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Research Paper

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

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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].

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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].

$$Z = h(X) + e \tag{1}$$

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.

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

The diagonal covariance matrix is defined by (2) in which the σ_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).

$$J(X) = \left[Z - h(X)\right]^T R^{-1}\left[Z - h(X)\right] \tag{3}$$

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

$$\frac{dJ(X)}{dX} = H^T R^{-1}\left[Z - h(X)\right] = 0 \tag{4}$$

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

$$\begin{cases} G\left(X^k\right) \times \Delta X^k = H^T R^{-1}\left[Z - h\left(X^k\right)\right] \\ X^{k+1} = X^k + \Delta X^k \end{cases} \tag{5}$$

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).

$$\rho_d = a_d + \sum_{k=1}^{i}\left(X_k \times W_{kd}\right) \qquad d = 1, 2, ..., n \tag{6}$$

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).

$$\theta_d = f\left(\rho_d\right) \tag{7}$$

$$Y_c = b_c + \sum_{k=1}^{i}\left(\theta_k \times W_{kc}\right) \qquad c = 1, 2, ..., m \tag{8}$$

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

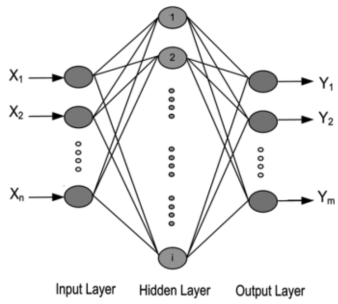

Fig. 1 MLP structure including input, hidden, and output layers.

system includes two inputs (x, y) and one output (f). In such a structure, two fuzzy rules based on the first-order Sugeno are utilized by (9) and (10).

For x equal to A_1 and y equal to B_1, then
$$f_1 = p_1 x + q_1 y + r_1 \tag{9}$$
For x equal to A_2 and y equal to B_2, then
$$f_2 = p_2 x + q_2 y + r_2 \tag{10}$$

The ANFIS structure for the mentioned description is exhibited in Fig. 2 and the structure of layers are explained as follows:

Each node in the first layer produces grades of membership for input variable through node functions as shown by (11) and (12).

$$O_{1,i} = \mu_{Ai}\left(x\right) \qquad i = 1,2 \tag{11}$$
$$O_{1,i} = \mu_{Bi-2}\left(x\right) \qquad i = 3,4 \tag{12}$$

where, i and $O_{1,i}$ are the membership grade of a fuzzy set and output of node i. All input signals are multiplied in the second layer as (13).

$$O_{2,i} = w_i = \mu_{Ai}\left(x\right) \times \mu_{Bi}\left(x\right) \quad i = 1,2 \tag{13}$$

In the third layer, the nodes calculate the ratio of the i^{th} rule's firing strength by (14).

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{14}$$

All of the fourth layer nodes are adaptive with an output node as (15). The normalized firing strength and consequent parameters are defined by $\bar{w}_i$ and p_i, q_i, and r_i.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i\right) \quad i = 1,2 \tag{15}$$

Each node in the fifth layer determines the overall output as stated by (16).

$$O_{5,i} = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{16}$$

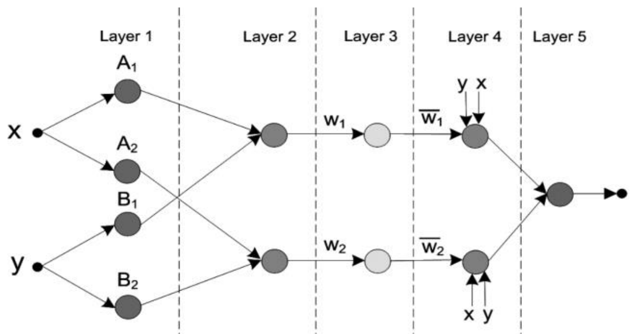

Fig. 2 ANFIS structure for two inputs and one output.

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).

$$S(X) = PDF(X, dv) \tag{17}$$
$$E(X) = \sum_{dv=1}^{dv_n} \left[\sum_{g=1}^{g_n} S(X) \times prob(g) \right] \times prob(k) \tag{18}$$

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.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left| X_i(\exp) - X_i(pred) \right| \tag{19}$$

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

$$\mathrm{MRE}\%=100\times\frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i(\exp)-X_i(pred)}{X_i(\exp)}\right| \tag{21}$$

where N is the number of data, $X_i(exp)$ and $X_i(pred)$ 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 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 1 Specification of the ANN model.

Specification	ANN
Neural network	MLP
Number of hidden layer	2
Number of neurons in the first hidden layer	6
Number of neurons in the second hidden layer	4
Number of neurons in the output layer	4
Learning rate	0.5
Number of epochs	250
Adaption learning function	Trainlm
Activation function	Tansig

Table 2 Specification of the ANFIS model.

Specification	IEEE-14 bus	IEEE-30 bus
Type	Sugeno	Sugeno
Inputs/outputs	47/1	225/1
No. of membership functions for each input	7	15
No. of output membership functions	7	15
Membership function type	Sub.clustring	Sub.clustring
Range of influence	0.001	0.001
Squash factor	1.25	1.25
Accept ratio	0.5	0.5
Reject ratio	0.15	0.15
Optimal method	Hybrid	Hybrid
No. of nodes	722	1254
No. of linear parameters	336	632
No of nonlinear parameters	658	1124
Total number of parameters	994	1756
No. of training data pairs	7	15
No. of fuzzy rules	7	15
No. of epochs	250	250

Table 3 List of scenarios for analyzing the performance of the method.

Test system	Scenario	Scenario explanation	Variable	Actual data	False data
IEEE 14-bus	1	Without false data	-	-	-
	2	Single false data	$P_{2\text{-}3}$	0.81465	-0.81465
	3	Five false data	P_{11}	-0.035	-0.015
			Q_{12}	-0.016	-0.008
			$P_{3\text{-}4}$	-0.31574	-0.15
			$P_{7\text{-}9}$	0.28298	0.14
			$Q_{7\text{-}8}$	-0.24856	-0.12
IEEE 30-bus	2	Single false data	$P_{2\text{-}3}$	0.88038	-0.88038
	3	Five false data	Q_{21}	-0.112	0.112
			$P_{3\text{-}4}$	0.82517	0.62517
			$P_{6\text{-}7}$	0.38326	0.48326
			$Q_{9\text{-}11}$	-0.22967	-0.12967
			P_{30}	-0.106	-0.09

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.

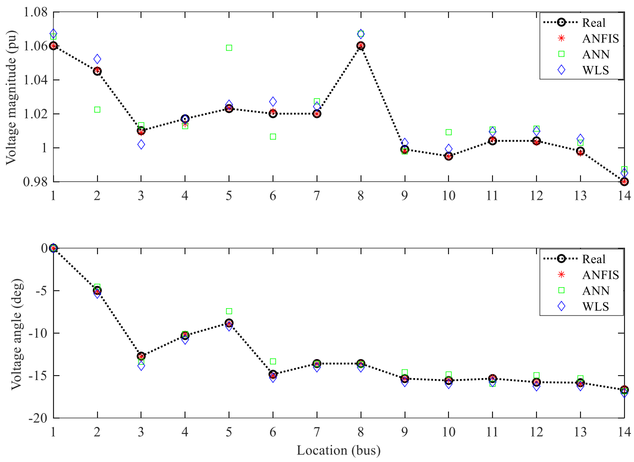

Fig. 3 Comparing voltage magnitude and angle for IEEE 14-bus test system in the first scenario.

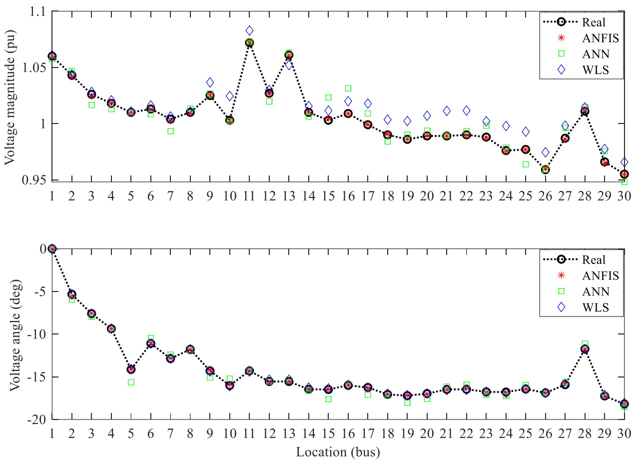

Fig. 4 Comparing voltage magnitude and angle for IEEE 30-bus test system in first scenario.

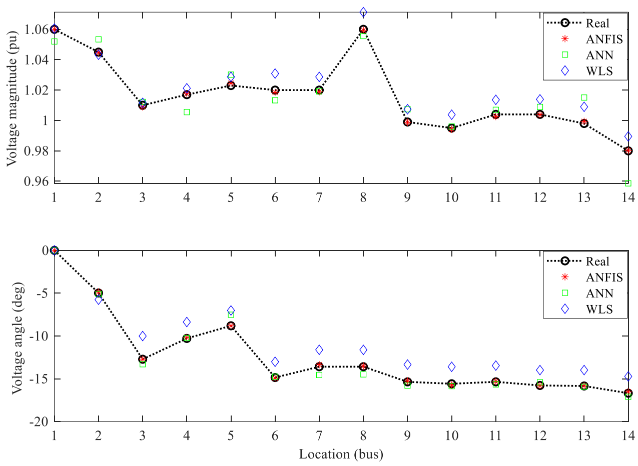

Fig. 5 Comparing voltage magnitude and angle for IEEE 14-bus test system in the second scenario.

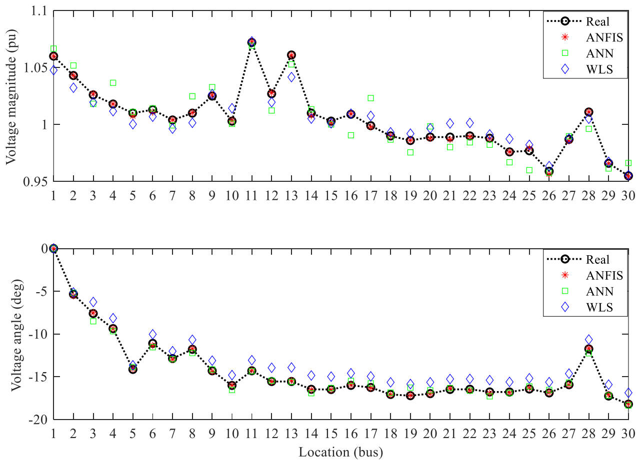

Fig. 6 Comparing voltage magnitude and angle for IEEE 30-bus test system in the second scenario.

Table 4 False data correction in the second scenario.

Test system	Variable [p.u]	Actual data	False data	WLS	ANN	ANFIS
IEEE 14-bus	P_{2-3}	0.81465	-0.81465	0.4137	0.6966	0.8172
IEEE 30-bus	P_{2-3}	0.88038	-0.88038	0.710085	0.7587	0.8799

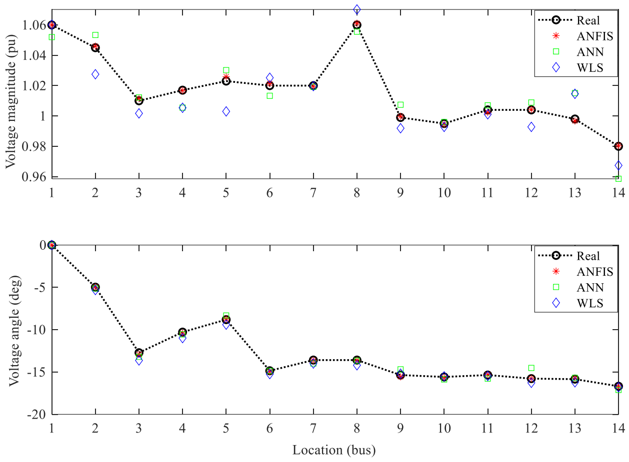

Fig. 7 Comparing voltage magnitude and angle for IEEE 14-bus test system in the third scenario.

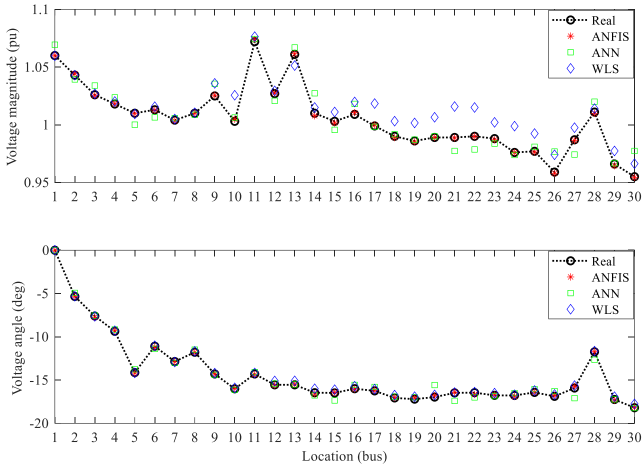

Fig. 8 Comparing voltage magnitude and angle for IEEE 30-bus test system in the third scenario.

Table 5 False data correction in the third scenario.

Test system	Variable [p.u]	Actual data	False data	WLS	ANN	ANFIS
IEEE 14-bus	P_{11}	-0.035	-0.015	-0.026	-0.029	-0.035
	Q_{12}	-0.016	-0.008	-0.0091	-0.011	-0.016
	P_{3-4}	-0.31574	-0.15	-0.2605	-0.3018	-0.3128
	P_{7-9}	0.28298	0.14	0.1948	0.2761	0.2829
	Q_{7-8}	-0.24856	-0.12	-0.1950	-0.2350	-0.2505
IEEE 30-bus	Q_{21}	-0.112	0.112	-0.099643	-0.0998	-0.109
	P_{3-4}	0.82517	0.62517	-0.015333	0.6971	0.8118
	P_{6-7}	0.38326	0.48326	0.774576	0.37525	0.3812
	Q_{9-11}	-0.22967	-0.12967	0.410323	-0.2301	-0.2189
	P_{30}	-0.106	-0.09	-0.201892	-0.0986	-0.105

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.

8 Conclusion

This paper proposes a new state estimator based on a neuro-fuzzy system considering load uncertainty and false data injection. To show the capability of the presented procedure, three different scenarios are defined including no false data, single false data and

Table 6 Error indices for voltage magnitude and angle of IEEE 14-bus in all scenarios.

Variable	Scenario	WLS			ANN			ANFIS		
		MAE	RMSE	MRE%	MAE	RMSE	MRE%	MAE	RMSE	MRE%
Voltage magnitude [p.u]	1	0.0088	0.0095	0.8769	0.0454	0.0518	4.4681	0.00265	0.00287	0.26333
	2	0.0109	0.01281	1.0951	0.0038	0.0084	0.3877	0.00135	0.00244	0.13477
	3	0.00742	0.0089	0.7360	0.0017	0.0042	0.6958	0.00135	0.00244	0.13477
Voltage angle [rad]	1	0.00342	0.0037	1.5028	0.00201	0.00216	0.9267	0.0005	0.0008	0.1946
	2	0.04019	0.0434	1.76228	0.00364	0.00380	0.9733	0.0012	0.0013	0.6457
	3	0.00504	0.0067	2.0767	0.0039	0.00186	1.6777	0.0012	0.0013	0.6457

Table 7 Error indices for voltage magnitude and angle of IEEE 30-bus in all scenarios.

Variable	Scenario	WLS			ANN			ANFIS		
		MAE	RMSE	MRE%	MAE	RMSE	MRE%	MAE	RMSE	MRE%
Voltage magnitude [p.u]	1	0.0079	0.0085	0.9112	0.0087	0.0096	0.9321	0.00261	0.00277	0.26433
	2	0.0432	0.0628	1.0951	0.0322	0.0518	1.07	0.00155	0.00274	0.14477
	3	0.00623	0.0073	0.8152	0.0043	0.0061	0.7515	0.00155	0.00274	0.14477
Voltage angle [rad]	1	0.00431	0.0042	1.7238	0.00211	0.0039	1.6238	0.0006	0.0009	0.1965
	2	0.06809	0.0694	1.9812	0.055	0.0564	1.7519	0.0013	0.0015	0.7342
	3	0.00714	0.0082	2.1577	0.0059	0.0063	1.9233	0.0013	0.0015	0.7342

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.

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