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Classification of power quality disturbances using S-transform and TT-transform based on the artificial neural network

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Abstract: The classification of power quality (PQ) disturbances to improve the PQ is an important issue in utilities and industrial factories. In this paper, an approach to classify PQ disturbances is presented. First, a signal containing one of the PQ disturbances, like sag, swell, flicker, interruption, transient, or harmonics, is evaluated using the proposed approach. Afterwards, S-transform and TT-transform are applied to the signal and an artificial neural network is used to recognize the disturbance using S-transform and TT-transform data, like the variance and mean values of S-transform and TT-transform matrices. The main features of the proposed approach are the real-time and very fast recognition of the PQ disturbances. Finally, the proposed method's results are compared with the support vector machine and k-nearest neighbor classification methods to verify the results. The results show the effectiveness of this state-of-the-art approach.

Key words: Power quality, disturbances, short-time Fourier transform, S-transform, TT-transform, artificial neural network

1. Introduction

Nowadays power quality (PQ) is an important issue for electrical equipment and electrical energy consumers. Electronic equipment (like computers) are sensitive to various disturbances in the power system, while nonlinear loads (such as fluorescent lamps or speed control drives) create some distortions in the current that produce a disturbance in the system. Therefore, there is a need to monitor, control, and improve the PQ of electrical equipment and networks [1]. In most cases, monitoring the PQ's data can be a cumbersome and complicated calculation. Therefore, it is necessary to develop practical tools for the measured data classification so that regulators and electrical loads can have a comprehensive understanding of what kind of distortions occur in the network [2,3].

Many methods have been used to extract features related to PQ disturbances, such as Fourier transform [4] and wavelet transform (WT) [3,5,6]. For the classification of PQ disturbances, heuristic methods like artificial neural networks (ANNs) [3], fuzzy logic [5], and expert systems [7] are used, while other methods are applied to only certain kinds of disturbances to cover a wider range of disturbances. In most studies, short-time

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Fourier transform (STFT) and WT have been used for PQ disturbance identification. In recent years, the S-transform and TT-transform, because of having the features of time–frequency and the features of time–time, respectively, have become effective tools for evaluating PQ disturbances [8,9]. A support vector machine (SVM) constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification. Both the radial basis function and SVM networks are considered to be appropriate tools for classification problems [10]. An integrated model for recognizing PQ disturbances using wavelet multiclass SVM was introduced in [11]. In pattern recognition, the k-nearest neighbor (K-NN) algorithm is a method for classification based on the closest training examples in the feature space. An automatic classification of different PQ disturbances using the wavelet packet transform and fuzzy K-NN–based classifier was presented in [12]. These methods do not have the shortcomings of the STFT and WT. In this paper, first, the identification and classification of PQ disturbances is procured using S-transform and TT-transform based on ANNs, and then the classification procedure is also performed using SVM and K-NN methods to verify the proposed state-of-the-art method's results.

2. STFT, S-transform, and TT-transform

2.1. Short-time Fourier transform

Fourier transform is usually used to detect signal frequency contents. In many cases, there is a need to not only know the signal frequency content's data but also the distribution of the frequency in the time domain, while the Fourier transform cannot describe the distribution of the frequency in the time domain. One way to find the data of the frequency components of a signal in the time domain is STFT. In this method, to determine the frequency components of a signal around τ, the signal is multiplied in the window function and the frequency components are extracted by taking the Fourier integral from this multiplication. The STFT is presented mathematically in Eq. (1):

$$STFT(t,f)=\int_{-\infty}^{+\infty} h(\tau)w(t-\tau)e^{-2\pi i f\tau}d\tau. \tag{1}$$

In Eq. (1), h is the primary function, and τ and f are time and frequency. The position of the window function is determined by t, which is similar to τ in dimension. If in Eq. (1), 1 is substituted for W, the Fourier signal is obtained. If there is no time parameter in the signal features, this transform works fairly well for the stationary signals. Due to the limitation of the fixed width of the window function, the STFT cannot properly express the dynamic behavior of the transient signals, including the high- and low-frequency components.

2.2. S-transform

The S-transform expresses the time–frequency representation of the time series. This transform exclusively produces a resolution based on frequency that simultaneously localizes the real and imaginary spectrums. The basis functions for the S-transform are sinusoidal Gaussian modulated functions, and this makes it possible to use sinusoidal frequencies to perform the time–frequency analysis.

The S-transform, like Fourier transforms, has the advantage of the transformation of a signal from the time domain to the time–frequency domain without losses quickly, and vice versa. If there is a nonstationary distortion in the data, like noise, the S-transform presents patterns similar to the type of investigated disturbance, which requires an easy classification process. Using a scalable window in the STFT, a STFT method called modified S is achieved. In addition, to create the time–frequency separation capability, a direct relationship with the Fourier spectrum is preserved in the S-transform, which is the most important feature of the S-transform.

The S-transform of the time series $h(\tau)$ is presented in Eq. (2):

$$S(t,f) = \int_{-\infty}^{+\infty} h(\tau)\frac{|f|}{\sqrt{2\pi}}e^{-\frac{f^2(t-\tau)^2}{2}}e^{-2\pi i f\tau}d\tau \quad , \tag{2}$$

where τ and f represent, respectively, time and frequency. It can be easily proven that:

$$H(f) = \int_{-\infty}^{+\infty} S(\tau,f)d\tau \quad . \tag{3}$$

In Eq. (3), $H(f)$ is the Fourier transform of $h(t)$. Using Eq. (3), it is obvious that the S-transform is completely a reversible transform.

2.3. TT-transform

The STFT and S-transform have the capability of converting a 1-dimensional signal in the time domain into a 2D signal in the time-scale and time-frequency domains. In 2003, a novel transform based on the S-transform was introduced, called TT-transform [13]. The advantage of this transform over the 2 previous transforms is that it can convert a 1D signal in the time domain into a 2D signal in the time–time domain, which can be used in signal classification.

As was mentioned, the $TT(t,\tau)$ function presents time–time distribution and is calculated by taking the inverse Fourier transform from the S-transform:

$$TT(t,\tau) = \int_{-\infty}^{+\infty} S(t,f)e^{+2\pi i f\tau}df. \tag{4}$$

Just as with the S-transform, it is obvious from Eq. (5) that the TT-transform is a completely reversible transform:

$$h(\tau) = \int_{-\infty}^{+\infty} TT(t,\tau)dt. \tag{5}$$

2.4. Discrete S-transform and TT-transform

A power system disturbance signal expressed by $h(t)$ can be written in discrete form as $h(kT)$, which varies from 1 to $N-1$. T is the sampling time interval and N is the total number of samples. The discrete Fourier transform $h(kT)$ is calculated using Eq. (6):

$$\begin{gathered} H\left(\tfrac{n}{NT}\right) = \tfrac{1}{N}\sum_{k=1}^{N-1} h(kT)e^{-\frac{i2\pi nk}{N}} \\ n = 0,1,2,\ \ldots\ ,N-1 \end{gathered} \quad . \tag{6}$$

The discrete S-transform and discrete TT-transform of the $h(kT)$ series are calculated, respectively, using Eqs. (7) and (8):

$$S\left(jT, \frac{n}{NT}\right) = \sum_{m=-N/2-1}^{N/2-1} H\left(\frac{m+n}{NT}\right) e^{-\frac{2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{NT}} \quad , \tag{7}$$

$$TT\left(jT, kT\right) = \sum_{n=-N/2-1}^{N/2-1} S\left(jT, \frac{n}{NT}\right) e^{\frac{i2\pi nk}{N}} \quad . \tag{8}$$

In the aforementioned equations, j is a nonnegative integer time index, while m and n are frequency indices.

3. Back-propagation neural network

In this paper, a back-propagation neural network is used. Back-propagation networks are multilayer networks with nonlinear transfer functions. Back-propagation networks are used to approximate a function, finding the relationship between the inputs and outputs and the classification of the inputs. Back-propagation networks usually have one or more hidden layers of neurons with a sigmoid transfer function and an output layer that mainly uses a linear function. Figure 1 shows a 2-layer Tansig/Purelin network architecture, which includes a hidden layer and an output layer with a back-propagation structure. This network can be used to approximate any function with a limited number of discontinuities [14].

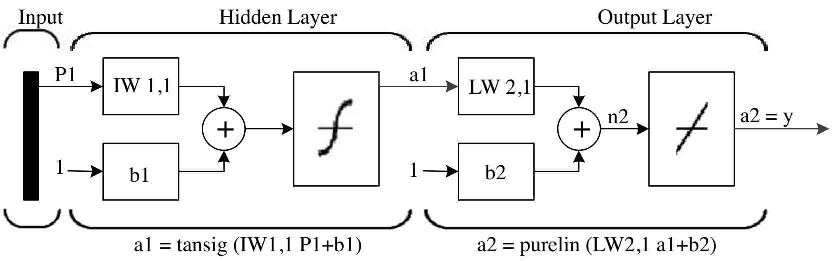

Figure 1. The back-propagation network structure.

3.1. Preparation of the training patterns of the neural network

In order to train the neural network, 2040 training patterns are used. Of those patterns, 1560 patterns are used as training patterns and 480 patterns are used for testing the neural network, where the variance and mean values of the S-transform and TT-transform matrices are used as inputs and the codes of each disturbance are considered as the outputs of the neural network.

The specifications of the neural network used are shown in Table 1. The number of hidden neurons has been determined experimentally. After deciding on the structure of the ANN, it is trained by the Levenberg–Marquardt training algorithm for 21 epochs. The final error becomes 0.0015707 in terms of the mean square error. Next, the ANN is tested by 480 unseen testing patterns, whose error becomes 10^{-6}. After completing the training and testing procedure of the ANN, it is applied to the proposed approach. The following matrix represents the mean and variance of different disturbances. Each column of this matrix proposes the mean and variance of a specific disturbance, which are considered as the inputs of the neural network. The index m represents the number of samples for each type of disturbance.

$$
\begin{array}{cccccc}
Sag & Swell & Transient & Interruption & Flicker & Harmonic \\
\end{array}
$$
$$
\begin{bmatrix}
mean_S & mean_S & mean_S & mean_S & mean_S & mean_S \\
var_S & var_S & var_S & var_S & var_S & var_S \\
mean_{TT} & mean_{TT} & mean_{TT} & mean_{TT} & mean_{TT} & mean_{TT} \\
var_{TT} & var_{TT} & var_{TT} & var_{TT} & var_{TT} & var_{TT} \\
. & . & . & . & . & . \\
. & . & . & . & . & . \\
. & . & . & . & . & .
\end{bmatrix}_{(4\times m)\times 6}
$$

Each column of the following matrix represents the unique code of a specific type of disturbance.

$$
\begin{array}{cccccc}
Sag & Swell & Transient & Interruption & Flicker & Harmonic \\
\end{array}
$$
$$
\begin{bmatrix}
0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 1
\end{bmatrix}_{3\times 6}
$$

Table 1. Specifications of the used neural network.

	Input layer	Hidden layer	Output layer
Number of neurons	10	10	3
Activation function	-	Sigmoid	Purelin

4. Case study

The PQ disturbance identification and classification algorithm using the S-transform and TT-transform based on the ANN is presented in Figure 2.

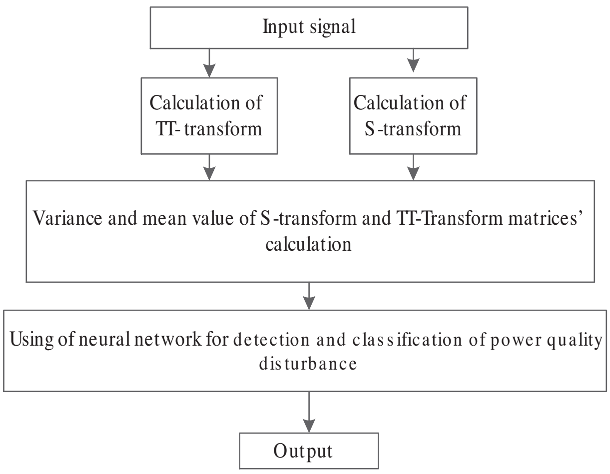

Figure 2. The algorithm of the detection and classification of the power quality disturbances using S-transform and TT-transform based on ANN.

In order to study the PQ disturbances, the related waveforms of the sag, swell, flicker, interruption, transient, and harmonic are simulated by a standard method [13], and the S-transform and the TT-transform related to any of these waveforms are obtained. For obtaining training samples of the neural network for any

PQ disturbances, several standard shapes are constructed and then the variance and mean values of the S-transform and TT-transform matrices are calculated. Using these values, the neural network is trained with good accuracy, which can detect any signal containing the mentioned disturbances. Figure 3 is presented to evaluate the performance accuracy of the S-transform and TT-transform for a sample signal that corresponds to the results in [13] and clearly shows that these 2 transforms are proper and powerful tools to identify the PQ disturbances.

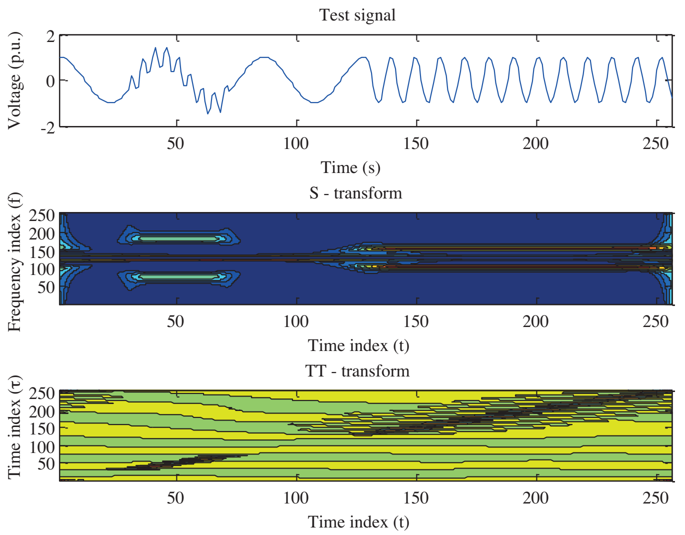

Figure 3. Representation of S-transform and TT-transform of a sample signal for evaluating the accuracy of their performance.

Figures 4–9 present a signal containing the PQ disturbance, S-transform, and TT-transform related to that signal. Sample values of the mean and variance related to each matrix of the S-transform and TT-transform are presented in Table 2.

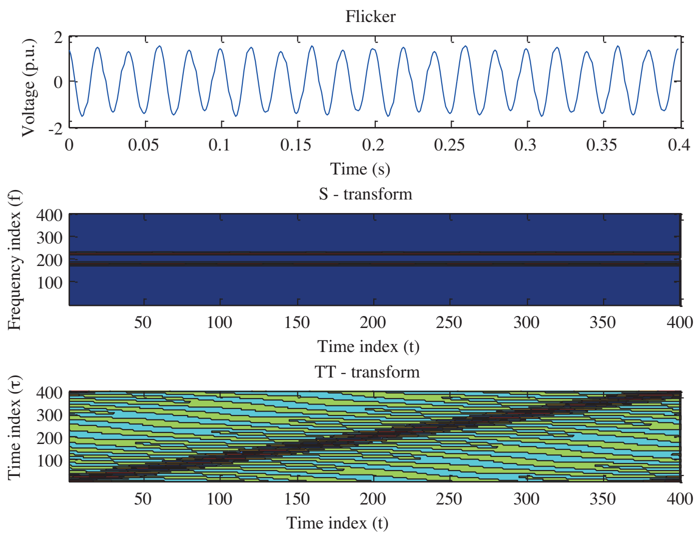

Figure 4. Representation of S-transform and TT-transform during the occurrence of a flicker.

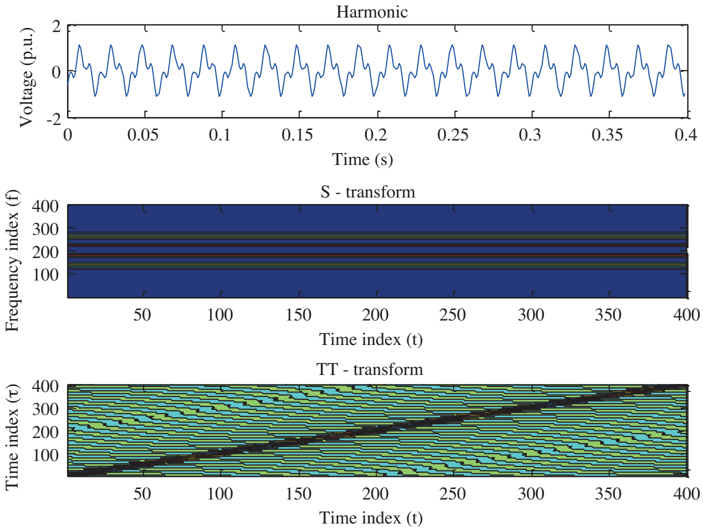

Figure 5. Representation of S-transform and TT-transform during the occurrence of a harmonic.

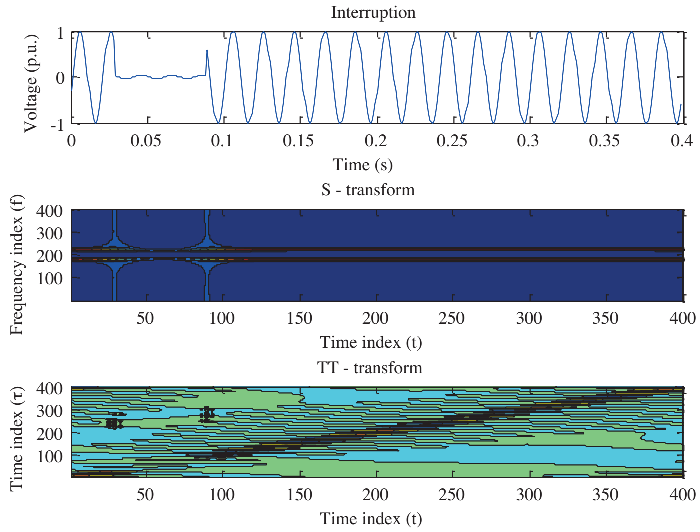

Figure 6. Representation of S-transform and TT-transform during the occurrence of an interruption.

Table 2. The sample values of the means and variances regarding the S-transform and TT-transform matrices.

	S-transform		TT-transform	
	Variance	Mean	Variance	Mean
Sag	5.8023×10^{-5}	0.0014	4.1953×10^{-6}	-7.7254×10^{-4}
Swell	1.5674×10^{-5}	7.4398×10^{-4}	2.3308×10^{-5}	0.0022
Flicker	2.6448×10^{-3}	1.0319×10^{-7}	5.4357×10^{-5}	0.0034
Harmonic	1.2415×10^{-2}	2.2658×10^{-6}	4.8124×10^{-5}	-0.0033
Interruption	8.1821×10^{-5}	0.0017	4.2008×10^{-6}	-7.9244×10^{-4}
Transient	0.0019	0.0143	1.4477×10^{-5}	6.4884×10^{-4}

As the mean and variance values that are used in order to train the neural network are close to each other, the neural network has an error in the recognition and classification of each disturbance type. Table 3 proposes the number of test samples and the trained neural network error. As shown in Figures 4–9, since both the S-transform and TT-transform of any mentioned disturbance have unique features, ANNs can be used for the detection and classification of the PQ disturbances.

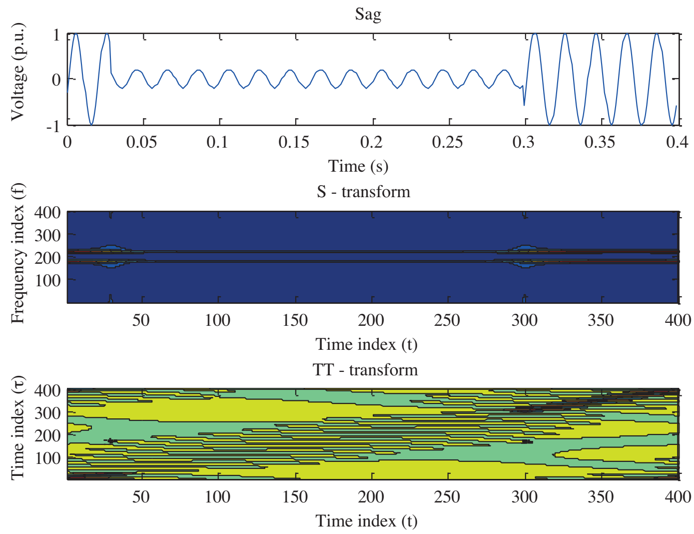

Figure 7. Representation of S-transform and TT-transform during the occurrence of a sag.

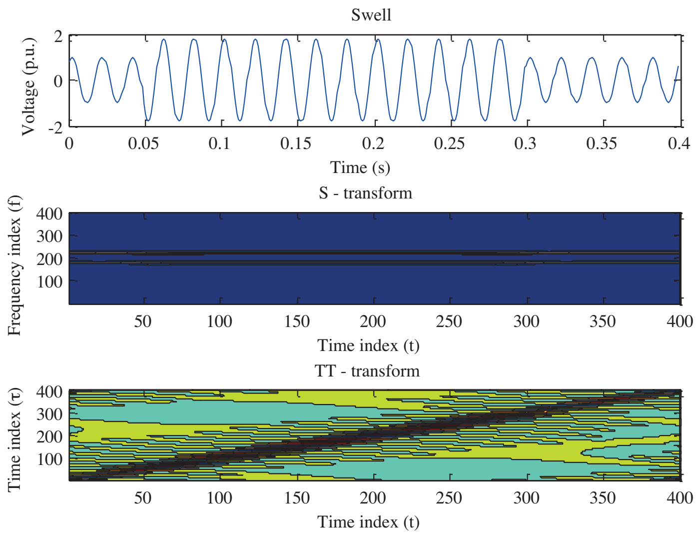

Figure 8. Representation of S-transform and TT-transform during the occurrence of a swell.

Table 3. The outcome of the ANN test procedure.

	Number of test samples	Error
Sag	80	4
Swell	80	5
Flicker	80	7
Harmonic	80	8
Interruption	80	6
Transient	80	7

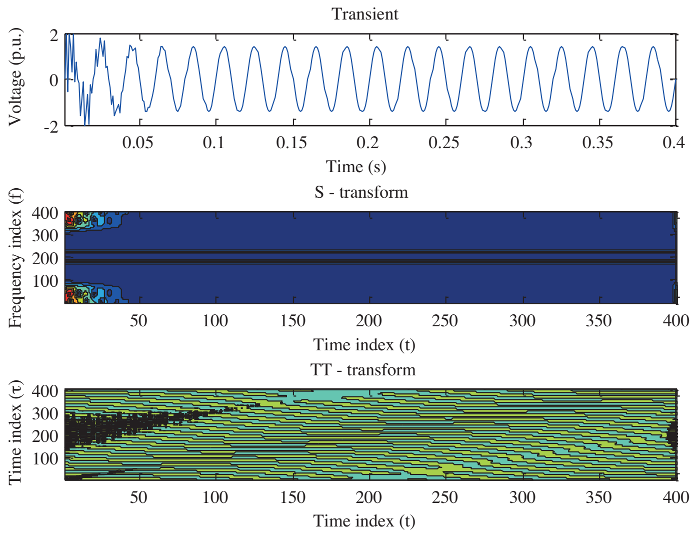

Figure 9. Representation of S-transform and TT-transform during the occurrence of a transient.

Next, in order to compare the proposed method with the 2 mentioned common methods, 80 samples of 6 kinds of disturbances are classified using the SVM and K-NN methods. The receiver operating characteristic (ROC) curve in every case shows the accuracy of the mentioned method. If the result is distinguished correctly using the SVM and K-NN methods, it is in the true class; otherwise, it is in the wrong class.

Hence, the ROC curve is obtained using double-classification of the outputs of the mentioned method. The results of the SVM method are shown in Table 4 and the corresponding ROC curve is shown in Figure 10.

Table 4. Confusion matrix for the SVM method.

	Sag	Swell	Flicker	Harmonic	Interruption	Transient
Sag	78	2	0	0	7	1
Swell	0	69	0	1	0	3
Flicker	0	1	79	5	3	0
Harmonic	0	3	1	71	4	1
Interruption	2	0	0	2	64	0
Transient	0	5	0	1	2	75

The confusion matrix for the SVM method is shown in Table 4, where the success rate is 90.83%.

The accuracy of this method can be obtained using a confusion matrix. The accuracy of this method is 90.83%.

The results of the K-NN (in this article K = 3) method are shown in Table 5 and the corresponding ROC plot is shown in Figure 11.

Table 5. Confusion matrix for the K-NN method.

	Sag	Swell	Flicker	Harmonic	Interruption	Transient
Sag	70	2	0	4	6	0
Swell	0	72	0	1	0	1
Flicker	2	1	75	4	2	1
Harmonic	1	3	3	69	0	0
Interruption	5	0	1	2	60	0
Transient	2	2	1	0	2	78

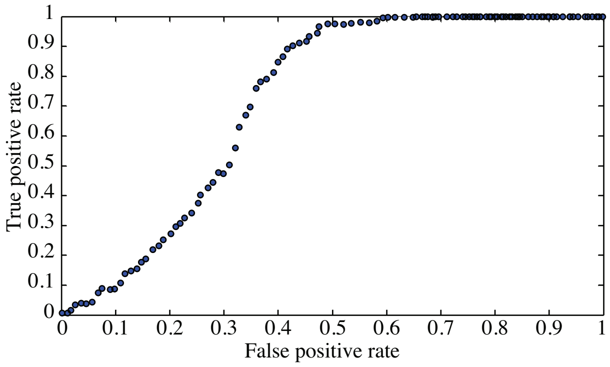

Figure 10. Representation of the accuracy of the SVM method.

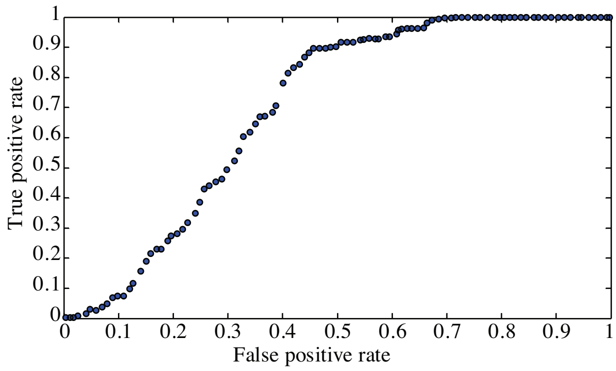

Figure 11. Representation of the accuracy of the K-NN method.

The confusion matrix for the K-NN method is shown in Table 5, where the success rate is 88.33%.

The accuracy of this method can be obtained using a confusion matrix. The accuracy of this method is 88.33%.

Table 6 represents a comparison between the proposed method and the SVM and K-NN methods. As can be seen, the proposed method, for some of the disturbance contained signals, has less accuracy than the SVM and K-NN methods. As is shown, the proposed method, according to the average, produces more correct results.

Table 6. Comparison of the classification results.

	Accuracy of the classification methods (%)						
	Sag	Swell	Flicker	Harmonic	Interrupt	Transient	Average
Proposed method	95	93.75	91.25	88.75	92.5	91.25	92.083
SVM	97.5	86.25	98.75	88.75	80	93.75	90.833
K-NN	87.5	90	93.75	86.25	75	97.5	88.333

5. Conclusion

In this paper, a method was presented that uses the S-transform, TT-transform, and ANNs for the identification and categorization of PQ disturbances in a very short time and in real-time. It was also shown that using the S-transform and TT-transform, the frequency spectrum, time spectrum, and the time of the disturbance occurrence during time variations can be achieved with very high accuracy. However, the investigation and comparison between the back-propagation network and the SVM and K-NN classifier results showed better classification results for the back-propagation network. Since this method is dynamic and has very high accuracy in frequency and time analysis for any kind of disturbance, using this method in industrial centers with sensitive loads is recommended.

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