Data driven approach for power system state estimation with consideration of multi-level noise

Shariq Shaikh
Department of electrical engineering
NEDUET
Karachi, Pakistan
shariqshaikh@neduet.edu.pk

Mohammad Mohsin Aman
Department of electrical engineering
NEDUET
Karachi, Pakistan
mohsinaman@gmail.com

Usman Ahmed
Department of electrical engineering
NEDUET
Karachi, Pakistan
usman_ahmed2017@hotmail.com

Sameer Murtuza Shariff
Department of electrical engineering
NEDUET
Karachi, Pakistan
sameersms2018@gmail.com

Hasan Khan
Department of electrical engineering
NEDUET
Karachi, Pakistan
hasansarwar41@gmail.com

Hamza Azeem
Department of electrical engineering
NEDUET
Karachi, Pakistan
Hamzaazeem187@gmail.com

***Abstract*—State estimation is vital tool in observing electrical power system. It is always important to know the operating state of the system with accuracy and less computational efforts. This paper presents a novel data driven approach to perform state estimation of power transmission system using deep neural networks (DNN). The network is trained offline using dataset prepared by generating multiple loading scenarios through programming. The proposed method is evaluated using IEEE 14 bus system with variable Gaussian measurement error at different load buses.**

Keywords—state estimation, neural networks.

I. INTRODUCTION

Accurate monitoring of power system is much needed in modern era. By knowing the actual operating state of the system, operators can identify and respond to problems more quickly and effectively. This can help to prevent or minimize disruptions to the power supply. Earlier formulation for state estimation in power system was first proposed by Fred C. Schweppe and fellows using weighted least square estimation (WLS) with its mathematical modelling, issues and algorithm implementation in a series of papers in 1970[1-3].

WLS based state estimation is an iterative process and do not converge under certain conditions. This happens due to local minima, measurement unavailability and others. Several attempts were made by the researchers to improve performance of WLS and to overcome mentioned issues[4-6].

Another approach used by several researcher for state estimation is used of neural networks in mapping input-output relationship as they are well known for their learning and generalization features. In [7], authors has used Hopfield neural network and modelled state estimation as cost minimization problem. In another paper, author has used principal component analysis for feature engineering and reduced parameter approach was proposed [8]. Mosbah and fellows used multiple neural network topologies for estimating complex voltages[9]. It was deduces that different topologies works satisfactory for small and large power system.

It is to highlight here that in previous research work, some authors used ideal data or added noise with some specific standard deviation to measurements data to mimic the metering errors.. In this paper, state estimation with consideration of variable measurement errors from the measuring devices has been presented. This assumption mimics practical scenario as aging effect of device and length of data transmission to central control system can be different as transmission system is geographically spread over hundreds of miles.

II. WLS STATE ESTIMATION

State estimation is an iterative process and serves as an alternative to load flow studies where the objective is to find out the complex voltages at each bus in the system. It is a key component of modern transmission systems. It makes use of variety of measurements available from various locations and meters. These measurements include line flows real and reactive, injected powers real and reactive and current-voltage magnitudes. The measurement model can be mathematically represented as:

$$z = h(x) + e \tag{1}$$

where z is measurement matrix, $h(x)$ is depicting the non-linear relationship between measurements and state variables and e is the error matrix in measurements. To minimize the cost function $E(x)$ mentioned in eq.(2) is the objective function of the WLS method.

$$E(x) = (z - h(x))^{T} W (z - h(x)) \tag{2}$$

Where W is the weight matrix comprising of reciprocal of the covariance error in measurements.

In minimizing the above-mentioned cost function, solution sometime diverge and therefore there is a need to create state estimator that works better, faster and robust in providing actual operating state of the system. Overall, state estimation can help improve the stability and reliability of the system. By using the DNN discussed below, issues of WLS can be overcome.

III. DEEP NEURAL NETWORKS

DNN is a fully connected neural network architecture with two or more hidden layers in it. Learning capabilities for non-linear relationship between input and output are well explored and proven. Training process of DNN is time consuming but once trained it can produce output with relatively less computational time. This makes DNN feasible for state estimation too where system complex voltages are mapped through the relationship presented in (3):

$$(V,\delta) = f\,(P_L, Q_L) \qquad (3)$$

DNN general representation is shown in Fig.1 in which input layer, hidden layers and output layer is evident.

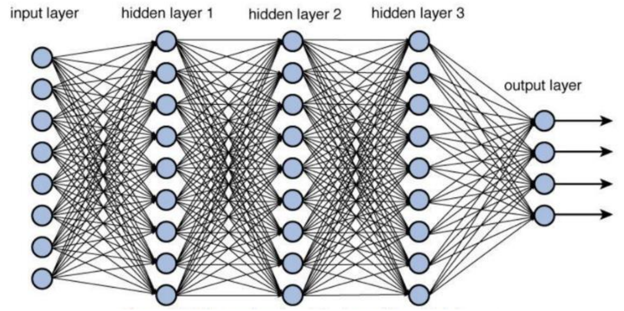

Fig. 1 Architecture of a Deep Neural Network

IV. METHODOLOGY

Neural network methodology can be explained in two steps. First, to create a large dataset and perform its refinement such as scaling, removal of unwanted samples and others and secondly, training the neural network model with variety of possible variations to find optimum model.

A. *Data generation and refinement*

Offline data has been used in this paper which was obtained by performing load flow on MATLAB by generating different scenarios with P and Q load variations. IEEE 14 bus system was used having 22 P_L, Q_L values and 27 output variables including voltage angle and magnitude to estimate. Test system with metering buses is shown in Fig. 2. Detailed process of dataset generation, refinement and noise addition is presented in Fig. 3. In order to mimic real world scenario, Gaussian noise has been added to the metered data with standard deviation S.D as follows:

- At buses 2, 3 and 5, 3* S.D = 0.5%
- At buses 4, 6, 9 and 12, 3* S.D = 1%
- At buses 10, 11, 13 and 14, 3* S.D = 2%.

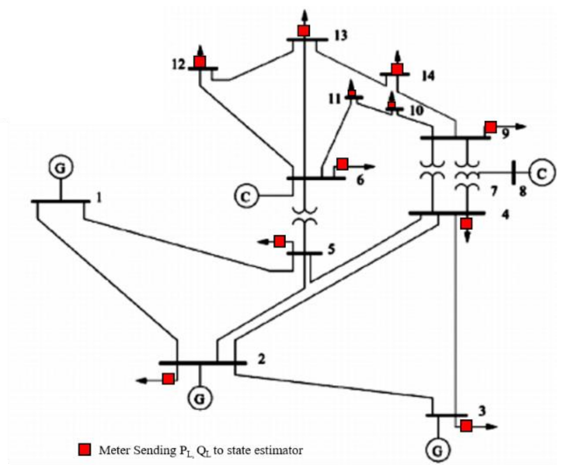

Fig.2. IEEE 14 bus system with meter placement

B. *DNN training*

The input and output data set is used to train DNN which consists of 8838 samples. Data division among training, validation and test set was done with ratio of 70-15-15 percent respectively. Fig. 4 represents training and state estimation process using trained DNN.

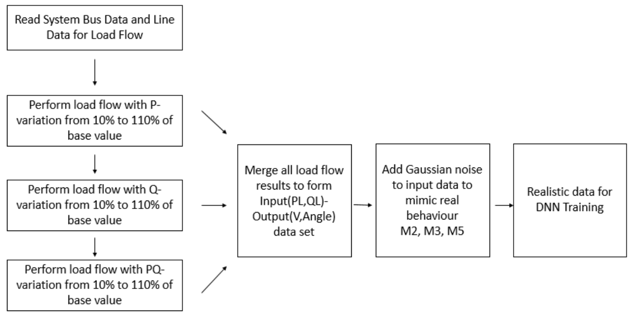

Fig. 3 Dataset generation Through MATLAB for DNN

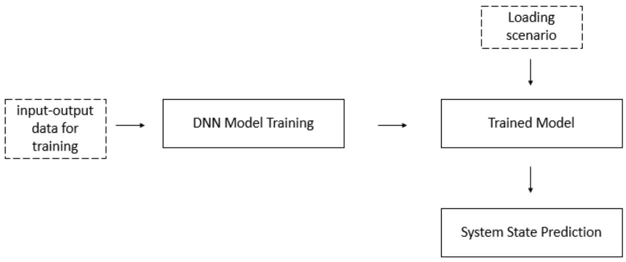

Fig. 4 DNN Training And State Estimation Process

V. RESULTS AND DISCUSSION

Several architectures of DNN with varying number of neurons and their quantity per hidden layer was varies. Satisfactory results were found on 2 hidden layers, with 11 neurons in the first one and 18 neurons in the second one. Performance plot for DNN training is shown in Fig. 5

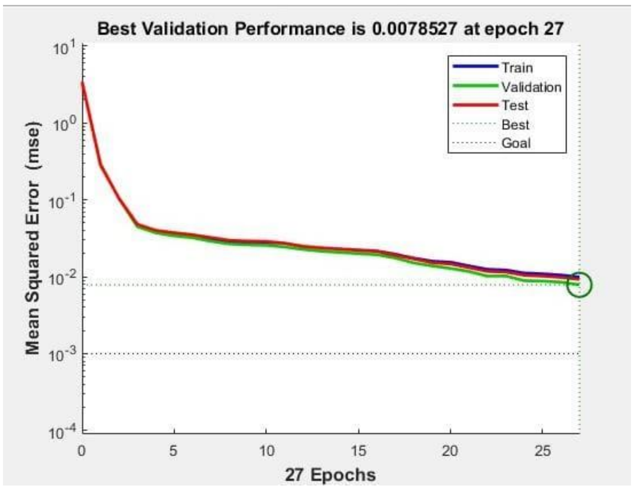

Fig. 5 Performance plot of DNN trained model

VI. CONCLUSION

The present study found that proposed DNN based state estimator serves satisfactory for voltage magnitude and angle prediction even when variable metering error is present in the system. Future research will include testing of parallel architecture with decoupled approach for state estimation.

VII. References

[1] F. C. Schweppe, "Power system static-state estimation, Part III: Implementation," *IEEE Transactions on Power Apparatus and systems,* no. 1, pp. 130-135, 1970.

[2] F. C. Schweppe and D. B. Rom, "Power system static-state estimation, Part II: Approximate model," *IEEE Transactions on Power Apparatus and Systems,* no. 1, pp. 125-130, 1970.

[3] F. C. Schweppe and J. Wildes, "Power system static-state estimation, Part I: Exact model," *IEEE Transactions on Power Apparatus and systems,* no. 1, pp. 120-125, 1970.

[4] G. L. Kusic and W. H. Allen, "State estimation using admittance matrices (of space power systems)," in *Proceedings of the 24th Intersociety Energy Conversion Engineering Conference*, 1989: IEEE, pp. 545-550.

[5] A. El-Keib and H. Singh, "Linear programming based state estimation in power systems," in *Proceedings The Twenty-Second Southeastern Symposium on System Theory*, 1990: IEEE Computer Society, pp. 265,266,267,268-265,266,267,268.

[6] I. Habiballa and V. Quintana, "Modified fast-decoupled state estimation in rectangular-coordinates (for power systems)," in *Proceedings of the Twenty-Second Annual North American Power Symposium*, 1990: IEEE, pp. 102-111.

[7] H. Mori, "An artificial neural net based method for power system state estimation," in *Proceedings of 1993 International Conference on Neural Networks (IJCNN-93-Nagoya, Japan)*, 1993, vol. 2: IEEE, pp. 1533-1536.

[8] A. Onwuachumba and M. Musavi, "New reduced model approach for power system state estimation using artificial neural networks and principal component analysis," in *2014 IEEE Electrical Power and Energy Conference*, 2014: IEEE, pp. 15-20.

[9] H. Mosbah and M. El-Hawary, "Multilayer artificial neural networks for real time power system state estimation," in *2015 IEEE Electrical Power and Energy Conference (EPEC)*, 2015: IEEE, pp. 344-351.