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Artificial Neural Networks – Based Method for Enhancing State Estimation of Grids with High Penetration of Renewables

S. Cosic[1], I. Vokony[1]

[1] Department of Electric Power Engineering
Faculty of Electrical Engineering and Informatics
Budapest University of Technology and Economics
BME V1 Building - Egry József u. 18., 1111 Budapest (Hungary)
Phone/Fax number: +36 463 1111 5408, e-mail: Saidcosic@edu.bme.hu, Vokony.istvan@vik.bme.hu

Abstract. This paper addresses state estimation as one of the most essential mechanisms in real-time operation and control of modern power systems, and proposes a novel solution to the issue of poor network observability, commonly faced in distribution system state estimation (DSSE) characterized by an ever-increasing penetration of renewable generation. The ongoing transformation from conventional passive, one-directional power systems to active smart grids necessitates more accurate and reliable system state estimation to achieve optimal system performance. Real-time grid monitoring and control has been a routine task in transmission networks, but distribution grids cannot successfully utilize these capabilities due to different topologies, specific electrical characteristics, the low amount of available real-time measurements, as well as substantial communication effort needed to handle the data. Furthermore, with the advent of distributed generation, new types of loads and the vast surge of prosumers, a substantial amount of data is required to maintain system stability and controllability. For these reasons, reliable state estimation requires a high-quality creation process of pseudo-measurement, in addition to an efficient algorithm and an extremely accurate estimator. Thus, this paper proposes a novel framework of dynamic estimation methodology that includes the use of Artificial Neural Networks (ANN) in the pseudo-measurements generation process, utilizes Iteratively Reweighted Least Squares (IRWLS) algorithm and Schweppe-Huber Generalized Maximum Likelihood (SHGM) estimator. The efficiency and accuracy of the proposed methodology were assessed and verified on a benchmark network model.

Key words. Artificial neural networks, state estimation, observability, pseudo-measurement generation, Iteratively Reweighted WLS, SHGM.

1. Introduction

Contemporary power systems are facing a vast number of challenges in their pursuit for satisfying the requirements of security, equity, and sustainability. One of the major tasks in daily power system operation is maintaining the normal state, which heavily relies on the ability of supervisory control and data acquisition (SCADA) systems to continuously monitor the system through the acquisition of various measurements, their processing and determining the system state [1]. This process of inferring the values of system state variables using a limited number of measured data at certain locations is referred to as state estimation (SE) [2].

State estimation is well-established at the transmission system level, where it has been in use for the last few decades and is a most vital component of energy management systems [3]. However, distribution system state estimation still faces many challenges due to several issues [4], such as complex network topology, low X/R ratio, measurement scarcity, renewable energy penetration, unbalanced operation, communication issues etc. The aforementioned problems lead to distribution grids being essentially unobservable.

This paper suggests an approach to offset the poor observability and achieve accurate state estimation by using ANN in the pseudo measurement generation process, as well as utilizing an alternative SE algorithm and a nonconventional estimator for better robustness. The subsequent sections include a brief overview of crucial state estimation steps in Section II, and a description of the proposed methodology in Section III. Simulation results and discussion are presented in Section IV, whereas main conclusions are given in Section V.

2. State Estimation

SE is fundamentally a process which consists of several critical steps or modules that perform specific functions, such as topology identification, observability assessment, bad data detection, pseudo-measurement generation, and state estimation solver. The interactions between different modules are illustrated in Fig. 1.

Topology identification gathers data about states of circuit breakers and switches in the system, assuming that the network topology is known to the system operator, except in the case of a fault or contingency. It aims to utilize the metered data throughout the network and update the switching states to avoid topology errors. Recent methods used in literature are based on maximum likelihood estimation [5], Probabilistic recursive Bayesian approach [6], and Nonlinear Least Absolute Value [7].

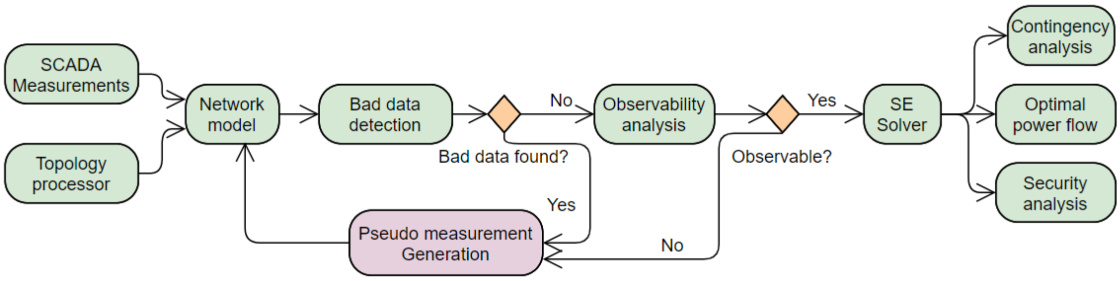

Fig. 1. State estimation flow chart.

Bad data detection searches for errors in the measurement dataset and eliminates faulty measurements only if there is enough measurement redundancy and a single source of the erroneous measurement [1]. Conventional bad data detection relies on the assumption that faulty data follows a particular probability density function, such as Chi-squared, and performs statistical hypothesis testing [8]. Novel approaches have utilized linear WLS frameworks with equality constraints [9], largest normalized residual test of PMU data [10], and advanced statistical analyses based on penalized semidefinite programming conic relaxation [11].

Bad data detection is followed by observability analysis, which determines if an SE solution exists, i.e., if the state variables can be inferred from the available measurements, and identifies portions of the network which are unobservable due to bad or missing data, by several different topological (graph theory-based, searching the full spanning tree of the network, such as [12]), numerical (decoupled DC model [13], based on the gain, Jacobian, or the gram matrix) and hybrid methods [14].

In case measurement redundancy is insufficient and the system is unobservable, the input set is artificially expanded by introducing pseudo measurements, which are usually generated according to the network's historical data by various probabilistic methods. Most recently, the surveyed methodologies involved a game-theoretic expansion of relevance vector machines to estimate the nodal power consumption with advanced metering infrastructure (AMI) [15], a gradient boosting tree method trained by user-level data [16], and a kernel density estimation (KDE) technique to develop the conditional probability density function of PV outputs [17].

The SE solver (estimator) aims to find an optimal solution for the system states according to the network model constraints and given measurements. Conventionally, the solver consists of a linear optimization problem such as Weighted Least Square (WLS) and contains an algorithm that minimizes an objective function in an iterative way, such as Gauss-Newton [18], quasi-Newton techniques [19], or a linear algorithm such as CLSE-PN [20].

3. Proposed Methodology

The proposed methodology seeks to exploit deficiencies of conventionally used SE aspects, with the particular focus on enhancing pseudo-measurement generation and state estimator capabilities by utilizing artificial neural networks concepts, replacing the WLS algorithm with the notion of iteratively altering weights, as well as using a Schweppe-Huber Generalized Maximum Likelihood (SHGM) solver.

A. ANN for Pseudo Measurement Generation

Artificial neural networks are computational networks which attempt to simulate the decision process in networks of nerve cells (neurons) of the biological central nervous system [21]. They play an important role in several aspects of decision theory, information retrieval, prediction, detection, diagnosis, pattern recognition, control, classification, and data processing. A neuron is the basic building block of an ANN, and it can be structured as a perceptron, artron, or adaline. The commonly used perceptron is defined by the following input/output relation:

$$z = \sum_i w_i x_i \tag{1}$$

$$y = f_A(z) \tag{2}$$

where z is the node (summation) output of linearly combined weighted (w_i) inputs, x_i, used as an argument of activation function, f_A, which is typically linear, unipolar, binary or sigmoid. Perceptrons are combined into various topologies, such as back-propagation, Hopfield, counter-propagation, LAMSTAR etc. The ANN parameter estimation is done by a learning (training) process called the optimization algorithm, formulated in terms of the minimization of a loss function that consists of an error and regularization terms. Most common algorithms are gradient descent, Newton's Hessian matrix-based method, conjugate gradient, and Levenberg-Marquardt. Recently, the attractive properties of ANN have sparked a lot of research interest, and ANN-based methods for pseudo measurement generation in DSSE were introduced as different topologies and applications by [22], [23] and [24].

This paper suggests a feed-forward ANN topology with three hidden layers, demonstrated in Fig. 2, which takes historical load active and reactive power data, together with static generators' profiles as inputs and 200 neurons in each layer to train the network to successfully predict bus voltages as the output. The obtained data is then used as pseudo measurements to account for missing measurement data in the dynamic state estimation process. The data set consists of one-year load and static generator data in 15-minute resolution, adding up to 35136 time steps, out of which 25% (8784) were used in the training set, and the rest was used in the validation set. The logistic sigmoid function was set as the output activation function, while stochastic gradient-based optimizer "Adam" [25] was used as a solver.

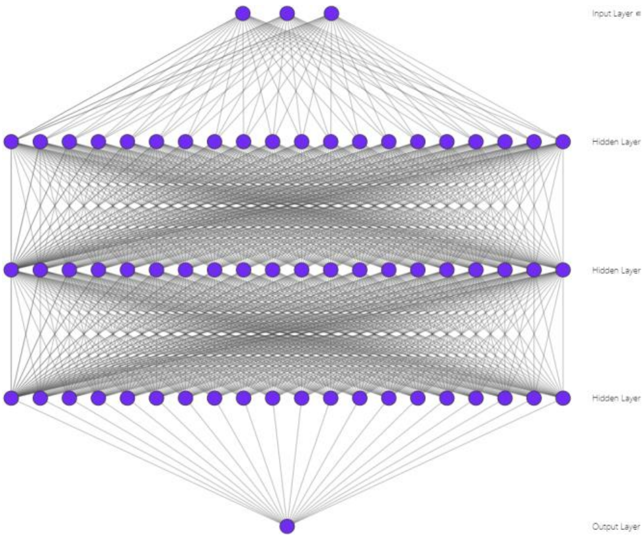

Fig. 1. Proposed ANN structure.

B. Iteratively Reweighted Weighted Least Squares

IRWLS algorithm assumes that a robust signal recovery can be achieved by global minimization of the sparse vector of sensing data by solving a least-square problem in each iteration. However, it is capable of adjusting several constraints from active to inactive in one iteration by using only certain samples, thus using only a portion of the kernel matrix, which significantly decreases the run-time complexity [26].
This algorithm was chosen due to its proven signal recovery from incomplete and inaccurate linear measurements, high robustness against noise and fast convergence. However, its application on SE problems has been very limited. As a modification of the conventional WLS, it is assumed that it can improve the SE's robustness against bad data by performing a quick constrained log-likelihood maximization.

C. SHGM Estimator

In poorly observable networks subject to topology errors and frequent load changes, the conventional estimator may yield highly biased state estimates or suffer from divergence problems [27]. To overcome these issues, this paper suggests an SHGM Likelihood estimator, whose statistical and numerical robustness has been proven.
Mathematically, the relationship between measurement vector $\boldsymbol{z}$, the state vector, $\boldsymbol{x}$, containing bus voltage magnitudes, and the error vector $\boldsymbol{e}$ can be expressed as:

$$z = h(x) + e \tag{3}$$

The state estimator aims to minimize the objective function:

$$J(x) = \sum_{i=1}^{m} \omega_i^2 \rho(r_{si}) \tag{4}$$

where ω_i is the weight which decreases the impact of bad data, ρ is the cost function, and r_{si} is the normalized residual. The SHGM estimator calculates the weights as:

$$\omega_i = \min\left[1, \frac{\chi_{v,0.975}}{PS_i}\right] \tag{5}$$

where PS_i is a parameter with χ^2 distribution calculated by projection statistics. The cost function of SHGM is defined as:

$$\rho(r_{si}) = \begin{cases} r_{si}^2/2, & for\ r_{si} \le \lambda \\ \lambda|r_{si}| - \lambda^2/2, & for\ r_{si} > \lambda \end{cases} \tag{6}$$

where λ is the breakpoint that balances the trade-off between the least squares and the least absolute criterion.
Using IRWLS, after differentiating $J(x)$, rearranging terms, first-order Taylor series expansion of $h(x)$, the general solution given in terms of Jacobian matrix, J, covariance matrix, R, and matrix $Q = diag(q(r_{si}))$, for l iterations is given as:

$$\Delta\hat{x}^{(l)} = \left(H^T R^{-1} Q^{(l)} H\right)^{-1} H^T R^{-1} Q^{(l)} \left(z - h\left(\hat{x}^{(l)}\right)\right) \tag{7}$$

D. Grid Description

The analyzed grid is an urban HV/MV network with rated voltage levels of 220, 110 and 10 kV, which contains PV, wind, and hydro generators, 15 distribution feeders with the total length of 37.82 km, and 751.6 km of HV lines. The basic grid data is summarized in Table I, and the topology is given in Fig. 3. The default measurement number in the network is 190, which makes it inherently unobservable for SE calculations, as 461 measurements are required for full observability; hence, the rest must be produced by the pseudo measurement generating algorithm.

Table I. – Test Grid Data

TYPE	NO OF ELEMENTS
Transformer	5
Static generator	232 (212 PV, 1 hydro, 19 wind)
Bus	514
Switch	802
Load	218

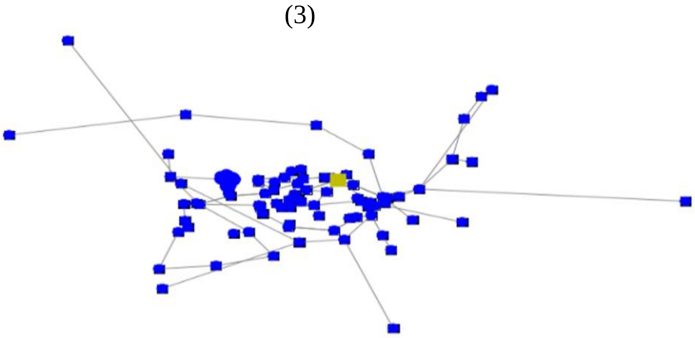

Fig. 2. Network topology.

E. *Software Environment*

The research used a Python environment to create and simulate all SE modules. The network model and SE were created in pandapower library [28], which is a stand-alone power system analysis toolbox with extensive power system model library and several power systems analyses. The ANN were modelled using scikit-learn machine learning library's [29] Multi-layer Perceptron regressor. The network data were taken from the SimBench dataset [30], publicly available comprehensive dataset which contains electrical parameters for modelling and benchmarking of electric grids, together with time series data for the analysis.

4. Results

In the ANN-based pseudo measurement generation process, load profiles were firstly obtained from the SimBench database, and the input sets for load active and reactive power and static generation were created, which can be observed in Fig. 4.

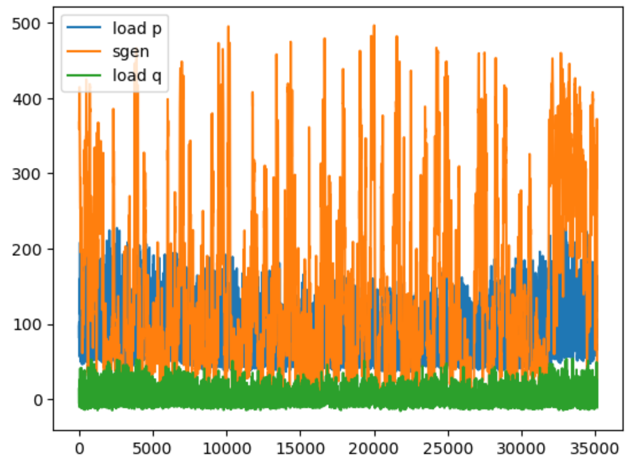

Fig. 3. ANN input time series data.

After the output set Y was obtained for bus voltages (vm_pu) from timeseries calculations, a train/test dataset split was performed, as previously explained, in the 1:3 ratio. The data were scaled and saved. After 37 iterations, the training was successful, as the training loss did not improve more than 10^{-4} for 10 consecutive epochs. The achieved mean squared error, whose exponential convergence is depicted in Fig. 5, was 0% after 300 ms, which indicates remarkable accuracy and computational efficiency. As a result, a 24-hour voltage profile is given in Fig. 6, for Bus 53 with particularly significant overvoltage.

In the state estimation process, all initial measurements were removed from the SimBench dataset to avoid having double measurements at the same grid locations. Afterwards, load reactive power (and a small portion of active power data to assure the 2n-k criterion) from the time series calculation were added as measurements, and the ANN-obtained voltage values were used as pseudo measurements to achieve full observability in the SHGM solver. To analyze the algorithm accuracy, another state estimation was performed with the voltage data from the test set (the "real" load flow-based values) as pseudo measurements. The root means square SE error of all time steps between the real and estimated active power injections at indicated buses were given in Fig. 7. It is worth noting that the bus P estimates bear the biggest errors, and thus their RMSE was presented. However, other states such as voltage angle carried a negligible RMSE of 0.02 %.

To compare the IRWLS with the conventional WLS with respect to accuracy, another WLS-based SE was performed on the same measurement and pseudo-measurement datasets. However, since overall differences were very subtle, the error metrics graph is not included in the report. However, in terms of robustness against sudden data fluctuations, it could be seen that whenever measurements had such a behavior, the consecutive state estimation errors on several buses differed in the two methods. While the proposed method generally yielded smaller errors, the WLS errors displayed values north of 17% on rare occasions. However, the convergence of both methods was constant throughout the whole time, which could be attributed to the high accuracy of ANN-generated pseudo-measurements.

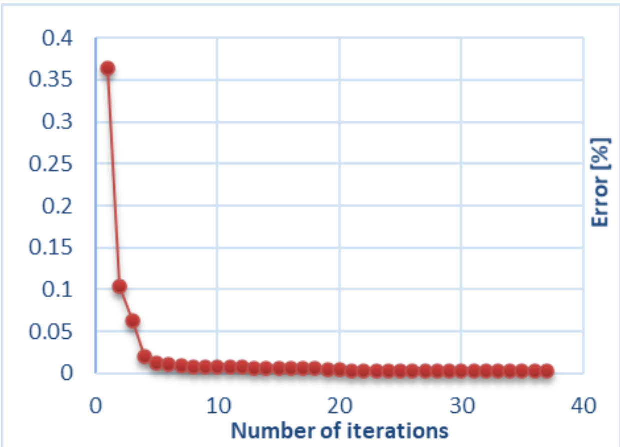

Fig. 4. ANN training error convergence.

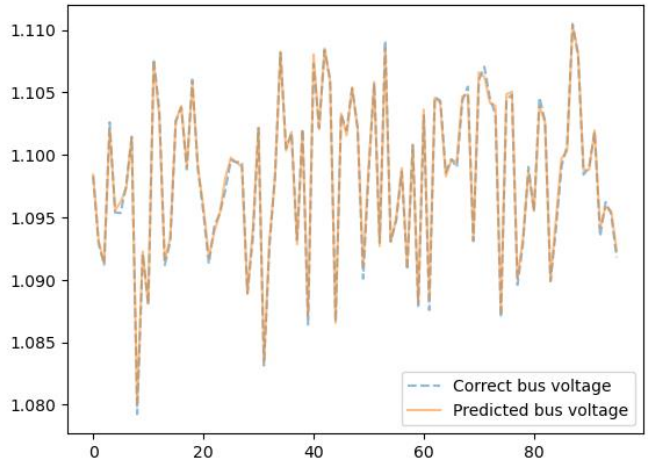

Fig. 5. ANN output for Bus 53.

Thus, the proposed solver and the algorithm arrangement are comparably accurate to the widely established WLS and display significant robustness in all circumstances.

A drawback of this method is increased computational time by 11.4% on this particular grid. Nevertheless, the estimations were not necessarily performed under the same conditions, as other simultaneously running software might have contributed to the processing time.

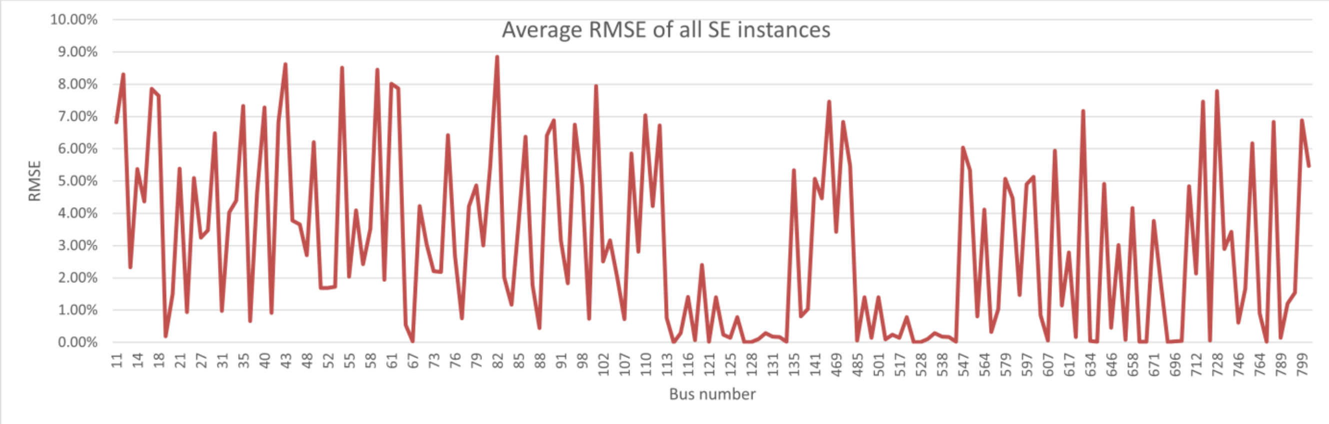

Fig. 6. State estimation error at selected buses.

5. Conclusion

This paper tackled the issue of state estimation in poorly observable networks with high renewable penetration, which arises due to low measurement redundancy and plenty of faulty metering data. The basic goal was to develop a framework of methodologies that improve the shortcomings of conventional SE process by proposing three vital modifications to the traditional algorithm.

The first and most significant suggestion was the use of artificial neural networks in the pseudo-measurement generation process. The paper proposed a feed-forward topology with three hidden layers, which successfully created missing pseudo-measurements with remarkable computational speed and accuracy.

The second proposal aimed to boost the properties of SE algorithm by introducing the Iteratively Reweighted Least Squares algorithm, thereby offering a higher robustness against noisy data and a faster convergence. The benefits of this method were attested by the fact that full convergence was achieved for all time instances of state estimation, as well as displaying substantial computational robustness during consecutive high measurement differentials.

The third major method relied on the utilization of the Schweppe-Huber Generalized Maximum Likelihood estimator. Moreover, the proposed SE solver, whose solution existence was mathematically proven, exhibited a level of accuracy comparable to the one of conventional WLS, without yielding a statistically significant number of highly biased state estimates.

The simulations of the initially unobservable HV/MV grid confirmed the initial hypothesis about accuracy, convergence, robustness, and computational efficiency enhancements achieved by the proposed framework.

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