A Portable Power Quality Monitoring Approach in Microgrid with Electromagnetic Sensing and Computational Intelligence

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Monitoring power quality in microgrids is gaining increasing attention in recent years due to the popularity of microgrids and power quality disturbances caused by renewable energies. Many techniques based on artificial neural networks (ANNs) are proposed for monitoring the power quality with no need to pre-set thresholds. However, the necessity of retraining the ANN is a big problem when the electrical parameters vary. This paper proposes a new approach to detect and classify the power quality disturbances accurately in multi microgrids based on electromagnetic sensing and portability-enhanced ANN. The proposed ANN-based approach avoids the retraining of weights, when the voltage, current and frequency varies with microgrids. Two steps are critical for achieving the portability of the ANN in various microgrids, which are pre-normalization and using the same maximum and minimum feature vectors for feature matrix normalization. Meanwhile, the electromagnetic sensing facilitates non-intrusive monitoring and easy installation. The high accuracy of simulation and experimental results in various scenarios validate the effectiveness and efficiency of this portable and non-invasive approach for monitoring power quality in multi microgrids without retraining ANN.

***Index Terms*—Power quality, microgrid, magnetic sensor, electromagnetic sensing, artificial neural network.**

I. Introduction

The energy crisis and global warming are becoming increasingly severe due to the excessive exploitation of fuel resources. Such situations render renewable energy resources (RERs) and distributed power systems important. Extensive research about relative topics is underway, especially in the area of microgrids [1-4]. Microgrids are featured by high penetration of RERs. They can relieve the burden on the utility grid, reduce the emission of greenhouse gases, and bring economic benefits to both electric providers and consumers. Despite the advantages of microgrids, there is a problem that is caused by the high penetration of RERs. The power from most RERs is stochastic and intermittent, such as photovoltaic (PV) panels [5, 6] and wind turbines [7]. Such inherent characteristics of RERs can result in various disturbances of power quality (PQ). Moreover, nonlinear loads are increasing dramatically in power systems nowadays, especially in residential buildings, and they are sensitive to the PQ. Hence, both facts make PQ monitoring in microgrids a necessary and critical task.

Nowadays, there are many techniques for PQ monitoring [8]. A digital instrument prototype was designed for measuring main PQ indexes with high accuracy in [9]. However, eight intrusive transducers were installed in the prototype. Such a design could result in safety hazards, more installation, and maintenance. Another nonintrusive technique for monitoring load and diagnosing was proposed in [10] with Hall-effect current sensors. Although this technique can keep the targeted system intact, the detection capability of the technique is limited to current related anomalies. In many existing techniques for monitoring PQ, pre-setting thresholds is required to detect PQ disturbances [11, 12]. These thresholds are usually determined empirically and need resetting adhering to changing definitions of PQ disturbances. This drawback promotes the application of artificial intelligence in monitoring systems [13]. Artificial neural network (ANN) is increasingly popular in monitoring PQ since no thresholds are needed. Nevertheless, the computational burden of some ANN-based approaches is heavy, such as the multiwavelet transform of original signals in [14] or applying a complex network called adaptive wavelet networks in [15]. Besides, one inevitable problem in ANN-based approaches is that the ANN trained in one power system needs retraining when the voltages, currents or frequencies are different in another power system [16-18], which is troublesome. In summary, these techniques are not entirely satisfactory in four respects: (1) invasive to systems; (2) relying only on one measurement of voltage or current; (3) complicated computation; (4) unable to be applied in different systems.

In this paper, a portable PQ monitoring approach in multi microgrids using electromagnetic sensing and computational intelligence is proposed to tackle the problems in existing approaches. The proposed approach is to monitor the PQ of single-phase systems, which are common in power delivery to local customers. Electromagnetic sensing in the approach leads to the non-invasiveness to the monitoring subjects, which means easy installation, and expand the detection capability of PQ disturbances concerning voltage and current. Also, the influence of the proposed method on the original system is minimized. Due to easy calculations of features and the application of a feed-forward neural network (FFNN), the computation time for training ANN and classifying PQ disturbances is greatly reduced. Meanwhile, the portability of the ANN is enhanced by the proposed method to solve the problem which occurs in a traditional ANN-based approach. Such portability-enhanced ANN only needs once training and can be used in different microgrids regardless of the voltage, current, and frequency. Hence, the proposed approach possesses great potential to be part of a monitoring system in

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microgrids because of its non-invasiveness, broad detection capability, light computation burden, and portability in various environments with high accuracy.

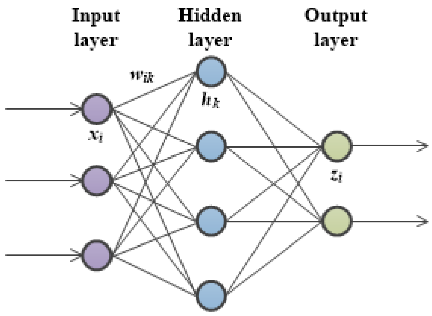

Fig. 1. A typical structure of a multi-layer FFNN.

II. Portability Enhancement of ANN

A. Artificial Neural Network

An ANN is based on the imitation of the biological neural network [19]. One commonly used ANN is FFNN. A typical structure of a multi-layer FFNN is shown in Fig. 1, which contains three layers: an input layer, a hidden layer, and an output layer. The initial data in an FFNN are propagating along a forward path from the input layer to the output layer. The data processing in an FFNN can be generalized as two steps. The first step is that the value of a neuron in the hidden layer is obtained by the linear combination of weights and a constant bias, which can be represented as:

$$h_k = \sum_{i=1}^{m} w_{ik} \cdot x_i \qquad (1)$$

where h_k denotes the output of the kth neuron in the hidden layer, w_{ik} is the weights of the input i to the kth neuron in the hidden layer, m is the number of the inputs and x_i is the ith input.

The second step is applying a transfer function to the obtained results from (1), which can be written as:

$$z_i = f(h_k) \qquad (2)$$

where z_i is the ith output and f is the transfer function.

B. Enhancing the Portability of ANN

The ANN technology has already been applied in many fields including PQ monitoring, and achieved great success in tackling the uncertain relationships between multiple variables. However, the drawback of ANN technology is bad portability. A trained ANN is difficult to be directly applied in a different environment. For example, a trained ANN for monitoring PQ in a microgrid must be retrained to adapt to another microgrid with different voltage, current or frequency. This is because the features of input data in the new microgrid differ from those in the original microgrid, which can lead to misclassification of PQ disturbances.

ANN technology has taken some measures to deal with the portability problem. One way is the normalization of the data after inputting an ANN, which can be written as:

$$z = 2 \cdot (y - y_{\min}) / (y_{\max} - y_{\min}) - 1 \qquad (3)$$

where y is a set of data before normalization and z is the normalized data for training or testing an ANN. Symbols $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of multiple y. The units and ranges of measured data are different. Thus, the normalization of data is necessary and can eliminate these effects. All the data are normalized from -1 to 1.

Despite data are normalized in an ANN algorithm, $y_{\max}$ and $y_{\min}$ in the original environment can vary a lot from those in a new environment. Such variance can result in misclassification of testing data. Thus, it is necessary to keep $y_{\max}$ and $y_{\min}$ constant in the proposed method during training and testing an ANN. To eliminate the effects of different ranges of input data in multi environments, the pre-normalization of data before inputting into an ANN is proposed in this paper and defined as:

$$y = x / x_c \qquad (4)$$

where x is the initial data and x_c is a constant as a base. With data pre-normalization before inputting an ANN, and using the same $y_{\max}$ and $y_{\min}$ for data normalization in an ANN, the trained ANN is enhanced in the portability and can be applied in different environments.

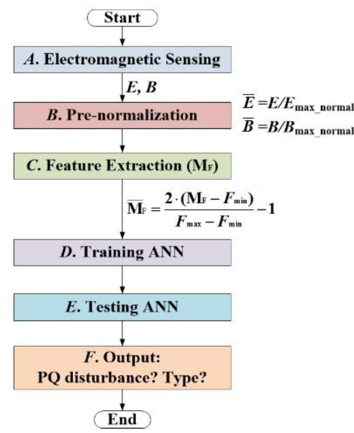

Fig. 2. The flowchart for the proposed power quality monitoring approach.

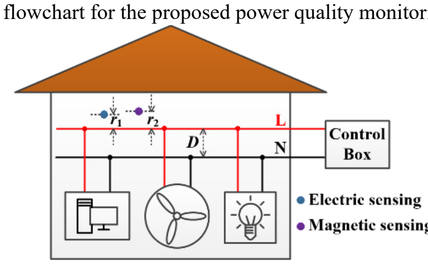

Fig. 3. The placement of electric and magnetic field sensors in the single-phase system.

III. Operating Principle

The proposed approach is aimed at monitoring PQ of single-phase systems which are commonly used for power delivery in residential buildings. Nevertheless, it is easy to adopt this approach in three-phase systems. The flowchart of the proposed approach is illustrated in Fig. 2 including seven stages, and explained as followed:

A. Electromagnetic Sensing

In the proposed approach for monitoring PQ in microgrids, the electric and magnetic field sensors are placed near the target phase as shown in Fig. 3 to measure the electric and magnetic fields, respectively, which are emanated by the voltage and current in the energized phase. The distance between live and neutral wires should be greatly larger than that between the sensing points and the live wire ($D \gg r_1$, and $D \gg r_2$).

Meanwhile, the non-invasiveness of these sensors facilitates easy installation and maintenance.

TABLE I

FEATURES USED IN THE PROPOSED APPROACH FOR PQ MONITORING

Symbol	Description
$\overline{E}_{\max}$	The maximum pre-normalized electric field value in a period.
$\overline{E}_{\min}$	The minimum pre-normalized electric field value in a period.
$\overline{E}_{\mathrm{rms}}$	The RMS value of pre-normalized electric field in a period.
$\lvert\overline{E}_{f}\rvert$	The fundamental component of pre-normalized electric field in a period.
$\lvert\overline{E}_{3f}\rvert$	The 3rd harmonic of pre-normalized electric field in a period.
$\lvert\overline{E}_{5f}\rvert$	The 5th harmonic of pre-normalized electric field in a period.
$\overline{B}_{\max}$	The maximum pre-normalized magnetic field value in a period.
$\overline{B}_{\min}$	The minimum pre-normalized magnetic field value in a period.
$\overline{B}_{\mathrm{rms}}$	The RMS value of pre-normalized magnetic field in a period.
$\lvert\overline{B}_{f}\rvert$	The fundamental component of pre-normalized magnetic field in a period.
$\lvert\overline{B}_{3f}\rvert$	The 3rd harmonic of pre-normalized magnetic field in a period.
$\lvert\overline{B}_{5f}\rvert$	The 5th harmonic of pre-normalized magnetic field in a period.

B. Pre-normalization

The electric and magnetic field data from sensors (E and B) in any conditions (normal and anomaly conditions) in a microgrid are divided by the maximum electric and magnetic fields in the normal condition ($E_{\max\_normal}$, and $B_{\max\_normal}$), respectively. The pre-normalized electric and magnetic field data ($\overline{E}$ and $\overline{B}$) can be obtained by:

$$\begin{cases} \overline{E} = E / E_{\max\_normal} \\ \overline{B} = B / B_{\max\_normal} \end{cases} \tag{5}$$

C. Feature Extraction

The features of the pre-normalized data are extracted to characterize each case. Extracted features contain the maximum, the minimum and the root-mean-square (RMS) values of the pre-normalized data in a period. Considering possibly existing harmonics, harmonic components obtained from Fast Fourier Transform are also included. All these features are listed in Table I and form a feature matrix ($\mathrm{M_F}$) to describe the measurement signal.

D. Train ANN

After being inputted into an ANN, $\mathrm{M_F}$ is normalized by:

$$\overline{\mathrm{M}}_{\mathrm{F}} = 2 \cdot (\mathrm{M_F} - F_{\min}) / (F_{\max} - F_{\min}) - 1 \tag{6}$$

where $\overline{\mathrm{M}}_{\mathrm{F}}$ is the normalized $\mathrm{M_F}$. $F_{\max}$ and $F_{\min}$ are maximum and minimum feature vectors, which comprise maximum and minimum values for each feature under various PQ disturbances. An ANN is trained with $\overline{\mathrm{M}}_{\mathrm{F}}$ and training is only for one time. The ANN applied in the paper is FFNN containing three layers: one input layer, one hidden layer, and one output layer. The two transfer functions in the FFNN are linear and log-sigmoid transfer functions.

E. Testing ANN

Data of E and B measured in the same or different microgrid are processed in the same way at *Stage B* and *C*. Corresponding $\mathrm{M_F}$ are normalized by the same $F_{\max}$ and $F_{\min}$ in *Stage D*. New $\overline{\mathrm{M}}_{\mathrm{F}}$ are then used for testing the portability-enhanced ANN.

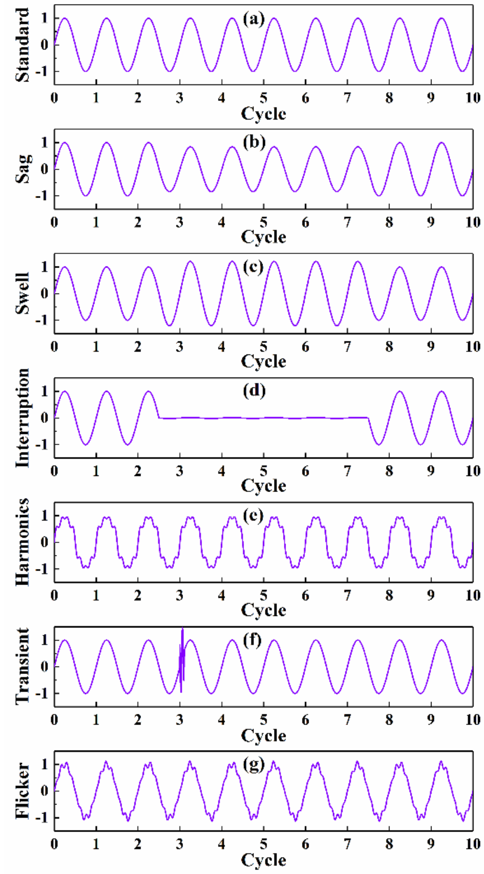

Fig. 4. A series of power quality disturbance categories include: (a) standard, (b) sag, (c) swell, (d) interruption, (e) harmonics, (f) transient, and (g) flicker

F. Output

Eventually, the portability-enhanced ANN outputs whether there is a PQ disturbance and the type of disturbance.

It should be noted that portability in the paper has two meanings. One is that the platform based on the proposed method is portable and removable due to electromagnetic sensing. The other is that the proposed method functions well in various power systems when the voltage, current, or frequency are diverse. To achieve the latter one, the pre-normalization in *Stage B* and using the same $F_{\max}$ and $F_{\min}$ in *Stage E* are critical. It is because $F_{\max}$ and $F_{\min}$ may vary in a new microgrid. Using new $F_{\max}$ and $F_{\min}$ for normalization would lead to drastic changes of ANN inputs, resulting in misclassification of PQ disturbance. Moreover, the pre-normalization of these data can eliminate the effect of the absolute values of data. Hence, *Stage B* and using the same $F_{\max}$ and $F_{\min}$ in *Stage E* are necessary for the portability of the proposed method. In this way, the accuracy is greatly improved comparing with traditional ANN in different environments. The portability-enhanced ANN can be applied in various environments with only once training.

IV. SIMULATION VALIDATION

To verify the proposed approach for monitoring PQ, many

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scenarios with different voltages, currents, and frequencies were emulated. A series of PQ disturbances were emulated in a single-phase system in MATLAB, including (1) standard, (2) sag, (3) swell, (4) interruption, (5) harmonics, (6) transient and (7) flicker as shown in Fig. 4.

TABLE II
ACCURACY OF TRAINED ANN IN DIFFERENT SCENARIOS

U_{rms} (V)	I_{rms} (A)	f (Hz)	Accuracy (%)	U_{rms} (V)	I_{rms} (A)	f (Hz)	Accuracy (%)
220	5	50	98.857	220	20	50	99.714
210	5	50	99.286	220	25	50	99.000
200	5	50	98.571	220	30	50	99.000
190	5	50	99.286	220	35	50	99.286
180	5	50	98.857	220	40	50	98.714
170	5	50	99.857	220	45	50	99.000
160	5	50	99.429	220	50	50	98.714
150	5	50	98.857	220	55	50	99.286
140	5	50	99.429	220	60	50	99.143
130	5	50	99.714	220	5	60	99.571
120	5	50	99.000	220	5	70	99.000
110	5	50	99.286	220	5	80	99.286
110	10	50	98.857	220	5	90	99.571
110	15	50	99.429	220	5	100	98.429
110	20	50	98.714	220	5	110	99.286
110	25	50	98.857	220	5	120	98.714
110	30	50	99.286	220	5	130	99.286
110	35	50	99.000	220	5	140	98.571
220	10	50	98.857	220	5	150	98.857
220	15	50	99.286	220	5	160	99.714

In the simulation, a portability-enhanced ANN for monitoring PQ in a sing-phase system was trained by 700 pairs of M_F and given outputs in one scenario. In this scenario, RMS values of voltage and current (U_{rms}, and I_{rms}) are 200V and 5 A, and the frequency (f) is 50 Hz for standard PQ. Other scenarios with different voltages, currents, and frequencies are generated by MATLAB and employed to test the trained ANN. In each scenario, 700 cases with different PQ disturbances were used to test the accuracy of the portability-enhanced ANN, and the results are listed in Table II. The accuracies are all more than 99% in the forty scenarios. Thus, it is feasible to apply the proposed approach for monitoring PQ in different microgrids with one single trained ANN.

Meanwhile, to prove the necessity and importance of two steps (pre-normalization in *Stage B* and maintaining the same F_{max} and F_{min} in *Stage E*), four different ways of processing data were compared in scenarios where U_{rms} = 220 V, I_{rms} = 5 A, and varying frequencies. They are: Configuration (1) without *Stage B* and without using the same F_{max} and F_{min} in *Stage E*, (2) without *Stage B* but using the same F_{max} and F_{min} in *Stage E*, (3) with *Stage B* but without using the same F_{max} and F_{min} in *Stage E*, and (4) with *Stage B* and using the same F_{max} and F_{min} in *Stage E*. It should be noted that the proposed approach is Configuration (4). The results of these four configurations are shown in Fig. 5. The accuracy in Configuration (4) was significantly increased and much more consistent comparing with Configurations (1) ~ (3), and remained consistently high around 99%. The performance in Configurations (2) and (3) was much better than that in Configuration (1), but still inferior to that in Configuration (4). So, *Stage B* and *E* are necessary for improving the accuracy of ANN in various scenarios, and the proposed approach for monitoring PQ is portable in multiple systems.

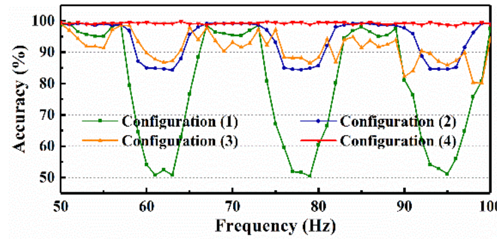

Fig. 5. Accuracy under four configurations with U_{rms} = 220 V, I_{rms} = 5 A and varying frequencies.

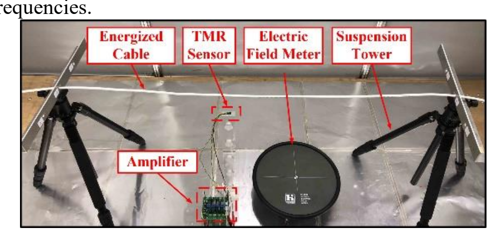

Fig. 6. Laboratory testbed for PQ monitoring in a single-phase system.

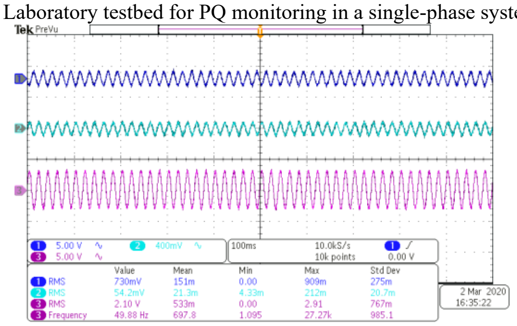

Fig. 7. Acquired voltage signals for standard PQ in scenario A (Channel 1: signals of the electric field meter; Channel 2: amplified signals of the TMR sensor; Channel 3: signals of a current probe).

V. EXPERIMENTAL RESULTS

To experimentally validate the proposed approach for PQ monitoring in multi single-phase systems, a laboratory setup shown in Fig. 6 was built. The cable is energized by Chroma Programmable AC Source model 61704, which can generate various PQ disturbances. HI-3638 Electric Field Meter and tunneling magnetoresistive (TMR) sensor TMR2001 are used to measure electric and magnetic fields due to their high sensitivity and excellent linearity [20, 21]. The electric field meter is set 41.5 cm away from the cable whilst the distance between the TMR sensor and the cable is 4 cm. The signal from the electric field meter is directly transferred to an oscilloscope (MDO3014). Meanwhile, the signal from the TMR sensor is amplified 100 times by the instrumentation amplifiers (AD620) and captured by an oscilloscope.

In the experiments, the programmable AC source generated different PQ disturbances. The electric and magnetic fields were measured by the electric field meter and TMR sensor, respectively, and digitally filtered for training and testing an ANN. First, 140 cases, 20 for each PQ disturbance category, were generated in Scenario A (U_{rms} = 100 V, I_{rms} = 2.1 A, f = 50 Hz for standard PQ). Signals of the electric field meter, TMR sensor and a current probe (Fluke 434) for reference were captured. These signals in one case of standard PQ are shown in Fig. 7. A total of 140 sets of data were used for training an ANN. Then, another 140 cases were still conducted in Scenario A, and acquired data were employed for testing the ANN. Finally, electrical parameters were adjusted in Scenario B (U_{rms} = 120 V, I_{rms} = 2.5 A, f = 60 Hz for standard PQ). Corresponding data were captured in 140 randomly generated cases to test the trained ANN.

In the practical application of the proposed approach, when the trained ANN is applied in different power systems, the corresponding F_{max} and F_{min} are not available. So, two ways of processing data were compared, which are Configuration (2) and Configuration (4). The classification accuracies in two scenarios are listed in Table III. The accuracies with Configuration (4) in Scenario A and B were 97.143% and 99.286%, respectively. But the accuracy with Configuration (2) decreased sharply from 95.714% in Scenario A to 70.714% in Scenario B. Meanwhile, the total time in Configuration (2) and Configuration (4) for processing data, training ANN, and obtaining classification results are 3.624s and 3.626s, respectively. Once an ANN is trained, the time needed for processing data and producing results is around 0.382s. Hence, the consistently high accuracy and calculation speed with Configuration (4) experimentally proved the feasibility of the proposed approach of PQ monitoring with one portability-enhanced ANN in different systems.

TABLE III
ACCURACY IN TWO SCENARIOS WITH CONFIGURATIONS (2) AND (4)

Scenario	Configuration (2)	Configuration (4)
A	95.714	97.143
B	70.714	99.286

VI. CONCLUSION

A new approach for monitoring power quality in multi microgrids with electromagnetic sensing and computational intelligence is proposed. This technique is capable of precisely detecting and classifying PQ disturbances with one portability-enhanced ANN in different microgrids. It overcomes the drawbacks of ANN-based techniques and avoids retraining an ANN when the voltage, current, and frequency are diverse. Electromagnetic sensing and two critical steps (pre-normalization and usage of the same F_{max} and F_{min}) guarantee the portability of the proposed approach in different environments. High accuracies in simulations and experiments validate the effectiveness of the proposed method. Thus, this technique has great potential to be integrated into monitoring systems in various microgrids.

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