optimization problem, which is convex in nature, is now converted to the minimization of geometric margin. This objective is subjected to the minimization of the error between predicted values and simulated values. The objective function I can be represented as:

$$I = min\frac{1}{2}\|w\|^2 \tag{6}$$

$$Subjectto(y - W.f(z) - d - \varepsilon) \leq 0 \tag{7}$$

$$(W.f(z) + d - y_i) \leq \varepsilon \;\; i = 1, 2, \ldots, m \tag{8}$$

Since the problems of PQ disturbance identification is data specific and also system specific, hence, it is necessary to add the non-negative slack variable χ. The convex optimization problem can be converted as follows:

$$I = min\frac{1}{2}\|w\|^2 + A\sum_{i=1}^{m}\chi_i \tag{9}$$

$$Subjectto(y - Wf(z) - d) \leq (\varepsilon + \chi_i), \;\; \chi_i \geqslant 0 \;\; i = 1, 2, \ldots, m \tag{10}$$

To find the optimal values, the problem (6) can be rearranged by the Langragian saddle point method, that is

$$L = \frac{1}{2}\|w\|^2 + A\sum_{i=1}^{m}\chi_i + \beta\sum_{1}^{m}(-y + Wf(z) + d + \varepsilon + \chi_i) - \sum_{1}^{m}\gamma\varepsilon_i \tag{11}$$

Hence, the classification-based optimization problem can be solved with respect to the primal variables W, d, ε, and χ. However, as per reported results in reference [30], we used a Radial Basis Function (RBF) kernel for the classification task. In general, also, the RBF function is the most common choice as the mercer kernel function because of its Gaussian function form. However, for tuning the parameters of SVM, we have experimented with 6 advanced algorithms. The detailed analysis of these algorithms and experimental results tuning are shown in the following subsection.

Choice of Algorithm for Parameter Tuning

In the past, various attempts have been made to tune the hyperparameters of the SVM in many approaches. Proper tuning of these parameters enhances the classification accuracy of the classifier. For constructing the optimization routine, an objective function that is based on the maximization of classification accuracy of the PQ events is considered here. For robustness of optimization, we have taken 2500 samples of different PQ events and classify according to the discussion presented in previous sections. For comparing the optimization performance, the search agents no. along with maximum iteration have been kept constant for all algorithms. Also, the parameter pertaining to algorithms are taken from the references. The following algorithms are considered for tuning tasks:

1. Augmented Crow Search Algorithm (ACSA): The author of the ACSA has developed a new variant of the Crow Search Algorithm. The author modified the algorithm by incorporating Opposition based learning and a gradient-based scheme for better exploration and exploitation.
2. Whale Optimization Algorithm (WOA): The recent application of WOA in the field of Demand Side Management (DSM) inspired authors to design and optimize the hyperparameter of SVM with the help of WOA.
3. Intelligent Grey Wolf Optimizer (IGWO): In a recent application of IGWO, the estimation of solar panel parameters attracted the interest of researchers, as well the authors of this paper for employing the algorithm for tuning task. The algorithm employs a sinusoidal bridging parameter and Opposition based learning.
4. Gaining Sharing Knowledge based Algorithm (GSK): The algorithm has previously been applied for classification tasks. The performance of the algorithm on various mathematical functions primarily became the criterion for choosing it.

5. Chaotic Marine Predator Algorithm (CMPA): A recently published chaotic version of the Marine Predator Algorithm and its performance on feature selection tasks inspired the authors to employ CMPA in tuning tasks. The algorithm embeds a chaotic function for position update in its intermediate stage.
6. Augmented Whale Optimization Algorithm (AWOA): This algorithm primarily works on Opposition based learning and updating of position based on the Cauchy mutation operator. The AWOA has been tested over a number of benchmark functions along with the real application.

The analysis of the results is shown in Table 3. For comparing the optimization performance, search agents no., maximum no. of iteration are kept constant. From the table, it has been observed the highest classification rate acquired with the help of ACSA that is 96.2%. Hence, for further analysis, ACSA has been taken for tuning the parameters of SVM. The following section presents the feature selection process based on PCA.

Table 3. Comparative analysis of different optimization algorithms for hyper-parameter tuning.

Size of Data Sets	Algorithm	Attribute of Algorithm	Regularization Parameter	Kernel Parameter	Classification
2500	ACSA [16]	Inculcation of OBL and bridging of the exploration and exploitation phase	10.523	0.325	96.2
2500	WOA [31]	hunting behavior of the whale	10.365	0.315	94.35
2500	IGWO [32]	OBL and Bridging through sinusoidal turncated function	10.245	0.369	92.65
2500	GSK [33]	Based on the behavior of gaining and sharing knowledge	10.362	0.354	91.25
2500	CMPA [34]	Chaotic algorithm that employs chaotic position update system	10.012	0.3257	94.21
2500	AWOA [35]	Cauchy mutation operator based position update	10.215	0.366	94.36

5. PCA-Based Feature Selection for PQ Event Classification

The efficiency of the supervised learning models is highly affected by the size of the features. To reduce the dimensionality of the input feature matrix, PCA is a well-known methodology. Recently PCA is used for wind speed prediction [19], building forecasting models for electricity consumption prediction [36] and for fault detection [37]. In PQ event detection problem, different statistical attributes of the output of signal processing techniques are chosen as input features. In this work, the dimension of the input feature size is 9. The first five attributes are from Wavelet transform and the last four are extracted from the Hilbert transform technique. It is necessary to select the major factors that contribute to the relevant information about the event using the well-known principal component analysis. The observation matrix (O) is first designed as:

$$O = \begin{bmatrix} k_1 & k_2 & k_3 & k_4 & k_5 & k_6 & k_7 & k_8 & k_9 \end{bmatrix} = \begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} & k_{15} & k_{16} & k_{17} & k_{18} & k_{19} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \\ k_{s1} & k_{s2} & k_{s3} & k_{s4} & k_{s5} & k_{s6} & k_{s7} & k_{s8} & k_{s9} \end{bmatrix} \tag{12}$$

where s is the sample size (2500), the remaining variables are as follows:

$$k_1 = \frac{1}{s}\sum_{j=1}^{7} A_b(j) - \frac{1}{s}\sum_{j=1}^{7}\left(A_b(j)^2\right) \tag{13}$$

$$k_2 = min(A_b) \tag{14}$$

$$k_3 = norm(A_b) \tag{15}$$

$$k_4 = max(A_b) \tag{16}$$

$$k_5 = \frac{1}{s}\sum A_b \tag{17}$$

$$k_6 = \frac{1}{s}\sum_{j=1}^{j=s} X_h - \frac{1}{s}\sum_{j=1}^{j=s}(X_h)^2 \tag{18}$$

$$k_7 = minX_h \tag{19}$$

$$k_8 = normX_h \tag{20}$$

$$k_9 = maxX_h \tag{21}$$

Here $k_1 = \begin{bmatrix} k_{11} & k_{21} & \ldots & k_{s1} \end{bmatrix}$ and so on $k_9 = \begin{bmatrix} k_{19} & k_{29} & \ldots & k_{s9} \end{bmatrix}$ and A_b is the detailed coefficients of seven-level MRA of Wavelet transforms. X_h is the Hilbert transform of the voltage signals. Further, these features are normalized between 0.1 to 0.9 and the correlation coefficient matrix C_R is created as follows.

$$C_R = \begin{bmatrix} R_{11} & R_{12} & \ldots & R_{19} \\ R_{21} & R_{22} & \ldots & R_{29} \\ \vdots & \vdots & \vdots & \vdots \\ R_{91} & R_{92} & \ldots & R_{99} \end{bmatrix} \tag{22}$$

where

$$R_{ij} = \frac{\sum_{m=1}^{m=s} k^*_{mi} k^*_{mj}}{s-1} \tag{23}$$

and

$$k^*_{ij} = \frac{k_{ij} - k_j}{\sqrt{var(k_j)}}, k_j = \frac{\sum_1^s k_{ij}}{s} \tag{24}$$

Hence, the eigenvalue associated with this correlation matrix will be ($E_1 \ldots E_9$). The contribution rate γ_i associated with each principal component can be calculated as:

$$\gamma_i = \frac{E_i}{\sum_{j=1}^{j=9} E_i} \tag{25}$$

The contribution rates of the different transforms are shown in Table 4. Based on the contribution rates various permutations of input features are constructed for SVM. Three modules are constructed with three different permutations of features; details and analysis of the results are given in the following sections.

Table 4. Results of Principal Component Analysis.

Signal Processing Technique	Principal Components	Eigenvalues	Contribution Rates (%)	Accumulative Contribution (%)
Hilbert Transform	Standard Deviation	3.1176	34.64	34.64
	Minimum Value	2.6355	29.28	63.92
	Norm Value	0.9305	10.34	74.26
	Maximum Value	0.8502	9.44	83.71
Wavelet Transform	Standard Deviation	0.6518	7.24	90.95
	Minimum Value	0.4394	4.88	95.83
(Detailed Energy coefficients)	Norm Value	0.2778	3.09	98.92
	Maximum Value	0.0969	1.08	100
	Mean Values	0.0001782	0.01	100

6. Results

This section presents a comparative analysis of the results obtained from the application of different combinations of SVMs obtained from PCA in the classification of different PQ events. The real power system model is simulated in Matlab. Different PQ events such as sag, swell, normal (without sag and swell), transients, and harmonics are simulated with the consideration of interruptions. Binary classification is used with five target classes namely sag, swell, transient, harmonics, and normal. Table 2 shows binary classification for PQ event detection. Total 2500 samples are generated for this classification task i.e., 500 for each event. Out of 2500 samples, 70% datasets are used for training purposes, the remaining 15% for testing, and 15% for validation. Signals are sampled at 256 points/cycle and the normal frequency is 50 Hz.

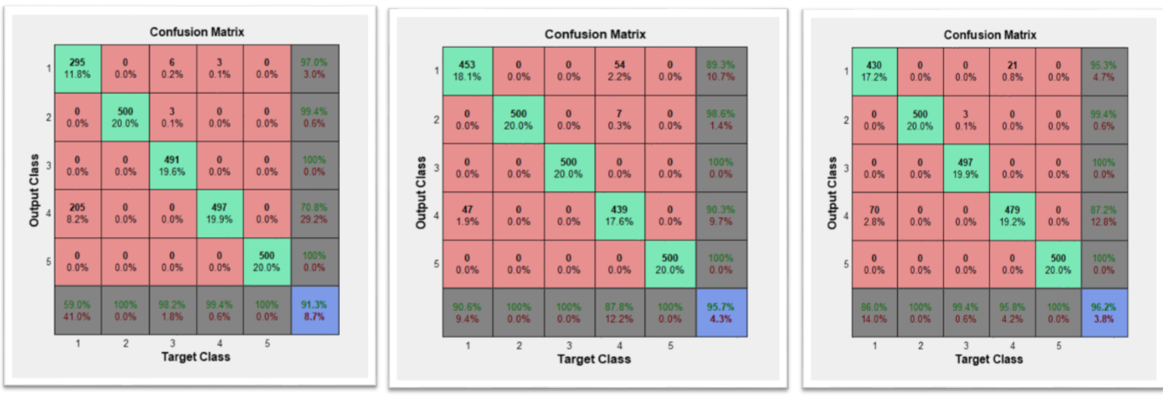
Hilbert transform and Wavelet transforms are applied to extract the information from the generated signals. Different statistical attributes of Hilbert transforms and Wavelet transforms namely minimum, maximum, standard deviation, and norm of the Hilbert coefficients and detailed energy coefficients are employed as an input feature for SVM. The nine significant features are extracted from this simulation process. The contribution rates and accumulative contribution rates are shown in Table 4. To carry out this analysis in a meaningful manner, different possible combinations of SVMs are employed and efficacy of the each module is tested.

The results of PCA are shown in Table 4. As per the datasets obtained from PCA, it is observed that the values of contribution rates for all statistical attributes of Hilbert coefficients along with standard deviations and minimum values of detailed energy coefficients of the Wavelet transform contribute around 95.82%. For this reason, these features are employed to construct the different architecture of SVMs.

Observation sets for SVM-1: In this observation set two extinct features of highest contribution rates (standard deviations and minimum values of Hilbert transform coefficients) are selected as input features. The confusion value for this module is 0.087. The confusion diagram for this classifier is exhibited in Figure 6a.

Observation sets for SVM-2: In this observation set all four features extracted from the statistical attributes of Hilbert transforms are employed. The confusion rate for this module is 0.043 and the confusion diagram for this classifier is shown in Figure 6b.

Observation sets for SVM-3: In this observation set all four features extracted from the statistical attributes of Hilbert transforms and two distinct features namely minimum values and standard deviations of detailed energy coefficients of Wavelet transforms are employed. The confusion rate for this module is 0.038 and the confusion diagram for this classifier is presented in Figure 6c.



(a) (b) (c)

Figure 6. Comparative Analysis of Observation sets for SVM module 1 (**a**–**c**) to SVM module 3.

6.1. Discussions

Three standard error criteria are applied to measure the efficacy of these modules. These are Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Definitions of these indices are taken from [19]. From Figure 7, it is empirical to judge that the values for these error indices are minimum for SVM-3. Moreover, higher values are obtained for SVM-1 and RBFNN. The corresponding values of these error indices are shown in Table 5. In order to judge the classifier performance, confusion diagrams are utilized.

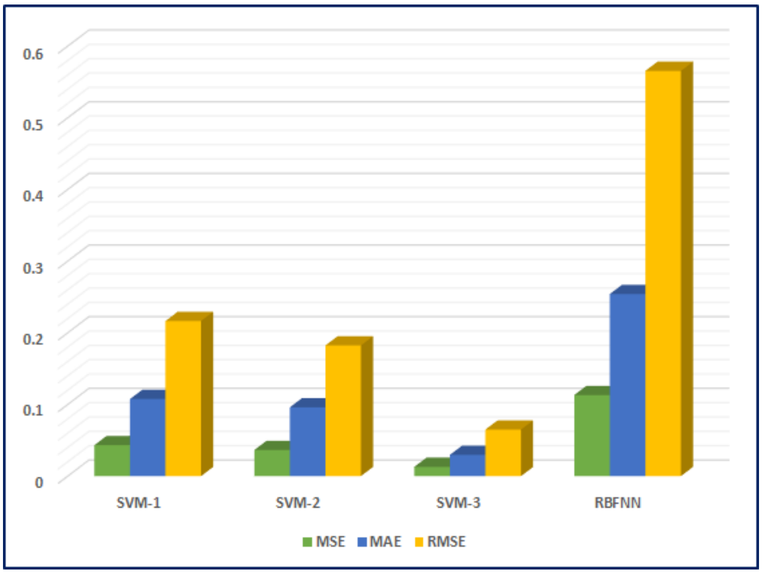


Figure 7. Error Indices.

Table 5. Comparison of Error Indices.

Supervised Learning Model	MSE	MAE	RMSE
SVM-1	0.0433	0.1076	0.2164
SVM-2	0.0365	0.0960	0.1824
SVM-3	0.0130	0.0297	0.0649
RBFNN	0.1131	0.2541	0.5655

The lower value of confusion indicates the higher classification efficacy of the classifier. As calculated, in this case, SVM-3 proves to be a better classifier. From Figure 6a it is empirical to judge that the classifier is able to judge the 91.3% events only. For class 1 the classification efficiency is 59% only. However, in classes 3 and 4, 98.2% and 99.4% efficiency are achieved by SVM-1 respectively. Figure 6b shows the classification accuracy of SVM module 2.

Similarly for SVM-3 as shown in Figure 6c the performance is 96.2%. Classification efficiencies for each class are indicated in the confusion diagrams and these are (86, 100, 99.4, 95.8, and 100%). It can be concluded that the statistical attributes of Hilbert coefficients and Wavelet energy coefficients provide a good combination as input features and SVM-3 gives a good performance as compared with the other two modules and RBFNN. To compare the performance of these classifiers few statistical tests are conducted here.

6.2. Statistical Analysis

The improved performance of SVM-3 over the existing method and other modules can be realized through statistical analysis. This module should be statistically significant in terms of error measures, classification accuracy, or any other classification problems. Implications of statistical tests and analytical measures in classification problems are discussed by Demsar [38]. In this paper one-way ANOVA test (fisher) [39,40] has been performed. The objective of ANOVA is to test the hypothesis to evaluate variability in the performance of the models. A null hypothesis can be constructed that all classifiers have the same classification accuracy. Rejection of this hypothesis can be based on error variability. To conduct this test, 5 fold cross validation technique is used. Classifier accuracies of different datasets of different capacities on all three SVMs are exhibited in Table 6. Datasets of different capacities are prepared and all three SVM models are applied. The simulation results are depicted in Figure 8.

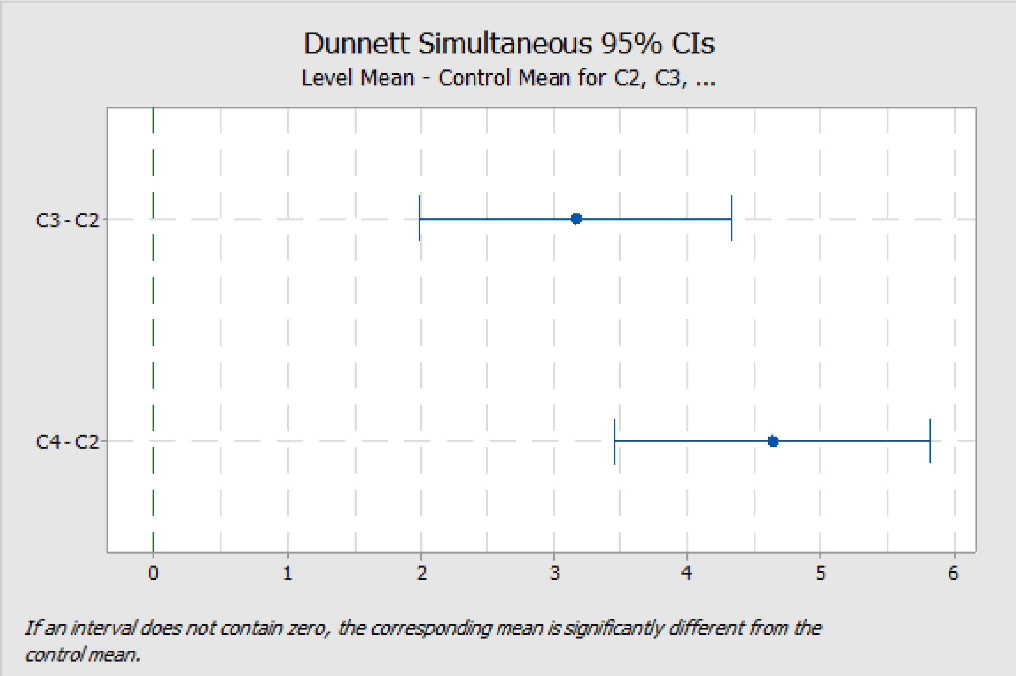


Figure 8. Test results for ANOVA—Dunnett simultaneous statistical test.

Table 6. Classification Accuracy of All SVM models for different datasets.

Model	Size of Datasets				
	500	**1000**	**1500**	**2000**	**2500**
SVM-1	90.89	91.01	90.49	90.36	91.3
SVM-2	93.14	92.98	93.75	94.29	95.7
SVM-3	94.9	95.4	94.76	95.78	96.2

6.3. Null Hypothesis

All means are equal (the classification efficiency of all classifiers is the same). This test has been carried out using one-way ANOVA in Duncan multiple test range [41] with 95% confidence interval, (0.05) significance level, and linear polynomial contrast and the results have been presented in Table 7 and Figure 8 shows the results of ANOVA test. In Duncan, multiple tests a control variable is considered, and the classification accuracy of SVM-2 (C2) is taken as a control variable.

Table 7. ANOVA results.

Model	Factor (N)	Mean	Standard Deviation	Confidence Interval for Mean	
				Upper Bound	**Lower Bound**
SVM-1	5	90.81	0.385	90.086	91.534
SVM-2	5	93.97	1.097	93.248	94.696
SVM-3	5	95.44	0.551	94.724	96.172

7. Conclusions

With the ever-rising concern of design engineers to attain a high quality of power, the focus is on PQ event classification and mitigation of unwanted signals. This paper had presented a combined application of SVM and signal processing techniques in PQ event classification. The salient features of this work are as follows:

1. Combined input features based on Wavelet and Hilbert transforms are employed to train, test, and validate the supervised learning module SVM for efficient detection of PQ events.

2. The tuning of SVM hyperparameters is carried out with the help of the latest developed versions of optimization algorithms. Some of the algorithms are developed by the authors, it has been concluded that ACSA yields the best classification accuracy.
3. Principal Component Analysis is carried out to detect efficient features from a large pool, based on different features; three models of SVMs are constructed. The comparison of these three modules is carried out based on the three-error criteria MSE, MAE, and RMSE.
4. Classification accuracy of these modules is tested based on confusion values and diagrams, it is concluded that SVM-3, possesses features from both transforms and gives the best results.
5. Last but not least, the validation of obtained results is carried out with a statistical ANOVA test. Rejection of the Null hypothesis is done based on obtained statistical values and the Dunnett test.

Application of these modules on a wind dominating system will be addressed in the future. Also, the application of deep learning models will be explored with the combined application of optimization, signal processing, and data mining.

Author Contributions: Formal analysis, K.A.A. and A.S.; Funding acquisition, K.A.A.; Investigation, K.A.A.; Methodology, A.F.A. and A.S.; Project administration, A.W.M.; Software, A.S.; Supervision, A.S. and A.W.M.; Validation, A.F.A. and A.W.M.; Visualization, A.F.A. and A.M.A.; Writing—original draft, A.S.; Writing—review & editing, A.M.A. and A.S. All authors have read and agreed to the published version of the manuscript.

Funding: The research is funded by Researchers Supporting Program at King Saud University, (RSP-2021/323).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not Applicable.

Acknowledgments: The authors present their appreciation to King Saud University for funding the publication of this research through the Researchers Supporting Program (RSP-2021/323), King Saud University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PQ	Power Quality
SVM	Support Vector Machine
ACSA	Augmented Crow Search Algorithm
PCA	Principal Component Analysis
FS	Feature Selection
MSE	Mean Square Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error

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