AUT Journal of Electrical Engineering

AUT J. Elec. Eng., 55(3) (Special Issue) (2023) 351-364
DOI: 10.22060/eej.2023.22232.5525

Power System State Estimation through Optimal PMU Placement and Neural Network using Whale Algorithm

S. H. Roudaki, M. Abedi*, I. Pourkeivani

Amirkabir University of Technology, Tehran, Iran

ABSTRACT: The efficient operation and planning along with the security of power systems have always occupied an important position. The power system becomes increasingly complex due to the rapid growth in energy demand. Such a system requires a real-time approach to monitoring and control. Therefore, State Estimation (SE) tools are necessary, especially for nonlinear power grids. Most network applications use the real-time data provided by the state estimator. Therefore, an optimal performance of state estimation output is the ultimate concern for the system operator. This need is particularly more in focus today due to deregulated and congested systems and smart grid initiatives. The output of the state estimator nearly represents the true state of the system. The present paper describes the general framework of state estimation in power networks. Also, in the present study linear state estimation method accompanied by optimal placement for Phasor Measurement Unit (PMU) for complete observability and artificial neural network (ANN) trained by Whale Optimization Algorithm (WOA) is employed. The trained model can be used to estimate voltage magnitudes and phase angles as the power system states. The proposed method increases accuracy and execution speed while the complication in the formulation will be reduced considerably. A seasonal load profile is considered to measure the accuracy of the state estimation and make the simulation more realistic. Finally, the minimum estimation error will be shown for IEEE 14 and 30 buses benchmarks.

Review History:

Received: Mar. 04, 2023
Revised: Jun. 10, 2023
Accepted: Jul. 23, 2023
Available Online: Dec. 01, 2023

Keywords:

Whale optimization algorithm
power system state estimation
optimal placement of phasor measuring unit
artificial neural network

1- Introduction

The power grid has developed over time and around the world it has become a complex system that combines conventional and renewable energy sources, various consumers, and an extensive transmission system. A failure in such a system can lead to severe consequences. Therefore, some errors should be predicted and prevented from occurring. Therefore, the ability to monitor such a complex system is an essential prerequisite for the stable and reliable operation of today's network.

When the issue of grid stability is addressed, one of the most critical issues is determining the states of the power system (State Variables) at any point of the grid and at a given moment. State variables include voltage magnitudes and relative phase angles of system buses. State estimation in a system is the determination of the unknown state variables of the system, which is based on the necessary measurements and according to specific criteria. Of course, it must be acknowledged that some measurements are incomplete and redundant.

State estimation is based on statistical criteria in which absolute values for state variables are estimated by minimizing or maximizing specific criteria. Then the estimated output data are used in the system control centers or the dispatching center with security restrictions. The best estimate helps to maintain power system monitoring, security, reliability, and proper control of the system [1].

The common acceptance criterion in this matter is to minimize the Sum of the Square of Differences between the estimated and measured values. The idea of state estimation by the least square method was proposed in the 19th century in aerospace applications [2]. Later, Static State Estimator and Dynamic State Estimator were developed for power systems. The initial state estimation algorithms used the measurement of the power flow in the lines to calculate the best estimate of the system state [3]. However, they cannot measure the state of the system directly.

Although the concept of using phasors to describe power system operational quantities was introduced in 1893, the first application of phasor measurement units was presented in the early 1980s by Dr. A.G. Phadke. The first commercially available PMUs were developed in the early 1990s [3].

The PMU prototype used Global Positioning System (GPS) technology to achieve time synchronization between remote measurements. Implementing such equipment not only provided the possibility of direct measurement of system state variables but also provided the possibility of

*Corresponding author's email: abedi@aut.ac.ir

re-evolution of the state estimation method. Using PMU, the repetitive and time-consuming process of state estimation can be replaced with a set of linear equations, reducing the number of calculations and increasing the refresh rate. The continuous development and integration of PMU technology worldwide can give system operators a better picture of the grid and improve the quality of power grid monitoring.

Therefore, power systems require a comprehensive and accurate monitoring system to guarantee observability of the power system. However, additional measurements cause problems in control, management, and cost. The problem of optimal placement of phasor measurement units (Optimal PMU Placement) is said to minimize the number and choose the best place to install them in a power system and, at the same time to maintain complete visibility of the system. This article introduces how to analyze the observability of the power system based on PMUs and examines the problem of optimal PMU placement.

Nowadays, with the help of a state estimator based on an artificial neural network, given the measurements as input, we get direct estimates of state variables. Therefore, there is no need to store the complex admittance matrix of the network and include the learning data according to the load changes and different states of the network to obtain better and faster results than the linear state estimator used in load distribution centers as well as smart networks.

Finally, in this research, an online PMU-based state estimation method in the observable state of the system using Multi-Layer Perceptron Neural Networks trained using the Whale Optimization Algorithm to reduce errors and increase speed and accuracy is suggested. This paper is organized as follows. Section 2, formulation of the problem such as linear state estimation, optimal PMU placement, and WOA-MLP optimized for SE are discussed; Section 3, results of simulation for two test systems have been analyzed, while the conclusion presented in Section 4.

2- Formulation of the Problem

2- 1- Linear State Estimation using PMU

Conventional measurements are generally asynchronous. Also, these meters, also called SCADA meters, have a slow sampling rate (typically 4-5 seconds), and due to the asynchronous nature of the measurements, it isn't easy to obtain a broad, real-time view of the power system [4]. Currently, most measurements in power systems are conventional asynchronous measurements. Although phasor measurement units are increasingly installed in different parts of the world, a measurement system with only PMUs is not yet possible due to economic and technical reasons. The state estimation problem becomes a nonlinear estimation problem only in the presence of conventional measurements or a combination of conventional measurements and PMU [5,6]. Typically, estimators based on the weighted least square method (WLS) are used to find the optimal states of the system based on such a set of measurements. However, processing the measurements in a time window and performing the state estimation process with several iterations takes considerable time (3-5 minutes). Therefore, this method is not suitable for real-time decision-making.

With the ability of PMUs to directly measure system state, using phasor measurements for state estimation increases the speed and accuracy of the process. Unlike the classical state estimation method that deals with the iterative solution of nonlinear equations, PMU measurements are linear functions of the state variables. Therefore, the calculation process can be significantly simplified.

The linear estimator can be described as an efficient tool that uses only PMU measurements to estimate system states. The measurements are formulated as equation (1):

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

Where z is the vector of measurements, $h(x)$ is the vector of nonlinear functions (relationship between measurement and state vector x), and ε is the measurement error vector. The objective function to be minimized, according to equation (2), is:

$$J(x) = \sum_{i=1}^{m} \frac{(z_i - h_i(x))^2}{R_{ii}} \tag{2}$$

Or in matrix form in equation (3):

$$J(x) = [z - h(x)]^T R^{-1} [z - h(x)] \tag{3}$$

The only difference is that the measurement functions $h(x)$ are linear. Therefore, equation (1) can be expressed as equation (4):

$$z = h(x) + \varepsilon = Bx + \varepsilon \tag{4}$$

Where B is the system matrix.

Therefore, the state vector x can be calculated by having the equation (5):

$$x = [B^T R^{-1} B]^{-1} B^T R^{-1} z = Mz \tag{5}$$

Where R , according to equation (6), is the diagonal covariance matrix related to the errors of the measuring devices.

$$R = \begin{bmatrix} \delta_1^2 & & \\ & \ddots & \\ & & \delta_m^2 \end{bmatrix} \tag{6}$$

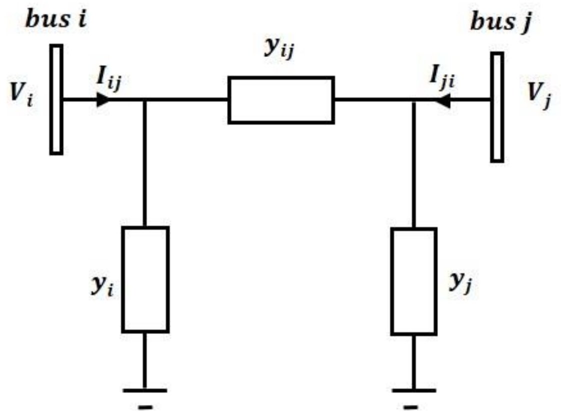

Fig. 1. π equivalent circuit of a transmission line

Where m is the total number of measurements.

The matrix M is constant as long as the structure and parameters of the system do not change. It can be calculated offline once and stored for use at another time.

To implement state estimation in a network, the π equivalent circuit of a transmission line is shown in Figure (1).

According to Figure 1, V_i and V_j are the measured complex voltages in bus i and j, respectively. Current flows from bus i to bus j and vice versa are I_{ij} and I_{ji}, respectively. Assuming the state vector according to equation (7), we have:

$$x = \begin{bmatrix} V_i \\ V_j \end{bmatrix} \tag{7}$$

equation (8) is the measurement vector:

$$z = \begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} \tag{8}$$

Then equation (4) is expressed as equation (9) [3]:

$$\begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ y_{ij} + y_i & -y_{ij} \\ -y_{ij} & y_{ij} + y_i \end{bmatrix} \begin{bmatrix} V_i \\ V_j \end{bmatrix} \tag{9}$$

$$B = \begin{bmatrix} II \\ yA + y_s \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ y_{ij} + y_i & -y_{ij} \\ -y_{ij} & y_{ij} + y_i \end{bmatrix} \tag{10}$$

In equation (10), we have:

y is the branch series admittance diagonal matrix, A is the junction matrix of the measuring currents unit, and y_s is the parallel admittance matrix, whose rows and columns refer to the meters and buses, respectively.

Finally, the measurement function is expressed according to equation (11):

$$\begin{bmatrix} V_{PMU} \\ I_{PMU} \end{bmatrix} = \begin{bmatrix} II \\ yA + y_s \end{bmatrix} V \tag{11}$$

Where V_{PMU} and I_{PMU} are the vectors of the measured complex voltages and currents, and V is the state vector of the system's complex voltages.

2- 2- Formulation of Optimal PMU Placement

The observability analysis of the power system is performed before performing the state estimation. If a system is determined to be unobservable, additional gauges must be placed in specific locations to make the system visible. System observability analysis identifies visible islands and unobservable bifurcations, and gauges placement locations to make informed decisions.

Placing PMUs on all buses of a power system measures the system states directly, so state estimation is no longer needed. However, such a solution can be pretty expensive.

On the other hand, the measurement of line currents can

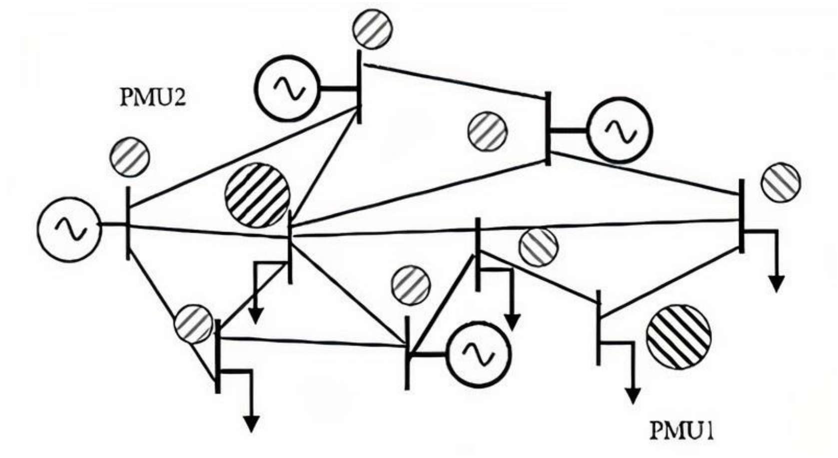

Fig. 2. An example of a complete observable 9-bus system [3]

extend the voltage measurement to buses where the PMU is not installed. Therefore, a minimum number of PMUs can be installed to measure all bus voltages in the system indirectly. Finding this number of PMUs and their location in the network has brought optimization algorithms to this topic. An overview of the methods to solve this problem is discussed in [7].

As mentioned above, a PMU can indirectly view the lines connected to the installed bus and all the buses connected to the lines. Figure 2 describes a system that is fully observed by two PMUs marked with large circles. Smaller circles indicate buses that are indirectly visible by the line connected to the bus having the PMU [3].

The placement problem for complete power system observability starts with finding a minimal set of PMUs such that each bus is observed at least once by a PMU [8]. The formulation of the optimal placement problem for the N-bus system is described by equations (12) to (14):

$$\begin{cases} \min & \sum_{k=1}^{N} x_k \\ subject\ to & T_{PMU} X \geq b_{PMU} \\ X = [x_1 \quad \ldots \quad x_N]^T & \\ x_i \epsilon \{0,1\} & \end{cases} \tag{12}$$

$$T_{PMU\,i.j} = \begin{cases} 1, if\ i = j \\ 1, if\ i\ and\ j\ are\ connected \\ 0, o.w. \end{cases} \tag{13}$$

$$b_{PMU} = [\,1 \quad \ldots \quad 1]_{1\times N}^{T} \tag{14}$$

By using optimization algorithms, the topological observability of the network can be fully assured. Moreover, some optimization methods do not guarantee that they can always find the optimal solution for OPP problems. The reasons that lead to incorrect results are also different. Some algorithms may get stuck in local minima and thus not reach the global optimal solution. In this research, Integer Linear Programming (ILP) implemented in MATLAB software using the CPLEX toolbox is used for the optimal placement of PMU.

2- 3- Artificial Neural Network

An artificial neural network is an information processing system that tries to imitate the characteristics of the human nervous system and create a computer model through which patterns in data can be found, and correlations between variables can be obtained. Practically, the neural network is used in state estimation due to its high efficiency in signal processing and fast and accurate prediction of the output. A neural network model often consists of two layers (the first layer for input data and another layer for output results) or multiple layers. There are many algorithms for training neural networks. One of the common methods is the Back Propagation (BP) learning method, which can model nonlinear data if the network structure is chosen correctly. Figure 3 shows a neural network with one neuron.

The connecting lines w and b represent weights and biases. The output of a neuron can be expressed as equation (15):

$$y_{pred} = \sum_{i=1}^{n} x_i w_i + b \tag{15}$$

In which the sum of inputs x_i is multiplied by the weights

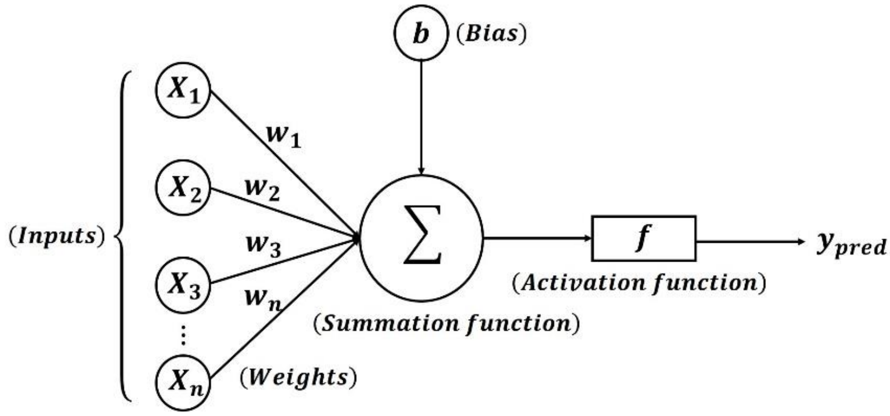

Fig. 3. Neural network architecture

w_i and finally added to the bias b [9]. In BP learning using equation (16), the weights are updated in each iteration until the errors reach a level equal to or less than the specified minimum value.

$$w_{new} = w_{old} + \alpha(y_{actual} - y_{meaured}) \tag{16}$$

where α is the learning rate which is set to a small value. Reducing the amount of network error and achieving a network with minimum error is the goal of a training process that is achieved by an optimization algorithm and by adjusting the weights and biases of the network.

The error backpropagation algorithm may converge to local minimum points in the parameter space. However, when this algorithm converges, it cannot be sure that it has reached an optimal solution. Therefore, for better learning performance, the best output can be predicted by optimizing the weights and biases of the neural network.

2- 3- 1- Optimization of Neural Network using Whale Algorithm

The whale meta-heuristic algorithm was proposed as one of the newest population-based optimization algorithms in 2016 by Mirjalili and Lewis [10]. Inspired by the nature and social behavior of whales, this algorithm uses the bubble network hunting strategy for exploration and exploitation. By avoiding local optimal points, it can achieve the optimal solution with less computational time wasted with an integrated adaptive technique. The most exciting thing about hunting whales is their unique method of hunting prey, which is known as a bubble net. In the bubble net method, the whales circle around a group of fish and produce distinctive bubbles that trap the fish and cause the fish to escape to the sea's surface. Then they approach the fishe and hunt them.

Bait encirclement is the first stage of prey hunting in the best situation. Whales look at prey for the correct position and choose their positions based on an optimal solution for hunting fish. This solution can be expressed by equations (17) and (18):

$$\vec{D} = \left|\vec{C}\vec{X}^*(t) - \vec{X}^*(t)\right| \tag{17}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \times \vec{D} \tag{18}$$

Where $\vec{X}$ and $\vec{X}^*$ are two position vectors and $\vec{X}^*$ represents the optimal solution obtained at each moment and t represents the current iteration. In addition, $\vec{A}$ and $\vec{D}$ are coefficient vectors defined by equations (19) and (20):

$$\vec{A} = 2\vec{a} \times \vec{r} - \vec{a} \tag{19}$$

$$\vec{C} = 2\vec{r} \tag{20}$$

Where a is a linear decreasing variable and r is a vector containing random values between 0 and 1.

In the next step, the whales attack the prey, and in this phase, the encirclement of the prey becomes smaller, and based on this mechanism, $\vec{a}$ and $\vec{A}$ in the previous two relationships are reduced. The vector $\vec{A}$ contains random values in the interval $[-a, a]$ and decreases from the value of 2 to 0. The new position can be obtained using the optimal and current positions. Next, the spiral position is updated.

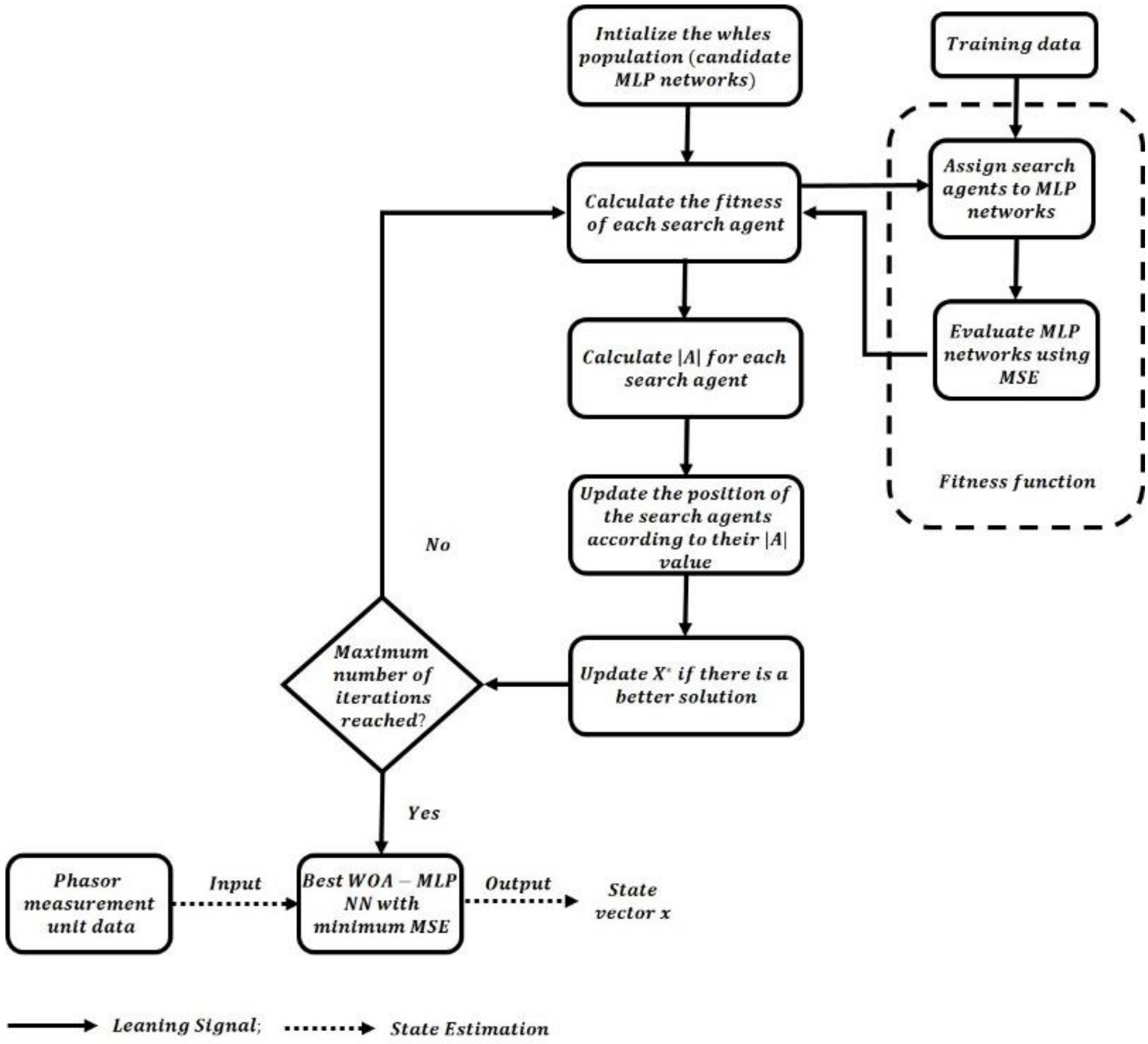

Fig. 4. Steps of learning and state estimation in the proposed algorithm

In the process of multi-layer perceptron neural network training by the Whale algorithm, tried to adjust the weights in each iteration of the learning algorithm so that the approximation error is minimized. Accordingly, first, the population of the algorithm is randomly initialized, and the error rate is calculated using the training data.

Next, the constants of the model or the regulatory characteristics affecting the mapping of the input data are updated, and this process continues until the termination conditions are reached, or the minimum allowable error is obtained. Therefore, it is necessary to determine appropriate values for these parameters based on the complexity and dimensions of the problem so that the algorithm finds the optimal answer to the problem efficiently. The general steps of the WOA-MLP and SE approach are depicted in Figure 4.

3- Simulation Results

All the implementation steps and conclusions in this section have been done using a system with the specifications of Intel® Xeon® Silver 4214 CPU@2.2GHz, 16GB RAM.

To analyze the data with the help of an artificial neural network first, the data obtained from the linear state estimation with PMU by changing the local load in each bus, taking into account the characteristics of the summer seasonal load, was done hypothetically for a period of 24 hours with two peaks, day and night. Here, a conventionally distributed swing with standard mean power of IEEE network loads in 14 and 30 bus systems (Figures 5 and 6) and with standard deviation is shown in Figures 7 and 8, respectively.

The power factor and reactive power of the system load are assumed to be constant during the simulation.

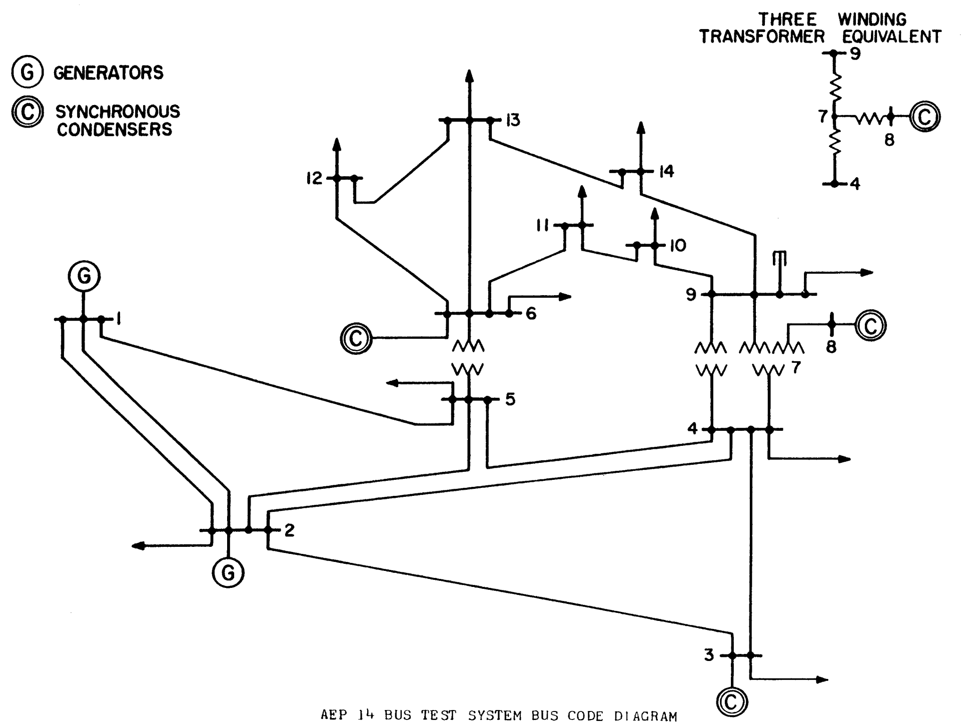

Fig. 5.IEEE 14-bus system topology

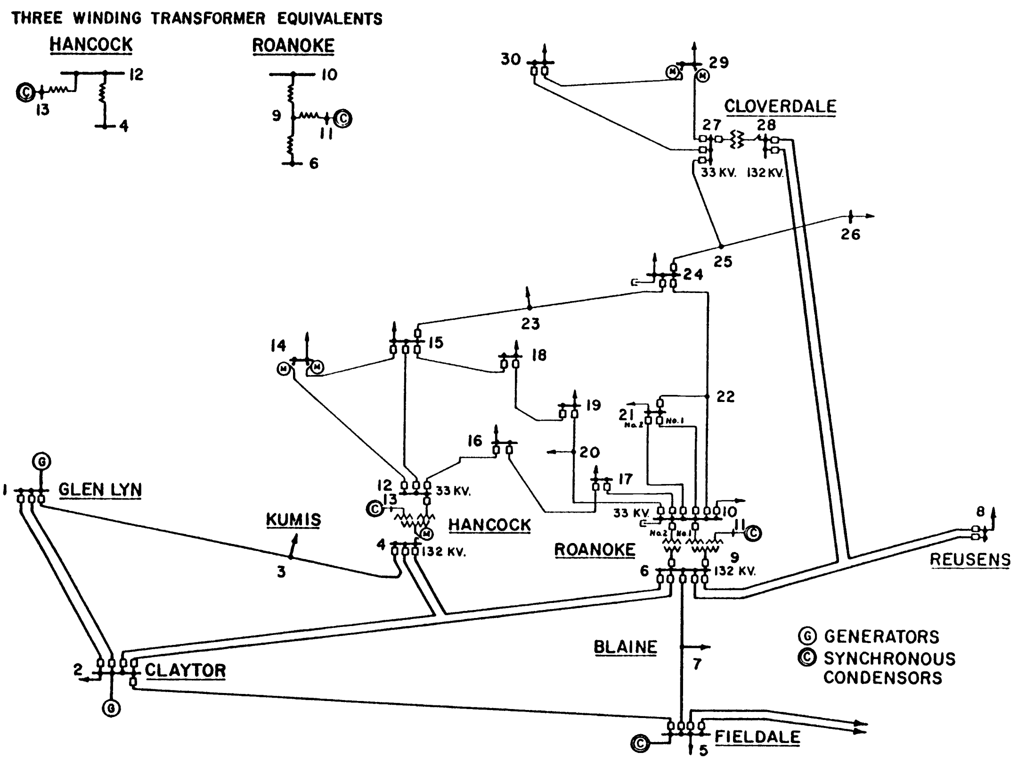

Fig. 6. IEEE 30-bus system topology

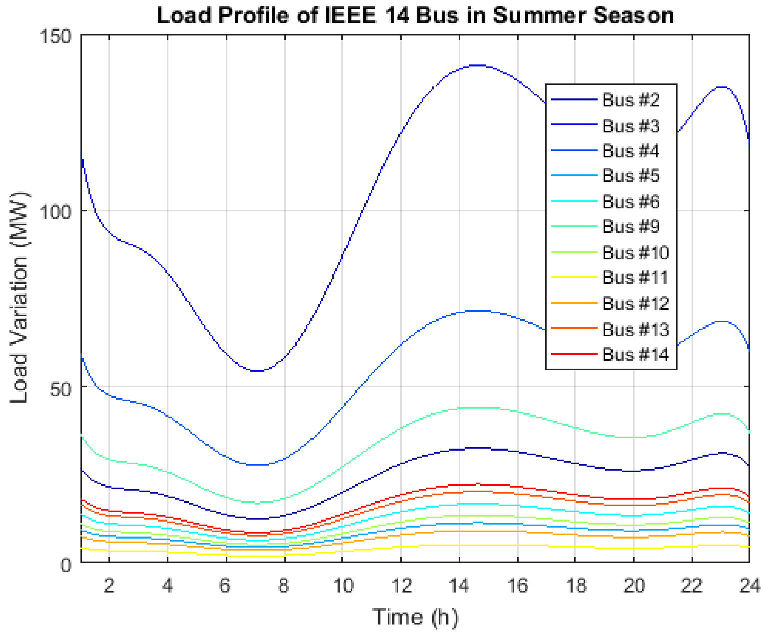

Fig. 7. IEEE 14-bus system summer load profile

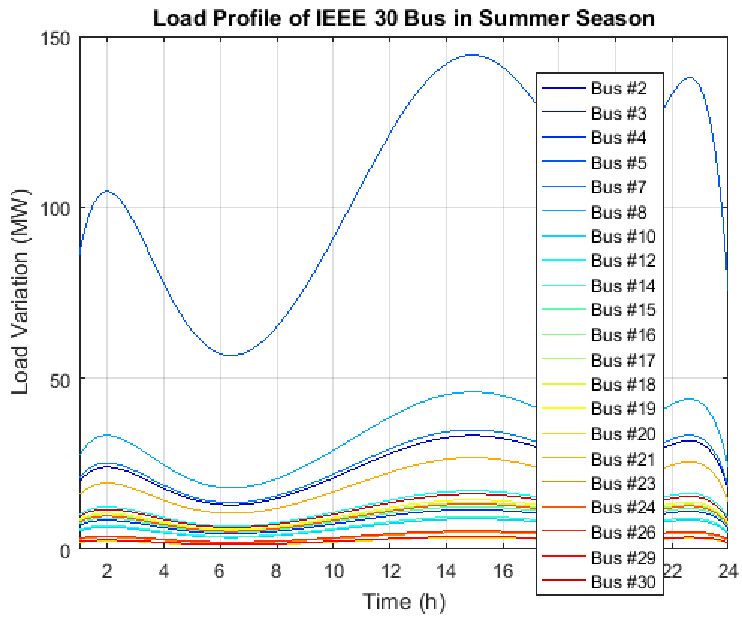

Fig. 8. IEEE 30-bus system summer load profile

The data obtained from Linear-SE includes the PMU measurements as input and the resulting state estimates as the output of the neural network. State estimation has been done 24 hours a day with time intervals every 10 minutes in different network loads according to Figures 7 and 8, and the Gaussian noise resulting from the measurement has been assumed with a tolerance of 15%. In addition, the optimal placement of PMUs in the state of complete visibility of the power system is shown in Table 1.

The data obtained from the simulation includes 83100 samples, 80% of which are for the training samples and 20% of which are randomly divided for the test samples. The population size is 100. Then feature selection was made by the Whale optimization algorithm (WOA) using two mathematical models of encirclement and bubble net attack.

According to data classification by the WOA algorithm

Table 1. Optimal PMU placement in test systems for complete network observability

Test System	Optimal PMU Placement (#Bus)
IEEE 14 Bus	2,8,10,13
IEEE 30 Bus	1,5,8,10,11,12,19,23,26,29

Table 2. The error obtained from the neural network test with two BP and WOA learning algorithms of the IEEE 14-bus system

Results	RSE	MAE	MSE	RMSE
BP-MLPNN	1.0507	0.0497	3.3e-4	0.0559
WOA-MLPNN	0.0749	0.0146	2.77e-5	0.018

Table 3. The error obtained from the neural network test with two BP and WOA learning algorithms of the IEEE 30-bus system

Results	RSE	MAE	MSE	RMSE
BP-MLPNN	1.009	0.172	0.0018	0.199
WOA-MLPNN	0.0508	0.0382	9.58e-5	0.0484

(Figure 4), they were trained in a three-layer perceptron artificial neural network. These three layers include the input layer consisting of measurement data, the hidden layer, and the output layer consisting of system states. To achieve the best classification, different architectures were used for the neural network from 5 to 40 neurons in the hidden layer and weight optimization through WOA in 100 Epochs. Finally, the number of states of each system was chosen as the number of hidden layer neurons.

The Root Mean Square Error (RMSE) index was used as a performance calculation index, and in the first iterations with WOA learning, a noticeable reduction in error was obtained from 1.115 to 0.995 for the 14-bus system and from 2.11 to 1.45 for the 30-bus system, and finally the lowest The amount of error based on the methods of Root Square Error (RSE), Mean Absolute Error (MAE), Mean Square Error (MSE) and RMSE, obtained for the neural network test for training with BP and WOA algorithms in the best condition was obtained according to Tables 2 and 3.

Figures 9 and 10 show the fitting of the curve of the actual values of the state estimation against the output values of the neural network trained with two algorithms for the two parts of training and testing.

According to Figures 11 to 14, to better examine the simulation, the state estimation of the power system for two systems of 14 and 30 buses has been performed every 10 minutes, 24 hours a day. Due to the network load changes and its inverse relationship with the voltage profile, the accuracy of the state estimator is of particular importance for the network operator. According to equation (2), the value of the objective function for the three WOA-MLPNN, Linear-SE, and BP-MLPNN estimators, respectively, is 0.036, 4.12 and 12 for the 14-bus system and 0.013, 3.1 and 10 for the 30-bus system. the results indicate the effectiveness of the WOA-MLPNN state estimator and the importance of proper and intelligent learning of neural networks using optimization algorithms.

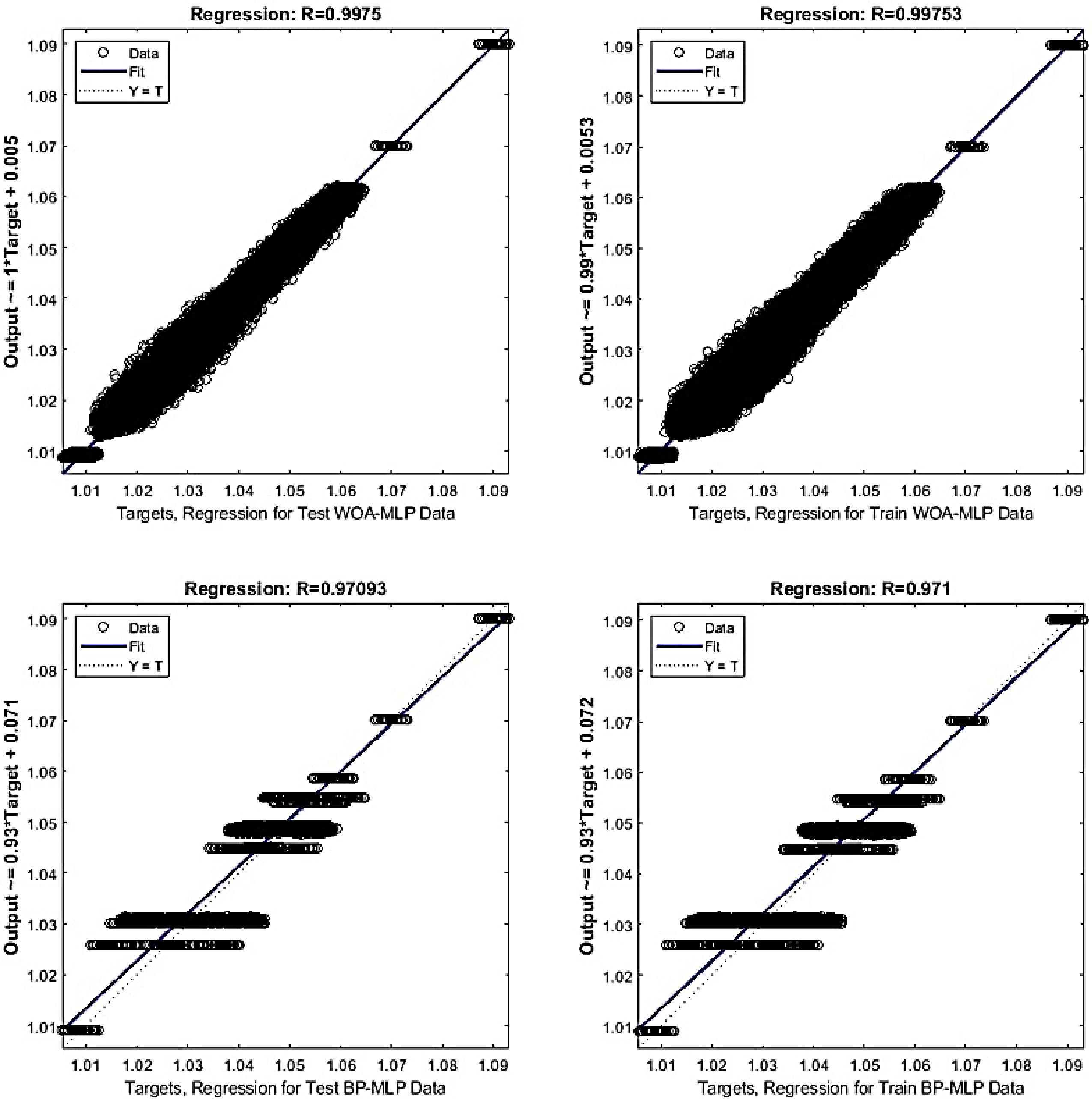

Fig. 9. Showing the correlation between the correct value and the predicted value for the training and test data sets of the IEEE 14-bus system

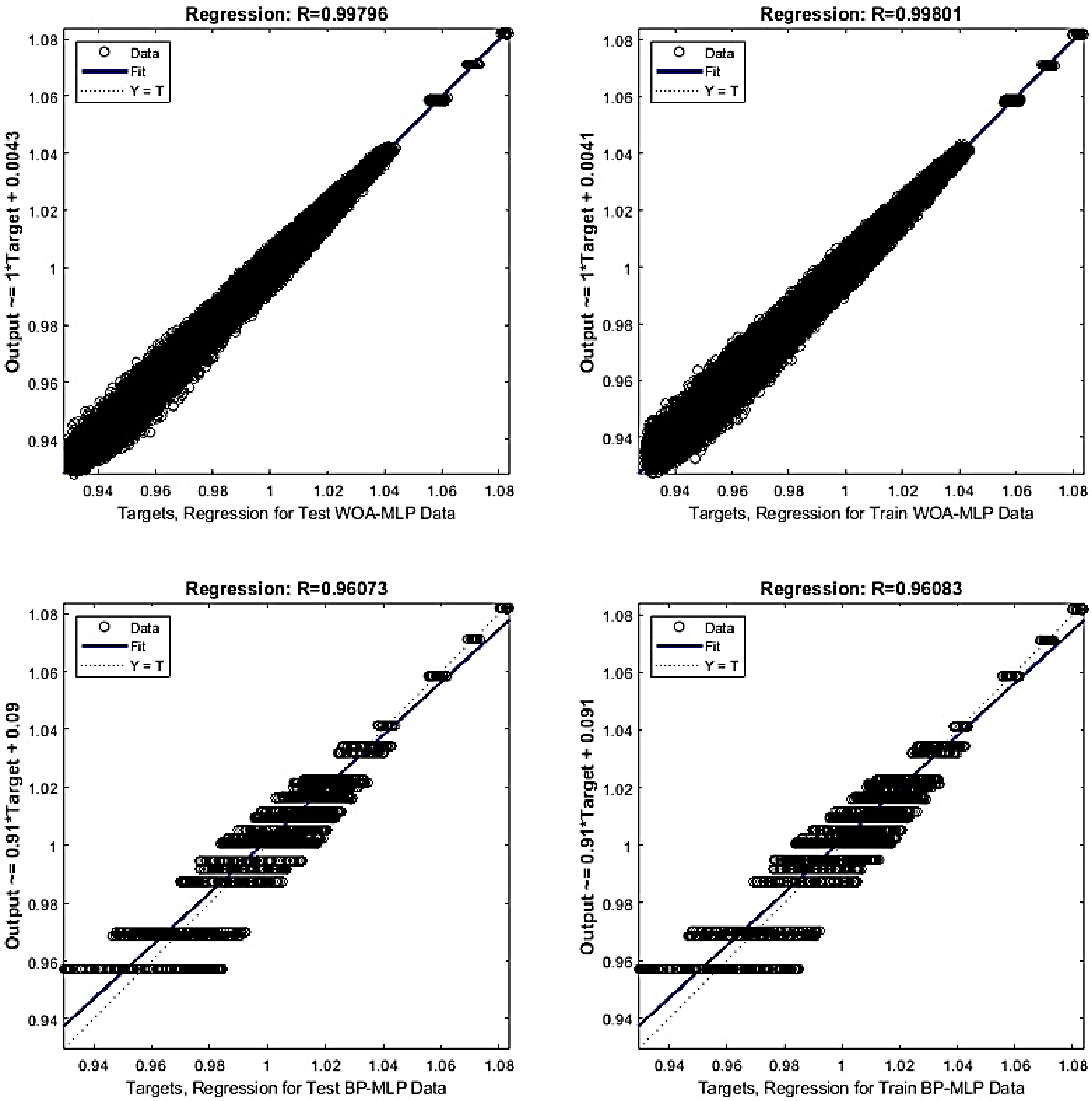

Fig. 10. Showing the correlation between the correct value and the predicted value for the training and test data sets of the IEEE 14-bus system

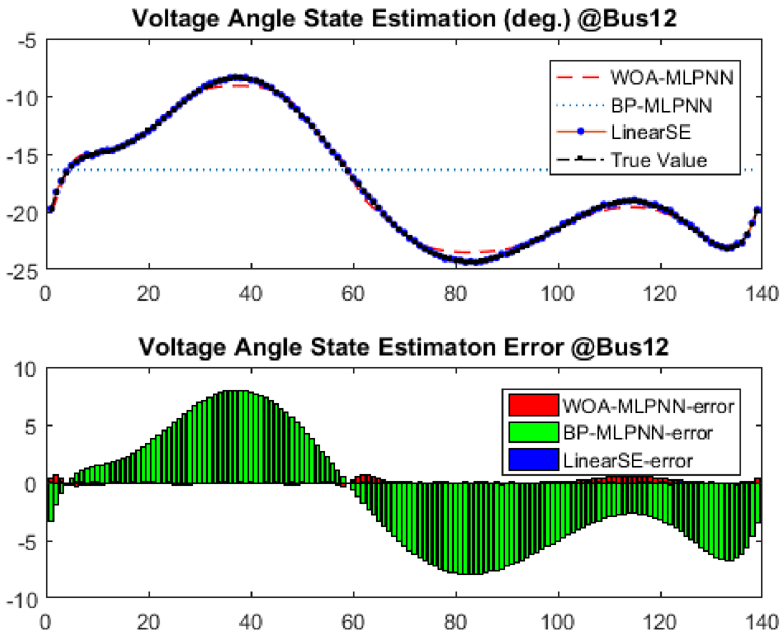

Fig. 11. IEEE 14 Bus state estimation results (Bus #12 voltage angle)

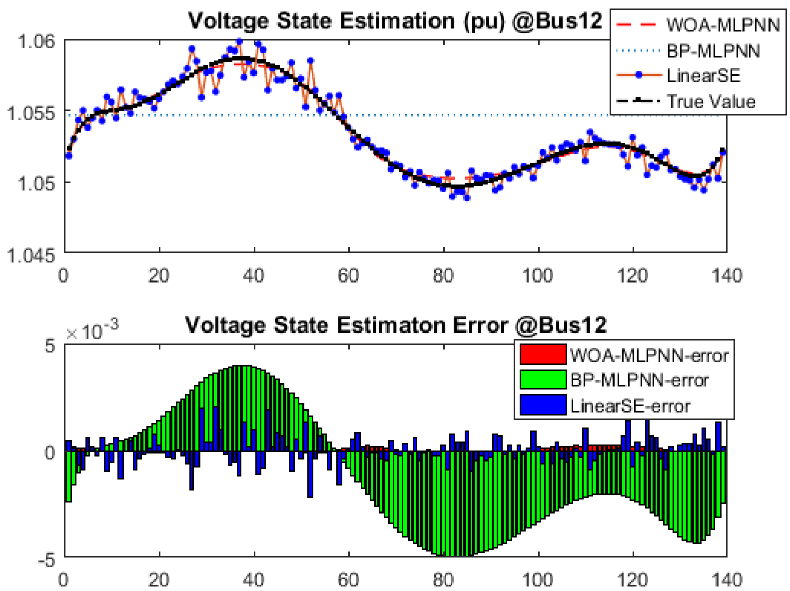

Fig. 12. IEEE 14 Bus state estimation results (Bus #12 voltage mag.)

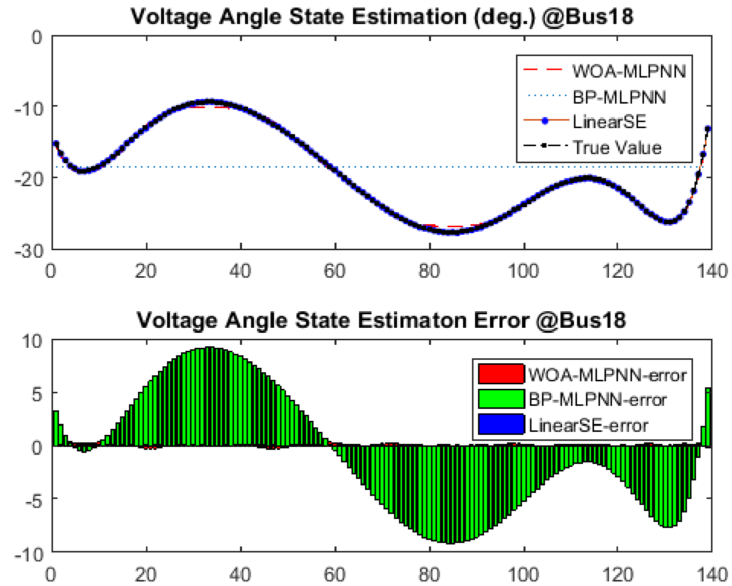

Fig. 13. IEEE 30 Bus state estimation results (Bus #18 voltage angle)

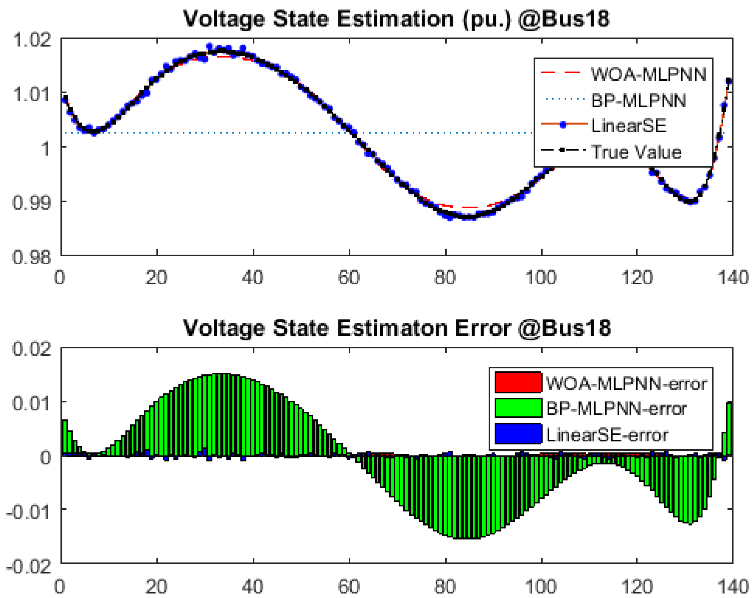

Fig. 14. IEEE 30 Bus state estimation results (Bus #18 voltage mag.)

4- Conclusion

In this article, firstly, the development process of power system state estimation, the optimal placement of phasor measurement units, and the advantages of linear state estimation were discussed. Due to the importance of accuracy and speed for real-time decision-making and reaction by the power grid operator, the best option for performing state estimation was the artificial neural network. One of the advantages of the neural network is that it does not rely on relationships and complex calculations. Neural network training is one of its main pillars, and by optimally determining its weights, the best output can be expected from it. The results of state estimation using a neural network optimized with a Whale optimization algorithm show that its performance is verified and its error is more suitable than the conventional neural network training method.

References

[1] M. Abedi, Operation, Optimization and control in Electric Power Systems. Tehran: Nahardanesh., 2018.

[2] A. J. Wood, B. F. Wollenberg, G. B. Sheble, Power generation, operation, and control, 3rd ed., Wiley, 2014.

[3] A. G. Phadke, J. S. Thorp, Synchronized Phasor Measurements and Their Applications. New York: Springer, 2008.

[4] H. Mosbah and M. El-Hawary, "Evaluating the Impact of Phasor Measurement Units on the Accuracy of State Estimation," 2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), pp. 1-5, 2018.

[5] S. Chakrabarti, E. Kyriakides, G. Ledwich, and A. Ghosh, "Inclusion of PMU current phasor measurements in a power system state estimator," IET Gen. Trans. Dist., Vol. 4, No. 10, pp. 1104-1115, 2009.

[6] G. Valverde, S. Chakrabarti, E. Kyriakides, and V. Terzija, "A constrained formulation for hybrid state estimation," IEEE Trans. Power Syst., Vol. 26, No. 3, pp. 1102-1109, 2011.

[7] R. F. Nuqui and A. G. Phadke, "Phasor Measurement Unit Placement Techniques for Complete and Incomplete Observability", IEEE Transactions on Power Delivery, vol. 20, no. 4, pp 2381–2388, Oct. 2005.

[8] B. Gou, "Optimal placement of PMUs by integer linear programming", IEEE Transactions on Power Systems, vol. 23, no. 3, pp 1525–1526, Aug. 2008.

[9] S. C. Huang and Y.-F. Huang, "Learning algorithms for perceptions using back-propagation with selective updates," IEEE Control Syst. Mag., vol. 10, no. 3, pp. 56–61, Apr. 1990.

[10] Seyedali Mirjalili, Andrew Lewis, "The Whale Optimization Algorithm," Advances in Engineering Software., pp. 51–67, 2016.

[11] Aljarah, I., Faris, H. and Mirjalili, S., Optimizing connection weights in neural networks using the whale optimization algorithm. Soft Computing, 22(1), pp.1-15. 2018.

[12] E. Manitsas, R. Singh, B. C. Pal and G. Strbac, "Distribution System State Estimation Using an Artificial Neural Network Approach for Pseudo Measurement Modeling," in IEEE Transactions on Power Systems, vol. 27, no. 4, pp. 1888-1896, Nov. 2012.

[13] S. Soni, S. Bhil, D. Mehta and S. Wagh, "Linear state estimation model using phasor measurement unit (PMU) technology," 2012 9th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE), pp. 1-6, 2012.

[14] Power Svstems Test Case Archive. llniversitiv of Washington. Website: http://www.ee. washington. edulresearch/pstca

[15] Tian, G., Gu, Y., Shi, D., Fu, J., Yu, Z., & Zhou, Q. (2021). Neural-network-based power system state estimation with extended observability. Journal of Modern Power Systems and Clean Energy, 9(5), 1043-1053.

[16] Mishra, B., Thakur, S. S., Rai, P., & Tanti, D. K. (2021). Linear State Estimation for Power Systems Based on PMU Measurements. In Intelligent Communication, Control and Devices: Proceedings of ICICCD 2020 (pp. 249-261). Springer Singapore.

HOW TO CITE THIS ARTICLE

S. H. Roudaki, M. Abedi, I. Pourkeivani, Power System State Estimation through Optimal PMU Placement and Neural Network using Whale Algorithm, AUT J. Elec. Eng., 55(3) (Special Issue) (2023) 351-364.

DOI: 10.22060/eej.2023.22232.5525