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FEATURE EXTRACTION AND CLASSIFICATION OF POWER QUALITY EVENTS BASED ON FAST FOURIER TRANSFORMATION AND ARTIFICIAL NEURAL NETWORK

Ezgi GÜNEY[1]*, Çağrı KOCAMAN[2]

[1]*Sinop University, Vocational High School, Department of Electrical and Energy, 57000, Merkez, Sinop, Turkey*
[2]*Turkish Airlines Flight Management, 34180, Bahçelievler, İstanbul, Turkey*

Abstract: This paper presents an effective method for detection and classification of Power Quality Events (PQE), based on Fast Fourier Transformation (FFT) for event identification and Artificial Neural Network (ANN) technique for classifying of these events. Firstly, synthetic data such as pure sine as a reference, voltage sag, voltage swell, flicker, transient, voltage with harmonics are created in MATLAB based on TS EN 50160 standard. Database with 480 PQE waveforms is generated with 80 samples for each of the 6 types of the waveform with randomly different event amplitude, beginning occurrence time, time duration, frequency component and angle according to a type of event. FFT is used to extract features of the events by decomposing the signal. Then, 16384×480 data are reduced to 480×480 data by applying Principal Component Analysis (PCA) that is prevent over-learning, obtain less runtime using less computing power and reduce data and storage space. Finally, a total of 480 PQE are classified by using ANN. 336 of these PQE are used for training cluster, 72 of PQE are used for verification and the remaining 72 are used for testing. Firstly, the ANN has been trained correctly. The classification performance of the ANN in PQE has been examined by inserting the test into ANN. The performance of ANN is 99.8% for these PQE. The purpose of this research is to provide an artificial intelligence assistant that can fast and accurately advise the power system operators for the networks, and the results also show that the goal has been achieved.

Keywords: Power quality event, Feature extraction, Classification, FFT, PCA, ANN

***Corresponding author:** Sinop University, Vocational High School, Department of Electrical and Energy, 57000, Merkez, Sinop, Turkey
E mail: eguney@sinop.edu.tr (E. GÜNEY)
Ezgi GÜNEY https://orcid.org/0000-0003-4868-0626
Çağrı KOCAMAN https://orcid.org/0000-0001-9763-7603

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1. Introduction

In recently, the power quality issue is the subject of much research for an increasing number of electronic and power electronic equipment components, nonlinear loads, unbalanced power systems and solid-state switching devices used in industrial and public sectors. PQE is an important issue due to complicated power distribution because of increasing in grid connection for the new energy resources such as wind and solar energy conversion systems. Therefore, PQE detection and classification is extremely important for the protection of power distribution network. This sensitivity, which occurred in recent years in the case of power quality, it has forced the development of intelligent methods to reduce the negative effects of PQEs the least (Li et al., 2016; Jamali et al., 2018).

Various approaches for the detection and classification of PQE are developed in the literature. Several of papers based on different techniques such as Fourier transform (FT) (Polat and Güneş, 2007; Ipinnimo and Chowdhury, 2013; Deokar and Waghmare, 2014; Karasu and Saraç, 2018), wavelet transform (WT) (Ucar et al., 2018), S-transform (ST) (Saini and Kapoor, 2012; Satao and Kankale, 2016; Daud et al., 2017), Hilbert-Huang Transform (HHT) (Das et al., 2017; Sahani and Dash, 2018), Gabor-Wigner Transform (GWT) (Shilpa et al., 2015) and Kalman-Filter (Abdelsalam, 2012). Several intelligent classifiers such as Artificial Neural Networks (ANN) (Naik and Kundu, 2014; Lopez-Ramirez et al., 2016), Fuzzy Logic Controllers (FLC) (Polat and Güneş, 2007), Support Vector Machines (SVM) (Li et al., 2016), Rule-Based systems (Rodríguez et al, 2012) are used for classification and recognition of PQE. These methods are basic steps of pattern recognition that use signal-processing techniques (Stoica and Moses, 2005).

The purpose of this research is to provide an artificial intelligence assistant that can fast and accurately advise the power system operators for the networks. The critical task in developing such a system is to select the appropriate marking analysis technique for classifying PQE. In order to achieve this purpose, five different PQE including voltage sag, voltage swell, flicker, transient and voltage with harmonic and pure sine as a reference are produced in different amplitude, beginning occurrence time, time duration, frequency component and angle according to a type of event. These types of PQE with parametric equations and event parameter variations are given in Table I. Voltage sag and voltage swell signals are produced with different amplitudes, lengths and time duration. Voltage sag species the decrease in voltage from 0.9 to 0.1 pu for a typical period from 0.5 cycles to 1 minute. Voltage swell is the increase in voltage from 1.1 to 1.8 pu for a representative period from 0.5 cycles to 1 minute. Voltage sag and voltage swell are created in different amplitude, beginning occurrence time, time duration, and angle. A flicker is a systematic variation of the voltage waveform or a series of random voltage changes. Flicker signal is created with time scale ranges from tens of nanoseconds to steady-state and frequency ranges from 58 Hz to 60 Hz. This frequency range is chosen because the best-distinguished flicker frequency by the human eye is between 8 and 10 Hz. Transient is a sudden high peak event that raises the voltage levels in either a positive or a negative direction. Transient is created with different time duration, angles, frequency and amplitude which occur in voltage from 50 nanoseconds to 50 milliseconds. Harmonic distortion is the corruption of the fundamental sine wave at frequencies that are multiples of the fundamental. Voltages with harmonics are created with different amplitudes and frequency components such as 3th, 5th and 7th.

The organization of the paper is as follows: FFT (Fast Fourier Transform) based feature extraction stage is discussed in Section 2.1 in Section 2. The fundamental of FFT is detailed in Section 2.1.1. Section 2.1.2 presents the reduction data size with PCA. In Section 2.2, the classification of PQE by using ANN is presented. Section 2.2.1 presents the ANN classification approach. The results are shown in Section 3. Finally, the conclusion is in Section 4.

2. Material and Methods

In this section, the methods used to classify the signals produced by the types of distortion based on ANN are described in detail.

2.1. Feature Extraction Method Based on FFT

2.1.1. Fast fourier transformation

FFT is a fast and efficient numerical algorithm that computes the Fourier transform. The FFT does not refer to a new or different type of Fourier transform. It refers to a very efficient algorithm for computing the discrete Fourier transform (DFT). The Fourier transform maps time domain functions into frequency domain representations and is defined as;

$$X(f)=F\{x(t)\}=\int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{1}$$

where $x(t)$ is the time domain signal, and $X(f)$ is its Fourier Transform. DFT maps discrete-time sequences into discrete-frequency representations and is given by;

$$X_k=\sum_{i=0}^{n-1} x_i e^{-\frac{j2\pi ik}{n}} \quad k=0,1,2,...,n-1. \tag{2}$$

x_i is the input data, X_k is its DFT, and n is data number in both the discrete-time and the discrete-frequency domains. If it is applied directly, DFT requires nearly n2 complex operations. On the other hand, computationally efficient algorithms can require as little as $n\log2(n)$ operations with FFT, which is named fast Fourier transform. It is assumed that N is a power of 2,

$$N=2^m \tag{3}$$

For some integer m = 1,2,….

By splitting the sum in, from the definition of the DFT, equation 2 into two parts, it is gotten

$$X(k)=\sum_{t=1}^{N/2} x(t)W^{tk}+\sum_{t=N/2+1}^{N/2} x(t)W^{tk} \tag{4}$$

Define

$$W=e^{-i\frac{2\pi}{N}} \tag{5}$$

The twiddle factors are simply the sine and cosine basis functions written in polar form. This leads to the definition of the twiddle factors as;

$$W^{Nk/2}=\begin{Bmatrix} 1, & for\, even\, k \\ -1, & for\, odd\, k \end{Bmatrix} \tag{6}$$

If the function that is wanted to be expanded is even: $f(k) = f(k)$, or odd: $f(x) = -f(x)$. Because the Fourier modes are also even $\cos(\frac{t\pi k}{N})$ or odd $\sin(\frac{t\pi k}{N})$, the Fourier expansion can be simplified (Peacock, 2014). Using this observation in equation 4, it is obtained:

For k=2p= 0,2,…

$$X(2p)=\sum_{t=1}^{\overline{N}}[x(t)+x(t+N)]\overline{W}^{tp} \tag{7}$$

For k=2p+1=1,3,…

$$X(2p+1)=\sum_{t=1}^{\overline{N}}\left\{\left[x(t)-x(t+\overline{N}\right]W^{t}\right\}\overline{W}^{tp} \tag{8}$$

where $\overline{N}=N/2$ and $\overline{W=W^2=e^{-i2\pi/\overline{N}}}$.

The equation (7) and (8) are the core of the FFT algorithm and represents DFTs for data of length equal to $\overline{N}$. Computation of the sequences transformed in equations (7) and (8) requires $\overline{N}$ flops. Therefore, the computation of an N–point transform has been reduced to the evaluation of two $N/2$–point transforms plus a sequence computation requiring about N/2 flops. This reduction process is continued until $\bar{N}$ = 1 (Changjie and Buxiang, 2015).

2.1.2. Principal component analysis

PCA, which has been widely used in many applications, is an unsupervised method for feature extraction and data reduction. The main reasons for using this method are as follows:

- To increase the accuracy score
- To prevent over-learning (overfitting)
- To achieve less runtime using less computing power
- To shrink data and reduce storage space
- To remove noise (unnecessary information, noise) in the data
- To be able to analyze and visualize data effectively cause unnecessary information and overfitting problems in the model.

So, in this work, PCA is used to prevent over-learning, obtain less runtime using less computing power and reduce data and storage space. PCA analyzes a data Table I in which observations are described by several inter-correlated quantitative dependent variables. Its goal is to extract the important information from the table, to represent it as a set of new orthogonal variables called principal components, and compress the size of the data set by keeping only this important information. The process steps to reduce the data size with PCA are as follows (Tan and Ramachandaramurthy, 2010; Shen et al., 2019). Firstly, data is processed to normalize its mean and variance;

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x^{(i)} \tag{9}$$

Each $x^{(i)}$ is replaced with $x^{(i)} - \mu$. These steps zero out the mean of the data, and may be omitted for data known to have zero mean.

$$\sigma_j^2 = \frac{1}{m}\sum_i (x_j^{(i)})^2 \tag{10}$$

Each $x_j^{(i)}$ is replaced with $x_j^{(i)}/\sigma_j$. These steps rescale each coordinate to have unit variance, which ensures that different attributes are all treated on the same "scale." Consider that given a unit vector u and a point x, the length of the projection of x onto u is given by $x^T u$. I.e., if $x^{(i)}$is a point in the dataset, then its projection upon u is distance $x^T u$ from the origin. Therefore, to maximize the variance of the projections, is chosen a unit-length u for maximize;

$$\frac{1}{m}\sum_{t=1}^{m}\left(x^{(i)T}u\right)^2 = u^T\left(\frac{1}{m}\sum_{i=1}^{m} x^{(i)} x^{(i)T}\right)u \tag{11}$$

It is easily recognized that the maximizing this subject to $||u||_2 = 1$ gives the principal eigenvector of

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x^{(i)} \tag{12}$$

To project the data into a k-dimensional subspace ($k < n$), it should be chosen $u_1, \ldots, u_k$to be the top k eigenvectors of $\sum$. The ui's form a new, orthogonal basis for the data. Then, to represent $x^{(i)}$ in this basis need only compute the corresponding vector;

$$y^{(i)} = \begin{bmatrix} u_1^T x^{(i)} \\ u_2^T x^{(i)} \\ \cdot \\ \cdot \\ \cdot \\ u_k^T x^{(i)} \end{bmatrix} \in R^k \tag{13}$$

Thus, whereas $x^{(i)} \in R^k$, the vector $y^{(i)}$ now gives a lower, k-dimensional, approximation/representation for $x^{(i)}$. PCA is therefore also referred to as a dimensionality reduction algorithm. The vectors $u_1, \ldots, u_k$ are called the first k principal components of the data (Tan and Ramachandaramurthy, 2010).

The classification accuracy depends on both extracted features and the classifier. Selecting a robust classifier is essential to detect and classify of PQE accurately.

In this study, six voltage waveforms including pure sine, voltage sag, voltage swell, flicker, transient, voltage with harmonic are produced by using mathematical models in MATLAB. TS EN 50160 standard is used as a reference for feature extraction based on FFT. The parametric equations for the generated signals are shown in Table 1 (Vankatesh et al., 2010).

The healthy simulation model operates at 1 pu voltage amplitude. Sampling frequency is 25.6 kHz. PQE is produced as 5120 samples in 10 periods length. The frequency components of the signals are generated by using FFT analysis. The amplitude of the coefficients obtained from the FFT transform can be seen in the Power Spectrum (PS) graph visually. The PS of a signal shows how the power of signal is distributed throughout the frequency domain. FFT is used to get the frequency-domain voltage data from the time domain. The PQE is generated and the properties of PS graphs are obtained by using FFT analysis are given in Figure 1.

Table 1. Numerical modelling of the simulated PQE

PQE	Numerical model	Parameters
Pure Sine	$v(t) = \sin(\omega t)$	$\omega = 2\pi 50\ rad/sec$
Voltage Sag	$v(t) = [1 - \alpha(u(t-t_1) - u(t-t_2))]\sin(\omega t)$	$0.1 \leq \alpha \leq 0.9, T \leq t_2 - t_1 \leq 9T$
Voltage Swell	$v(t) = [1 + \alpha(u(t-t_1) - u(t-t_2))]\sin(\omega t)$	$0.1 \leq \alpha \leq 0.9, T \leq t_2 - t_1 \leq 9T$
Flicker	$v(t) = A(1 + \alpha_f \sin(\beta_f \omega t))\sin(\omega t)$	$0.01 \leq \alpha_f \leq 0.25$ $2\ Hz \leq \beta_f \leq 8\ Hz$
Transient	$v(t) = A[1 + \alpha(u(t-t_1) - u(t-t_2)]\sin(\omega t)$	$A = 5 - 10, 0.05T \leq t_2 - t_1 \leq 0.06T$
Harmonics	$v(t) = (\alpha_1 \sin(\omega t) + \ \alpha_2 \sin(3\omega t)$ $+ \alpha_3 \sin(5\omega t) + \alpha_4 \sin(7\omega t)$	$\alpha_1 = 1, \alpha_2 = 0.6 - 0.06,$ $\alpha_3 = 0.2 - 0.02, \alpha_4 = 0.08 - 0.008$

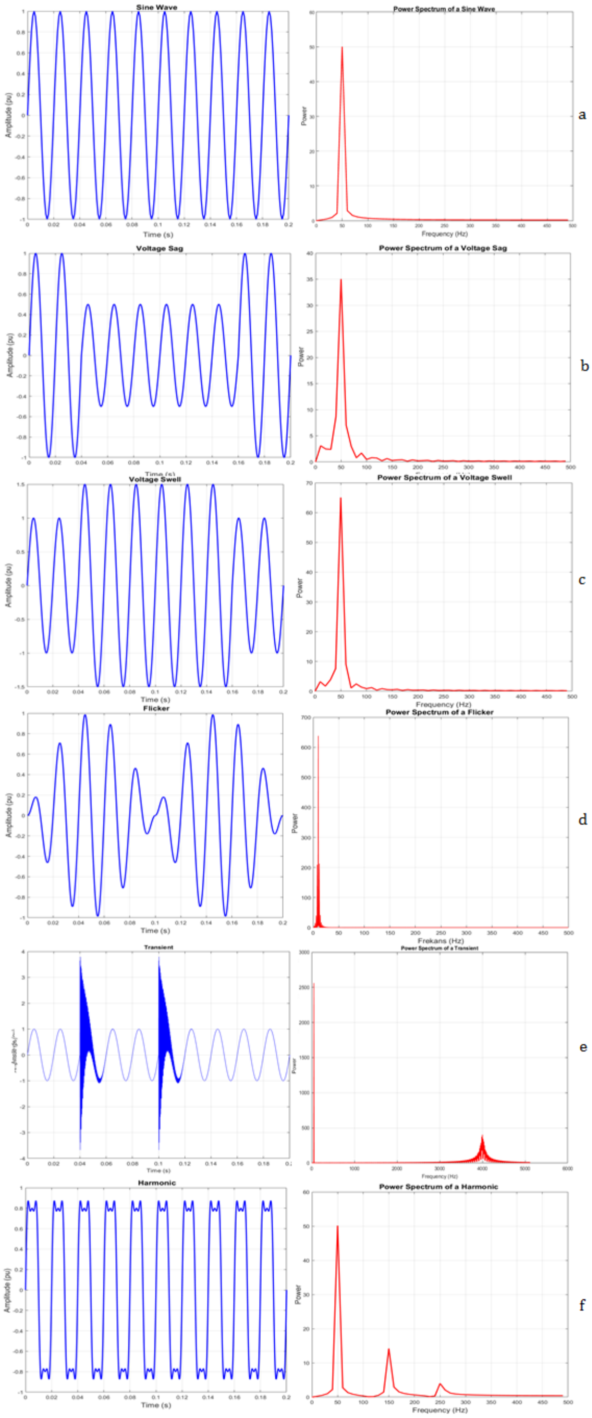

Figure 1. Sample waveforms of PQE and PS graphs.

The pure sine signal and its PS are given in Figure 1(a). Voltage sag and voltage swell signals contain 50 Hz frequency component. Therefore, there is a decrease in the component corresponding to 50 Hz for voltage sag signal given in Figure1(b) while an increase in voltage swell signal given in Figure 1(c) is observed. The flickering signal is given in Figure 1(d) is generated by adding 58-60 Hz component on a 50 Hz component. The frequency ranges are shown in the PS graph. In transient signal, a 4 kHz transient is generated and an increase in the coefficient corresponding to 4 kHz component is observed. The PS of the transient signal with a transient frequency of 4 kHz is given in Figure 1(e). Figure 1(f) gives the voltage with the signal obtained by adding 3th and 5th harmonic component on the 50 Hz fundamental frequency component. It is seen in the PS of the harmonic signal that an increase in the component coefficients corresponding to the 3rd and 5th harmonic is observed.

2.2. Classifying of PQE Based on ANN

2.2.1. Artificial neural network

ANNs are a new generation of information processing systems and are good at, classification, optimization and data clustering (Saini and Kapoor, 2012). In addition, the ANNs are good at recognizing patterns and they are extensively applied for the analysis of PQE (Kumar et al., 2015; Kow et al., 2016; Khokhar et al., 2017; Luo et al., 2017). Basically, an ANN consists of an input layer, one or more hidden layers, and an output layer. The number of neurons and hidden layers depends on the problem and can be determined by trial and error until a target performance is achieved (Uyar et al., 2013). In ANN, network entries are first multiplied by weights. It is then summed with the bias value and passed through the transfer function to calculate the output. However, in order for the neuron to produce the desired output, it is necessary to set the weight values w and b. During the learning process, the ANN weights are adapted to the desired output vectors. The transfer function is a linear or non-linear derivable function.

In this paper, we propose pattern recognition and classification training methodology for the input signals. The proposed features can be used for any classification. The present study proposes the use of ANN for classification. The structure of the ANN used in this study is shown in Figure 2. The training parameters are selected to obtain the best performance, after several different experiments, such as the number of hidden layers, learning rate, and type of the activation functions.

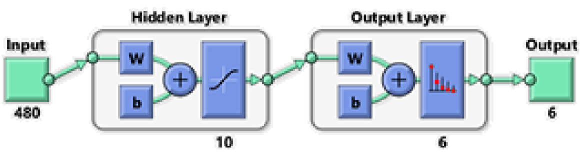

Figure 2. Two-layer neural network architecture with feed forward.

The proposed ANN architecture is selected from MATLAB / Neural Network Toolbox. As seen in Figure 2, a two-layer feed-forward network, with a hyperbolic tangent sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer are used as a classifier. The hyperbolic tangent sigmoid function is used since inputs have negative and positive values. Multilayer feed forward ANNs are chosen because of their ability to solve many engineering problems such as function approach, pattern recognition and classification. Pattern recognition and classification based on ANN is successfully used by selecting the output that represents the best-unknown input sample (Manjula and Sarma, 2010; Alshahrani et al., 2016; Feilatla et al., 2017). The number of input is 480. The hidden layer has 10 nodes while the output layer has 6 nodes. PQE that is classified is given in Table 2.

Table 2. Class of PQE

PQE	Class
Pure Sine	C1
Voltage Sag	C2
Voltage Swell	C3
Flicker	C4
Transient	C5
Voltage with harmonics	C6

3. Results

In order to detect and classification of the PQE, firstly, five different PQE and pure sine are created in MATLAB based on TS EN 50160 standard. Each sign in the PQE data set is generated with different amplitude, beginning occurrence time, time duration, frequency component and angle according to the event. Pure sine is selected as a reference. Then, the frequency components of the obtained waveforms are extracted by using FFT analysis. 16384 samples are taken and reduced to 480 data by applying PCA. The total size of the data set is 480 × 480, where 480 is the size of the feature set and 480 is the number of PQE with 80 samples of each class. Finally, the feature vector of 480 × 480 is applied for training the ANN classifier. From 480 PQE, 336 PQE are used for training cluster, 72 for validation and the remaining 72 for testing the ANN classifier. The number of samples for training, validation and testing is chosen at random and given in Table 3.

Table 3. The number of samples for training, validation and testing

Mode	Samples in %	Number of Samples
Training	70	336
Validation	15	72
Testing	15	72

The network reaches its best validation performance in 7.8073e-07, when generalization stops improving after some iteration and then there is an increase in the mean square error of the validation samples. The smallest error between test and validation occurred in 23 iterations. Receiver Operating Characteristic (ROC) is a statistical method of decision making and is a graphical representation of the relationship between sensitivity and selectivity. For each class of classifier, the ROC applies threshold values along with the output [0,1] interval. For each threshold, two values are calculated: True Positive Rate and False Positive Rate. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. ROC can also be expressed as the fraction of the correct positives and the fraction of the false positives. If the positives are perfectly separated from the negatives, the area value under the ROC curve is 1, and if there is no positive value, the value under the ROC curve is 0. The larger this area, the more it has the sort of discrimination (Zweig and Campbell, 1993).

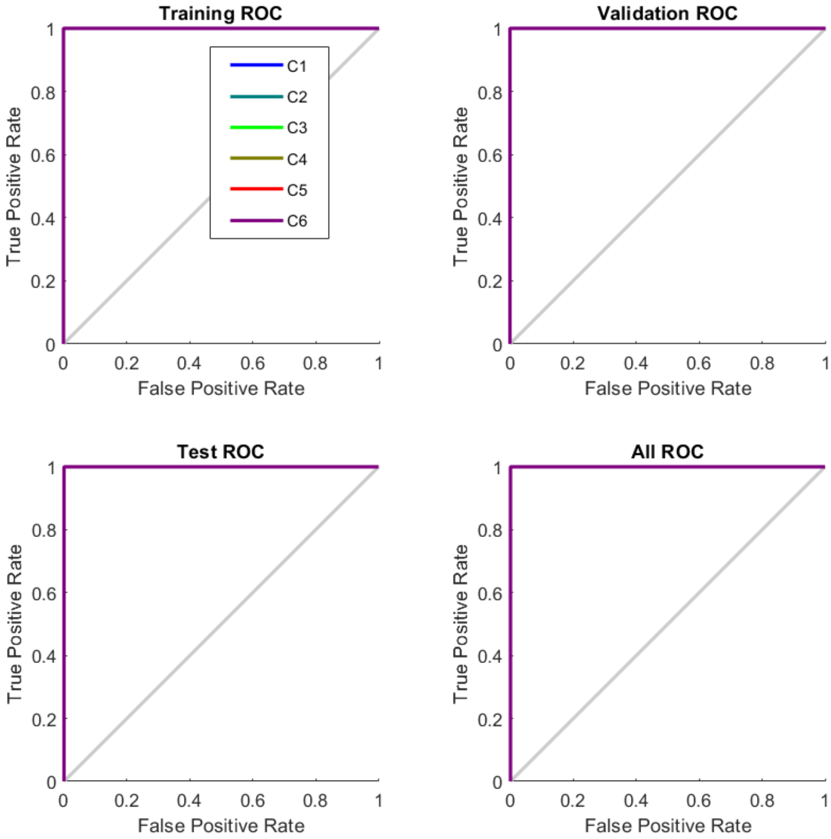

Figure 3. Receiver operating characteristic.

A test with perfect discrimination (no overlap in the two distributions) has a ROC curve that passes through the upper left corner (100% sensitivity, 100% specificity). Therefore, the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test (Atapattu et al, 2010). It is shown in Figure 3 that there is a perfect hug in ROC curves to the left and top edges and this test indicates that the ability of discrimination is excellent. In addition, in Figure 4, confusion matrices for training, testing and validation, and the six kinds of data are combined. The green squares indicate correct responses and red squares show incorrect responses. The lower right blue squares illustrate the overall accuracies So, as seen in Figure 4, the 99.8%recognition performance shows that the training performs well. ANN was trained with 100% accuracy and tested with 100% accuracy. This ratio is thought to be very successful and sensitive. Considering the effectiveness of the method and the success of the results, the result of this study can be deduced.

4. Conclusion

A system for the recognition and classification of PQEs by using FFT and ANN is presented in this paper. For this purpose, five different PQE and pure sine are created in MATLAB based on TS EN 50160 standard. 480 PQE waveforms are generated with 80 samples for each of the 6 types of the waveform with randomly different amplitude, beginning occurrence time, time duration, frequency component and angle according to the event. The sampling frequency of the waveforms is 25.6 kHz and the power frequency is 50 Hz. PS graphs obtained from the FFT analysis show that the 50 Hz frequency components of voltage sag decrease while 50 Hz frequency components of voltage swell increase. 3th, 5th and 7th frequency components are increased in voltage with harmonic. Corresponding to the generated transient frequencies increase. Flicker signal is created in frequency ranges from 58 Hz to 60 Hz. This frequency range is chosen because the best distinguished flicker frequency by the human eye is between 8 and 10 Hz. It is obtained increase in flicker frequency components between 8 Hz to 10 Hz. It is seen that five kinds of PQE and pure sine are distinguished visually. Totally, 16384 data are obtained. In the next step, these huge 16384 data are reduced to 480 data by applying PCA.

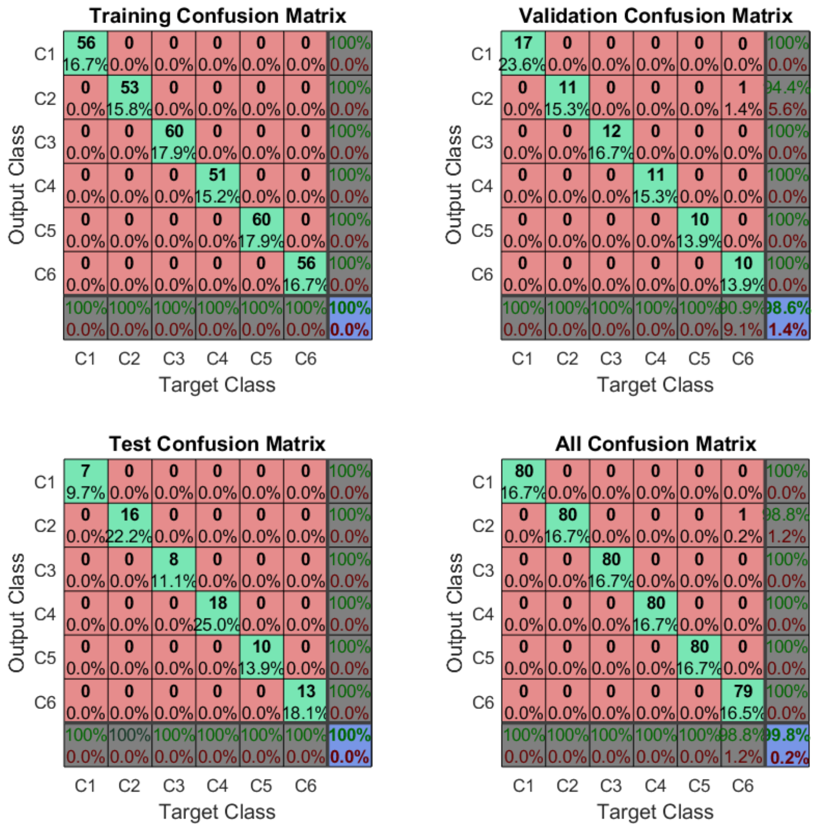

Figure 4. Confusion matrix

The ANN classifier is used for the classification. Multilayer feed forward ANNs which is good at pattern recognition and classification. From 480 PQE of each event, 336 PQE are used for training cluster, 72 are used for validation and the remaining 72 are used for testing. The proposed system is capable of recognition of various PQE with 100% accuracy. It is also shown that the overall accuracy is 99.8 %: FFT, which is used for feature extraction in this paper, can classify the PQE problems. Feature extraction and classification of PQE based on FFT and ANN gives satisfactory results. When the ANN model proposed in this paper is applied in any power distribution system, it can be observed that the network can provide fast and accurate consultancy to grid power system operators.

Author Contributions

CK; originally conceived the idea. EG; collected the data. EG and CK; drafted the manuscript. EG and CK; designed the study. All authors reviewed and approved the manuscript.

Conflict of Interest

The authors declared that there is no conflict of interest.

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