State Estimation in Electric Power Systems Based on Adaptive Neuro-Fuzzy System Considering Load Uncertainty and False Data

M. Ahmadi Jirdehi* (C.A.) and V. Sohrabi Tabar*

Abstract: Control center of modern power system utilizes state estimation as an important function. In such structures, voltage phasor of buses is known as state variables that should be determined during operation. To specify the optimal operation of all components, an accurate estimation is required. Hence, various mathematical and heuristic methods can be applied for the mentioned goal. In this paper, an advanced power system state estimator is presented based on the adaptive neuro-fuzzy interface system. Indeed, this estimator uses advantages of both artificial neural networks and fuzzy method simultaneously. To analyze the operation of estimator, various scenarios are proposed including impact of load uncertainty and probability of false data injection as the important issues in the electrical energy networks. In this regard, the capability of false data detection and correction are also evaluated. Moreover, the operation of presented estimator is compared with artificial neural networks and weighted least square estimators. The results show that the adaptive neuro-fuzzy estimator overcomes the main drawbacks of the conventional methods such as accuracy and complexity as well as it is able to detect and correct the false data more precisely. Simulations are carried out on IEEE 14-bus and 30-bus test systems to demonstrate the effectiveness of the approach.

Keywords: Adaptive Neuro-Fuzzy System, Artificial Neural Network, False Data, Load Uncertainty, State Estimation.

1 Introduction

1.1 Motivation

POWER system state estimation (SE) is a key tool for management systems [1]. In fact, different proceedings such as energy management [2] and network control [3] are not possible without availability of accurate information. Hence, if the unknown data are predicted by SE, the operators will easily monitor and control the network [4]. Through application of such methodology, safe and efficient operation can be achieved [5-7]. Thus, the development of SE tools is inevitable for the optimal protection, optimization, and control of power systems especially with increasing information exchange due to smart grids [8].

1.2 Literature Review

The SE consists of estimating the bus voltage magnitude and phase angle using redundant active-reactive power injection measurements and line active-reactive power flows at different locations [9-12]. The weighted least square (WLS) method is the most common approach to solve the SE problem. In this procedure, SE is formulated as an optimization problem and solved by an iterative method [13]. This process includes several drawbacks such as ill-conditioning of gain matrix, slow detection of false data, and numerical problems in some cases (e.g., simultaneous connection of short and long line to bus and high weighting coefficients for pseudo measurements) [14]. According to the presented issues, WLS algorithm may provide unacceptable outputs as well as its convergence is not...
guaranteed. In recent years, various methods are suggested by researchers to improve the SE and resolve the mentioned problems. Reference [15] proposes a past-aware SE (PASE) based on Ensemble Kalman Filter (EKF) for distribution systems to enhance accuracy. In this method, fewer phasor measurement units (PMUs) are required to achieve the same estimation error as well as power flow equations are not embedded into the estimator. The interconnected optimal filtering problem for distributed dynamic SE based on the mean squared error between the real and estimated states is investigated by considering packet losses [16]. In this regard, the system is modeled as a state-space linear equation where sensors are utilized to obtain measurements and the optimal local and neighboring gains are computed to reach a consensus estimation. A model-free and fully data-driven approach is developed for power system static SE based on a conditional generative adversarial network in [17]. Comparing with the WLS, any appropriate knowledge about system model is not needed. Reference [18] presents a novel decentralized load frequency control (LFC) approach based on dynamic SE where employs an unknown input observer including demand fluctuation and tie-line power deviations to track the dynamic states in real-time operation. A distributed unscented information filtering (UIF) is proposed for SE of interconnected nonlinear dynamic systems [19]. This method is based on unscented transformation where the local estimate is calculated based on the local observations, and then gradually integrates the neighboring information by an iterative method to obtain a more accurate distributed estimate. In the same way, a hybrid SE approach is developed based on the two-stage iterative algorithm in [20]. Reference [21] uses two novel algorithms including deterministic and stochastic schemes derived from composite optimization to improve the low speed and accuracy of conventional least-absolute-value (LAV) for real-time estimating and monitoring.

Besides mathematical methods, heuristic or meta-heuristic algorithms can be utilized for various goals such as estimating, predicting and learning. Recently, applications of intelligent algorithms, artificial neural networks (ANNs), fuzzy method and combination of them are widely developed in electrical power systems [22]. For instance, the electricity consumption patterns of customers in response to electricity price of demand response (DR) program are modeled by ANN [23]. An economic load dispatch issue is solved using dragonfly algorithm to minimize the cost in the power system including thermal power plant, renewable resources and different load conditions [24]. In order to validate the effectiveness, the results are compared to different intelligent algorithms such as crow search algorithm (CSA), ant lion optimizer (ALO), oppositional real-coded chemical reaction optimization (ORCCRO), biogeography-based optimization (BBO), particle swarm optimization (PSO) and genetic algorithm (GA). As well, load dispatch problem is studied by utilizing ALO [25] and grey wolf optimizer (GWO) [26]. Reference [27] proposes a robust SE utilizing a re-weighted moving horizon estimation. This method decreases the sensitivity to the outliers by real-time updating the error variances and re-weighting the contributions adaptively. Due to dependency of some algorithms such as PSO to the system dimension, a hybrid state estimator includes a cellular computational network (CCN) and GA is designed [28]. In this research, the CCN is improved by GA and used to distribute the whole computation into computation cells and execute local estimation. Since ANN is a machine learning, such a network can be utilized to estimate and approximate functions which are related to a large number of inputs and unknown data. ANN is widely applied to different power system problems such as power system restoration [29], reactive power transfer allocation [30], transient response prediction [31], controlling a hybrid power filter [32], and power flow [33]. Reference [34] utilizes ANN to solve power flow problem under different loading and contingency conditions for computing bus voltage magnitudes. In the mentioned study, two supervised learning networks are used including counter propagation neural networks and multi-layer feed-forward network with back propagation algorithms. Furthermore, in order to take advantages of ANN speed over the conventional power flow methods, multi-layer perceptron neural networks trained with the second order Levenberg-Marquardt are successfully developed [35]. Due to need for many iterations to obtain reasonable results and converge problem of Gauss-Newton as a key component in distribution system SE, reference [36] uses historical or simulation-derived data to train a shallow neural network and initialize Gauss-Newton network. The results validate that this hybrid machine learning/optimization approach yields superior performance in terms of stability, accuracy and runtime efficiency. According to voltage fluctuations caused by large-scale deployment of renewable generators, electric vehicles and DR programs, monitoring in real-time becomes increasingly critical. Hence, physics-inspired deep neural networks (DNNs) is utilized for real-time power system monitoring [37]. Numerical tests show improved performance of the proposed DNN-based estimation and forecasting approaches compared with existing methods. To improve the operation of neural networks, this structure is combined with fuzzy logic. Adaptive neuro-fuzzy inference system (ANFIS) is the combination of ANN and fuzzy logic and comprises the specifications of both methods [38]. ANFIS is implemented on power system problems such as maximum power point tracking in photovoltaic systems [39], fault location in power distribution systems [40], fast power restoration plan in distribution
systems [41], and power flow in distribution networks [42]. However, the application of ANFIS is not well analyzed as the SE in the presence of false data injection (FDI).

1.3 Contribution of Paper
As investigated, various methods are presented to improve the SE of power systems as a new tool. In this regard, some studies are based on mathematical procedures, while the others use intelligent algorithms. The main problems of mathematical methods are the complexity and solving time. In return, intelligent procedures are not accurate enough. In this paper, a new method is proposed to estimate the power system states based on the combination of neural network and fuzzy logic. Hence, the main contribution and key points of the paper are summarized as follows:
- Proposing an intelligent state estimator based on adaptive neuro-fuzzy inference system.
- Comparing the accuracy of the presented estimator by ANN and WLS.
- Analyzing the capability of the method to detect and correct the injected false data.
- Considering the probability of load variation as a practical condition in power system.

1.4 Paper Organization
The rest of the paper is organized as: Section 2 summarizes the state estimation formulation. In Section 3, the ANFIS and ANN are modeled and the load uncertainty is presented in Section 4. As well, algorithm constructing and accuracy analysis are explained in Section 5 and the understudy test system is introduced in Section 6. Finally, Sections 7 and 8 are devoted to the simulation results and conclusions, respectively.

2 State Estimation Formulation
The goal of a static SE is finding the best estimation for state $\dot{X}$. If the $X$ is the state vector, the measurement vector will be determined by (1) [7].

$$Z = h(X) + e$$

where, $Z$ and $h(X)$ are the measurement and a nonlinear vectors related to state components, respectively. Moreover, $e$ is the Gaussian noise vector with zero mean and diagonal covariance matrix.

$$R = \text{diag}\left\{\sigma_1^2, \sigma_2^2, \ldots, \sigma_m^2\right\}$$

The diagonal covariance matrix is defined by (2) in which the $\sigma_m^2$ exhibits the covariance. It should be noted that the state vector comprises voltage phase angle and magnitude and the measurement vector includes active-reactive power flow through the lines, the injected powers and voltage magnitudes. To find the state vector that minimizes the objective function, $J(X)$ can be defined as (3).

$$J(X) = \left[Z - h(X)\right]^T R^{-1} \left[Z - h(X)\right]$$

The state estimation of states $\dot{X}$ which minimizes $J(X)$ can be obtained by (4).

$$\frac{dJ(X)}{dX} = H^T R^{-1} \left[Z - h(X)\right] = 0$$

where, an iterative process is caused as (5).

$$\begin{align*} G(X^k) \times \Delta X^k & = H^T R^{-1} \left[Z - h(X^k)\right] \\ X^{k+1} & = X^k + \Delta X^k \end{align*}$$

In (5), $k$ is the iteration index, $G(X)=H^T R^{-1} H$ and $H(X)=dh(X)/dX$ are the system gain matrix and the measurement Jacobian matrix, respectively.

3 Modeling of ANN and ANFIS

3.1 Structure of Artificial Neural Network
ANN operates based on biological neural networks. Multi-layer perceptron (MLP) network consists of a large number of processing elements (i.e., neurons) and at least three layers including input, hidden, and output layers [32, 33]. Each layer of the MLP network comprises several neurons. The node $d$ input in the hidden layer is stated by (6).

$$\rho_d = a_d + \sum_{i=1}^{j} (X_i \times W_{id}) \quad d = 1,2,\ldots,n$$

where, $X$, $n$, $i$, $a$ and $W$ shows the inputs, number of neurons in the hidden layer, number of neurons in the input layer, bias term and the weighting factor, respectively [31, 32]. The output from $d_{th}$ hidden layer is determined by (7). As well, the activation function of the hidden layer is defined by $f$ and the output of $c_{th}$ neuron in the output layer is given by (8).

$$\theta_c = f(\rho_d) \quad c = 1,2,\ldots,m$$

where $b$ and $m$ are the bias term and number of neurons in the output layer.

3.2 Structure of Adaptive Neuro-Fuzzy Interface System
The ANFIS is constructed from the multi-layer feed-forward network that combines the capability of fuzzy logic and ANN simultaneously [41, 42]. To show the ANFIS structure, a simple model is presented where the
State Estimation in Electric Power Systems Based on Adaptive...

M. Ahmadi Jirdehi and V. Sohrabi Tabar

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4 Load Uncertainty Modeling

To model the uncertainty of load and simulate a practical condition, a probability distribution function (PDF) with 10%-60% standard deviations is considered for each load and 2000 random data are generated for each deviation (17). Afterward, the expected value is calculated for all data in each deviation. Eventually, the expected value of all deviations should be determined for each load (18).

\[ S(X) = PDF(X, dv) \]  
\[ E(X) = \sum_{x=1}^{\infty} \sum_{y=1}^{\infty} S(X) \times prob(g) \times prob(k) \]  

where, \( S \) and \( dv \) are the generated scenario for variable \( X \) and standard deviation, respectively. Moreover, \( E, prob \) and \( g \) are the expected value, probability matrix and generated data.

5 Algorithm Constructing and Accuracy Analysis

The ANFIS and ANN are the training-based algorithms where several data sets are required to construct their networks. In this regard, real values including slack bus voltage magnitude, active-reactive power and voltage phasor of test systems are used for learning goal. The mentioned data sets are gathered from measurement units under different conditions such as load uncertainty. After learning process, a data set is used to calculate the accuracy of the model. If the prediction accuracy is lower than an acceptable threshold, the learning will be finished. Otherwise, the input data sets are updated and the mentioned steps are repeated.

In order to analyze the performance of the method, the outputs of WLS, ANN, and ANFIS should be compared to the real values. To order to provide an extensive comparison, the error indices can be calculated for all cases as proposed by (19)-(21). These indices are mean absolute error (MAE), root mean square error (RMSE), and mean relative error percentage (MRE), respectively.

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |X_i (exp) - X_i (pred)| \]  

Fig. 1 MLP structure including input, hidden, and output layers.

Fig. 2 ANFIS structure for two inputs and one output.
data sets including voltage, active-reactive power injection, and active-reactive power flow through the lines are used. In order to simulate the errors, Gaussian errors with zero mean and known standard deviation are added to the actual data. The standard deviations for voltages, power injections and power flows are equal to 0.004, 0.008, and 0.001, respectively.

7 Simulation Results

In order to test the presented SE and show the efficiency, three scenarios are analyzed, as shown in Table 3. In the first scenario, the performance of ANFIS is compared to ANN and WLS without considering false data. In the next scenario, a single false data is injected and the capability of each method for false data detection and correction is evaluated. Then, to validate the capability of the method against critical conditions, multi-false data is considered and the results are proposed in the third scenario. Eventually, the error indices for all scenarios are proposed in the last section for clear analysis.

<table>
<thead>
<tr>
<th>Test system</th>
<th>Scenario</th>
<th>Scenario explanation</th>
<th>Variable</th>
<th>Actual data</th>
<th>False data</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE 14-bus</td>
<td>2</td>
<td>Single false data</td>
<td>P_{21}</td>
<td>0.81465</td>
<td>-0.81465</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P_{11}</td>
<td>-0.035</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Q_{12}</td>
<td>-0.016</td>
<td>-0.008</td>
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<tr>
<td></td>
<td>3</td>
<td>Five false data</td>
<td>P_{34}</td>
<td>-0.31574</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P_{56}</td>
<td>0.28298</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Q_{34}</td>
<td>-0.24856</td>
<td>-0.12</td>
</tr>
<tr>
<td>IEEE 30-bus</td>
<td>2</td>
<td>Single false data</td>
<td>P_{23}</td>
<td>0.88038</td>
<td>-0.88038</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Q_{23}</td>
<td>-0.112</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P_{14}</td>
<td>0.82517</td>
<td>0.62517</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Five false data</td>
<td>P_{47}</td>
<td>0.38326</td>
<td>0.48326</td>
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<td></td>
<td></td>
<td></td>
<td>Q_{611}</td>
<td>-0.22967</td>
<td>-0.12967</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P_{10}</td>
<td>-0.106</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

\[ \text{RMSE} = \left[ \frac{1}{N} \sum_{i=1}^{N} (X_i(\text{exp}) - X_i(\text{pred}))^2 \right]^{0.5} \] (20)

\[ \text{MRE\%} = 100 \times \frac{1}{N} \sum_{i=1}^{N} \frac{|X_i(\text{exp}) - X_i(\text{pred})|}{X_i(\text{exp})} \] (21)

where \( N \) is the number of data, \( X_i(\text{exp}) \) and \( X_i(\text{pred}) \) show the experimental/real and predicted values, respectively. Moreover, \( N \) is equal to bus number for all error indices except for phase angles in MRE, because the phase angle of the slack bus is always zero and should be removed to get a better result.

6 Test System

In this paper, the proposed state estimator is implemented on the IEEE 14-bus and IEEE 30-bus test systems. It is worth mentioning that all input data are taken from IEEE standards [7]. In addition, the specifications of ANN and ANFIS are listed in Tables 1 and 2, respectively. To train the ANFIS and ANN, ten
7.1 Analyzing performance without false data

In this scenario, capability of ANFIS for SE is investigated and compared with ANN and WLS. It should be noted that false data is not considered in this section. The final results for IEEE 14-bus and 30-bus system are illustrated in Figs. 3 and 4, respectively. As seen in Fig. 3, it is clear that ANFIS estimates state variables with more accuracy and less error than WLS and ANN methods. In fact, the estimated voltage magnitude by ANFIS is equal or near to real data. In return, the estimated data by ANN and WLS in several buses are far from real data such as buses 2 and 5. Such errors in estimation make the operator select a wrong decision. Moreover, it is obvious that the same operation has occurred for phase angle. According to Fig. 4, increasing the number of data points or state variables cannot influence the operation of ANFIS. However, the operation of ANN and WLS is still far from ANFIS.

7.2 Impact of single false data

As proposed in Table 3, this scenario consists of a single false data in the measurement sets for both test systems. The false data for IEEE 14-bus and 30-bus system is active power flow in line 2-3 that is changed from 0.81465 p.u to -0.81465 p.u and from 0.88038 p.u to -0.88038 p.u, respectively. Such false data injection maybe occurred by non-legitimate agents or even human mistakes. In this regard, Figs. 5 and 6 show the state estimation results and Table 4 exhibits the corrected false data by each method. The estimated values of active power flow through line 2-3 are 0.4137, 0.6966, and 0.8172 p.u by WLS, ANN and ANFIS for IEEE 14-bus, respectively. Moreover, the results for IEEE 30-bus are equal to 0.710085 p.u, 0.7587 p.u and 0.8799 p.u for WLS, ANN and ANFIS, respectively. Furthermore, according to Figs. 5 and 6, the operation of ANFIS in the presence of false data is still reliable and accurate. In return, the operation of ANN is far from real data but more precise than WLS in most buses.
7.3 Impact of Multi-False Data

To validate the robustness of method, this scenario considers five false data in the measurement sets as specified in Table 3. The false data includes injected active-reactive power and power flow between buses. Hence, a critical condition is occurred in this section due to the presence of different false data injection. Figs. 7 and 8 show the state estimation results and Table 5 proposes the corrected false data by each method. As seen in Table 5, the performance of ANFIS is much better than other methods. Moreover, one important point in this scenario is the low accuracy of WLS in the presence of multi-false data. Indeed, the accuracy and robustness of WLS decrease if the number of false data increases. However, the ANN is more capable than WLS but it is not reliable compared to ANFIS. The mentioned points are observable in the Figs. 7 and 8 clearly.

7.4 Evaluating Performance by Error Indices

In this section, three error indices including MAE, RMSE, and MRE% are used to investigate the accuracy of each algorithm and validate the previous results. As seen in Tables 6 and 7, all error indices are calculated for voltage magnitude and angle in IEEE 14-bus and 30-bus. It is worth mentioning the angle of the slack bus is not considered in MRE% due to the zero value and causing an infinite amount. According to the results, it is clear that the proposed ANFIS method provides less error and estimates the variable as accurately as possible. In fact, all error indices validate that the robustness and accuracy of ANFIS are more than ANN and WLS. Moreover, it is obvious that the operation of WLS will be troubled if the number of false data increases. In return, ANN has a rather stable operation in all scenarios but the accuracy is much less than ANFIS.

Table 4 False data correction in the second scenario.

<table>
<thead>
<tr>
<th>Test system</th>
<th>Variable [p.u]</th>
<th>Actual data</th>
<th>False data</th>
<th>WLS</th>
<th>ANN</th>
<th>ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE 14-bus</td>
<td>P_{2-3}</td>
<td>0.81465</td>
<td>-0.81465</td>
<td>0.4137</td>
<td>0.6966</td>
<td>0.8172</td>
</tr>
<tr>
<td></td>
<td>P_{3-4}</td>
<td>0.88038</td>
<td>-0.88038</td>
<td>0.710085</td>
<td>0.7587</td>
<td>0.8799</td>
</tr>
</tbody>
</table>

Table 5 False data correction in the third scenario.

<table>
<thead>
<tr>
<th>Test system</th>
<th>Variable [p.u]</th>
<th>Actual data</th>
<th>False data</th>
<th>WLS</th>
<th>ANN</th>
<th>ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE 14-bus</td>
<td>P_{11}</td>
<td>0.035</td>
<td>-0.015</td>
<td>-0.026</td>
<td>-0.029</td>
<td>-0.035</td>
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<tr>
<td></td>
<td>Q_{12}</td>
<td>-0.015</td>
<td>-0.008</td>
<td>-0.0091</td>
<td>-0.011</td>
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<td>P_{4-5}</td>
<td>-0.31574</td>
<td>-0.15</td>
<td>-0.2605</td>
<td>-0.3018</td>
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<td>P_{5-9}</td>
<td>0.28298</td>
<td>0.14</td>
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<td>Q_{7-8}</td>
<td>-0.24856</td>
<td>-0.12</td>
<td>-0.1950</td>
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<tr>
<td>IEEE 30-bus</td>
<td>Q_{22}</td>
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<td>P_{34}</td>
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<td>P_{47}</td>
<td>0.38326</td>
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<td>Q_{9-11}</td>
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<td></td>
<td>P_{10}</td>
<td>-0.106</td>
<td>-0.09</td>
<td>-0.201892</td>
<td>-0.0986</td>
<td>-0.105</td>
</tr>
</tbody>
</table>

Fig. 7 Comparing voltage magnitude and angle for IEEE 14-bus test system in the third scenario.

Fig. 8 Comparing voltage magnitude and angle for IEEE 30-bus test system in the third scenario.
multi-false data. Moreover, three error indices consisting of MAE, RMSE, and MRE% are used to validate the accuracy of results. Based on the obtained results from the mentioned scenarios on IEEE 14-bus and 30-bus test systems, it is demonstrated that the ANFIS estimator significantly robust and more accurate than the other methods even in the presence of multi-false data injection. Moreover, if false data is not considered, WLS has a better estimation than ANN. In return, the estimation by WLS will be troubled if the number of false data increases. Hence, the ANN has a rather stable operation and more accurate compared to WLS if false data is considered. Eventually, according to the calculated error indices, ANFIS is more accurate and reliable than ANN and WLS.

References


State Estimation in Electric Power Systems Based on Adaptive … M. Ahmadi Jirdehi and V. Sohrabi Tabar


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