Multipoint Voltage Disturbance Identification using Neural Network

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***Abstract*—Voltage disturbance, as well as other power quality issues which include electromagnetic interference phenomena, are dangerous power quality issues that can cause sensitive equipment to fail, especially in industrial or hospital environments. Identifying voltage disturbance has an important role to mitigate the degradation of power quality disturbances due to their negative impact on the equipment. The Neural network is used to identify voltage disturbance. This paper presents a combination of identification of voltage disturbance by using a neural network with a multipoint measurement method. This method simplifies the identification of voltage disturbance at multiple point using only one measurement.**

Keywords—voltage disturbance, electromagnetic interference (EMI), power quality, multipoint measurement, neural network

I. INTRODUCTION

Electromagnetic interference (EMI) is one of the main factors that can degrade the power quality (PQ) in a power system. The EMI in the form of voltage disturbance such as voltage sag and swell can cause sensitive equipment to fail, shut down, and create current imbalance. Furthermore, the impact of poor power quality on daily operations has become a major concern for utilities and customers. It can cause many problems such as high energy costs, malfunctions, and production disruptions. Companies, industries, and many organizations lose billions of dollars each year as a result of poor power quality [1]. Voltage disturbance can be divided into two categories: short-duration voltage variation and long-duration voltage variation. The short-duration is refer to voltage dips and short interruptions, and the long-duration is refer to long interruption, which was added to deal with the limits in ANSI C84.1-2016 [2]. The disturbance classification and identification are commonly based on standards and recommendations [3]. Furthermore, to mitigate PQ issues, it is necessary to determine and identify the disturbance before appropriate mitigation measures can be taken. The PQ monitoring is an effective way to provide better customer service and ensure a competitive environment among utility companies. In most cases, PQ monitoring is done by capturing disturbances or events. [4].

Moreover, in a power system, the PQ degradation is not only related to the quality of the generator, but also the characteristics of the installed load. Therefore, PQ monitoring using a multipoint measurement technique that can measure several subsystems is required. A multipoint measurement technique is the best alternative to investigate the root cause (performance) of EMI in complex installations. In a power system, the multipoint measurement technique can monitor multiple points in one system or multi-system simultaneously. It can be utilized to identify EMI propagation in all directions and correlation between EMI [5] [6].

Many studies on the identification of power quality disturbances with neural networks have been carried out because of the reliable function of the neural network to identify disturbance [7] [8] [9], but no one has combined the identification method using neural networks with multipoint measurement techniques. Neural networks are made up of simple elements that run in parallel. These elements are inspired by the biological nervous system. Neural networks are trained to perform complex functions in a variety of application areas, including pattern recognition, identification, classification, speech, vision, and control systems [10].

In this study, we propose a new method of voltage disturbance identification using a combination of a multipoint measurement technique and a neural network approach. By this method, the voltage disturbances identification process at several points can be done with just one measurement simultaneously. The program is a MATLAB based and was developed based on IEEE 1159-2019 voltage disturbances classification [2]. According to this standard there are two parameters to classify these categories: duration and voltage magnitude.

II. THEORETICAL BACKGROUND

A. Voltage Disturbance Classification

Classification of voltage disturbance used in this study is based on standard IEEE 1159-2019. Momentary Short-duration root-mean-square (rms) variation is used as the basic

TABLE I. CATEGORIES OF VOLTAGE DISTURBANCE

Categories	Typical duration	Typical voltage magnitude
Interruption	0.5 cycles – 3s	< 0.1 pu
Voltage Sag	30 cycles – 3s	0.1 – 0.9 pu
Voltage Swell	30 cycles – 3s	1.1 – 1.4 pu
Voltage Imbalance	30 cycles – 3s	2% - 15%

data for constructing a neural network so that the network can detect differences in voltage disturbances. The categories of voltage disturbances with typical disturbance magnitudes and typical disturbance durations according to standard IEEE 1159-2019 are shown in Table I. The quantity pu refers to per unit, which is dimensionless. The nominal condition is often considered to be 1.0 pu which corresponds to 100%.

B. *Neural Network*

The neural network is part of artificial intelligence (AI), which is the automation of behaviors associated with human thinking, such as decision-making, problem-solving, learning, perception, and reasoning to address complicated issues. As a result of the rapid advancement of computers, AI tools such as neural networks have emerged as a viable alternative for solving problems that require some level of human reasoning. A neural network has all of the characteristics that make it a useful tool for classifying PQ disturbances. It represents a highly parallelized dynamic system, with a directional graph topology, and can receive output information through its state in response to input actions [11]. Artificial neural networks are very effective for pattern recognition problems and multi-variable problems with complex decision constraints. A neural network with enough neurons can classify given data very accurate. Therefore, the neural network is a good candidate to solve the PQ event identification problem.

III. Analysis Method

A. *Creating a MATLAB based neural network*

The neural network has been set up with two hidden layers, the first with 10 neurons and the second with 5 neurons, it is to identify voltage abnormalities. More layers will provide more accurate results, however, it requires a longer training process and more memory. The best suggestion is to set the number of layers with the best performance. The developed artificial neural network will learn to classify disturbances into

TABLE II. Value Code Representation of Voltage Disturbance

Condition	Value Code
Normal	0
Voltage Sag	1
Voltage Swell	2
Interruption	3
Voltage Imbalance	4

TABLE III. Training Parameters

Parameters	Value
Network Structure	2 hidden layers
Training type	Supervised
Training algorithm	Lavenberg-Marquardt
Input number	2
Output layer	1
Neuron in hidden layer 1	10
Neuron in hidden layer 2	5
Training epoch	1000

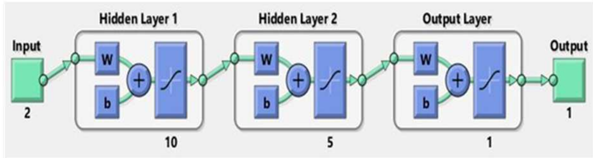

Fig. 1. Pattern recognition neural network.

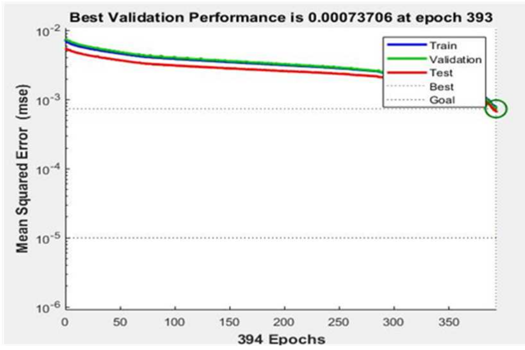

Fig. 2. Neural network training performance.

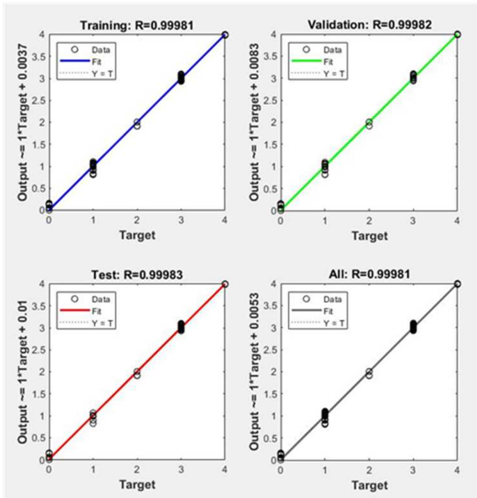

Fig. 3. Neural network regression analysis.

different categories. Due to the neural network starting with random initial weights, the problem results may vary significantly from run to run, thus to avoid it, random seeds can be set permanently. The magnitude voltage per unit in rms and the duration of the disturbance will act as input to the neural network, and the target or output of each category of disturbance will be presented with a value code that represents the position of the related disturbance condition as shown in Table II. In this case, the following code is used as a target for classifying. Fig. 1 shows the pattern recognition neural network. Two kinds of samples are provided separately for training and testing purposes. The training samples are taken according to the IEEE 1159-2019 standard, while the test samples are taken from the multipoint measurement carried out in the laboratory. The training process is carried out to derive weights and biases, which employs a total of 2976 training data. Table III shows the training parameter used in the neural network.

Fig. 2 shows the performance of the trained network. The network performance during training is improved and the value of mean square error is decreased. In the graph of neural network training performance, the training set, validation set, and test set are drawn separately by a different color (blue,

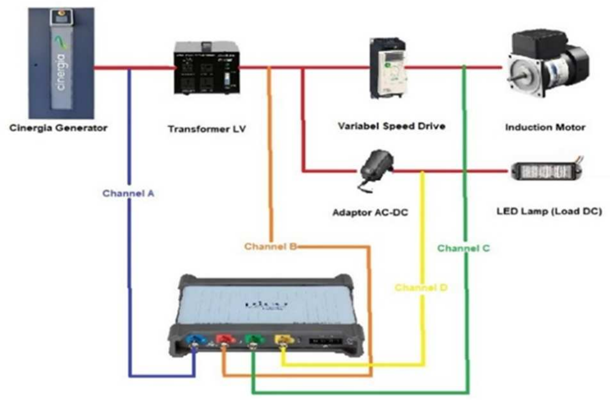

Fig. 4. Circuit setup on Laboratory.

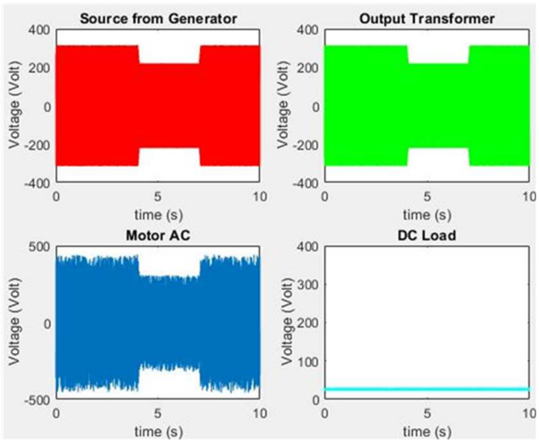

Fig. 5. Sinusoidal waveform each channel.

green and red). The best verification performance is 0.00073706 in the 394 epoch. The best performance is taken from the epoch with the lowest validation error. Fig. 3 is a regression plot of the neural network. It represents how fit the neural network with the data. The performance of the algorithm to identify the voltage variation event will have a significant impact on the training data results. The algorithm will be unable to properly distinguish voltage variation if the training results are inadequate. The result of this study shows that the simulation data fit is reasonably good for all data sets, with R values is 0.99981.

B. *Multipoint Measurement Setup*

Multipoint measurement is performed to serve as test samples to validate the neural network. Measurements were made using a Picoscope 4824 with 4 voltage probes TA043 from Pico technology. The equipment used in this experiment is a Cinergia Generator with an adjustable supply to generate voltage disturbance, a 110/220V reversible LV transformer. The first load is an AC load 90W AC motor which is connected using a variable speed drive, and the second load is a DC load LED lamp. Fig. 4 shows the circuit setup used in the laboratory.

Four voltage probes record the voltage at four different points simultaneously and each probe is connected to a channel in the Picoscope.

- Point A: Cinergia generator output
- Point B: 220-120 Transformer output
- Point C: Variable speed drive output

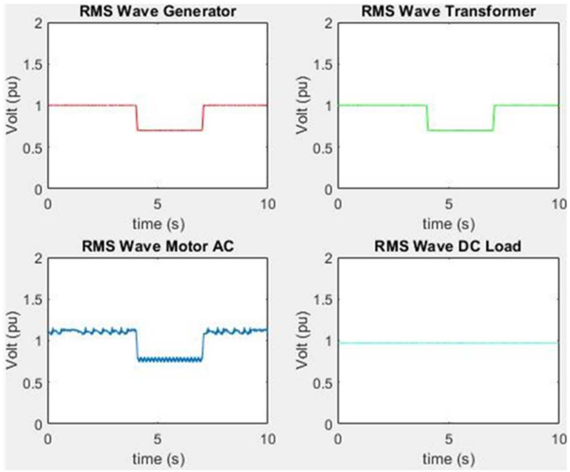

Fig. 6. The rms waveform.

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Voltage disturbance (RMS) on channel A is 0.702817 p.u
Voltage disturbance (RMS) on channel B is 0.701971 p.u
Voltage disturbance (RMS) on channel C is 0.736724 p.u
Voltage disturbance (RMS) on channel D is 1.000000 p.u
NOTE : IF Voltage disturbance (RMS) is 1, its mean normal condition
------------------------------------------------------------------------
Duration of disturbance voltage on channel A is 2.991177 sec
Duration of disturbance voltage on channel B is 2.991414 sec
Duration of disturbance voltage on channel C is 2.948615 sec
Duration of disturbance voltage on channel D is 0.000000 sec
------------------------------------------------------------------------
Starting time of Disturbance voltage on channel A is on 4.037770 sec
Starting time of Disturbance voltage on channel B is on 4.037680 sec
Starting time of Disturbance voltage on channel C is on 4.064010 sec
Starting time of Disturbance voltage on channel D is on 0.000000 sec
NOTE : IF Starting time is 0 with duration 0, its mean normal condition
------------------------------------------------------------------------
       DISTURBANCE RESULT
-----------------------------------------
Ch    V(p.u)       Dur(s)     Start(@s)
-----------------------------------------
A      0.70         2.99        4.04
B      0.70         2.99        4.04
C      0.74         2.95        4.06
D      1.00         0.00        0.00
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Fig. 7. The rms waveform result of conversion.

- Point D: AC-CD adaptor output

The result of measurement is in a sinusoidal waveform. This result is converted into an rms waveform, then, the program analyzes the magnitude of the voltage disturbance and the duration of the disturbance. Both are used as input to the neural network to determine the characteristics of each disturbance.

IV. Analysis Result

Fig. 5 shows the result of the multipoint measurement in a sinusoidal waveform. The red graph is the representation of the sinusoidal voltage at point A, the green graph is the representation of the sinusoidal voltage at point B, the blue graph is the representation of the sinusoidal voltage at point C, and the light-blue graph is the representation of the DC voltage at point D. For further analysis of the voltage disturbance at each point, these data are converted into rms form with the unit of pu.

Fig. 6 shows the conversion result of a sinusoidal waveform in the form of an rms waveform. It shows when a voltage disturbance occurs, which is the voltage at point A is decreased to 0.7028 pu for 3.00 seconds resulted in a voltage decrease at point B, its value becomes 0.7020 pu for 2.99 sec. Furthermore, due to this disturbance, the voltage at point C also decreases, its value becomes 0.7367 pu for 2.99 sec.

TABLE IV. SAMPLE MEASUREMENT AND NETWORK RESULT

Measurement Condition	Ch	V (pu)	Dur (s)	Start (s)	Value Code *Std*	Value Code *Act*	Category
Voltage Sag 0.9 p.u 3 sec	A	0,90	2,98	4,22	1	0,97	Voltage Sag
	B	0,90	2,98	4,22	1	0,98	Voltage Sag
	C	0,96	2,93	4,24	1	0,98	Voltage Sag
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Sag 0.7 p.u 3 sec	A	0,70	2,99	4,04	1	1,00	Voltage Sag
	B	0,70	2,99	4,04	1	1,00	Voltage Sag
	C	0,74	2,95	4,06	1	1,00	Voltage Sag
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Sag 0.5 p.u 3 sec	A	0,50	3,03	4,48	1	1,00	Voltage Sag
	B	0,50	3,03	4,48	1	1,00	Voltage Sag
	C	0,00	5,42	4,50	3	3,00	Interruption
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Sag 0.3 p.u 3 sec	A	0,30	3,08	4,30	1	1,00	Voltage Sag
	B	0,30	3,08	4,30	1	1,00	Voltage Sag
	C	0,00	5,60	4,33	3	3,00	Interruption
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Swell 1.1 p.u 3 sec	A	1,10	2,98	3,63	2	2,00	Voltage Swell
	B	1,10	2,98	3,63	2	2,00	Voltage Swell
	C	1,27	3,04	3,66	2	2,00	Voltage Swell
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Swell 1.2 p.u 3 sec	A	1,20	3,00	4,93	2	2,00	Voltage Swell
	B	1,20	3,00	4,93	2	2,00	Voltage Swell
	C	1,36	2,96	4,95	2	2,00	Voltage Swell
	D	1,00	0,00	0,00	0	0,00	Normal
Voltage Swell 1.4 p.u 3 sec	A	1,26	3,01	3,57	2	2,00	Voltage Swell
	B	1,26	3,01	3,57	2	2,00	Voltage Swell
	C	1,35	2,98	3,60	2	2,00	Voltage Swell
	D	1,00	0,00	0,00	0	0,00	Normal
Interruption 0.09 p.u 3 sec	A	0,09	3,16	4,37	3	2,99	Interruption
	B	0,09	3,16	4,37	3	2,99	Interruption
	C	0,00	5,53	4,43	3	3,00	Interruption
	D	0,04	3,09	4,80	3	3,00	Interruption

While the voltage at point D remains stable during this disturbance because the disturbance is still within the tolerance range of the adapter voltage input. Fig. 8 is an example of the program results on MATLAB that determine the voltage disturbance, duration disturbance, and starting time disturbance.

Furthermore, the voltage magnitude and duration of the disturbance are used as input to train the neural network. Using two hidden layers of neural network structure as mentioned in chapter III.a the character of the voltage disturbance for each point can be identified and categorized.

In this study, 22 variations of voltage disturbance, have been conducted to validate the neural network. Each rms value of each measurement result will be used as input to the neural network. The final output of this program contains information about voltage magnitude, start time, duration, and voltage disturbance categories. Table IV shows the sample result of each measurement and the results of the neural network output. Actual value code is output result from neural network program. Error value was calculated using the mean square error (MSE) method. The average error value from all total results is 0.0090484% which is close to 0.

V. CONCLUSION

The present study was designed to identify EMI characteristics, one of which is voltage disturbance. The study presented a MATLAB based program to identify voltage disturbance events in momentary short-duration classification which is voltage sag, voltage swell, interruption, and voltage imbalance using multipoint measurement method with the help of a neural network as a pattern recognition tool. This study has shown that the multipoint voltage disturbance identification method provides better identification accuracy, shown by the value of a total average of error of 0.0090484%.

This research is envisaged to serve as a base for future study to find EMI events correlation between subsystems in one power system. As an extension to the work, it would be interesting to develop a program with an expanded standard coverage and able to detect EMI disturbances in real-time.

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