IDENTIFICATION OF POWER QUALITY DISTURBANCES USING S-TRANSFORM AND MULTI-CLASS SUPPORT VECTOR MACHINE

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Abstract: An essential issue in power quality disturbances is identifying and classifying power quality disturbances from anywhere and at any time. This article proposed a new approach to identify and classify power quality disturbances over the web using S-transform, Multi-Class Support vector machine (SVM), and Matlab framework. S-Transform is used as an extraction feature to obtain the temporal frequency characteristics of power quality events. The development of the multi-class SVM classifier, in which the system classifies various power quality disturbances. Finally, the Matlab framework integrated the graphical and computational processes with remote access via the web. The test result indicated the suggested method's effectiveness and robustness for identifying and classifying power quality disturbances through the web.
Keywords: Power quality disturbances; Support Vector Machine; S-Transform

Abstrak: Masalah penting dalam gangguan kualitas daya adalah mengidentifikasi dan mengklasifikasikan gangguan kualitas daya dari mana saja dan kapan saja. Artikel ini mengusulkan pendekatan baru untuk mengidentifikasi dan mengklasifikasikan gangguan kualitas daya melalui web menggunakan S-transform, Multi-Class Support vector machine (SVM), dan Matlab. S-Transform digunakan sebagai fitur ekstraksi untuk mendapatkan karakteristik frekuensi temporal dari peristiwa kualitas daya. Multi class SVM classifier dikembangkan dimana sistem mengklasifikasikan berbagai gangguan kualitas daya. Akhirnya, Matlab framework mengintegrasikan proses grafis dan komputasi sehingga dapat diakses jarak jauh melalui web. Hasil pengujian menunjukkan efektivitas dan robustnes metode yang usulkan untuk mengidentifikasi dan mengklasifikasikan gangguan kualitas daya melalui web.
Kata kunci: Gangguna kualitas daya; support Vector Machine; S-Transform

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Introduction

The importance of good power quality for electronic equipment can be analogized with the food and drinks we consume every day. If the food and drinks that we eat every day are reasonable and lawful, they will give a positive impact on our bodies. Conversely, if the food and drinks we consume are not good, not halal, or consumed in excess, it will lead to a bad impact. This impact can be in the long term or the short term directly felt by the body. Likewise, electronic equipment uses electrical energy, if this equipment is provided with electrical energy that has good quality following the required requirements, the device will work optimally and have a long service life.

On the other hand, if this electronic equipment is supplied with poor-quality electrical energy, it can cause damage to the equipment, both in the long term and in the short term. In the long term, for example, the equipment can experience a decrease in service life, equipment performance is not optimal, the age of components that must be replaced before the replacement period, maintenance schedules that must be carried out before the time comes, or even the impact in the short term, the equipment is completely damaged so that it cannot be used. Conditions like this certainly have an impact on user losses. If the user is the community, then this will harm the community. Suppose this electronic equipment is the equipment used by industry. In this case, this will be detrimental to many parties, which will harm the country, and have an impact on the decline of a country's economy. Losses caused by power quality disturbances have been widely reported in previous studies (Beniwal et al., 2021; Byrd & Matthewman, 2014; Salim et al., 2014; Wang & Chen, 2019). Therefore, good quality electric power is important at this time.

The need for good quality electricity has grown in recent years. Low power quality is usually caused by power interference, interruptions, tone harmonics, high voltage, or shortage numerous electronic devices, including computers, process controllers, and networking facilities, are susceptible to power system disturbances. A series of short voltage fluctuations can lead to data loss and system errors. spikes in voltage caused by an instability in electronic counting equipment The emphasis on the standard of power is increasing rapidly in the next few years due to the revolution in power and electricity deregulation.

To maintain the consistency of power and to aid in the identification of power quality (PQ) issues, a large number of power quality meters have been installed in electric power systems, capturing a large number of disturbances waveforms. An in-depth manual review of PQ data processing is tedious and specialized. The research process would be facilitated by accurate identification, classification, and an automatic method for classifying power quality disturbances.

It has been mentioned in the literature that there are several approaches for the automatic classification of power quality disturbances, including fast Fourier Transforms (FFT) (Chawda et al., 2020; Deokar & Waghmare, 2014; Khetarpal & Tripathi, 2020; Mahela et al., 2015; Mishra, 2019), wavelets and S-Transform (Kankale et al., 2021; Mahela et al., 2020; Monteiro et al., 2018). The FFT has little ability to localize time and frequency. STFT cannot detect high-frequency (irregular) motion (transient) and persistent signals. The transformation of the wavelet was shown to be optimal for analyzing power quality, which is also used for the identification and classification of complex power quality disorder. The transform wavelet also has a location property However, its ability in noise-filled conditions is also significantly reduced.

The S-Transform (ST) is a subset of the continuous wavelet transform (CWT) (Stockwell et al., 1996). ST is based on a moving and scalable Gaussian window and is more efficient than Wavelet Transform and STFT. It is superior to the Fourier and wavelet transforms in a variety of ways. It is suitable for studying PQ disturbances due to the desired time-frequency characteristic.

After much increase in popularity, the support vector machine (SVM) has gained theoretical and practical importance. The SVM is a general classification scheme that is based on the principle of mathematical learning. Its theoretical underpinnings are described in (Vapnik, 1998).

SVMs can handle a multitude of problems while possessing special expressiveness, dimensionality, and nonlinearity. Classification SVMs are often used to decompose it into several binary problems, each of which can be solved using an SVM can solve the multi-class problem (BISCHL, 2013; Kächele, 2020; Tang et al., 2020). Any tool for analyzing PQ disturbances has been developed to automate the detection of PQ disturbances (Nolasco et al., 2019; Parvez et al., 2019; Ribeiro et al., 2018; Rodrigues Junior et al., 2019; Sahani & Dash, 2019). Most tools are based on well-known programs. This article explains how to identify and classify power quality disturbances anywhere and at any time. New technologies have influenced how software is created today. More internet-based methods have several advantages arranging device data in many ways makes the web interface cross-platform in architecture, easy to use at any time, as well as secure and inexpensive.

S-Transform

A law of movable and scalable Gaussian is used as a platform. It creates a time-frequency continuum of frequency-dependent resolution when referencing the Fourier spectrum by time averaging. To derive the S-transform from the CWT (Manimala et al., 2008; Wenda et al., 2010, 2011), one must first specify the CWT(, d) of a function x(t).

$$\mathrm{CWT}(\tau,d)=\int_{-\infty}^{\infty} x(t)w(t-\tau,d)dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where w(t, d) denotes the mother wavelet and d denotes the scale factor of *f*, Multiplying the CWT(τ, d) by a factor produces the S-transform.

$$S(\tau,f) = CWT((\tau,d)e^{i2\pi ft} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

When (1) and (2) are substituted, the S-transform becomes,

$$S(\tau,f)=\int_{-\infty}^{\infty} x(t)w\left(\tau\text{-}t,d\right)e^{i2\pi ft}dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(3)$$

In this instance, the mother wavelet is described as,

$$w(t,f) = g(t)e^{-i2\pi ft} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Expand: Let's use the term "Gaussian window" as an expansion of "where g(t) is given" to mean:

$$g(t)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\left(\frac{t^2}{2\sigma^2}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(5)$$

σ is the width of the Gaussian window as defined by

$$\sigma(f)=T=\frac{1}{|f|} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(6)$$

By substituting (5) and (6) for (4), we obtain

$$w(t,f)=\frac{|f|}{\sqrt{2\pi}}e^{-\frac{t^2f^2}{2}}e^{-i2\pi ft} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Substituting (7) into (3) results in the following final S-transform equation:

$$S(\tau,f)=\frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty} x(t)e^{-\frac{(t-\tau)^2f^2}{2}}e^{-i2\pi ft}\,dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Where f denotes frequency and t and τ denote time.

The discrete form of the PQ disturbances signal x(t) is x(kT), where k equals 0,1,...,N-1 and T equals the sampling time interval.
x(kT) is transformed into its discrete Fourier form as follows:

$$X\left[\frac{n}{NT}\right]=\frac{1}{N}\sum_{k=1}^{N-1}x[kT]\,e^{\left(-\frac{i2\pi nk}{N}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Where n=0,1,…N-1.
The discrete version of the S-transform of a signal in the discrete form can be calculated as follows (let τ be kT and f be n/NT):

$$S\left[kT,\frac{n}{NT}\right]=\sum_{k=0}^{N-1}X\left[\frac{m+n}{NT}\right]e^{-\frac{2\pi^2m^2}{n^2}}e^{\frac{i2\pi mk}{N}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

for $n \neq 0$

$$S[kT,0]=\sum_{k=0}^{N-1} x\left(\frac{m}{NT}\right) \quad \text{for } n=0 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

Where k, n, m=0,1,…,N-1.

With the discrete S-transform, the time-amplitude and time-frequency profiles are obtained as well as amplitude-amplitude profiles. A NxM matrix is generated using the S-transform any row contains the zero-order S-transform at zero frequency, and the other row represents the magnitude of the S-transform from n=0, 1/2, …, n=1/4-by-time.

Feature Extraction of Power Quality Data

Extraction of power quality data features is done by mapping the distorted signal data into its S-Transform domain. Then, the characteristics of the distorted signal extracted from the S-transform analysis were plotted into a time-frequency representation of a contour graph. To detect power quality disturbances, the value of the time-frequency representation of a signal is compared with the value of the time-frequency representation of a normal signal. Time-frequency representation graph can be obtained from S-transform analysis where the graph represents the distribution of energy in different frequency bands over a certain period of time. For normal signals, the time-frequency representation is linear throughout the range. This linear value is taken as a reference.

The following features are extracted from the S-transform analysis and used to classify PQ anomalies:

Feature1 is the amplitude factor, given by,

$$\text{Feature 1} = 1+\text{std1}+\text{std2}-\text{norm1}-\text{norm2} \;\ldots\ldots\ldots\ldots(12)$$

Where,

std1 – the sum of maximum value of standard deviation from the distorted signal.

std2 – the sum of the minimum value of standard deviation from the distorted signal

norm1 – The maximum value of standard deviation from normal signal

norm2 – The minimum value of standard deviation from the distorted signal

Feature2 represents the maximum deviation of the non-skewed and skewness signal

$$\text{Feature 2} = \text{std1}-\text{norm1} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

The mean of a distorted signal by Feature 3, denoted by,

$$\text{Feature 3} = \text{mean}(\text{mean}(\text{abs}\left(\text{ds})^2\right)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where *ds* is the S-transform absolute value of the distorted signal.
Feature 4 is the absolute value of the S-transform of the frequency with the highest amplitude, denoted by,

$$\text{Feature 4} = \text{abs}(\text{ds}(\text{fm})) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

Where the wavelengths of *fm* are the shortest
Absolute harmonic distortion is denoted by Feature5.

$$\text{Feature 5} = \text{THD}=\sqrt{\frac{\sum_{i=2}^{m} X_i^2}{X_1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (16)$$

Where 'i' is a voltage variable; X is the number of points in the FFT; X is the n^{th} harmonic component amplitude; TH is harmonic absolute amplitude.

In figure 1-4, a scatter pair of Features 1 – Feature 5 is shown in which Interruption (E1), Normal signal (E2), Notching (E3), Sag (E4), Swell (E5) and Transient (E6) are described. The values of different functions are shown in figures 1 - 4. This pattern represents an unequaled possibility to divide the region of the disturbances; certain classes are distinguished while other classes have different characteristics.

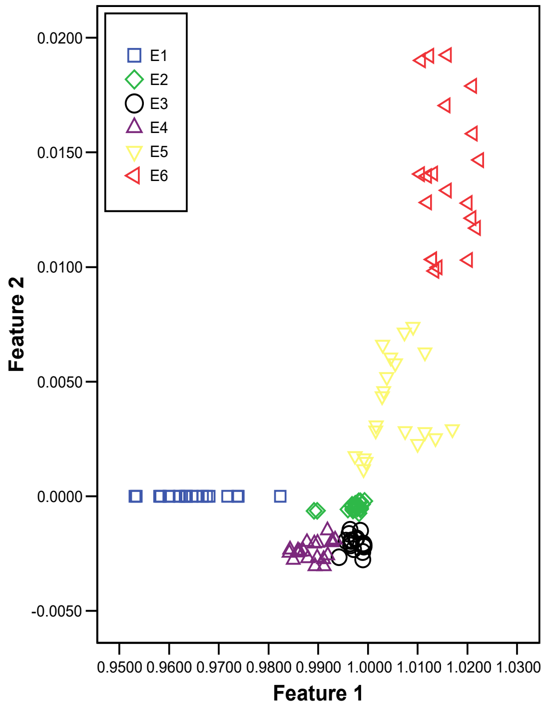

Figure 1. Feature 1 vs. Feature 2

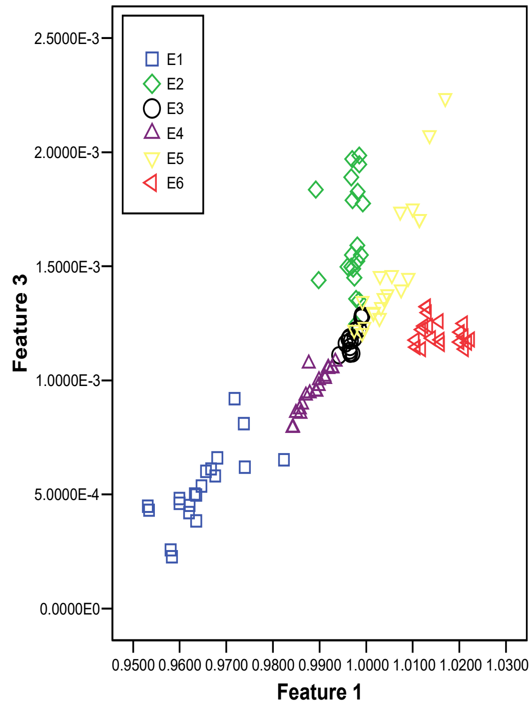

Figure 2. Feature 1 vs. Feature 3

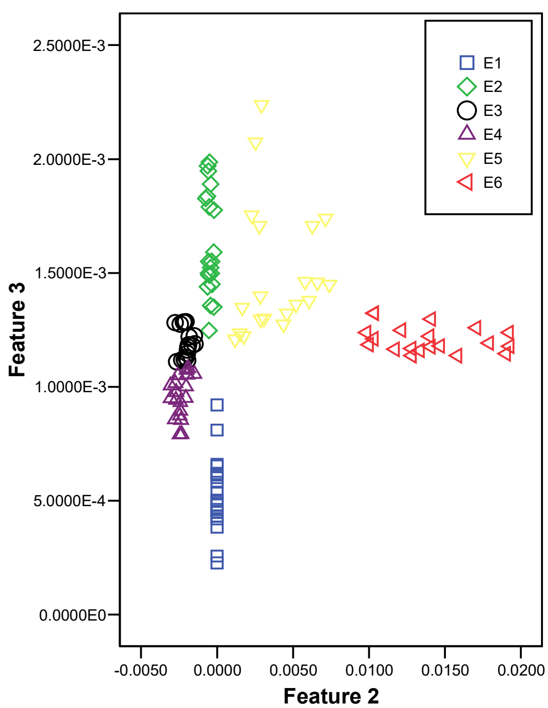

Figure 3. Feature 2 vs. Feature 3

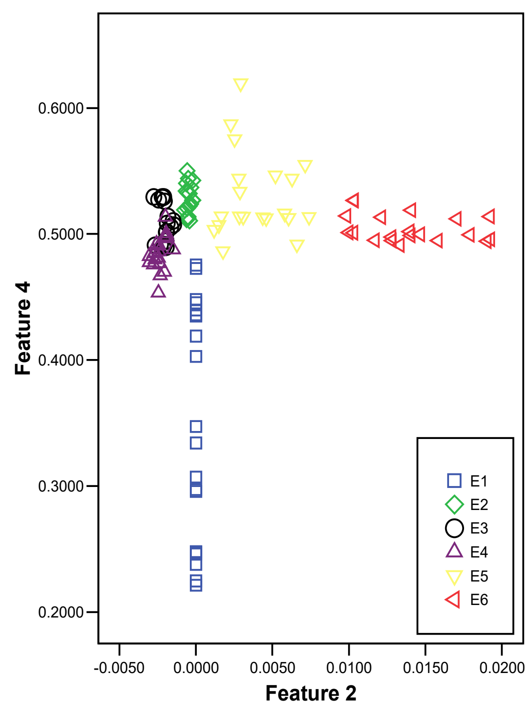

Figure 4. Feature 2 vs. Feature 4

Multi-Class Support Vector Machine Classifier

Support Vector Machine: a machine learning technology developed in the 1990s by Vapnik and his colleagues at Bell Labs that is based on the statistical theory the SVM removed both the VC risk and the machine risk at the same time SVM models with a good theoretical basis will reduce the number of samples required, the nonlinearity, and multidimensional complexity to the global minimum and avoid overfitting in networks (Kächele, 2020).

SVM was developed primaries for resolving binary grading problems and offers a range of approaches for solving multi-class grading problems, including "one against each other," "one against one" and Dendrogram SVM (DSVM). DSVM improved as a result of the evaluation (Bennani & Benabdeslem, 2006).

The DSVM classifier was used to distinguish between regular signals and the five types of PQ disturbances: voltage sag, voltage swell, interference, notching, and impulsive transient, based on the characteristics of various types of PQ disturbances. A class taxonomy was used in the DSVM technique to decompose a multi-class problem into a set of binary-class problems. To distinguish all groups, the ascending Hierarchical Clustering (AHC) procedure was used. Clustering divides the database into distinct subsets with distinct sub-problems. SVM classifiers are applied to construct the best-discriminating feature at each internal node (Bennani & Benabdeslem, 2006).

Figure 5 shows an example of a taxonomy which covers the groups of N at the classification stage. In the second step, any SVM must be connected to a node and trained on its two subsets of elements. For instance, in Figure 5, SVM 1 includes C2 elements as positive examples and all of the bad data, whereas C3, C4, and C5 are all considered negative examples. SVM 4 treats C1 elements as positive and C3 elements as negative. Finally, we'll be able to train a (N - 1) SVM to handle a problem with N classes.

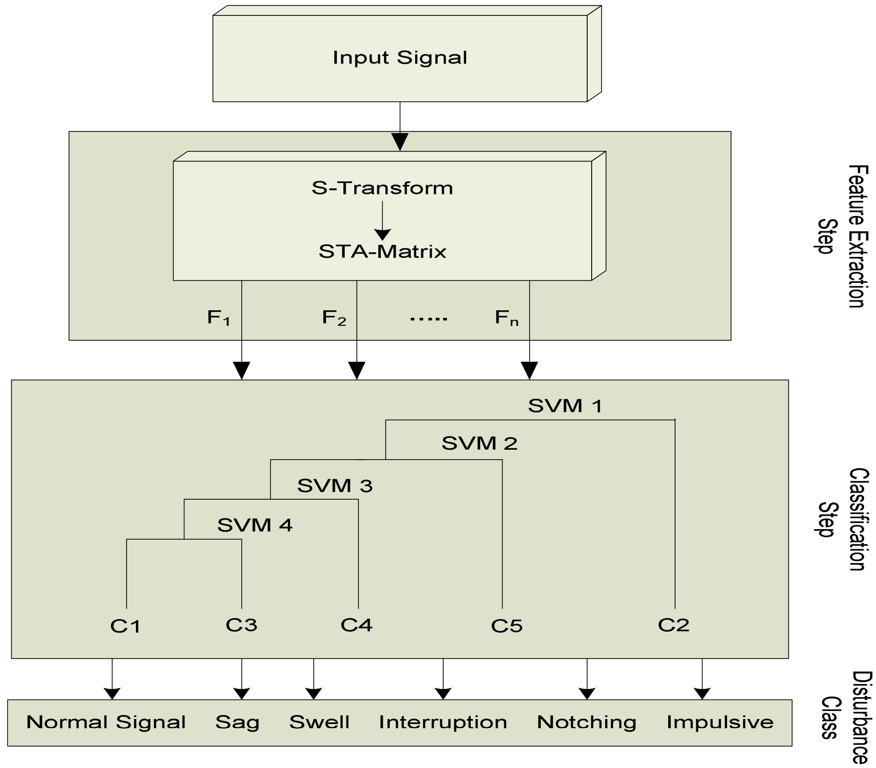

Figure 5. Block Diagram of the Propose System

Result

Web applications are developed using the Matlab framework, which consists of Matlab App Designer, Matlab Compiler, and Matlab Web App Server. Matlab App Designer is used to design the application interface, Matlab compiler is used to compile all the coding that has been created, while Matlab Web App Server is used to create a host server that allows Matlab applications to be accessed via the web.

This application can be accessed from anywhere and anytime using a web browser as long as the user is connected to the internet. There are two main ways that users can identify power quality problems. First, the existing database in the system can be obtained from measuring instruments that are directly stored on the computer server. Second, users can enter measurement data manually.

Figure 6-9 shows a web interface for the classification of PQ disorders using the first method, namely using the existing database in the system. Figure 6 it can be seen that the user can choose the power quality of the data that has been stored in the database, and then the system processes the data according to the algorithms and methods that have been developed, the result is a graphical interface that displays the input signal, the classification results, in this case, are the system identifies the presence of voltage swells, and a contour graph of the S-transform which visually follows the contour of the input signal. In Figure 7, the system identifies power quality disturbances in the form of voltage sag, and displays a graph of the input signal and a graph of the S-transform contour which is the same as the contour of the input signal. Figure 8, the system identifies power quality disturbances from the input signal as voltage interruption and displays a graph of the input signal and a graph of its S-transform contour. As for Figure 9, it can be seen that the system identifies that there is no interference from the input signal. it can also be seen visually from the graph of the input signal and the contour graph of the S-transform.

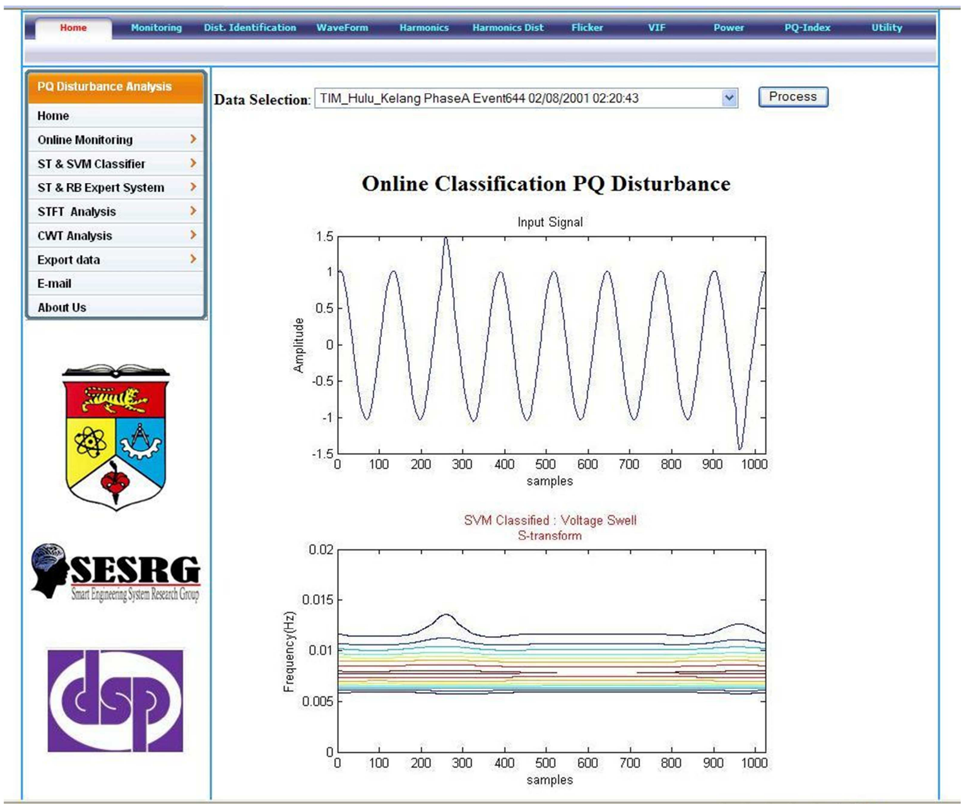

Figure 6. Web interface identification of PQ disturbances with the result of a voltage swell

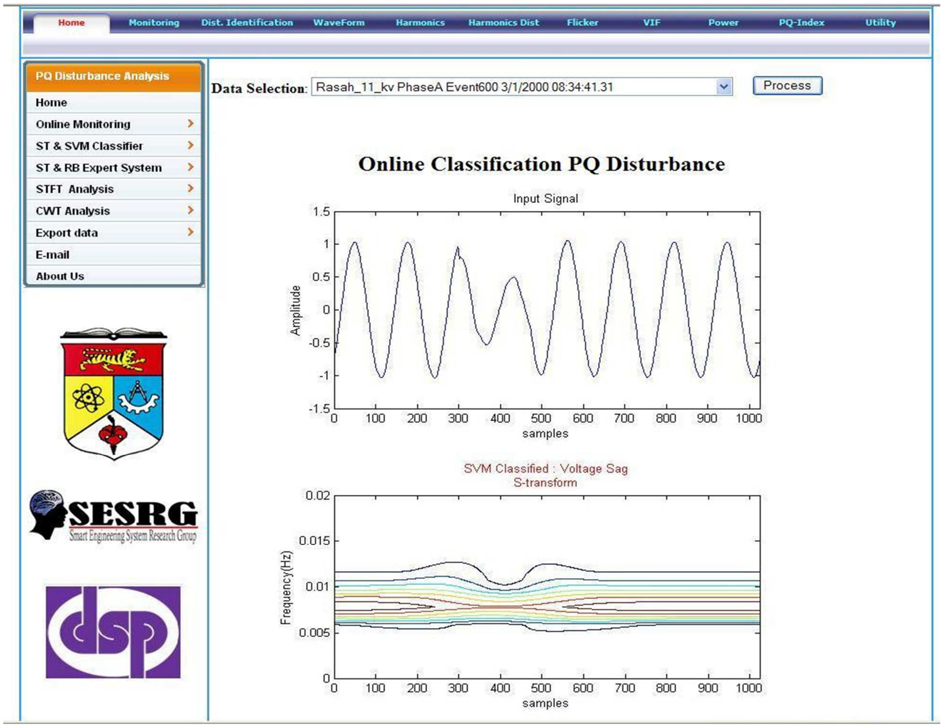

Figure 7. Web Interface Identification of PQ disturbances with the result of voltage sag

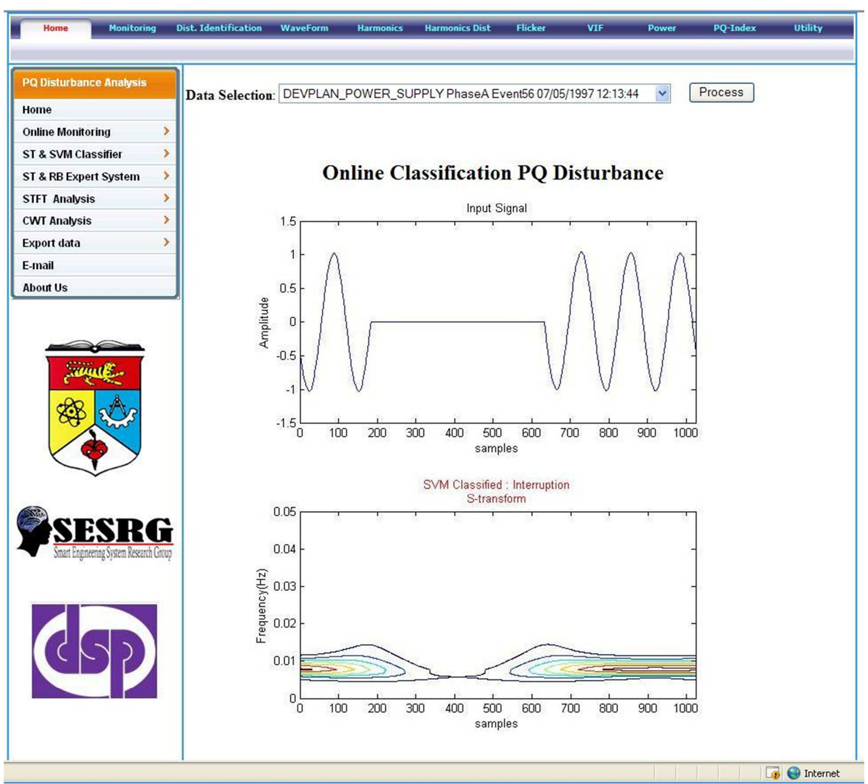

Figure 8. Web Interface Identification of PQ disturbances with the result of interruption

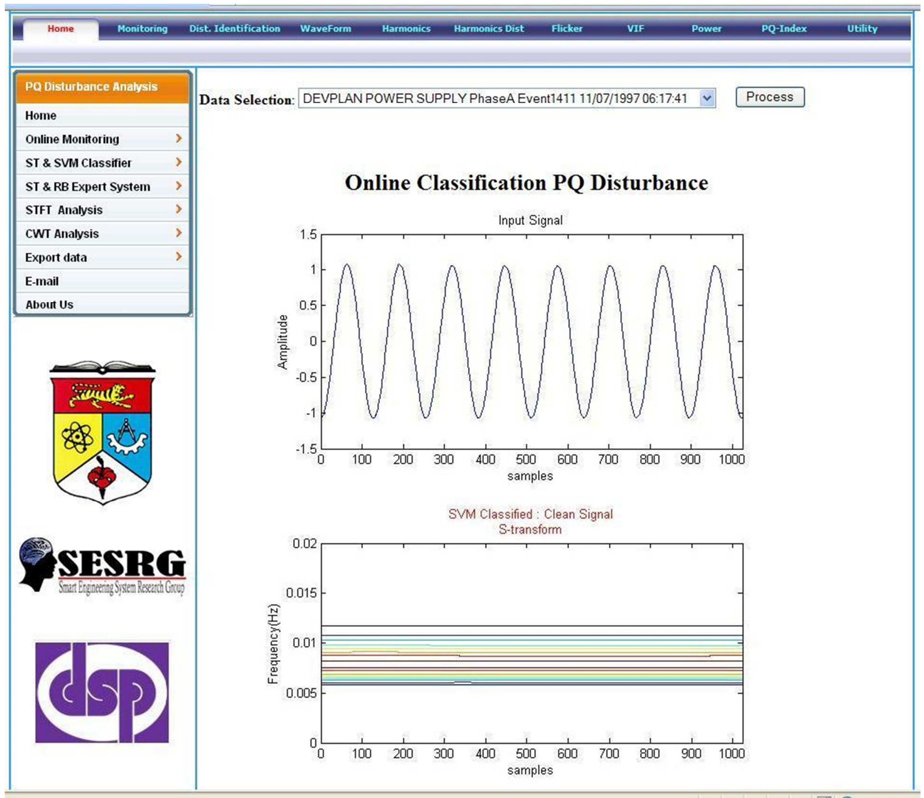

Figure 9. Web Interface Identification of PQ disturbances with the result of normal voltage

While Figure 10 shows the second method, where data from the measuring instrument is then uploaded to the system to identify the type of disturbance. There is a form that is used to upload data, and then carry out the identification process. The result is a graph of the input signal, the results of the identification of power quality disturbances which in this case is the voltage Swell, and a contour graph of the S-transform which visually has the same contour as the input signal.

From these two methods, it can be seen that the application correctly identifies power quality disturbances. The user can select data based on the measurement location, year, date, time range, or a specific measurement period for analysis purposes.

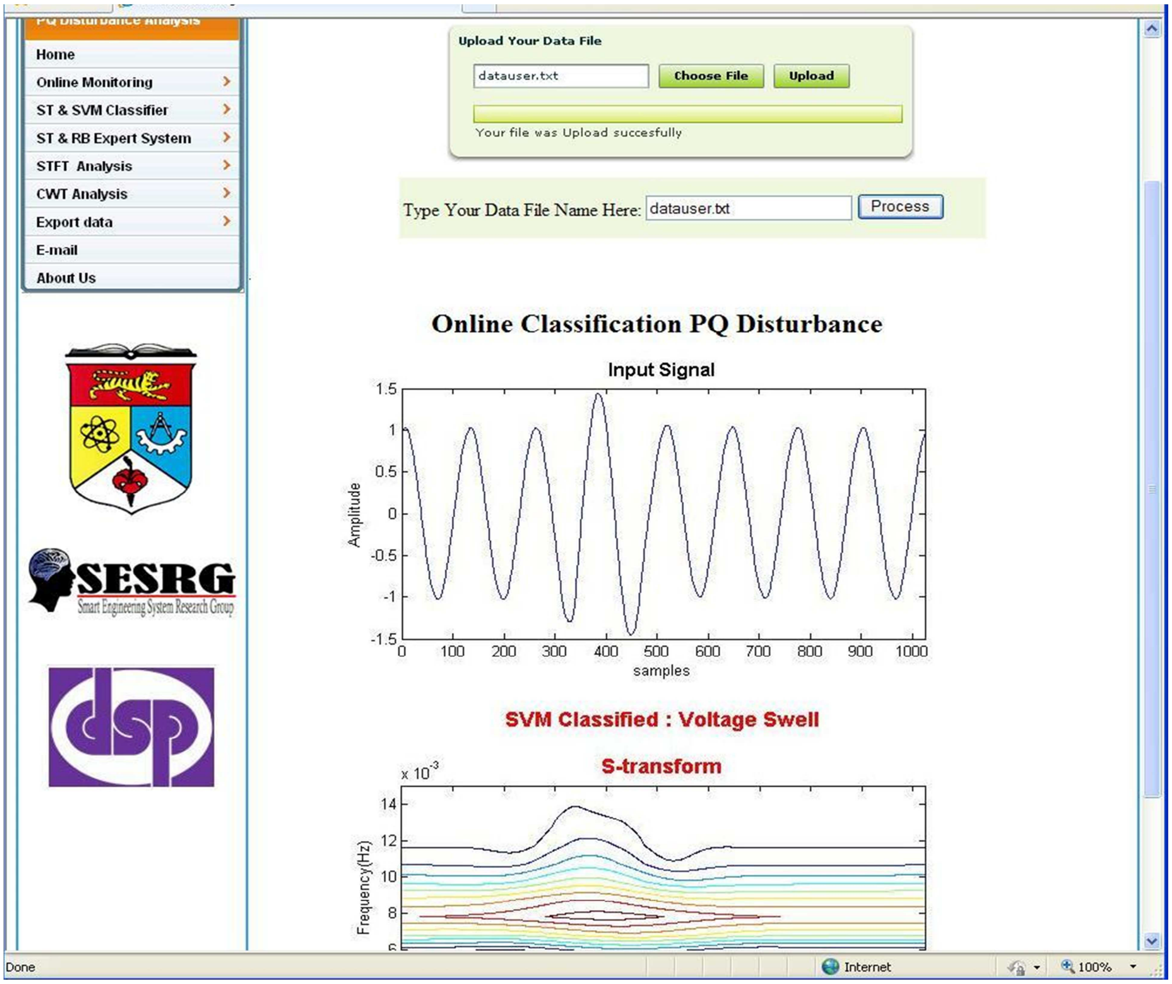

Figure 10. Disturbances identification web interface by using data provided by the user

An additional method validation study was done, where an additional 810 samples of disturbances data were compared to the proposal. The number of right cases in Table 1's definition of the PQ disturbances scale (i.e., 99.88% overall classification) is the result of the PQ disturbances assessment.

Table 1. Power Quality Disturbances Classification Result

Power Quality Event	Number of Correctly Identifies	Number of Incorrectly Identifies	Percent Correct (%)
Voltage Sag	150	0	100
Voltage Swell	150	0	100
Notching	119	1	99.30
Transient	120	0	100
Interruption	120	0	100

Power Quality Event	Number of Correctly Identifies	Number of Incorrectly Identifies	Percent Correct (%)
Normal Signal	150	0	100
Total	810	1	99.88

Conclusion

The article discussed a practical approach for automatically classifying PQ disturbances on the network. For the study and assessment of PQ disturbances on the internet, the proposed approach used S-transform, Multi-Class SVM graders, and Matlab framework, and could be accessed from any network point. The findings of the test indicated the effectiveness and stability of the suggested method even with the respect to place and time.

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