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State Estimation for Power Distribution Networks Using Deep Feed-Forward Neural Network Approach

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Research Article

Abstract

Conventional Power Distribution Networks (PDNs) are passive in nature. With the incorporation of distributed generations (DGs) in electric power systems, such distinctive feature of a traditional PDN is being distorted. DG penetration into the power distribution networks leads to serious technical problems in their operations. In order to effectively control a modern PDN, it is imperative to ascertain the state of that network. Existing works on state estimation as applied to PDNs are mostly hindered by the unbalanced nature of the network and inadequate real-time measurements which lead to poor estimation of the network. In this paper the state (voltage magnitude and angle) of PDNs are estimated using a Deep Feed-Forward Neural Network (FFNNSE) technique which was then compared with two estimators in Ahmad et al., 2019 using Mean Absolute Deviation (MAD) as well as Mean Square Error (MSE) state performance metrics for testing on a local network. The proposed estimator was tested on the 33-bus and 69-bus IEEE standard networks as well as the Zaria local distribution network under Normal and Dynamic conditions. The Simulation was implemented in MATLAB 2019a environment for both 69-bus and 33-bus Networks with 7.41% and 12.0% MAD reduction respectively. As it was clearly observed from the obtained results FFNNSE outperformed Artificial Neural Network State Estimator (ANNSE). It was however, performed excellently than WLSSE with the reduction of 66.0% and 78.0% MAD for both Networks. The Performance of the FFNNSE was tested on a 50-bus local distribution network under normal and dynamic conditions (Bad data and Load Variation) the performance was good for all conditions with minimal MAD of 0.0045, 0.0049 and 0.0051 for normal, Bad Data and Load Variation conditions respectively. However, MSE for all cases were computed as 0.000176, 0.000202 and 0.000215 or normal and two dynamical operations respectively. The State Estimation approach results show the viability of the FFNNSE for real-time distribution networks.

Keywords
feed-forward neural network state estimation; FFNNSE; MAD; MSE; power distribution network; WLSSE

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1. Introduction

Distribution System State Estimation (DSSE) is a process of determining the values of a system's state variables using a limited number of measured data at certain locations in the system (Dehghanpour et al., 2018). Estimation in a power system has been considered as the most important part of the operation and management of a transmission system (Sandhya et al., 2018). It is used to determine, to some certain high degree of accuracy, the state of the network based on some real time measurement data using some estimation criteria (New York State Energy Research and Development Authority (NYSERDA), 2018). With the expansion of distribution networks, increase in number of nodes and their measurement data, the computing scale of state estimation is increasing (Chen et al., 2019). Voltage magnitude and phase angle are considered as the state variables in a power system network (Sandhya et al., 2018). Other network parameters like power flows and currents can then be computed using the estimated network state (Amor *et al.*, 2018).

The state of a network can only be estimated if that network is both observable and controllable (Gelagaev *et al*., 2010). In the former, column rank of the Jacobian matrix is analyzed, while a spanning tree of full rank is formed in the topological method (Brinkmann & Negnevitsky, 2017). Large amount of renewable energy is being integrated in the networks, thereby making demand response popular between utilities and consumers. Under such situations, the distribution grid becomes active (Liu et al., 2018). DG penetration into the distribution network can decrease power loss caused by long-distance power transmission, and can improve power quality as well as network reliability to a certain extent (Zhu & Ramachandran, 2020).

2. State Estimation Techniques

State estimation (SE) is a technique used to ascertain the values of the state variables from some noisy measurements. The main function of the technique is error reduction that may be contained in the data (Baran & Kelley, 1994). Weighted least square (WLS) is one of the most common methods employed in the reduction of such inconsistencies (Gao & Yu, 2017).

2.1 State Estimation Approaches

Many approaches were introduced to solve the problems of S.E some of them are: Weighted Least Square (WLS), Kalman Filter (KF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Deep Learning approaches.

2.2 Feed Forward Neural Network (FFNN)

FFNN is a nonlinear function mapping a group of input variables to a group of output variables governed by a vector W of modifiable parameters. It learns by computing the output error for any given input data fed to the NN. This error is minimized by adjusting the weight vector. FFNN have the capability of handling complicated problems in a variety application areas (Mohammed *et al.*, 2020)

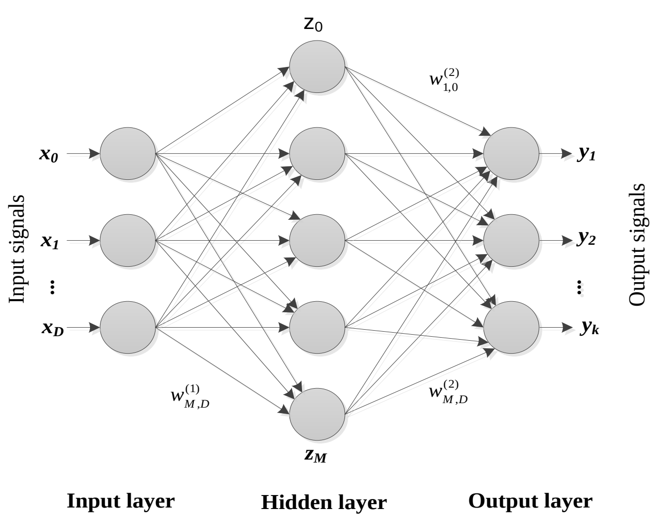

Figure 2: Feed Forward Neural Network (Mohammed *et al.*, 2020)

3. Methodology

3.1 Feed Forward Neural Network State Estimator (FFNNSE) for Distribution System.

Under this objective, Levenberg-Marquardt backpropagation algorithm was considered. A 4-layers FFNN was designed with 40 neurons in each of hidden layers. The iteration converges at 14 epochs and 16 epochs after 100 trials for 33-bus and 69-bus networks models respectively. The input-output of the model was partition into 70%, 15%, and 15% for training, testing, and self-validation respectively.

Equation 1 represents the mathematical definition of an FFNN.

$$y = f(\mathrm{x}, \mathrm{w}) \qquad (1)$$

An FFNN has three layers: input, hidden, and output layers. The number of hidden layers may be one for *shallow* network or more for *deep* networks (Leverington, 2009). From Figure 2.7, an N number of linear combinations of the input set $\boldsymbol{x_i} \ldots \boldsymbol{x_N}$ can be built in the form of:

$$a_j = \sum_{i=1}^{N} w_{ji}^{(1)} . x_i + w_{jo}^{(1)} \qquad (2)$$

Where

j= 1…N, a_j is a nonlinear activation function, the superscript (1) represents the first layer, while w_{ji} and w_{jo} are the weights and biases respectively.

The function $\mathbf{a_j}$ can be sigmoid, rectified linear unit (ReLu), tanh etc. (Zhang *et al*., 2020).

$$\boldsymbol{z_j} = \boldsymbol{\delta}(\boldsymbol{a_j}) \qquad (3)$$

Where

$\mathbf{z_j}$ represents the hidden unit and $\boldsymbol{\delta}$ is logsigmoid.

Similarly, output unit activations can be obtained using (4) - (6).

$$a_k = \sum_{j=1}^{N} w_{kj}^{(2)} . z_j + w_{ko}^{(2)} \qquad (4)$$

Where

$k = 1, 2, \ldots K$ which represents the number of outputs. $w_{kj}^{(2)}$ and $w_{K0}^{(2)}$ are the weights and biases respectively. This transformation matches layer number two of the network. The output functions converted using suitable activation function to give a set of network outputs $\mathrm{y_k}$ as follows:

$$y_k = \delta(a_k) \qquad (5)$$

$$y_k(x, w) = \delta\left(\sum_{j=1}^{N} w_{1j}^{(2)} h \left(\sum_{i=1}^{D} w_{ji}^{(I)} . x + w_{jo}^{(I)}\right) + w_{K0}^{(2)}\right) \qquad (6)$$

The FFNN was designed and trained using Levenberg–Marquardt algorithm. The FFNN synaptic weights were tuned based on the minimization of MAD.

4. Results of FFNNSE Performance on IEEE standard Test Networks

The developed estimator (FFNNSE) was tasted on the IEEE-33 and IEEE-69 bus networks. The true values for the network states were obtained using BFS algorithm.

4.1 Performance of FFNNSE on Voltage Magnitudes for 33-bus Network

The FFNNSE was able to track the actual voltage magnitude response of the network with 98.8% fitness and MAD of 0.0041. This shows the excellent capability of the estimator to learn the network behavior as illustrated in Figure 3.

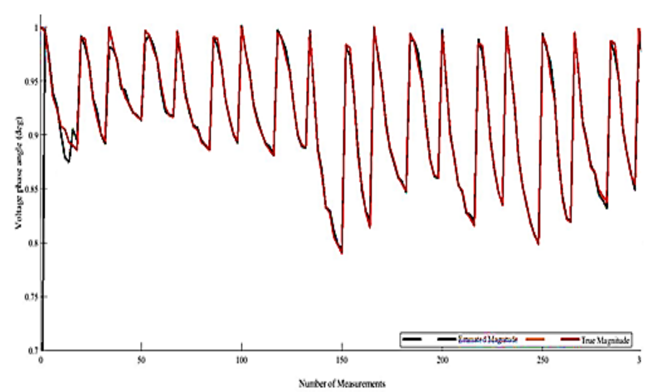

Figure 3: Performance of FFNNSE on Voltage Magnitudes for 33-bus Network

4.2 Performance of FFNNSE on Voltage Phase Angle for 33-bus Network

The actual voltage phase angle response of the network was also tracked by the developed state estimator with fitness of 97.4% and MAD of 0.0047. Figure 4, shows the estimated voltage phase angle profile compared to actual measurements. It is evident from the figure that the tracking performance of the FFNNSE is excellent.

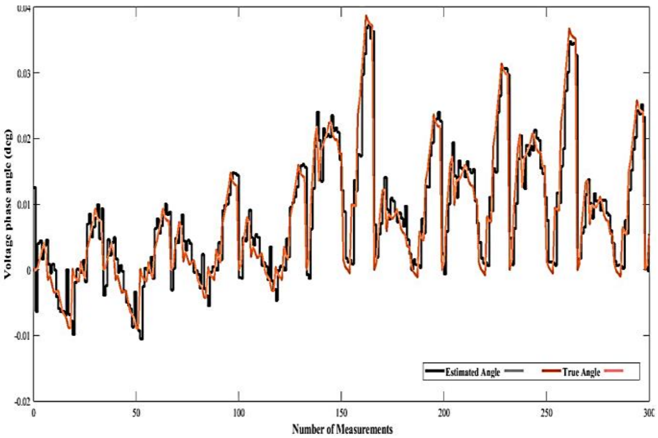

Figure 4: Performance of FFNNSE on Voltage Phase Angle for 33-bus Network

4.3 Performance of FFNNSE on Voltage Magnitudes for 69-bus Network

The FFNNSE was able to track the actual voltage magnitude response of the network with 99.1% fitness and MAD of 0.0056. This shows the excellent capability of the estimator to learn the network behavior as illustrated in Figure 5.

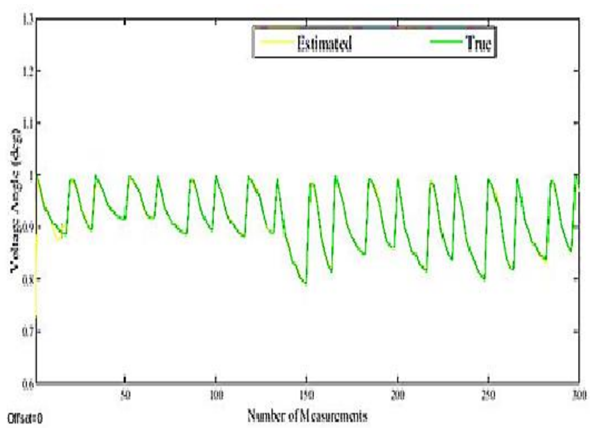

Figure 5: Performance of FFNNSE on Voltage Magnitude for 69-bus Network

4.4 Performance of FFNNSE on Voltage Phase Angle for 69-bus Network

The actual voltage phase angle response of the network was also tracked by the developed state estimator with a fitness of 96.9% and MAD of 0.0044. Figure 6, shows the estimated voltage phase angle profile compared to actual measurements. It is evident from the figure that the FFNNSE performance was excellent.

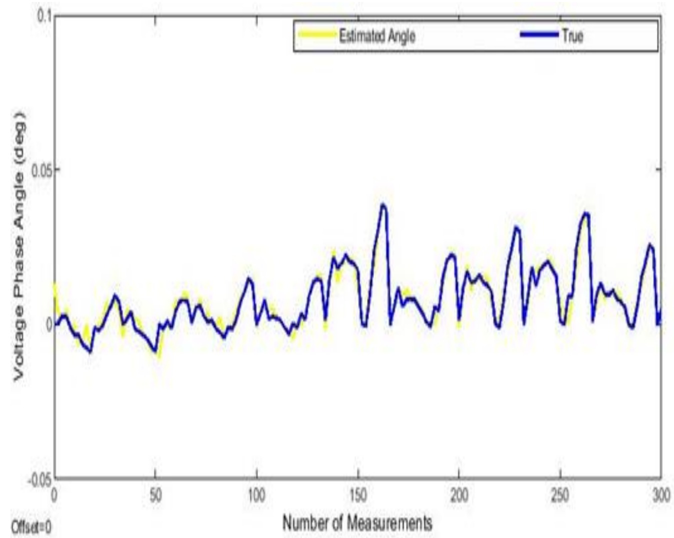

Figure 6: Performance of FFNNSE on Voltage Phase Angle for 69-bus Network

4.5 Results of FFNNSE Performance on Local Networks

The developed estimator was applied on Zaria Local Network (Canteen Feeder). The true values for the states of this network were obtained using BFS algorithm. Figure 7, shows the result for the case of normal operation. As it can be seen from the figure, the developed estimator was able to trace the actual voltage magnitude and angle, although it shows a better performance for angle than the magnitude of the actual voltage. The MAD for this case was computed to be 0.0045.

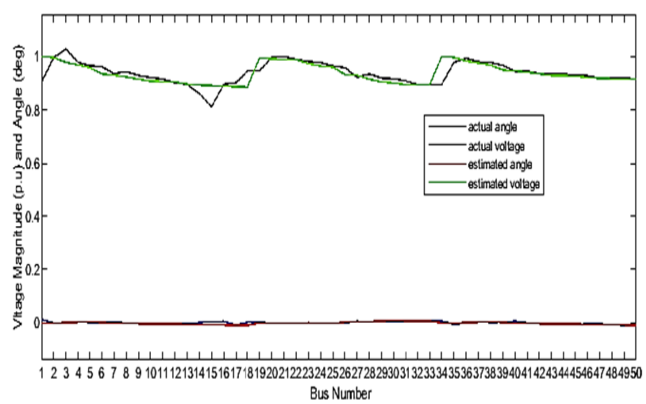

Figure 7: 50-bus Normal condition

Figure 8, shows the result for the case of the network operation under bad data condition. the figure shows that the tracking performance of the FFNNSE for both voltage magnitude and angle was not as good as the previous case, even though it performs better for voltage magnitude estimation than that of phase angle. it has a total MAD of 0.0049.

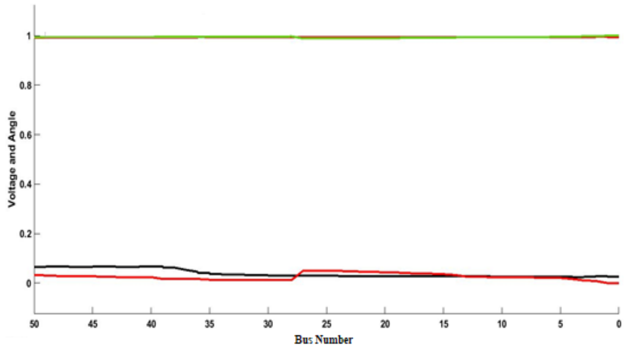

Figure 8: 50-bus Bad Data Condition

The result for the case of load variation on the network is shown in Figure 9. It is evident from the figure that the developed estimator has the least overall performance as compared with the two previous cases in tracking the actual network states. The MAD for this case was computed to be 0.0051.

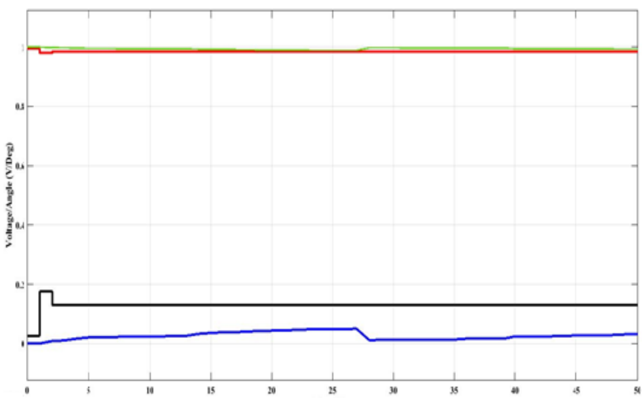

Figure 9: 50-bus Load Variation

4.6 Summary of the 50-bus canteen feeder simulation results

It is clear from Table 1, that the proposed estimator performs well for all the simulation scenarios for both condition cases. However, it can be noted that in load variation case state estimates deviation is more notable than that of other scenarios such as normal case and Bad data case.

Table 1: Summary of Results for 50-bus Network.

Case	Operation Condition	Mean Square Error	Mean Absolute Deviation
1.	Normal Condition	0.000176	0.0045
2.	Bad Data	0.000202	0.0049
3.	Load Variation	0.000215	0.0051

In testing the FFNNSE on local network (50-bus Network) under normal and dynamic conditions (Bad data and Load Variation) the performance was good for all conditions with the minimal MAD of 0.0045, 0.0049 and 0.005 for normal, Bad Data and Load Variation conditions. However, MSE for all cases was computed as 0.000176, 0.000202 and 0.000215for normal and the two dynamical operations respectively. As such the FFNNSE can be implemented in a local network for estimating the states of the network.

4.7 Performance of the developed FFNNSE over ANNSE and WLSSE

In order to justify the effectiveness of FFNNSE, it was compared with the ANNSE and WLSSE used in (Ahmad *et al.*, 2019). The Comparison was made base on the accuracy performance of the estimators using MAD performance metric. It was observed from the results that FFNNSE gives output with better accuracy than the above-mentioned estimators for the selected Networks based on the total computed MAD for each network selected. The Comparison of both estimators is shown in Table 2.

Table 2: Performance of the FFNNSE over ANNSE and WLSSE

Network Type	ANNSE (Ahmad *et al.*, 2019)	WLSSE (Ahmad *et al.*, 2019)	FFNNSE
69-bus	0.0054	0.015	0.0050
33-bus	0.0050	0.020	0.0044

5. Conclusion

In this work, a Feed-Forward Neural Network State Estimator (FFNNSE) for Power Distribution Network was developed. Performance of the estimator was tested on IEEE 33-bus and IEEE 69-bus as well as Zaria local distribution network under normal and dynamic conditions. It was noted that for the IEEE test distribution networks, the state estimates followed the true values pretty closely. Additionally, MAD was used to quantify the deviation of estimated quantities from the true values. It was observed that the proposed estimator demonstrated great effectiveness under all the considered network conditions thereby guaranteeing high accuracy.

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