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Sensorless Voltage Estimation for Total Harmonic Distortion Calculation using Artificial Neural Networks in Microgrids

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***Abstract*—In this work, a sensorless voltage estimation approach for total harmonic distortion (THD) calculation is proposed to reduce number of voltage sensors in the microgrids. The intelligent proposed method provides a cost-effective and reliable voltage estimation and THD calculation of the desired bus in the multi-bus microgrid based on the artificial neural networks (ANNs). In the proposed method, the output voltage and current of distributed generation units along with the voltage of the desired bus are used to train the ANN offline. The trained ANN is then used to estimate the voltage and calculate both harmonic components, and THD online at the desired bus. The Simulation results show that the proposed approach can effectively estimate the voltage and calculate THD of buses in the multi-bus islanded microgrids.**

***Index Terms*—Total harmonic distortion (THD), microgrids, artificial neural networks, voltage estimation, power electronics.**

I. Introduction

MICROGRIDS, have recently gained considerable attention due to their deniable advantages such as decreasing fossil fuel demands, improving system reliability, etc. The microgrid includes distributed generation (DG) units and linear and nonlinear loads. Due to the presence of the nonlinear loads and power electronic devices, harmonic distortion issue is one of the main concerns with the microgrid integration to the power system [1]. Hence, the important factor, which must be mitigated by the harmonic compensation methods is total harmonic distortion (THD) in microgrids. Therefore, the measurement and sensor devices are required to measure and calculate harmonic distortion in the existing harmonic mitigation methods. However, the microgrids may not be able to properly provide reliable power for critical loads once faults occur in voltage and current sensors. Moreover, implementing sensors may also cause complicated hardware structure and increase the costs.

Artificial neural networks (ANNs) are used in various applications in microgrids. For instance, in [2], an ANN-based approach is proposed to estimate the optimal tilt angle of the photovoltaic panel in the microgrid. An ANN-based fault detection method is proposed in [3] to detect and classify faults in microgrids. The proportional-integral controller in the storage system is replaced by an online trained ANN in [4]. An ANN-based sliding-mode controller is proposed in [5] to reduce voltage deviation caused by the primary controller of DG. In [6]–[8], the application of the ANNs is investigated to detect and mitigate false data injection cyber-attacks in DC microgrids. However, there is no previous research, to our knowledge, using DGs' output voltage and current to estimate the critical bus voltage and calculate the related THD by using ANNs.

In this paper, a novel voltage and THD estimation approach is proposed by using ANNs. In the proposed approach, the DGs' output voltage and current, which must be measured and used in the controller of DGs and also, the voltage of the desired bus are sent to data center of the microgrid in order to train offline the ANN. After training the ANN, the trained ANN is used as an online voltage and THD estimator of the desired bus in multi-bus microgrids. The key contribution and features of proposed method can be summarized as follows:

1) A novel voltage estimation approach is proposed based on artificial neural networks in multi-bus microgrids, in which the voltage of the desired bus can be estimated and THD of the bus can be calculated online by using the proposed approach.
2) The number of voltage sensors in the multi-bus microgrids are decreased by using the proposed approach. Hence, due to the reduction in the sensors, the reliability of the microgrid is improved and the measurement costs are reduced.
3) The voltage and THD of the desired bus can be estimated without requiring system information such as line impedances, DG's parameters, etc. since the ANNs are non-parametric models.
4) The voltage is estimated and THD is calculated subsequently by using the DG's information (measured current and voltage), which are always measured and used in the DG's controllers. Therefore, attaching new sensors to the microgrid is not necessary for the online phase of the ANNs.

II. Introduction to Neural Network

Artificial neural networks are a type of artificial intelligence based applications and they can generally respond to the problems such as regression, estimation, and prediction. ANNs can be adjusted to learn input-output mappings dependent on their own past data. The ANN consists of a series of simple computational items connected by weighted links. Regarding

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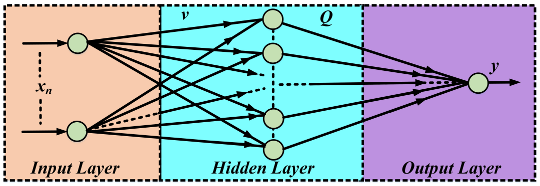


Fig. 1. The general structure of an ANN with n inputs and one output.

used feed-forward networks, the outputs of the cells in the layers are the input of the next layer. If the layer by layer network is examined, the input layer transmits the information from the external environment to the cells in the hidden layer. Feed-forward neural network are a type of ANNs, which is used in this work. The structure of the feed-forward neural network does not have any loops and it can be made based on a simple architecture to extract the relation between inputs and outputs. In this study,to avoid complexity, and also because of the proper obtained results, the ANN with a feed-forward based architecture is implemented [9]. As can be seen in Fig. 1, a basic multi-layer feed-forward neural network structure, in which v and Q are the input and output of the hidden layer, has been adopted to estimate the voltage and calculate THD at any bus of the multi-bus islanded microgrids in this study.

It is important to note that, to have a more dynamic and efficient ANN, historical values of inputs are considered to be used in the input layer of the ANN. A dynamic ANN method for time-series problem with their tapped delay is chosen as follows:

$$y(t) = f[x(t-1), x(t-2), \ldots, x(t-D)], \tag{1}$$

where, y is the output of the neural network and x is the input of the ANN. Also, D is the input-memory order and f is a function, which is represented the relation between the input and output of the ANN. If the ANN has n inputs, one hidden layer with m neurons, and one output, the output signal can be calculated as

$$y_t = f_{\text{out}} \left(\sum_{j=1}^{m} w_{t,j} Q_{t,j} + b_y \right), \tag{2}$$

where,

$$Q_{t,j} = f_{hid}\left(v_{t,j}\right), \tag{3}$$

$$v_{t,j} = \sum_{i=1}^{n} w_{t,ij} x_{t,i} + b_{z,j}, \tag{4}$$

where, b_y and $b_{z,j}$ are the bias factor of the neuron in the output layer and the i^{th} neuron of the hidden layer, respectively. Also, $w_{t,j}$ is the connection weight between the j^{th} neuron of the hidden layer and the neuron of the output layer. In addition, $w_{t,ij}$ is the connection weight between the i^{th} neuron of the input layer and the j^{th} neuron of the hidden layer.

III. Conventional Controllers of DGs

The multi-bus microgrid structure along with the DG's controllers and the data center are shown in Fig. 2. There are N buses and M DGs in the multi-bus microgrid. Each DG includes the controller, the inverter, and the renewable energy resources, and has to share active and reactive power

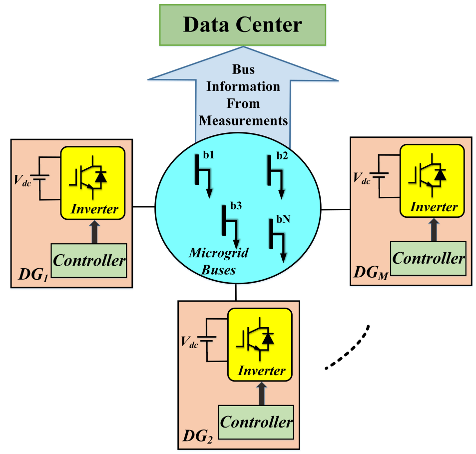


Fig. 2. Microgrid structure including data center and DGs.

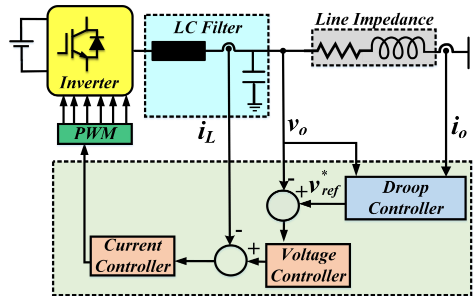


Fig. 3. Circuit and control parts of each DG.

in the microgrid. In the literature for the harmonic mitigation purposes, the main goal is to reduce THD of the desired bus or sometime THD of the whole microgrid as suggested in [10]. Therefore, to achieve these goals, the voltage harmonic distortion of the desired bus and in some cases, THD of all buses in the microgrid must be measured and collected. As shown in 2, the measured information from the buses in the microgrid is then transmitted to the data center.

The DG power circuit consisting of LC filter and inverter, and the controller are shown in Fig. 3. The controller of each DG has to provide proper power control, voltage and frequency regulations. The main parts of the DG's controller are droop controller, and inner controllers including voltage and current controllers, as shown in Fig. 3. The voltage reference (v^*_{ref}) is calculated by the droop controller based on the following equations [1]:

$$\omega_j = \omega^*_j - m_j\left(P_j - P_o\right), \tag{5}$$

$$E_i = E^*_i - n_i\left(Q_j - Q_o\right), \tag{6}$$

where ω^*_j and E^*_j are the system frequency and the rms value of the rated voltage of j^{th} DG, respectively. m_j and n_j are the droop controller parameters. P_o and Q_o are the rated active and reactive powers, respectively.

As discussed, the output voltage and current of each DG are measured and used in the DG's controller. Moreover, the buses information are measured and transmitted to the data center. Therefore, to reduce number of voltage sensors in the microgrid, a novel sensorless voltage and THD estimation approach based on the neural networks is proposed in next section.

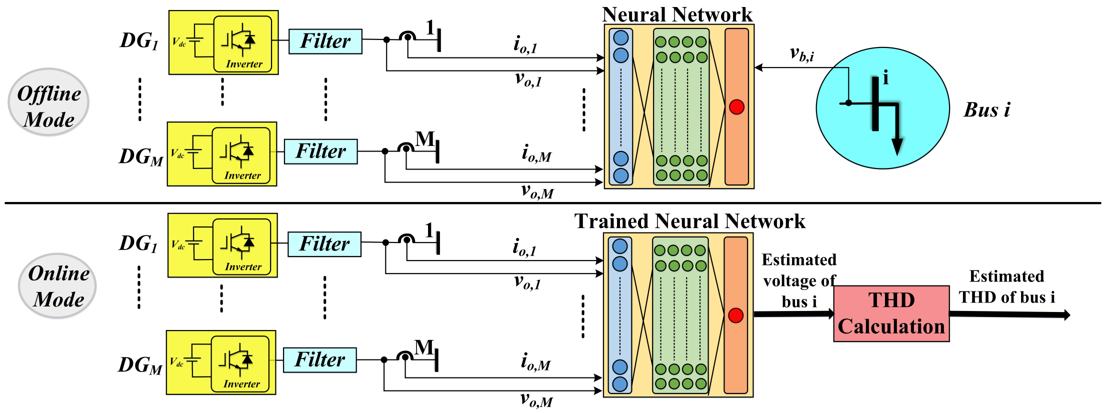


Fig. 4. Voltage and THD estimation of the desired bus by using ANN based proposed approach in multi-bus microgrids

IV. Proposed Approach

The main aim of the proposed method is to estimate voltage and calculate THD of the desired bus in the multi-bus microgrids. The output voltage and current of DGs are considered as the inputs of the ANN. As shown in Fig. 4, the proposed ANN-based approach is based on two main modes, known as online and offline modes as follows:

1) ***Offline mode***: In this mode, the DGs' information (both measured output voltages and currents) and the bus information are used to train offline the ANNs. For the offline training, several load changing scenarios are considered to have more dynamic data sets.
2) ***Online mode***: In this mode, the trained ANN are used as an online estimator of the voltage at desired bus in the multi-bus microgrid to calculate THD. The DGs' information are transmitted to the data center, and the estimated voltage and THD are exploited at data center by using the trained ANN.

The ANN using in this work has one input layer, one hidden layer, and one output layer. The inputs of the ANN are the output voltage and current of DGs in the multi-bus microgrid. Therefore, since there are M DGs in the microgrid, $2 \times M$ data would be used as the input of the ANN in data center of the microgrid. Moreover, a history of input data is gathered considering several load changing to have a proper dynamic behavior of the proposed ANN-based estimator. For instance, if there are two DGs in the multi-bus microgrid, the ANN's input can be expressed as follows:

$$\begin{aligned} x(t) = [&i_1(t-1), \cdots, i_1(t-D), \\ &i_2(t-1), \cdots, i_2(t-D), \\ &v_1(t-1), \cdots, v_1(t-D), \\ &v_2(t-1), \cdots, v_2(t-D)], \end{aligned} \tag{7}$$

where, $x(t)$ is the input vector of the ANN. Furthermore, the hidden layer has one layer, and one neuron is used as the output in the output layer of the proposed ANN. The estimated value of voltage at the desired bus ($\bar{v}_{bi}(t)$) is calculated by the proposed A as follows:

$$\bar{v}_{bi}(t) = f_2\left(f_1\left(x(t)w_1 + b_1\right)w_2 + b_2\right), \tag{8}$$

where, b_1 and b_2 are the bias vectors of the hidden and output layers, respectively. w_1 and w_2 are the weight matrices of the hidden and output layers, respectively. f_1 and f_2 are the activation functions of the hidden and output layers, respectively. In this work, the proposed ANN is trained offline to gain the optimized and accurate values of the mentioned variables for having a well-adjusted ANN. Also, as mentioned earlier, the implemented ANN has one hidden layer. As it will be shown later, the implemented ANN with one hidden layer has a proper performance to estimate the bus voltage. Therefore, to avoid the more complexity and reduce the computational burden, and also because of the proper results, the ANN with one hidden layer is used as a proper candidate to estimate the voltage of the bus.

V. Results

The proposed approach is verified on an islanded microgrid including six buses and two DGs meaning $N = 6$ and $M = 2$, as shown in Fig. 6. Two 3 kW inverters are used in the DGs to produce and share power. The microgrid parameters are given in Table I. The linear and nonlinear loads are resistors and three-phase diode rectifiers, respectively. Both current and voltage controllers are proportional controllers. Moreover, the bus number four (b4) is considered as the desired bus in Fig. 6. The effectiveness of the proposed approach is carried on under four case studies. The simulation time was selected as $10s$ for offline training of the proposed ANN. Moreover, the sampling time was considered as $10\mu s$. Therefore, the number of input samples would be 1×10^6. It also should be mentioned that the value of the input-memory order (D) is 3 in this work. Moreover, the activation function of the hidden layer is a tansig activation function, which is as follow:

$$f_1(X) = \frac{2}{e^{-2x} + 1} - 1. \tag{9}$$

In addition, the activation function of the output layer is a purelin activation function as follows:

$$f_2(x) = x. \tag{10}$$

To train the ANN, the dataset is divided into three sets, i.e., training, validation, and test. Also, the training set has 70% of the original dataset, while the validation set has 15% of the original dataset. Finally, the test set contains 15% of the original dataset. Also, to have a good point of view about the error of the estimation by the trained-ANN, the error Histogram is implemented in this study. Fig. 5 depicts the error histogram for the training, validation, and also test sets.

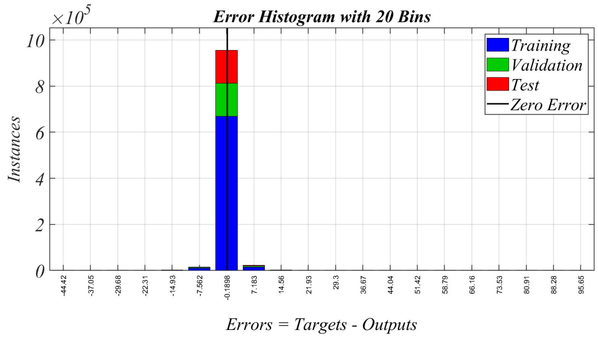


Fig. 5. Error histogram of the ANN with 20 bins. Targets are the real data and the outputs are the outputs of the ANN.

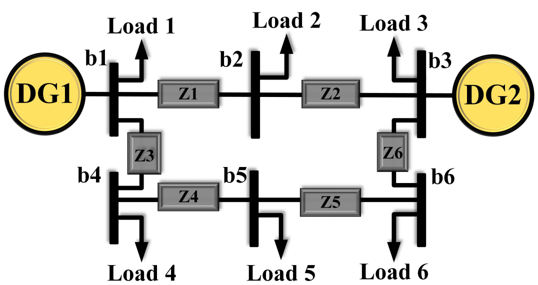


Fig. 6. Studied microgrid structure.

A. Case Study 1: Single Phase Estimation

In this case study, it is shown that the voltage of the phase a and related THD at the desired bus can be estimated properly by using the proposed ANN-based method. Both the measured and estimated voltages of the desired bus are shown in Fig. 7(a). Furthermore, To have a better look, a cycle of voltage (between $0.21s$ and $0.23s$) is magnified. It is observed that the proposed ANN-based approach can accurately estimate the voltage of the desired bus in the multi-bus microgrid. Moreover, the measured and estimated THD of the desired bus are shown in Fig. 7(b), and the errors for the measured and estimated harmonics and THD are also given in this figure. It can be seen that the harmonic components at 5^{th}, 7^{th} and 11^{th} harmonics, which are the most important harmonics in the harmonic studied and also THD of the desired bus can be estimated properly by using the proposed approach. Furthermore, the errors for the measured and estimated values are very low (near to 1 %).

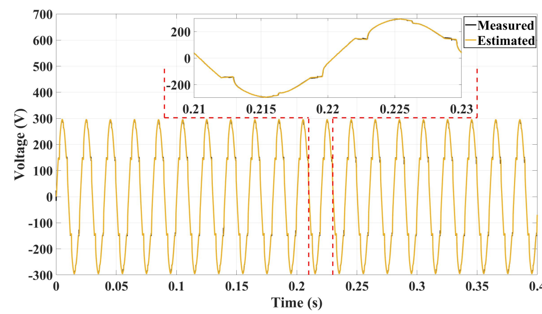
B. Case Study 2: Three Phase Estimation

In the first case study, the application of the proposed method for estimating voltage and THD of only phase a at the desired bus in the multi-bus microgrid is verified. In this case study, it is revealed that the voltage and THD of both phases b and c can also be estimated by using the proposed ANN-based approach. Figs. 8(a) and 8(b) show the measured and estimated voltage of the phase b and phase c at the desired bus in the multi-bus microgrid, respectively. Moreover, a cycle of voltage is magnified for both phases b and c to show that the proposed ANN-based approach can estimate accurately both phases at the desired bus.

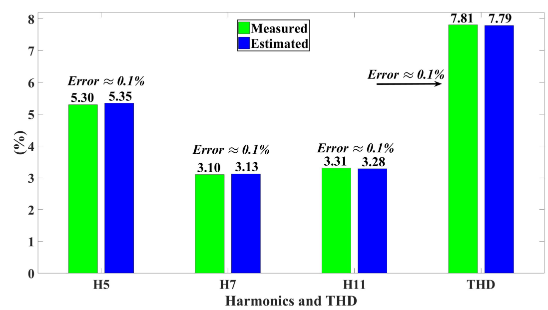
Finally, to conclude the first two case studies, it is confirmed that the three-phase and single-phase voltage and related THD at the desired bus of the multi-bus microgrid can be estimated by using the proposed ANN-based approach. Therefore, there is no need to use voltage sensors at the desired bus to measure and send information online to the data center.

TABLE I
MICROGRID PARAMETERS

System parameters	**Values**
DC Link Voltage V_{dc}	750 V
System Frequency f	50 Hz
Switching Frequency f_{sw}	10 kHz
LC filter	$L = 8\,mH, C = 22\,\mu F$
Line Impedances $(Z_1 - Z_6)$	$R_L = 0.8\,\Omega, L_L = 2\,mH$
Primary controller parameters	**Values**
Current and Voltage Controller	$k_{pi} = 20, k_{pv} = 5$
Droop Controller	$m = 1 \times 10^{-3}, n = 5 \times 10^{-5}$
Rated Voltage (rms)	230 V
Load parameters	**Values**
Linear Load	$R_{Linear} = 100\,\Omega$
Non Linear Load	$R_{NonLinear} = 55\,\Omega$



(a) Measured and estimated voltages of phase a at desired bus.

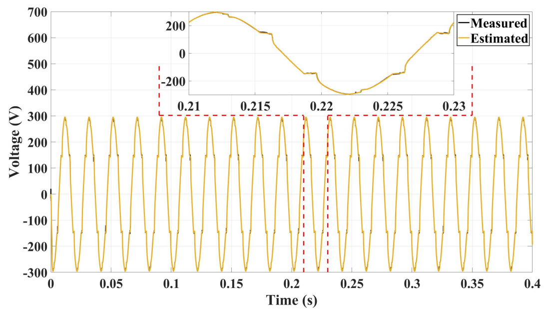


(b) Measured and estimated THD of phase a at desired bus.

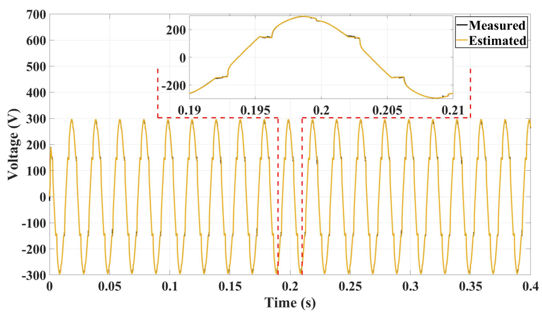
Fig. 7. Case study 1: Voltage and THD estimation of one phase.

C. Case Study 3: Load Changing

In the third case study, behavior of the proposed ANN-based approach is shown and discussed under the load changing situation. The measured and estimated voltage are shown in Fig. 9(a) in both before and after load changing situations. The load is changed after the microgrid works for $0.3s$. To have a better look, the results between $0.51s$ and $0.53s$, which is one cycle of microgrid operation are magnified. Moreover, the measured and estimated THDs and harmonic components are shown in Fig. 9(b). Furthermore, it is worth pointing out that the errors for the measured and estimated values, which are given in Fig. 9(b) are less than 1%. As shown in Fig. 9, the

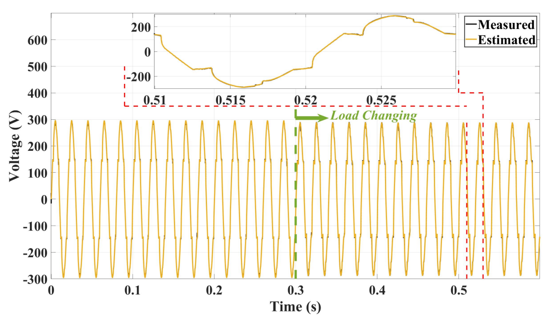


(a) Measured and estimated voltages of phase b at the desired bus.

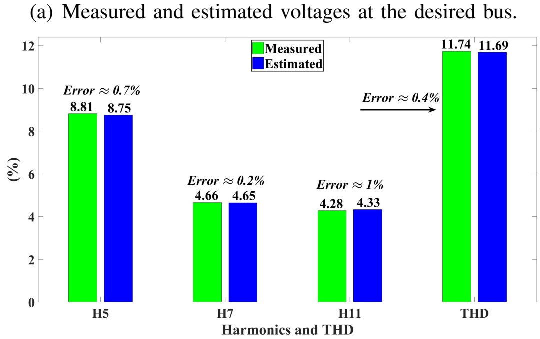


(b) Measured and estimated voltages of phase c at the desired bus.

Fig. 8. Case study 2: Three phase estimation.



(a) Measured and estimated voltages at the desired bus.



(b) Measured and estimated THD at the desired bus.

Fig. 9. Case study 3: Load changing.

ANN-based estimator can work accurately even in the case of the load changing.

D. Case Study 4: Communication Delay Analysis

For the purpose of this case study, a time delay, which is a fraction of the microgrid operation cycle is used for the input signals of the ANN. It means that the output voltages and currents of the DGs are sent to the ANN by the time delay. The time delay is considered $1/4, 2/4, 3/4, 1$ and 2 times of the microgrid operation cycle, which is $0.02s$. The results for the estimated harmonic components and THD are given in Table II. It can be seen that the harmonic components and THD can be estimated by using the proposed approach properly even in the presence of the time delay.

TABLE II
COMMUNICATION DELAY ANALYSIS OF THD CALCULATION

	Without delay	Delay (fraction of operation cycle)				
		1/4	2/4	3/4	1	2
H5	5.35	5.32	5.3	5.32	5.32	5.32
H7	3.02	3.02	3.02	3.03	3.06	3.07
H11	3.28	3.32	3.32	3.32	3.32	3.29
THD	7.79	7.74	7.74	7.74	7.79	7.79

VI. CONCLUSION

In this work, a sensorless voltage estimation method for THD calculation based on the ANN is proposed. The voltage, harmonic components, and THD at any bus of the multi-bus microgrid can be estimated by using the proposed ANN-based method. In the proposed method, the output voltages and currents of DGs along with the voltage of the desired bus are used to train the ANN offline and then, use the trained ANN in the online situations to estimate the voltage and calculate THD at the desired bus. The number of sensors in the multi-bus microgrids is reduced by using the proposed method, resulting in a cost-effective and reliable method for practical applications of microgrids. The results in four different case studies are effectively shown that the proposed ANN-based approach can successfully estimate voltage and calculate THD at the buses of the multi-bus microgrid.

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