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Efficient Power Quality Disturbance Classification Using Teager-Kaiser Energy Operator and Fast Walsh-Hadamard Transform Features

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Teager-Kaiser Enerji Operatörü ve Hızlı Walsh-Hadamard Dönüşümü Özelliklerini Kullanarak Verimli Güç Kalitesi Bozulması Sınıflandırması

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Abstract

Power Quality (PQ) disturbances play a critical role in ensuring the reliability and efficiency of electrical systems. These disturbances can severely impact device performance, leading to malfunctions and significant energy losses. Accurate identification and classification of PQ disturbances are therefore vital for maintaining system stability and optimizing energy consumption. The proposed method stands out by emphasizing two key feature extraction techniques: the Teager-Kaiser Energy Operator (TKEO) and the Fast Walsh-Hadamard Transform (FWHT). After applying the Fast Fourier Transform (FFT) to randomly generated PQ disturbance events from nine different types, TKEO and FWHT are used to extract features that capture both the energy dynamics and structural patterns of the disturbances. These features provide a highly detailed and compact representation of the signal, crucial for effective classification. The Random Forest (RF) classifier, powered by these robust features, achieves an impressive classification accuracy of 99.35% with pure signals. Moreover, the method demonstrates strong noise resistance, maintaining a high accuracy of 98.26% even under 40 dB noise conditions, highlighting the reliability and effectiveness of the extracted features in real-world environments where noise is a common challenge.

Keywords: *Power Quality (PQ), Fast-Walsh Hadamard Transform (FWHT), Teager-Kaiser Energy Operator (TKEO), Random Forest, Power Quality Disturbance Classification.*

Öz

Güç Kalitesi (PQ) bozulmaları, elektrik sistemlerinin güvenilirliği ve verimliliği açısından kritik bir öneme sahiptir. Bu bozulmalar, cihaz performansını ciddi şekilde etkileyerek arızalara ve önemli enerji kayıplarına yol açabilir. Bu nedenle, PQ bozulmalarının doğru bir şekilde tanımlanması ve sınıflandırılması, sistem kararlılığını korumak ve enerji tüketimini optimize etmek için hayati önem taşır. Önerilen yöntem, iki ana özellik çıkarma tekniğine odaklanarak öne çıkmaktadır: Teager-Kaiser Enerji Operatörü (TKEO) ve Hızlı Walsh-Hadamard Dönüşümü (FWHT). Dokuz farklı türden rastgele üretilen PQ bozulma olaylarına Hızlı Fourier Dönüşümü (FFT) uygulandıktan sonra, TKEO ve FWHT kullanılarak bozulmaların enerji dinamiklerini ve yapısal desenlerini yakalayan özellikler çıkarılır. Bu özellikler, sinyalin etkili bir sınıflandırma için kritik olan oldukça ayrıntılı ve kompakt bir temsilini sağlar. Bu güçlü özelliklerle donatılan Rastgele Orman (RF) sınıflandırıcısı, saf sinyallerde etkileyici bir doğruluk oranı olan %99.35'e ulaşmaktadır. Ayrıca yöntem, 40 dB gürültü altında %98.26 doğruluk sağlayarak güçlü bir gürültü direnci sergilemekte, bu da gerçek dünya ortamlarında yaygın bir sorun olan gürültüye karşı çıkarılan özelliklerin güvenilirliğini ve etkinliğini vurgulamaktadır.

Anahtar Kelimeler: *Güç Kalitesi (PQ), Fast-Walsh Hadamard Dnüşümü (FWHT), Teager-Kaiser Enerji Operatörü (TKEO), Rastgele Orman, Güç Kalitesi Bozulmalarının Sınıflandırması.*

1. Introduction

Power quality (PQ) has emerged as a critical concern in modern electrical systems due to rising power demands and the integration of renewable energy sources. The inclusion of these renewables necessitates the use of more switching devices and power electronics, contributing to PQ disturbances (PQDs). These disturbances manifest as voltage sags when large loads are connected, voltage swells often caused by load disconnections, and a variety of other issues such as harmonics. Such disruptions can negatively impact the performance and lifespan of electrical devices, damage electronic equipment, reduce energy efficiency, and lead to significant economic losses (Singh et al. 2014). Therefore, accurately identifying these PQDs is essential for maintaining reliable and efficient electrical system operations and for designing and implementing effective compensation devices to improve power quality.

Traditionally, the identification and classification of PQDs have relied on various signal processing techniques, including Fourier Transform (Gonzalez-Abreu et al. 2021), Wavelet Transform (Thirumala et al. 2018), and Short

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Time Fourier Transform (Priyadarshini et al. 2024). These methods are instrumental in detecting and analyzing transient disturbances, harmonic distortions, and other anomalies within power systems. PQ disturbances can include both single and mixed event types, as both have been studied extensively in the literature.

Yılmaz et al. (2022) have proposed a novel method combining the Undecimated Wavelet Transform (UWT) and support vector machine (SVM) using the "à trous" algorithm to classify nine different PQDs containing only single events in distributed generators (DGs). This method was tested using a LabVIEW-based experimental DG system, a MATLAB Simulink model, and real data under various grid conditions and noise levels, demonstrating high accuracy in both pure and noisy conditions. Singh et al. (2023) have developed a method for classifying 29 types of PQDs using dimensionality reduction, employing Linear Discriminant Analysis (LDA) to transform the dataset from a higher to a lower dimensional space by eliminating unnecessary features. This method, evaluated with four machine learning classifiers (k-Nearest Neighbor, Naive Bayes, SVM, and Random Forest), has achieved high classification accuracy under varying noise levels. Qaisar (2021) has introduced a novel method combining signal-piloted acquisition, adaptive-rate segmentation, and time-domain feature extraction with machine learning tools for classifying three types of PQDs involving single events. This approach facilitates real-time compression, significantly reducing data storage, processing, and transmission requirements, while also lowering computational costs and classifier latency. Robust machine learning algorithms, such as k-Nearest Neighbor, Naive Bayes, Artificial Neural Network, and SVM, are employed for classification, achieving acceptable results for the automated recognition of major voltage and transient disturbances. Mozaffari et al. (2022) addressed the real-time detection and classification of four types of PQDs in power delivery systems. Their proposed supervised approach learns both standard and anomalous patterns from training data that includes clean and disturbance signals. By processing data from multiple meters simultaneously, the method achieves faster detection through cooperative analysis. Additionally, the method is extended to a multi-hypothesis framework, enabling the prompt and accurate classification of disturbance events in real-time. Narayanaswami et al. (2020) have discussed a technique for detecting PQDs in power systems using mystery curves (MC). The method first estimates the analytic signal of real-valued input signals via the Hilbert transform. By representing this signal in polar form, which reveals magnitude and frequency variations, informative MCs are discovered in two dimensions and extended to three dimensions using Euler's rotation hypothesis. The technique's effectiveness was validated with synthetic signals generated in MATLAB and experimentally tested on a prototype bench. In recent years, there has been a substantial shift towards leveraging Deep Learning (DL) techniques for PQD analysis (Wang and Chen 2019, Wang et al. 2019). Notably, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have emerged as effective tools, demonstrating exceptional ability in identifying and classifying various PQDs with high accuracy. These DL models are particularly valued for their ability to autonomously learn complex patterns and dependencies in the data, bypassing the need for explicit programmatic instructions. Rodrigues Jr et al. (2021) have developed a deep learning-based approach to detect and classify 16 types of PQ disturbances, including both single and multiple events. Their method leverages CNNs with 1D convolution and Long Short-Term Memory (LSTM) networks to automatically extract, select, detect, and classify features in an integrated manner. The input for this method is a data window of one cycle, which moves incrementally to cover the entire signal length. The robustness of the method was tested with various sampling rates, and the impact of noise was also examined in this study. Guerrero-Sánchez et al. (2023) have introduced a novel Multitasking Deep Neural Network (MDL) designed to classify and analyze multiple electrical disturbances. This methodology employs Empirical Mode Decomposition (EMD) to extract characteristics from non-stationary signals. The MDL was tested on a diverse dataset comprising 4500 records of electrical disturbances, taking into account factors such as severity, disturbance duration, and varying noise levels. The results demonstrate high accuracy in both classifying multiple disturbances and analyzing crucial signal aspects, including crest factor, per unit voltage analysis, Short-term Flicker Perceptibility (Pst), and Total Harmonic Distortion (THD).

There has been a growing trend in converting signals into images (Sindi et al. 2021). This approach uses advanced techniques to transform raw signal data into visual representations, making the analysis of complex data patterns more intuitive and effective. The increasing adoption of these methods highlights their potential to enhance accuracy and efficiency. Liu et al. (2018) have introduced a novel approach for detecting and classifying PQD signals using singular spectrum analysis (SSA), curvelet transform (CT), and deep convolutional neural networks (DCNNs). PQD signals are decomposed using

SSA and fast discrete curvelet transform (FDCT), with initial six and three levels of decomposition serving as features. DCNNs and multiclass SVMs are then employed for classification. Tested on thirty-one categories of real and synthetic PQD waveforms, the proposed SSA-FDCT-DCNN classifier outperforms multiclass SVM and other existing methods, proving effective in classifying both single and complex PQ disturbances. Chen et al. (2022) have proposed a power quality classifier that utilizes signal processing techniques to convert signals into 2D grayscale images. These images are then processed through a deep CNN to classify five different quality disturbances. Tested on data from the Amrita Honeywell Hackathon 2021, the method demonstrated that using grayscale images captures more PQD information than 1D signals, thereby enhancing identification performance on real-world data. Özer et al. (2021) have introduced a novel deep learning algorithm for classifying power quality disturbances using an inverse signal approach. The method combines a CNN and bidirectional long short-term memory (Bi-LSTM) with spectrograms. It focuses on the region where the PQD event occurs, aiming to increase classification success rates. The approach involves finding the time shift of the signal relative to a pure sine wave, generating an inverse sine wave based on this shift, and combining it with the original signal to create spectrograms. These spectrograms are converted into RGB images and combined for classification via CNN/Bi-LSTM. The model was tested on 29 different disturbance events, both single and combined. As stated, DL methods are powerful but come with notable disadvantages, including a high demand for labeled data, substantial computational resources, and a heavy reliance on specific hyperparameter settings. This can make the practical implementation of DL for PQD analysis particularly difficult when access to adequate and relevant data is constrained.

This study introduces a signal processing-based methodology designed to classify PQ disturbances. Initially, the Fast Fourier Transform (FFT) is applied to a varied collection of nine types of synthetically generated PQ disturbance events. Following this preliminary transformation, we apply the Teager-Kaiser Energy Operator (TKEO) and the Fast Walsh-Hadamard Transform (FWHT) to further refine the signal analysis. These extracted features are subsequently used to train a Random Forest (RF) classification model. Remarkably, the model achieves an accuracy of 99.35% with pure signals and maintains an impressive accuracy of 98.26% even with 40 dB noise.

2. Proposed Methodology

Figure 1 illustrates the proposed methodology for classifying PQ disturbances. First, disturbances from nine different event types are generated randomly and processed using FFT. TKEO and FWHT values from the transformed signals are extracted as features, which are then used as input for a RF classifier. Detailed explanations of each stage are provided in the following subsections.

2.1 Creation of the Dataset

Due to the limited availability of real PQD data, this study generates cases of PQDs (including both single and multiple disturbances) by randomly varying the parameters of their numerical models as described in Igual et al. (2018). The dataset is created in MATLAB according to IEEE-1159 standards, closely mimicking real-time data.

For each class, 400 (Ns) samples are generated using a sampling frequency of 1.6 kHz (fs). The fundamental frequency is set to 50 Hz (f), with each class containing 10 cycles (N). The signal amplitude is set to 1 p.u. (A) Using these parameters, the total dataset size becomes 3600 x 320. Samples for each class are generated using the mathematical models and parameters given in Table 1 and 2 as described by Igual et al. (2018). Moreover, an example of each disturbance type is illustrated in Figure 2.

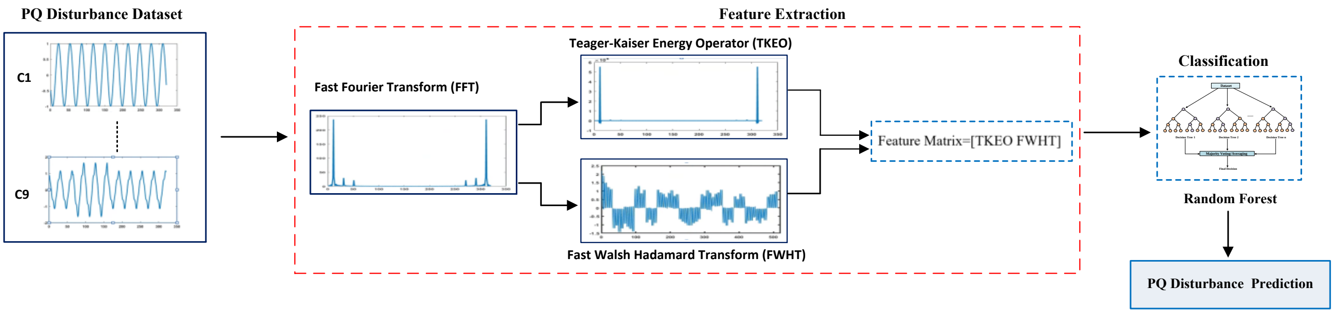

Figure 1. General block diagram of the proposed method.

Table 1. Mathematical model of the PQ Disturbance classes

Class	Disturbances	Mathematical Model
C1	Pure sinusoidal	$v(t) = Asin(\omega t - \varphi)$
C2	Sag	$v(t) = A(1 - \alpha(u(t - t_1) - u(t - t_2)))sin(\omega t - \varphi)$
C3	Swell	$v(t) = A(1 + \beta(u(t - t_1) - u(t - t_2)))sin(\omega t - \varphi)$
C4	Interruption	$v(t) = A(1 - \rho(u(t - t_1) - u(t - t_2)))sin(\omega t - \varphi)$
C5	Transient/impulse/spike	$v(t) = A[sin(\omega t - \varphi) - \psi(e^{-750(t-t_a)} - e^{-344(t-t_a)})((u(t - t_a) - u(t - t_b))]$
C6	Oscillatory transient	$v(t) = A[sin(\omega t - \varphi) + \beta e^{-(t-t_I)/\tau} sin(\omega_n(t - t_I) - \theta)((u(t - t_{II}) - u(t - t_I)))]$
C7	Harmonics	$v(t) = A[sin(\omega t - \varphi) + \sum_{i=3}^{7} \alpha_i \, sin(i\omega t - \theta_i)]$
C8	Harmonics with sag	$v(t) = A(1 - \alpha(u(t - t_1) - u(t - t_2)))[sin(\omega t - \varphi) + \sum_{j=3}^{5} \alpha_j \, sin(j\omega t - \theta_j)]$
C9	Harmonics with swell	$v(t) = A(1 - \beta(u(t - t_1) - u(t - t_2)))[sin(\omega t - \varphi) + \sum_{j=3}^{5} \alpha_j \, sin(j\omega t - \theta_j)]$

Table 2. Parameter ranges for disturbance types

Disturbances	Parameters
General	$\omega = 2\pi f; -\pi \le \varphi \le \pi; u(t) = \begin{cases} 0 & t < 0 \\ 1 & t \ge 0 \end{cases}$
Harmonic	$i = \{3,5,7\}; 0.05 \le \alpha_i \le 0.15; -\pi \le \theta_i \le \pi$ $j = \{3,5,7\}; 0.05 \le \alpha_j \le 0.15; -\pi \le \theta_j \le \pi$ $\begin{bmatrix} k = \{1,3,5\}; \alpha_k = 1 \xrightarrow{for} k = 1; \\ 0.05 \le \alpha_k \le 0.15 \xrightarrow{for} k = \{3,5\}; \; -\pi \le \theta_k \le \pi \end{bmatrix}$
Sag, swell, interruption	$T \le t_2 - t_1 \le (N-1)T; 0.1 \le \alpha \le 0.9; 0.1 \le \beta \le 0.8; 0.9 \le \rho \le 1$
Transient/impulse/spike	$0.222 \le \psi \le 1.11; T \le t_a \le (N-1)T; t_b = t_a + 1ms$
Oscillatory transient	$300Hz \le f_n \le 900Hz; \omega_n = 2\pi f_n; 8ms \le \tau \le 40ms; -\pi \le \theta \le \pi$ $0.5T \le t_{II} - t_I \le \frac{N}{3.33}T; 0.2T \le t_{II'} - t_{I'} \le t_2 - t_1; t_1 \le t_{I'}; t_{II'} \le t_2$

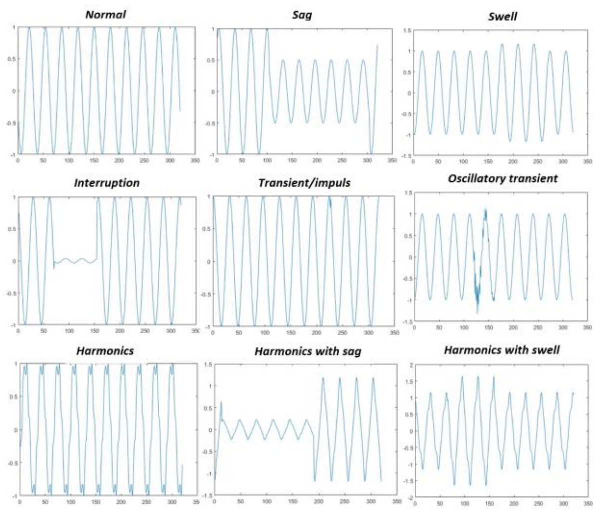

Figure 2. Example for each disturbance type

2.2 Feature Extraction

Fast Fourier Transform (FFT)

The Fourier Transform, a method commonly used in feature extraction, decomposes signals into their frequency components. This decomposition highlights various characteristics of the signals. In this study, the signals are initially transformed using the Fast Fourier Transform (FFT). Then, Teager-Kaiser Energy Operator (TKEO) and Fast Walsh-Hadamard Transform (FWHT) values are calculated separately for feature extraction.

Teager-Kaiser Energy Operator (TKEO)

The Teager-Kaiser Energy Operator (TKEO) is a method primarily designed for analyzing the energy content within a signal (Biswal et al. 2021). Operating as a nonlinear, local differential operator, the TKEO swiftly responds to variations in signal intensity, making it invaluable in various research areas. For an $x(n)$ signal TKEO is calculated as given in eq.1.

$$\Psi[x(n)] = x(n)^2 - x(n-1).x(n+1) \quad (1)$$

Fast Walsh Hadamard Transform (FWHT)

The Fast Walsh-Hadamard Transform (FWHT) is a transformation method developed to eliminate the computational complexity of the Walsh-Hadamard

Transform. The FWHT matrix (H_n) is a transformation matrix size of $2^n x 2^n$ as given in eq. 2. This matrix only takes the values of +1 or -1 (Ergün et al. 2020).

$$H_n = \frac{1}{\sqrt{2^n}} \begin{bmatrix} H_{n-1} & \cdots & H_{n-1} \\ \vdots & \ddots & \vdots \\ H_{n-1} & \cdots & -H_{n-1} \end{bmatrix}, H_0 = 1 \tag{2}$$

2.3 Classification Stage

To accurately classify various PQ disturbance events, a Random Forest (RF) classification model is employed. Random Forest is a powerful machine learning method used for both classification and regression tasks. It operates as an "ensemble" learning model by combining many decision trees, thereby reducing problems like overfitting and instability that a single decision tree might encounter. At the core of Random Forest is the technique known as "bagging" (Bootstrap Aggregating), where each tree is independently trained using randomly selected subsets of the training data. This ensures that each tree learns different aspects of the data. Additionally, at each split point in the tree, a random subset of features is chosen, which enhances the model's ability to generalize and prevents overfitting.

The typical configuration of a Random Forest is depicted in Figure 3. The accuracy of the model is assessed using out-of-bag data, which are the data not used by each tree during training. This allows performance testing without the need for an additional validation set like cross-validation. During prediction, the final outcome is determined either by averaging the predictions from all trees (for regression) or by selecting the class with the most votes (for classification). With its capability to handle high-dimensional data and model complex relationships in the data, Random Forest is a reliable model with a broad range of applications (Seyrek et al. 2022).

Performance Metrics

The performance of the proposed method is evaluated using a confusion matrix. In this study, we aim to classify 9 different types of PQ disturbances, making it a multi-class problem. Each PQ disturbance is assigned a label (*C1, C2, ..., C9*) as described in the previous section. For an *n*-class classification problem, the confusion matrix is an *n×n* matrix, given in Table 3, where each element r_{ij} represents the number of instances where the true class is *i* and the predicted class is *j*. From this confusion matrix, various performance metrics such as accuracy, sensitivity (Recall), precision, and the F1 score for each class can be derived to assess the classifier's performance, as shown in eq. (3) to (6). The overall accuracy is determined by dividing the number of correctly classified instances by the total number of predictions made.

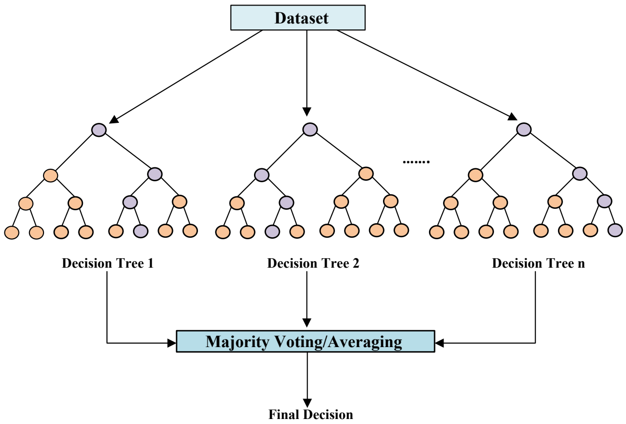

Figure 3. Structure of RF.

Table 3. Confusion Matrix

		Predicted Class				
		C1	***C2***	***C3***	**....**	***Cn***
Actual Class	***C1***	r_{11}	r_{12}	r_{13}	**...**	r_{1n}
	C2	r_{21}	r_{22}	r_{23}	**...**	r_{2n}
	C3	r_{31}	r_{32}	r_{33}	**...**	r_{3n}
	⋮	⋮	⋮	⋮	**...**	⋮
	Cn	r_{n1}	r_{n2}	r_{n3}	**...**	r_{nn}

$$Accuracy_i = \frac{r_{ii} + \sum_{j \neq i}^{n} \sum_{l \neq i}^{n} r_{jl}}{\sum_{i=1}^{n} \sum_{j=1}^{n} r_{ij}} \tag{3}$$

$$Precision_i = \frac{r_{ii}}{\sum_{j=1}^{n} r_{ji}} \tag{4}$$

$$Sensitivity\ _i = \frac{r_{ii}}{\sum_{j=1}^{n} r_{ij}} \tag{5}$$

$$F1 - Score_i = 2x \frac{Precision_i x Recall_i}{Precision_i + Recall_i} \tag{6}$$

3. Performance Results

In this study, 300 samples from each disturbance type are allocated for training and 100 samples for testing, ensuring equal distribution across classes. Given the randomness of the generated samples, the algorithm is executed 50 times to account for all possible variations, with the results presented as averages in the tables. Table 4 compares the performance metrics of the classification model under both no noise and 40dB noise conditions, offering insights into the model’s effectiveness and robustness. When there is no noise, the model performs exceptionally well across most classes. For classes C1, C3, C5, C6, C7, and C9, the model achieves perfect scores in accuracy, precision, recall, and F1 (all 1.0). This indicates flawless identification for these classes. Classes such as C2 and C4 also perform well, with slight variations; for instance, class C2 has an accuracy of 0.99, precision of 1, recall of 0.95, and an F1 score of 0.97, indicating only minor imperfections in recall. Class C4 has a precision value of 0.95 but maintains perfect recall, along with high accuracy and F1.

In the presence of 40dB noise, the model's performance remains strong, showcasing its robustness against noisy conditions. For classes C3, C6, C7, and C9, the metrics remain perfect (all 1.0) across accuracy, precision, recall, and F1, indicating no drop in performance. Other classes also maintain high performance levels; for example, class C1 has an accuracy of 0.99, precision of 0.93, recall of 0.97, and an F1 score of 0.95. Class C2 maintains an accuracy of 0.99 and perfect precision, with a recall of 0.95 and an F1 score of 0.97. Class C4 shows similar resilience with an accuracy of 0.99, precision of 0.95, recall of 1.0, and an F1 score of 0.97. Class C5, while having an accuracy of 0.99, has precision and recall of 0.97 and 0.93 respectively, balancing to an F1 score of 0.95.

Comparing both scenarios, it is clear that the model exhibits strong resilience to noise. The high-performance metrics across classes C3, C6, C7, and C9, which are perfect even under noisy conditions, highlight the model's robustness. The slight variations observed in other classes under noise do not significantly impact the overall reliability, as the model still maintains high accuracy and balanced F1 scores. This comparison underscores the model's capability to handle both noise-free and noisy environments effectively, making it a dependable tool for classification tasks in varied conditions.

The confusion matrices in Tables 5 and 6 summarize the average performance of the model over 50 runs, providing insights into how well the classifier distinguishes between different signal classes under both pure and noisy conditions. The rows of the matrices represent the actual classes, while the columns show the predicted classes, with the main diagonal containing the correct classifications. Off-diagonal values highlight the extent of misclassification between classes. For pure signals (Table 5), the model achieves an overall accuracy of 99.35%, indicating strong classification performance across most categories. Notably, classes such as C1, C3, C5, C6, C7, and C9 are classified with perfect accuracy (100%), suggesting the model's ability to distinguish these signals with zero errors. However, there are small misclassifications in some cases, such as C2, which, while achieving 94.74% accuracy, shows some misclassification into C4 (5.14%) and a minor error in classifying a very small percentage (0.12%) into C6 Similarly, C4 is classified with near-perfect accuracy at 99.82%, with only 0.18% of signals being misclassified as C2. Class C8 also demonstrates high precision, with 99.60% correct classifications and minimal misclassification into C4 (0.32%) and C2 (0.08%). When noise is introduced (Table 6), with a signal-to-noise ratio of 40 dB, the overall accuracy remains high at 98.26%, reflecting the model's resilience in the presence of noise.

Table 4. Performance metrics results

Class Label	*No noise*				*With 40 dB noise*			
	Accuracy	*Precision*	*Recall*	*F1*	*Accuracy*	*Precision*	*Recall*	*F1*
C1	*1*	*1*	*1*	*1*	*0.99*	*0.93*	*0.97*	*0.95*
C2	*0.99*	*1*	*0.95*	*0.97*	*0.99*	*1*	*0.95*	*0.97*
C3	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
C4	*0.99*	*0.95*	*1*	*0.97*	*0.99*	*0.95*	*1*	*0.97*
C5	*1*	*1*	*1*	*1*	*0.99*	*0.97*	*0.93*	*0.95*
C6	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
C7	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
C8	*1*	*1*	*1*	*1*	*1*	*1*	*0.99*	*1*
C9	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*

Table 5. Average confusion matrix for pure signals

Classes	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*
C1	100	0	0	0	0	0	0	0	0
C2	0	94.74	0	5.14	0	0.12	0	0	0
C3	0	0	100	0	0	0	0	0	0
C4	0	0.18	0	99.82	0	0	0	0	0
C5	0	0	0	0	100	0	0	0	0
C6	0	0	0	0	0	100	0	0	0
C7	0	0	0	0	0	0	100	0	0
C8	0	0.08	0	0.32	0	0	0	99.60	0
C9	0	0	0	0	0	0	0	0	100

Overall classification accuracy 99.35%

Table 6. Average confusion matrix for 40 dB noise

Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	97.48	0	0	0	2.52	0	0	0	0
C2	0	94.84	0	5.02	0.02	0.12	0	0	0
C3	0	0	100	0	0	0	0	0	0
C4	0	0.14	0	99.86	0	0	0	0	0
C5	7.32	0	0	0	92.68	0	0	0	0
C6	0	0	0	0	0.06	99.94	0	0	0
C7	0	0	0	0	0	0	100	0	0
C8	0	0.12	0	0.36	0	0	0	99.52	0
C9	0	0	0	0	0	0	0	0	100
Overall classification accuracy 98.26%									

Table 7. Comparison with the studies in the literature

Reference	Feature Extraction	Classifier	Classification Accuracy (%)	
			Pure	40dB
Li et al. 2016	DRST	DAG SVM	99.30	-
Ranjan et al. 2024	S-Transform	NN	99.50	-
Khan et al. 2021	7 features	Bagged Tree	96.3	-
Wang et al. 2017	S transform	NN	99.26	99.13
Thirumala et al. 2019	TQWT	SVM	97.22	
Garcia et al. 2020	-	CNN-LSTM	84.76	-
Proposed	TKEO+FWHT	RF	99.35	98.26

Although slightly lower than with pure signals, the drop in performance is relatively minor. Class C1, for example, maintains high accuracy with 97.48% of signals correctly classified, though there is a slight increase in misclassification, with 2.52% of the signals being mistaken for C5. Class C2 also retains a strong performance with 94.84% correct classifications, though it shows misclassifications into C4 (5.02%), C5 (0.02%) and C6 (0.12%). Class C3 continues to perform with 100% accuracy even under noisy conditions, showing that certain classes remain robust despite the added noise. Class C5 sees a more noticeable drop in accuracy, with 92.68% correct classifications and 7.32% of signals misclassified as C1. Nevertheless, Classes C6, C7, and C9 continue to maintain perfect accuracy, demonstrating the model's ability to handle noise without compromising accuracy for certain signal types. Class C8, though slightly impacted, retains 99.52% accuracy, with minimal confusion between C4 (0.36%) and C2 (0.12%).

In summary, the confusion matrices highlight the model's high reliability and its strong classification accuracy in both pure and noisy environments. The minor misclassifications observed, particularly under noisy conditions, do not significantly affect overall performance, indicating that the model is well-suited for applications involving signal classification, even in the presence of background noise. These results underscore the robustness and practicality of the model for real-world implementations.

Table 7 provides a comparative analysis of various studies in the literature on PQ disturbance classification. Li et al. (2016) employed the Double-Resolution S-Transform (DRST) in combination with a Directed Acyclic Graph Support Vector Machine (DAG SVM), achieving an accuracy of 99.30% with pure data. Although they explored the effect of noise by adding SNRs from 20dB to 50dB, the results for these noise levels were not disclosed. Ranjan et al. (2024) attained a slightly higher classification accuracy of 99.50% using the S-Transform and a Neural Network (NN), but they did not investigate the impact of noise on their method's performance. Khan et al. (2021) extracted seven features—standard deviation (std), energy, total harmonic distortion (THD), mean frequency, skewness (S kurtosis), average frequency, and total jitter—and applied a Bagged Tree classifier, reporting a lower accuracy of 96.3% under pure data conditions, which falls short compared to our proposed method. Thirumala et al. (2019) utilized the Tunable-Q Wavelet Transform (TQWT) for feature extraction, paired with SVM for classification, reaching 97.22% accuracy under pure data conditions. They also validated their approach using simulated data contaminated with white Gaussian noise across a range of SNRs from 25dB to 55dB. Wang et al. (2017) also examined the influence of noise, achieving an accuracy of 99.26% under pure data conditions and 99.13% under 40dB noise, using the S-Transform and a Neural Network classifier. In contrast, Garcia et al. (2020) employed a CNN-LSTM approach, reporting a lower accuracy of 84.76%, but they tackled a six-class PQ disturbance problem which was tested on experimental data. Our proposed method stands out by delivering highly competitive results using only two key features: TKEO and

FWHT. Despite the simplicity of using just two features, the method achieves a remarkable classification accuracy of 99.35% with pure data and demonstrates robust performance using RF under noisy conditions, reaching 98.26% at 40dB noise. The success of our approach highlights the effectiveness and efficiency of carefully selected features, offering both simplicity and high accuracy in PQ disturbance classification.

4. Conclusion

In this paper, we proposed a method to classify PQ disturbances in power systems. The method begins by obtaining the FFT of the input disturbance signals. These transformed signals are then processed through the TKEO and FWHT to extract features. Using these features, a Random Forest classifier predicts the final class of the disturbances.

The method was validated using an open dataset, where random PQ disturbance samples were generated with various parameters. The results demonstrate the method's success, achieving 99.35% accuracy with pure signals. Furthermore, the method's robustness was tested by introducing 40 dB noise to the pure signals, still resulting in an impressive 98.26% accuracy. These findings underscore the method's reliability and effectiveness, proving its suitability for PQ disturbance classification in both controlled and noisy environments. Although this study used only synthetic data, we plan to collect our own dataset in future studies, allowing us to test the proposed methods on real-world data. This will enable us to assess the method's real-world effectiveness and conduct a more detailed analysis of its impact on energy efficiency and system stability.

Declaration of Ethical Standards
The authors declare that they comply with all ethical standards.

Credit Authorship Contribution Statement
Author-1: Preparation of resources, methodology development, interpreting results, and writing the manuscript.

Declaration of Competing Interest
The authors have no conflicts of interest to declare regarding the content of this article.

Data Availability Statement
The authors declare that the primary data supporting the findings of this study are available within the article.

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