Jurnal Rekayasa Elektrika Vol. 19, No. 1, Maret 2023, hal. 9-17
ISSN. 1412-4785; e-ISSN. 2252-620X, Terakreditasi Dikbudristekdikti No. 105/E//KPT/2022
DOI: 10.17529/jre.v19i1.27120

Identification of Power Quality Disturbances Based on Fast Fourier Transform and Artificial Neural Network

Dimas Okky Anggriawan, Endro Wahjono, Indhana Sudiharto, and Anang Budikarso
Politeknik Elektronika Negeri Surabaya
Kampus PENS, Jl. Raya ITS, Sukolilo, Surabaya 60111
e-mail: dimas@pens.ac.id

***Abstract*—This paper presents the proposed algorithms for the identification of short duration RMS variations and long duration RMS variations combined with harmonic. The proposed algorithms are Fast Fourier Transform (FFT) and Artificial Neural Network (ANN). The Algorithms identify nine types of Power Quality (PQ) disturbances such as normal signal, voltage sag, voltage swell, under voltage, over voltage, voltage sag combined harmonic, voltage swell combined harmonic, undervoltage combined harmonic, and over voltage combined harmonic. FFT is used to obtain the frequency spectrum of each PQ disturbance with frequency sampling of 1000 Hz and data length of 200. Output FFT is used to input data for ANN. Output ANN is a type of nine PQ disturbances. The result shows that proposed algorithms (FFT combined ANN) are effective for identification, which ANN with 20 neurons in the hidden layer has an accuracy of approximately 99.95 %.**

Keywords: ***power quality disturbances, short duration RMS variations, long duration RMS variations, fast fourier transform, artificial neural network***

I. Introduction

Power quality disturbances, especially in voltage area, are hard to detect because it has a very short period when occurs. According to a research paper from Pallavi R. Kamthekar et al., [1] the disturbance's period happens in under one minute. Based on Alternating Current (AC) voltage disturbance duration, it can be divided into short and long duration Root Mean Square (RMS) variations [2]. Short duration RMS variation is a power quality disturbance that occurs in less than one minute such as voltage sag and voltage swell. Long duration RMS variation is a power quality disturbance that occurs for more than one minute such as undervoltage and overvoltage [3].

Voltage sag is a condition of RMS voltage which is decreasing between 0.1 to 0.9 per-unit (pu) from its value for 0.5 cycles until one minute. This disturbance can be caused by heavy motors starting. Voltage sag affects the sensitive loads in the power system network. Voltage swell is a condition of RMS voltage which is increasing above 1.1 pu from its value for durations between 0.5 cycle until one minute. Its typical magnitudes are between 1.1 to 1.2 pu. Voltage swell happens when a single line-to-ground fault occurs in the system. It makes temporary voltage rise in the normal phases [4].

Undervoltage is a decrease of RMS voltage is less than 0.9 pu in more than one minute. Typical magnitudes of undervoltage are between 0.8 and 0.9 pu. On or off switching of capacitor bank might cause undervoltage. Hence, undervoltage is overloaded. Overvoltage is an increase of RMS voltage greater than 1.1 pu in more than one minute. Typical magnitudes are between 1.1 to 1.2 pu. Large load switching or variations in the reactive compensation in the system (e.g., switching on a capacitor bank), incorrect tap settings on transformers, and incorrect system voltage regulation also can cause overvoltage [4].

Harmonics are sinusoidal voltages or currents having frequencies for integer multiples of the frequency at which the designed operating supply system (termed the fundamental frequency; usually 50 Hz or 60 Hz). Combined with the fundamental voltage or current, harmonics produce waveform distortion. It exists due to the nonlinear characteristics of devices and loads on the power system [4]. Among all these disturbances, they can cause sufficient damage to electrical instruments and equipment such as industrial consumer equipment that can ultimately lead to the shutdown of their system. Therefore, it requires the proposed algorithm that can accurately detect power quality disturbances [5].

Mohd Anuar bin Mohamed Ayub et al., [6] proposed an over and under-voltage detection system that integrated with an IoT monitoring system. The proposed method in this research for power quality disturbances was using a true-false logic. The author mentioned the system will give information about undervoltage disturbance when the RMS voltage of the electrical system was under 216 V and also information about overvoltage when the RMS voltage exceeds 253 V. This proposed method to know well the power quality disturbance couldn't be adaptable for the voltage fluctuation condition of the system. On

Received 24 July 2022 ; Revised 27 October 2022; Accepted 15 November 2022

another side, this system needs to develop for another power quality disturbance scope such as a short time power quality disturbance. Moreover, it might be a biased condition when a short-time period of power quality disturbance happens.

Billy Mahdianto Arsyad et al., [7] proposed a method of over/under voltage control by using a microcontroller implemented in the 220 V power system. This research only focused on long-period power quality disturbance and combined with a relay as an actuator to set off the main circuit. The author explained to determine the overvoltage condition, the RMS voltage should be equal to or higher than 225 V. For the Undervoltage condition, the RMS voltage value should be under 215 V. So, the main power system only can be detected as a normal condition when RMS value was between 215 V until 225 V. This paper could be more in-depth analysis when the proposed method can differentiate between any possible power quality disturbances.

Doan Duc Tung et al., [8] proposed a monitoring system that could protect the main system from overvoltage and undervoltage disturbance. This author proposed an algorithm that can be fit in fluctuation voltage conditions. It means the author didn't determine a fixed value to differentiate the undervoltage or overvoltage condition or normal condition. As a monitoring system, this research discusses the analytical scope expressed by graphs and waveforms. Based on this proposed algorithm, it might develop into a complex functional purpose for power quality disturbance also harmonics that may happen between the operation of the power system.

According to related works, methods are often to be applied to detect short-duration RMS variations and long-duration RMS variations for their value and time duration. Meanwhile, these methods are not capable to detect the short-duration RMS variations and long-duration RMS variations that are combined with harmonic disturbances. The method often used to analyze harmonics is Fast Fourier Transform (FFT), but FFT is not capable to detect non-stationary signals. Therefore, this paper proposed two methods, namely FFT and Artificial Neural Network (ANN). ANN uses data from the FFT output to detect and classify nine types of power quality disturbances such as voltage sag, voltage swell, under voltage, over voltage, voltage sag combined with harmonic, voltage swell combined with harmonic, undervoltage combined with harmonic, and overvoltage combined with harmonic. Furthermore, by this method which is implemented in electrical power systems, power quality disturbances as mentioned before could be detected and gives improvement against the related works.

II. Theoretical Background

This section presents the theoretical background of the paper topic which is a description of voltage variations and harmonic disturbances according to IEEE Std 1159, FFT, and ANN.

A. *Types of Voltage Variations and Harmonic Disturbances*

Types of voltage variations according to IEEE Std. 1159-2009 are short and long duration RMS variations. Short duration RMS variation is divided into 3 types such as instantaneous, momentary, and temporary which have different in duration and magnitude. Harmonic disturbances include waveform distortion. Characteristics of voltage variations and harmonic disturbances can be seen in Table 1.

B. *Fast Fourier Transform*

FFT algorithm supported the elemental principle of the DFT computation of a sequence of array data (N) length into smaller DFT. That algorithm only needs fewer multiplications and additions than direct DFT computation [9]. FFT during the process which is decomposition on a sequence $x[n]$ is turning into a smaller subsequence. This process is also known as the time simplification formula. The fundamental plan is illustrated by considering the special case of N as a number that has a value from exponent of 2, where illustrates a bit value. Then $X[k]$ may be computed by $x[n]$ separating into two sequences that include even numbers of points and odd numbers of points, in $x[n]$. With $X[k]$ given by [9]:

$$X\left[k\right]=\sum_{n=0}^{N-1}x\left[n\right]W_{N}^{kn} \qquad k=0,1\ldots..N-1. \tag{1}$$

C. *Artificial Neural Network*

ANN is the one artificial intelligence that represents the human brain form. As a complex architecture, ANN needs to reform input data into a value that can be processed by the neural network structure. Hence, ANN will convert the output neural network structure to a real value called as denormalization process.

Inside the neural network structure, it contains several

Table 1. . Characteristic of power quality disturbance [4]

Categories		Typical Duration	Typical Voltage Magnitude
Short duration RMS variation			
Instantaneous	Sag	0.5 - 30 Cycles	0.1 - 0.9 pu
	Swell	0.5 - 30 Cycles	1.1 - 1.8 pu
Momentary	Sag	30 cycles - 3 s	0.1 - 0.9 pu
	Swell	31 cycles - 3 s	1.1 - 1.4 pu
Temporary	Sag	3 s - 1 min	0.1 - 0.9 pu
	swell	4 s - 1 min	1.1 - 1.2 pu
Long duration RMS variation			
Undervoltage		> 1 min	0.8 - 0.9 pu
Overvoltage		> 1 min	1.1 - 1.2 pu
Waveform Distortion			
Harmonics		Steady State	0-9 kHz, 0-20 %

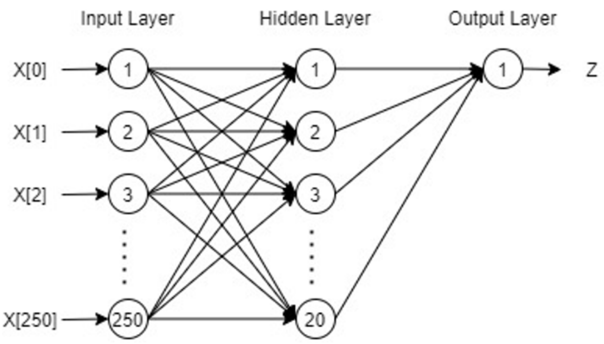


Figure 1. Simple architecture of ANN

Table 2. Artificial Neural Network Architecture

Parameter	Setting
Network structure	1 hidden layer
Ttraining type	Supervised
Training algorithm	Lavenberg-Marquarth
Activation function	Logsig-Purelin
Input number	250 x 9
Output layer	1
Neuron of hidden layer 1	20
Iteration	294
Training epoch	300
Min_grad	1.00E-07
Max_fail	400
Mu	0.001
Mu_max	10000000000

functional parts which are the input layer, hidden layer, an output layer, weight, and bias. Between all layers such as the input layer and the hidden layer, there is a connection that consists of weight and bias. For the mathematical form of neural network structure, there is an activation function that uses for processing output value from weight and bias calculation into the next layer [10]. A simple architecture of ANN will be shown in Figure 1.

Based on ANN architecture representing the human brain, it can identify, predict, and diagnose for a functional purpose. All of those are supported by the training process or learning process. By knowing raw and target data, it might process that training data to adjust the weight and bias value for the best ANN algorithm on the proposed system.

III. Proposed Method

This paper identifies short-duration RMS variation and long-duration RMS variation with temporary type and combined with harmonics.

Based on equation (1), the result of FFT is a matrix in the frequency domain. Fourier analysis provides a set of mathematical tools which can be used to break down a signal into its various fault components [11]. Then, it's possible to predict the effect of the signal from its individual fault component. Hence, Fourier analysis

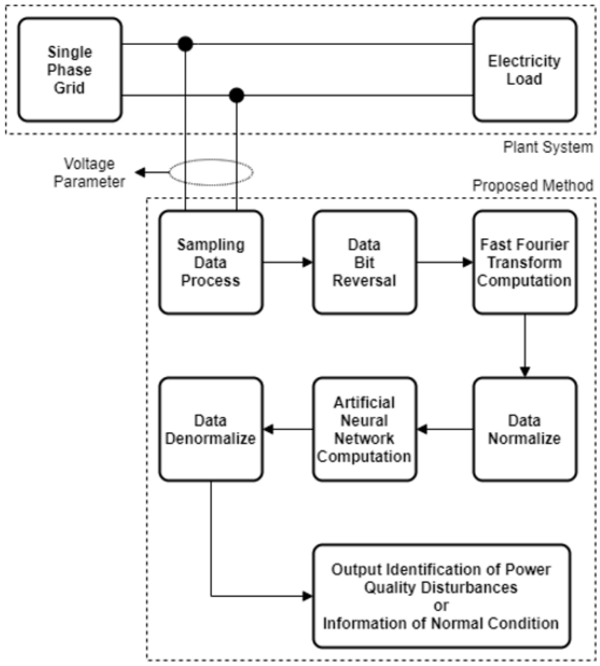


Figure 2. Block diagram of proposed method

can determine fault identification accurately by fault component characteristics. Fast Fourier Transform has been presented in this paper to the identification of faults in power system networks accurately [12]. The block diagram of the proposed method is presented in Figure 2.

ANN is applied to identify the type of power quality disturbances. The architecture of ANN consists of the input layer, hidden layer, and output. The input of ANN is output FFT. There is 250 x 9 data for input of ANN. 250 x 9 input data mean the fault components and their variations for all conditions. The important parameter of ANN is hidden layers. The hidden layer has 20 neurons, respectively. The iteration of ANN is 294. To describe the architecture of ANN, it can be shown in Table 2.

With the different number of neurons, same layer, and same parameters of training, the training has different results [13]. The training process of ANN and its result respectively are shown in Figures 3 and Figure 4.

The first layer is the input layer that receives data directly. The number of nodes in the input layer expressed the vector dimension. The hidden layer consists of some predetermined number of nodes and each of which is connected to each node of the input layer by some weight. Similarly, the output nodes are connected to each node of the hidden layer.

IV. Simulation Result and Analysis

To evaluate the performances of FFT and ANN, the proposed method required simulation with vary of power quality signals and several neurons in the hidden layer. Nine types of signals should be identified by FFT and ANN such as normal signal, voltage sag, voltage swell, undervoltage, overvoltage, voltage sag combined harmonic, voltage swell combined harmonic, undervoltage

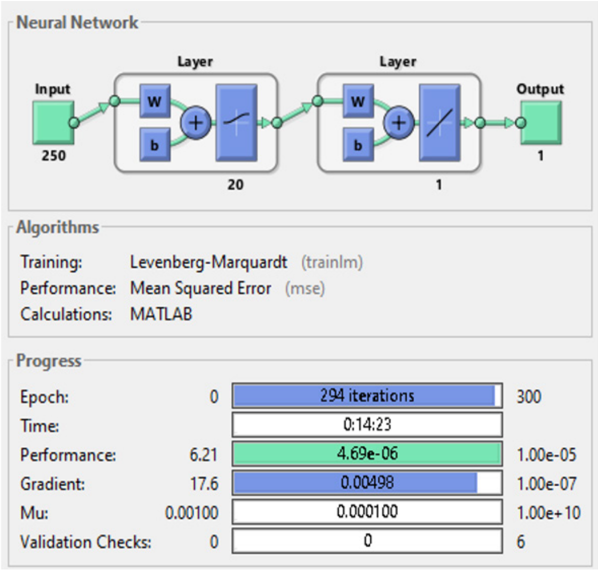


Figure 3. ANN training process

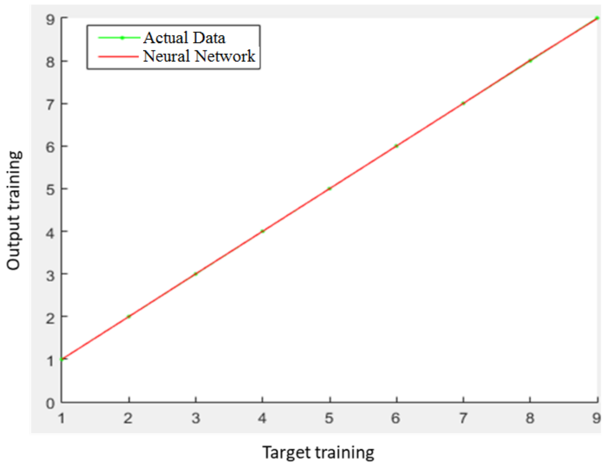


Figure 4. Training result of ANN

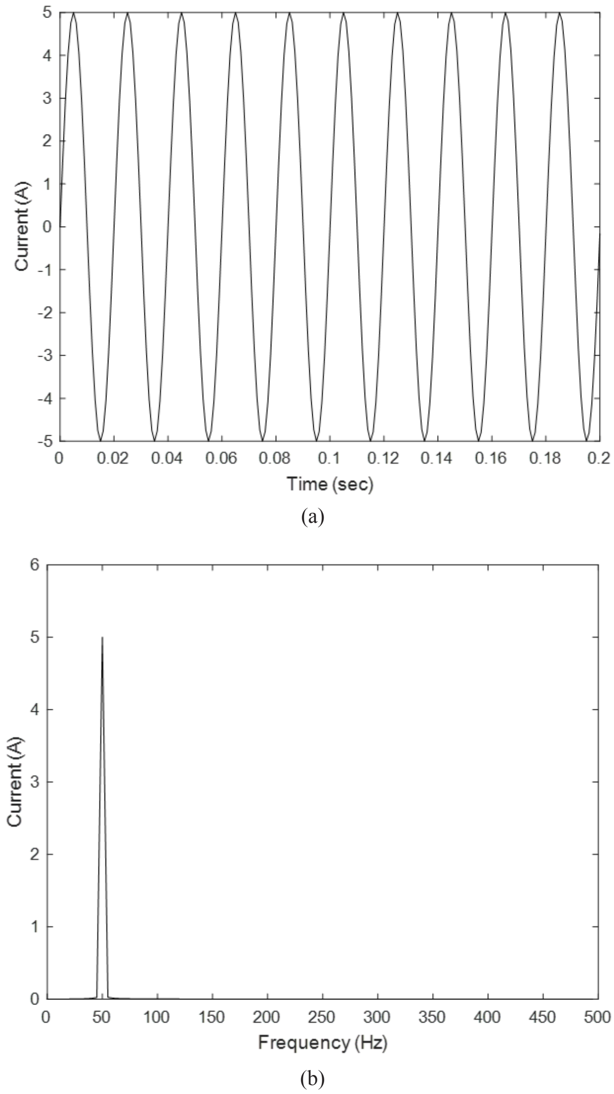


Figure 5. (a) Normal signal, (b) Normal signal analysis using FFT

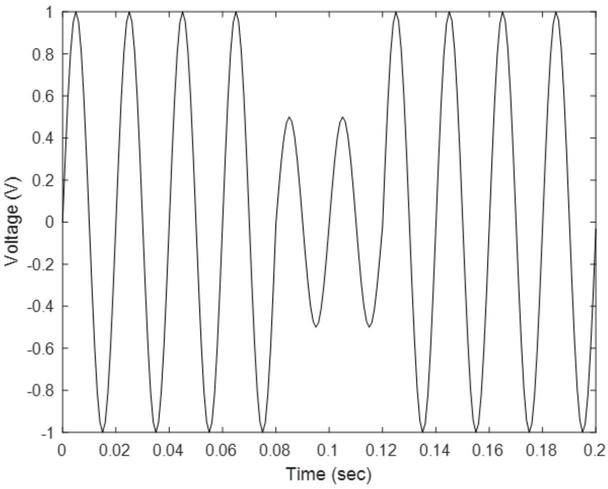
combined harmonic, and overvoltage combined harmonic. To process the signal, FFT required frequency sampling of 1000 Hz and a number of data of 500 data.

Figure 5 shows FFT for analyzing a sinusoidal signal. The simulation result shows that FFT analysis has accurately transformed sinusoidal signal into spectrum frequency. The spectrum magnitude in the frequency of 50 Hz is 5 and for other frequencies is 0. This value depends on the magnitude of the sinusoidal signal in the time domain because that's a pure sinusoidal signal.

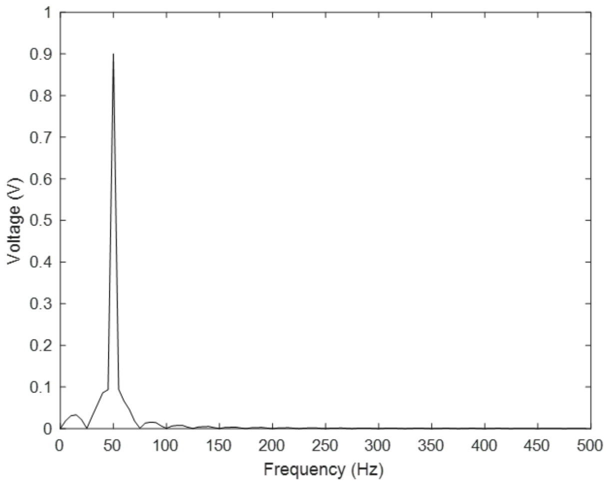
Figure 6 shows FFT for analyzing voltage sag. Voltage sag is modeled by degradation of voltage level from 0.08 until 0.12 s. The simulation result shows that FFT analysis has accurately transformed voltage sag into spectrum frequency which is different from the result of a sinusoidal signal. According to the FFT result, spectrum magnitude in the frequency of 50 Hz isn't 1 V because there's a disturbance between 0.08 and 0.12 s. Hence, the spectrum magnitude of 50 Hz is 0.9 V and there are spectrum magnitudes outside 50 Hz that appear in 0 – 50 Hz and 50 – 200 Hz below 0.1 V.

Figure 7 shows FFT for analyzing voltage swell. Voltage swell is modeled by the addition of voltage level from 0.06 until 0.14 s. The simulation result shows that FFT analysis has accurately transformed voltage swell into spectrum frequency which is different from the result of a sinusoidal signal and also voltage sag. According to the FFT result, spectrum magnitude in the frequency of 50 Hz isn't 1 V because there's a disturbance between 0.06 and 0.14 s. Hence, the spectrum magnitude of 50 Hz is 1.3 V and there are spectrum magnitudes outside 50 Hz that appear in 0 – 50 Hz and 50 – 200 Hz below 0.1 V. Compared with FFT analysis from voltage sag, the FFT result of voltage swell gives more spectrum magnitude values in the outside 50 Hz that appear in 0 – 50 Hz and 50 – 200 Hz. It happens because, in the voltage swell simulation, the duration of the disturbance is longer than the voltage sag. The main difference between voltage sag and voltage swell from this simulation result is the spectrum magnitude from voltage swell at 50 Hz has a greater value than voltage sag.

Figure 8 shows FFT for analyzing undervoltage. Undervoltage is modeled by the degradation of voltage

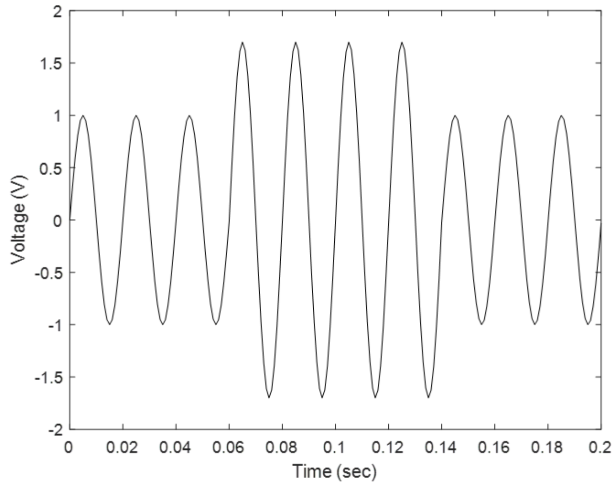


(a)

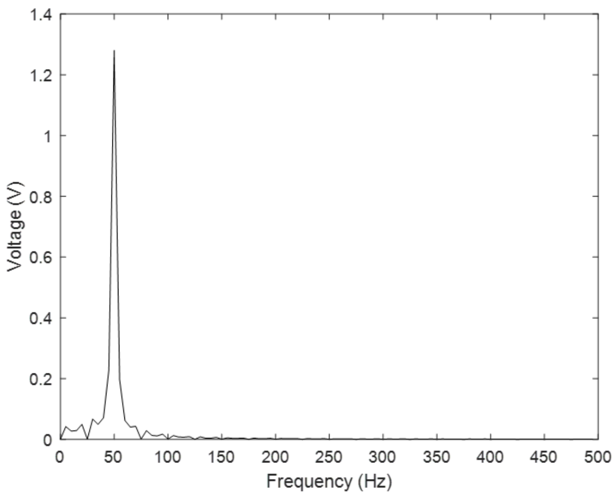


(b)

Figure 6. (a) Voltage sag signal, (b) Voltage sag analysis using FFT



(a)



(b)

Figure 7. (a) Voltage swell signal, (b) Voltage swell analysis using FFT

level from 0.2 until 1.8 s. The simulation result shows that FFT analysis has accurately transformed undervoltage into spectrum frequency which is different from the result of a sinusoidal signal, voltage sag, and voltage swell. According to the FFT result, spectrum magnitude of 50 Hz isn't 1 V because there's a power quality disturbance between 0.2 and 1.8 s. Hence, the spectrum magnitude of 50 Hz is 0.6 V and there are spectrum magnitudes outside 50 Hz that appear in 0 – 50 Hz and 50 – 200 Hz below 0.1 V. Compared with FFT analysis from voltage sag, the FFT result of Undervoltage gives less spectrum magnitude values in the 50 Hz. It happens because, in the undervoltage simulation, the duration of the disturbance is longer than the voltage sag.

Figure 9 shows FFT for analyzing overvoltage. Overvoltage is modeled by the addition of voltage level from 0.2 until 1.8 s. The simulation result shows that FFT analysis has accurately transformed overvoltage into spectrum frequency which is different from the result of a sinusoidal signal, voltage sag, voltage swell, and undervoltage. According to the FFT result, spectrum magnitude of 50 Hz isn't 1 V because there's a disturbance between 0.2 and 1.8 s. Hence, the spectrum magnitude of 50 Hz is around 1.55 V and there are spectrum magnitudes outside 50 Hz that appear in 0 – 50 Hz and 50 – 200 Hz below 0.1 V. Compared with FFT analysis from voltage swell, the FFT result of overvoltage gives more spectrum magnitude values in the 50 Hz. It happens because, in the overvoltage simulation, the duration of the disturbance is longer than the voltage swell.

Different from the previous FFT result, Figures 10 to Figure 13 have more complex disturbances which include harmonics. Harmonics that combined with previous power quality disturbances consist of fault components in the frequency of 150 Hz, 250 Hz, and 350 Hz respectively. Figure 10 shows FFT for analyzing voltage sag combined with harmonics. Voltage sag combined with harmonics is modeled by degradation of voltage level from 0.08 until 0.12 s which is including harmonic components in the frequency of 150 Hz, 250 Hz, and 350 Hz respectively. The simulation result shows that FFT analysis has accurately transformed voltage sag combined with harmonics into

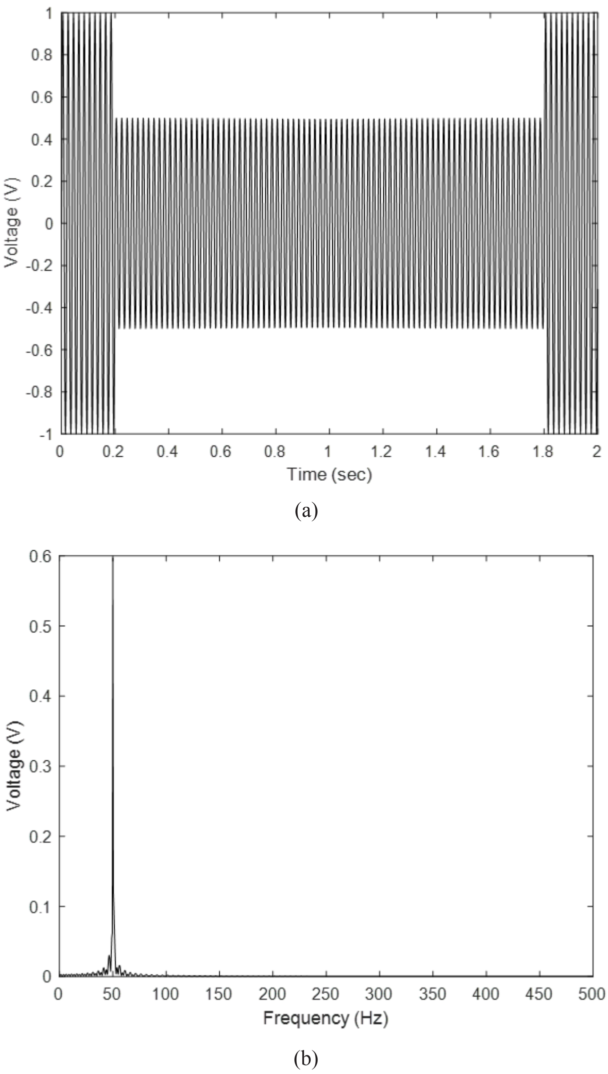


Figure 8. (a) Undervoltage signal, (b) Undervoltage analysis using FFT

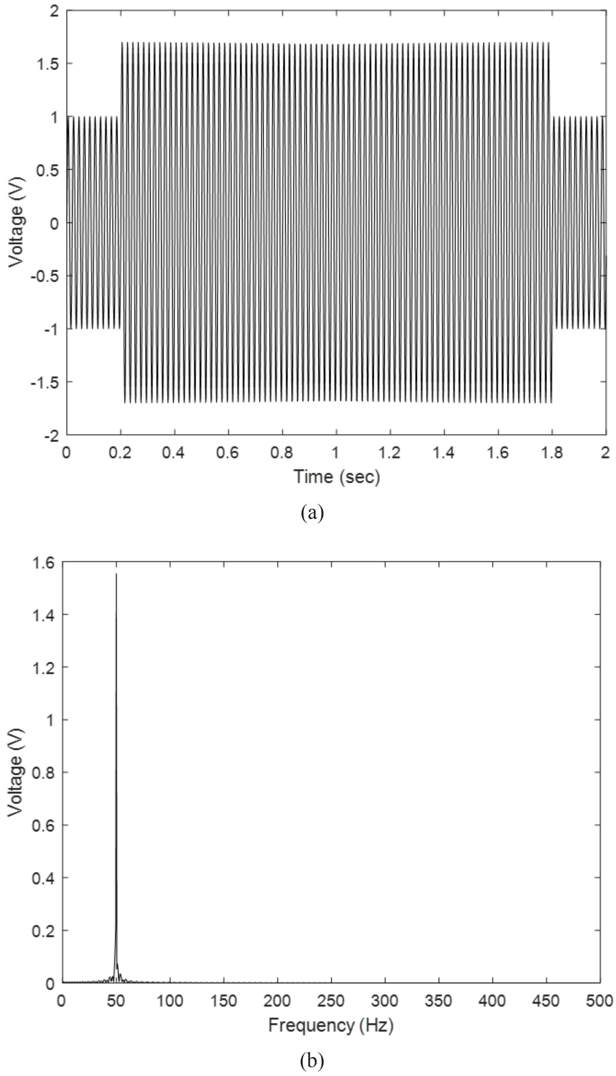


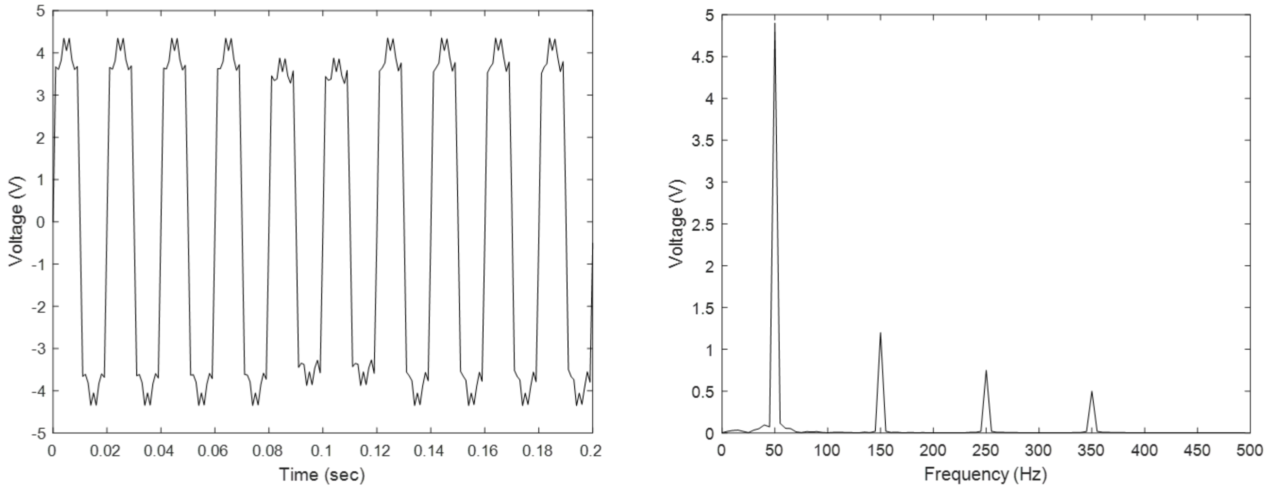
Figure 9. (a) Overvoltage signal, (b) Overvoltage analysis using FFT

spectrum frequency which is different from the previous result. According to the FFT result, spectrum magnitude in the fundamental frequency is around 5 V because there's a voltage sag combined with harmonics between 0.08 and 0.12 s. Hence, the spectrum magnitude of 150 Hz is 1.25 V, 250 Hz is 0.75 V, 350 Hz is 0.5 V, and there are spectrum magnitudes outside fundamental and harmonics frequency below 0.1 V.

Figure 11 shows FFT for analyzing voltage swell combined with harmonics. Voltage swell combined with harmonics is modeled by the addition of voltage level from 0.06 until 0.14 s which is including harmonic components in the frequency of 150 Hz, 250 Hz, and 350 Hz respectively. According to the FFT result, spectrum magnitude in the fundamental frequency is around 5.2 V because there's a voltage swell combined with harmonics between 0.06 and 0.14 s. Hence, the spectrum magnitude of 150 Hz is 1.25 V, 250 Hz is 0.75 V, 350 Hz is 0.5 V, and there are spectrum magnitudes outside fundamental and harmonics frequency below 0.1 V. It happens because harmonics appear following the voltage swell with its fault components.

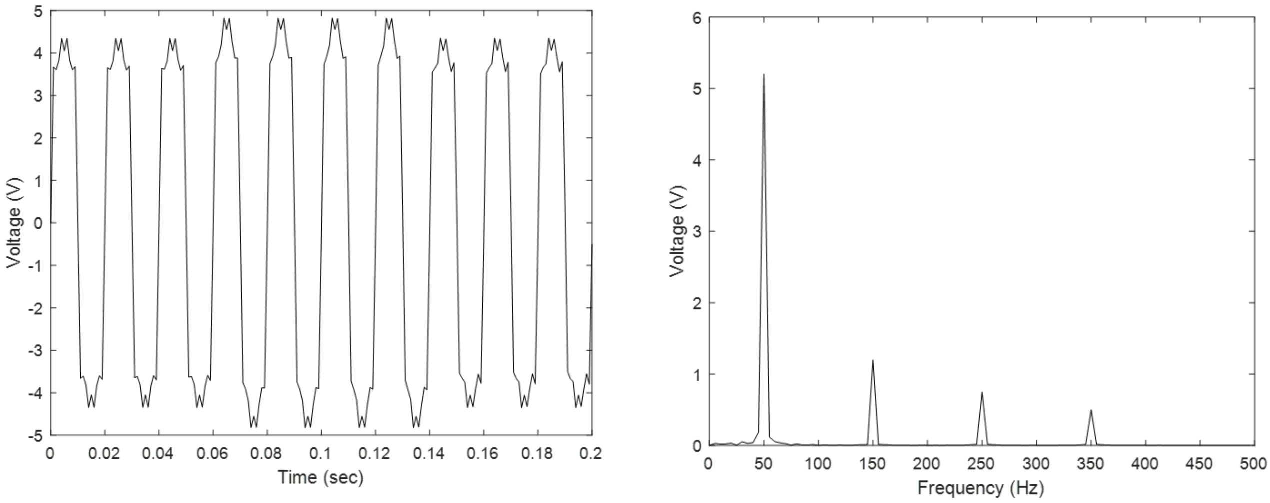
Figures 12 to Figure 13 show FFT for analyzing undervoltage combined with harmonics and overvoltage combined with harmonics. Those disturbances are modeled by degradation for undervoltage and the addition for overvoltage of voltage level from 0.2 until 1.8 s which is including harmonic components in the frequency of 150 Hz, 250 Hz, and 350 Hz respectively. According to the FFT result, spectrum magnitude in the fundamental frequency is around 4.2 V for undervoltage and 5.8 V for overvoltage because there are harmonics fault components between 0.2 and 1.8 s. Hence, the other spectrum magnitude appears such as 150 Hz is 1.25 V, 250 Hz is 0.75 V, 350 Hz is 0.5 V, and there are spectrum magnitudes outside fundamental and harmonics frequency below 0.1 V. It happens because harmonics appear following the undervoltage and overvoltage with its fault components. Compared between those two disturbances and voltage sag combined with harmonics also voltage swell combined with harmonics, the degradation or addition spectrum magnitude values depend on the duration of the power quality disturbances.

ANN is used to identify power quality disturbance types. Input ANN is the output of FFT which is magnitude



(a) (b)

Figure 10. (a) Voltage sag combined with harmonic signal, (b) Voltage sag combined with harmonic analysis using FFT



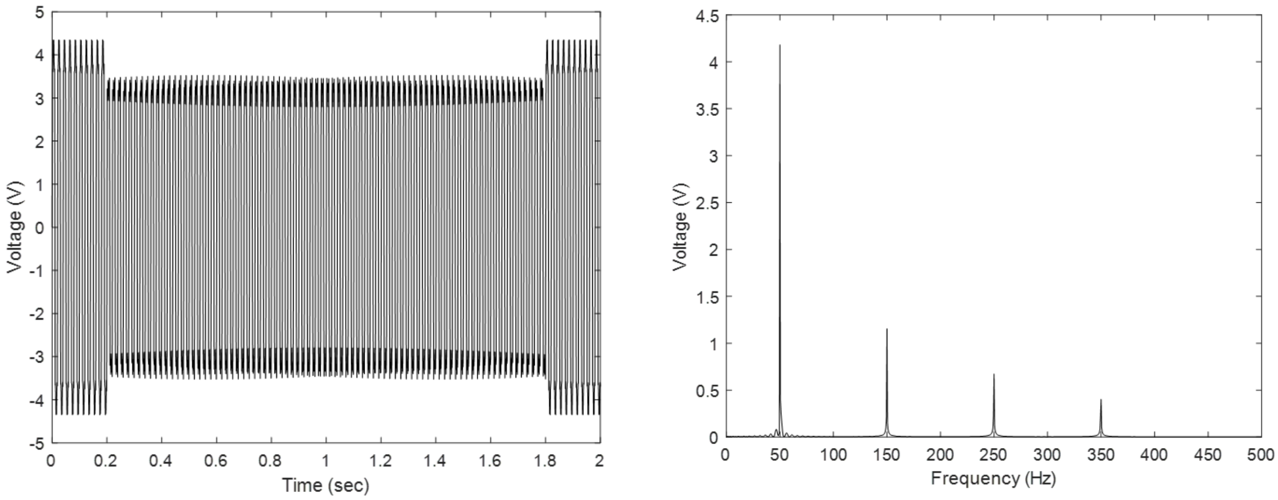
(a) (b)

Figure 11. (a) Voltage swell combined with harmonic signal, (b) Voltage swell combined with harmonic analysis using FFT

in the frequency domain. There are 200 magnitude data for each disturbance. To evaluate the performance, ANN required testing by a variety of neurons. The figure shows the identification result of each power quality disturbance. The training process used Matlab to get the weight and bias. The result of the training data will be affected by the performance of an algorithm to identify the voltage variation event. If the training result is bad, then the algorithm couldn't identify the voltage variation clearly [14].

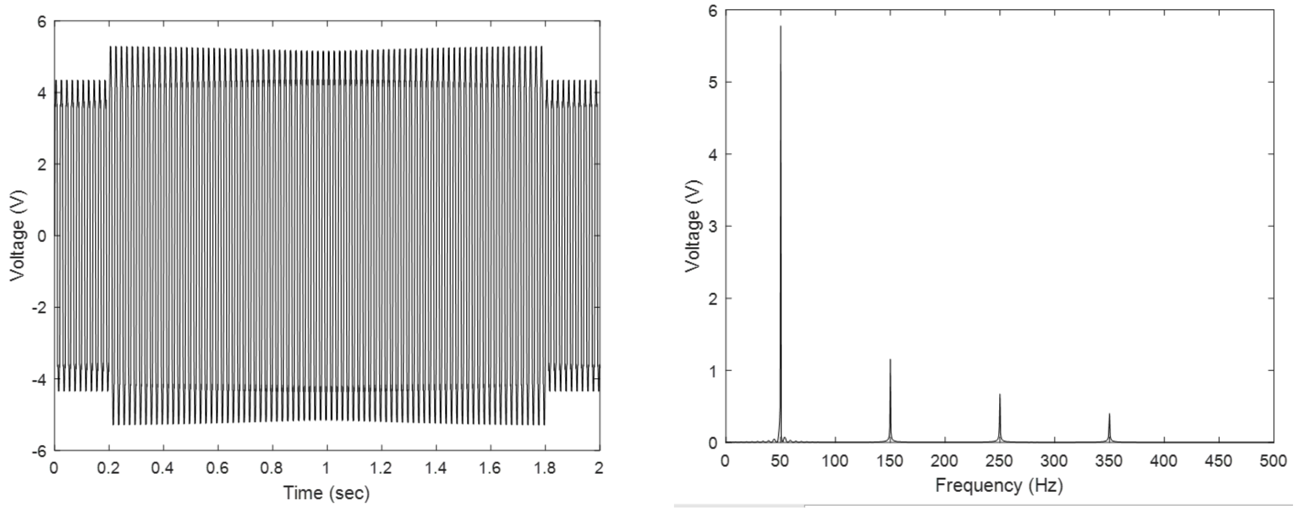
Refers to Figure 14, the error of identification result ANN of a normal signal is zero. Its regression is 100% because the ANN output must be 1. The error of identification result ANN of voltage sag is zero. Its regression is 100% because the ANN output must be 2. The error of identification result ANN of voltage swell is 0.13%. Its regression is 99.87% because the ANN output must be 3. The error of identification result ANN of undervoltage is 0.03%. Its regression is 99.97% because the ANN output must be 4. The error of identification result ANN of overvoltage is zero. Its regression is 100% because the ANN output must be 5. The error of identification result ANN of voltage sag combined with harmonics is zero. Its regression is 100% because the ANN output must be 6. The error of identification result ANN of voltage swell combined with harmonics is zero. Its regression is 100% because the ANN output must be 7. The error of identification result ANN of undervoltage combined with harmonics is 0.15%. Its regression is 99.85% because the ANN output must be 8. The error of identification result ANN of overvoltage combined with harmonics is 0.13%. Its regression is 99.87% because the ANN output must be 9. Hence, the ANN output error which approaches zero indicated the proposed method to identify power quality disturbance was good.

According to Table 3, there's the ANN result of power quality disturbances identification. It has good accuracy for types of power quality disturbances. The proposed method that consists of 20 neurons in a hidden layer could have 100% accuracy.



(a) (b)

Figure 12. (a) Undervoltage combined with harmonic signal, (b) Undervoltage combined with harmonic analysis using FFT



(a) (b)

Figure 13. (a) Overvoltage combined with harmonic signal, (b) Overvoltage combined with harmonic analysis using FFT

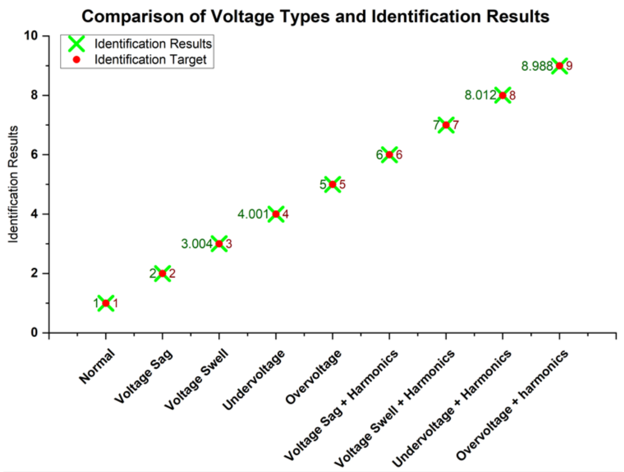


Figure 14. Identification result of ANN

Table 3. ANN result of power quality disturbances identification

Power Quality Types	ANN's accuracy of 20 Neurons of hidden Layer (%)
Normal	100%
Voltage sag	100%
Voltage swell	99.87%
Undervoltage	99.97%
Overvoltage	100%
Sag combined harmonics	100%
Swell combined harmonics	100%
Undervoltage combined harmonics	99.85%
Overvoltage combined harmonics	99.87%

V. CONCLUSION

This paper presents the identification of power quality disturbances using FFT and ANN. There are 8 types of power quality disturbances such as voltage sag, voltage swell, undervoltage, overvoltage, voltage sag combined harmonic, voltage swell combined harmonic, undervoltage combined harmonic, and overvoltage combined harmonic. Power quality disturbances are modelled by frequency sampling of 1000 Hz. Power quality disturbances signal is analysed by FFT. Output FFT is magnitude in the time domain, which is used to input ANN. The FFT combined with ANN can show good performance to detect and identify each power quality disturbance. In this case, more neurons give better performance than a few neurons. ANN with 20 neurons in the hidden layer can have an accuracy of approximately 99.95 %.

REFERENCES

[1] P. R. Kamthekar, P. V. Gautam, and R. K. Munje, "Detection, characterization and classification of short duration voltage events using DWT and fuzzy logic," in *Proc. Inter. Conf. on Innovative Mechanisms for Industry Apps.,* Feb. 2017, pp. 242–247.

[2] E. A. Nagata, D. D. Ferreira, C. A. Duque, and A. S. Cequeira, "Voltage sag and swell detection and segmentation based on independent component analysis," *Electric Power Systems Research*, vol. 155, pp. 274–280, Feb. 2018.

[3] H. Zang and Y. Zhao, "Intelligent identification system of power quality disturbance," in *Proc. WRI Global Congress on Intelligent Systems*, May 2009, pp. 258–261.

[4] IEEE, "IEEE recommended practice for monitoring electric power quality," in IEEE Std 1159-2019 (Revision of IEEE Std 1159-2009), Aug. 2019, pp.1–98.

[5] A. Hussain, M. H. Sukairi, A. Mohamed, and R. Mohamed, "Automatic detection of power quality disturbances and identification of transient signals," in *Proc. 6th Inter. Symp. on Signal Processing and its Apps.,* Aug. 2001, pp. 462–465.

[6] M. A. B. Mohamed Ayub et al, "Over voltage and under voltage protection system using IoT," *J. of Physics: Conf. Series.,* vol. 2319, no. 1, pp. 012009, Aug. 2022.

[7] B. M. Arsyad, A. Sofwan, and A. Nugroho, "Perancangan sistem kontrol over/under voltage relay berbasis mikrokontroler pada saluran tegangan 220 VAC," *Jurnal Ilmiah Teknik Elektro*, vol. 21, no. 1, pp. 25-32, April 2019.

[8] D. D. Tung, and N. M. Khoa, "An arduino-based system for monitoring and protecting overvoltage and undervoltage," *Engineering, Technology & Applied Science Research*, vol. 9, no. 3, pp. 4255–4260, June 2019.

[9] G. Devadasu and M. Sushama, "A novel multiple fault identification with fast fourier transform analysis," in *Proc. Inter. Conf. on Emerging Trends in Engineering, Technology and Science,* Feb 2016, pp. 1–5.

[10] E. C. Mendoza, P. Schweitzer, and S. Weber, "A double ended AC series arc fault location algorithm for a low-voltage indoor power line using impedance parameters and a neural network," *Electric Power Systems Research,* vol. 165, pp. 84–93, Dec. 2018.

[11] G. Devadasu and M. Sushama, "Identification of voltage quality problems under different types of sag/swell faults with fast Fourier transform analysis," in *Proc. 2nd Inter. Conf. on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics*, Feb 2016, pp. 464–469.

[12] Y. Zhao, Y. Xu, X. Xiao, Y. Zhu, and C. Guo, "Power quality disturbances identification based on dq conversion, wavelet transform and FFT," in *Proc. Asia-Pacific Power and Energy Engineering Conference*, March 2010, pp. 1–4.

[13] P. Patil, K. Muley, and R. Agrawal, "Identification of Power Quality Disturbance Using Neural Network," in *Proc. 3rd Inter. Conf. on Electronics, Communication and Aerospace Technology*, Jun 2019, pp. 990–996.

[14] M. K. Elango, A. N. Kumar, and K. Duraiswamy, "Identification of power quality disturbances using artificial neural networks," in *Proc. 3rd Inter. Conf. on on Power and Energy Systems*, Dec. 2011, pp. 1–6.