State Estimation for Unobservable Distribution Systems via Deep Neural Networks

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Motivation

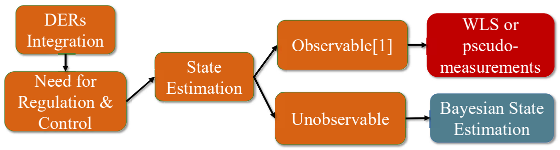

Fig.1 –Motivation flow chart

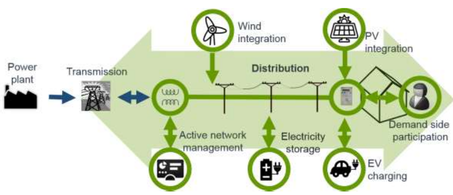

Fig.2 -Grid diagram with the distribution System and its participants marked in green

Approach

We estimate the state vector x, where each elements are the voltage magnitude and phase at each node of the grid, given the measurement vector z such that the mean squared error is minimized.
The **MMSE estimator** is defined as:

$$\hat{x}^*(z) = \arg\min_{\hat{x}} \mathbb{E}(||x - \hat{x}(z)||^2) = \mathbb{E}(x|z).$$

The functional form of this estimator is **complex to obtain**. Hence we turn to the feed-forward neural network model :

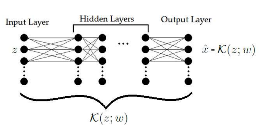

Fig.2 – Neural network representation

In approximating the MMSE estimator, the **neural network** weight parameter w is set to **minimize the MSE** of its estimate

$$w^* = \arg\min_{w} \mathbb{E}(||x - \mathcal{K}(z;w))||^2).$$

This w^* that minimizes the MSE is obtained through training of the neural network. The main characteristics of our training is:

- ❖ Adaptive Moment Estimation (ADAM)
- ❖ Early stopping
- ❖ Validation set used to choose best structure
- ❖ Clustering on neurons for pruning

Method Block Diagram

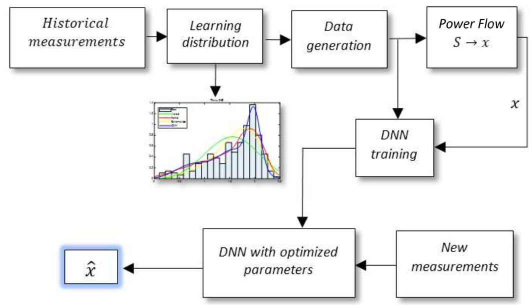

Fig.4- Block diagram of the proposed method[2]

An overview of our method starts by collecting historical data of the available measurement devices in the network. We learn their underlying probability distribution and generate training data to the neural network using **power flow equations**:

$$P_i^k = V_i^k \sum_{l=1}^{3}\sum_{j=1}^{n} V_j^l[G_{ij}^{kl}\cos(\theta_i^k - \theta_j^l) + B_{ij}^{kl}\sin(\theta_i^k - \theta_j^l)]$$

$$Q_i^k = V_i^k \sum_{l=1}^{3}\sum_{j=1}^{n} V_j^l[G_{ij}^{kl}\sin(\theta_i^k - \theta_j^l) + B_{ij}^{kl}\cos(\theta_i^k - \theta_j^l)]$$

Once trained, the neural network can be used with any new measurements to estimate the new states $\hat{x}$.

Evaluation

The approach was evaluated in a 85 and 144 node networks, from MATPOWER, using average square error(ASE) as error metric. The major conclusions are:

- ❖ A **deeper** neural network achieves **better performance**.
- ❖ **Beyond** certain number of layers all structures **perform similarly** without any improvement
- ❖ The deep neural network achieves in order of **eight times better** results than weighed least squares and pseudo-measurement methods.

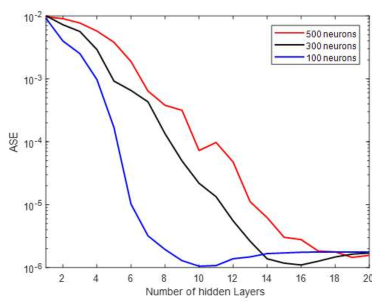

Fig.5 – Neural Network performance comparison between rectangular structures of different total number of neurons and layers

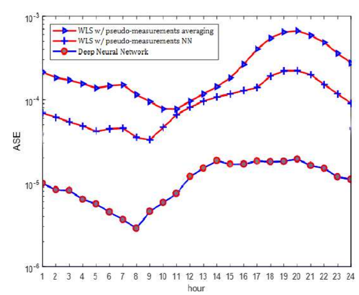

Fig.6 – Hourly simulation comparing neural network methods with weighed least squares and pseudo-measurements

Distribution Learning

Learning the distribution of the historical data poses a challenge due to:

- ❖ Scarcity of data available from arbitrary nodes
- ❖ Disparity between consumption and solar generation at different locations

Hence our selection process was:

1. Compute the empirical cdf from the samples
2. Obtain confidence intervals following DWK inequality[2].
3. See which models fall in between more often.

The chosen one was:

Gaussian Mixture model of 3 components

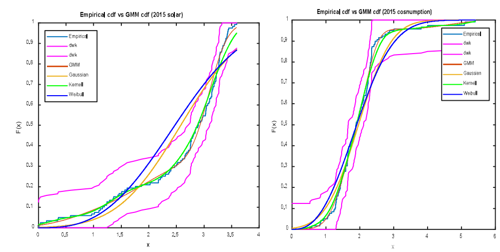

Fig.7 Different models of probability distribution cdfs for solar generation(left) and consumption(right) of a particular household and hour, with the confidence intervals marked in magenta.

Summary and future work

Main features:

- ❖ Learn from historical measurements and generates more training samples.
- ❖ Stochastic optimization methods and regularization methods used to avoid overfitting.
- ❖ Computationally efficient and robust against bad data, variation of net consumption distributions and high penetration of DERs

Future work:

- ❖ Simulation of the proposed method in a 3-phase network

Acknowledgements

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References

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[3] Dvoretzky, A.; Kiefer, J.; Wolfowitz, J. Asymptotic Minimax Character of the Sample Distribution Function and of the Classical Multinomial Estimator. Ann. Math. Statist. 27 (1956), no. 3, 642--669.