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Enhanced Power System State Estimation Using Machine Learning Algorithms

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***Abstract*—The widespread implementation of renewable energy sources is posing new and distinct challenges for power systems. Consequently, power system state estimation has become increasingly essential for monitoring, operating, and safeguarding modern power systems. Conventionally, physics-based models such as weighted least square or weighted least absolute value were utilized, which classically analyze a single snapshot of the systems and fail to capture the temporal connections of system states. Thus, this study exploits the potential of machine learning approaches to forecast the state values of power systems. The performance and stability of innovative machine learning methodologies are validated using the IEEE systems. The results of the simulations are encouraging, which shows the effectiveness and feasibility of the proposed machine learning methods for power system state estimation.**

***Keywords*—Power system state estimation, machine learning, deep learning, Random Forest, XGBoost**

I. Introduction

The power grids are rapidly changing due to the integration of extensive renewable energy sources, demand response strategies, and hybrid electric vehicles. This poses a challenge for grid operators to operate the power system in a stable and secure manner. Therefore, power system state estimation is a critical process in modern power systems, which is highly beneficial for several operational decision-making problems in power systems such as unit commitment, economic load dispatch, optimal power flow, network reconfiguration, and security analysis [1]. State estimation involves estimating the actual system state variables, such as voltage magnitudes and phase angles, based on raw measurement data collected from SCADA and PMUs. Grid operators need to have an accurate estimation of the system states in order to ensure the stability, reliability, and efficiency of the system.

Weighted least squares (WLS) and weighted least absolute value (WLAV) are traditional statistical techniques used for state estimation, which employ squared error and absolute error, respectively, to minimize measurement errors [2]. However, WLS and WLAV may take numerous iterations and may not achieve convergence due to the high dynamics and nonlinearity of the power systems. Thus, to reduce the likelihood of flawed results and calculation time, machine learning algorithms have been developed to estimate system states.

Applications of artificial neural networks (ANNs) are increasingly popular in power systems. ANNs are able to achieve accurate approximations based on appropriate training [3]. Multi-layer perceptron models are capable of comprehending the intricate connections between the input/output dataset of a system, and upon being trained effectively, they are applied to new datasets in real-time [4]. A hybrid model combined an ANN and a statistical method in [5] for estimating the states of a power system. An ANN was utilized to map the input variables to a point in the vicinity of the actual hidden states, and this information was then used as input for the statistical method, thereby resulting in enhanced convergence. In [6], a long-short-term memory (LSTM) neural network was applied in place of a neural network to estimate successive power system states. Wang et al. [7] estimated system states using a physics-guided deep learning approach, wherein a series of power flow equations is employed to verify the system states estimated by deep neural networks for adherence to the principles of physics. In [8], a deep ensemble learning called Residual Neural Networks (ResNetD) was developed to forecast states in real-time power system operation. Several other data-driven techniques have been utilized for power system state estimation in existing literature, including modified LSTM [9], conditional generative adversarial networks (GAN) [10], auto-encoders [11], k-nearest neighbor [12], and convolutional neural network (CNN) [13]. Due to the intricate nature of the power system, measurement data is substantial and is difficult to manage using a basic shallow neural network [13]. Additionally, the computational efficiency of such neural networks is low [14]. Therefore, machine learning applications for power system state estimation should be encouraged.

This study proposes machine learning algorithms for power system state estimation. Three machine learning algorithms, namely ANN, Random Forest, and Extreme Gradient Boosting (XGBoost) algorithms, are applied to learn temporal correlations among system states. The effectiveness of the proposed data-driven state estimation techniques is evaluated using the IEEE 14-bus and 30-bus systems. The simulation results demonstrate the high effectiveness of machine learning algorithms in state estimation.

II. State Estimation

A. Preliminaries

Power system state estimation determines the system states from raw measurements that may contain noise by minimizing the error in measurement data. The measurement equation is employed to calculate the system states as in (1) [1]:

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

where z is the measurement vector, x is the state vector, h is a nonlinear function between measurement and state vectors, and e is the noise vector in measurements.

The most commonly utilized approach for state estimation has traditionally been the WLS approach with the Gauss-Newton method. WLS approach determines the estimated state vector by minimizing the following equation:

$$J(x) = \frac{1}{2}(x - h(x))^T W (x - h(x)) \tag{2}$$

where weight vector W is formulated by considering the variance of the measurement errors. To obtain the solution, the Gauss-Newton method is applied as follows:

$$\hat{x}_{k+1} = \hat{x}_k + G(\hat{x}_k)^{-1} H^T(\hat{x}_k) W [1 - H(\hat{x}_k)] \tag{3}$$

where H and G are defined as follows:

$$H(\hat{x}_k) = \left[\frac{\partial h(x)}{\partial x}\right]_{x=\hat{x}_k} \tag{4}$$

$$G(\hat{x}_k) = H^T(\hat{x}_k) W H(\hat{x}_k) \tag{5}$$

B. Problem formulation

The task of power system state estimation using data-driven approaches is to create a mapping between the provided set of measurements (z_t) and state variables ($\hat{x}_k$), which is given as follows [8]:

$$\hat{x}_k = f(z_t) \tag{6}$$

where the measurement vector z includes the voltage magnitude V_t^i, phase angle δ_t^i, active power injection P_t^i and reactive power injection Q_t^i at the i^{th} bus at time t, transmission line loading S_t^l at the l^{th} branch (connecting the i^{th} bus and j^{th} bus) at time t. The estimated state vector x includes the voltage magnitude V_t^i and phase angle δ_t^i at the i^{th} bus at time t, wherein i varies from 1 to N_b for voltage magnitude and 2 to N_b for phase angle (phase angle at the 1$^{\text{st}}$ bus is taken as reference) with N_b the total number of buses in the power system.

The mapping function f involves weights that establish the mapping between the input measurements and output states. The aim of power system state estimation based on a machine learning approach is to determine the weights that minimize the difference between predicted and actual states. In contrast to the conventional physical model, the machine learning model uses measured data z as an input and state variable x as an output.

III. Methodology

To map from the input measurements to output states, this study proposes three machine learning algorithms, including ANN, Random Forest, and XGBoost, which can be briefly described in the following subsections.

A. ANN

ANNs are a powerful class of machine learning algorithms. Typically, ANN is trained on a dataset of input features and their corresponding target values. The input features are fed into the input layer of the network, which passes them through one or more hidden layers of neurons. Each neuron in the hidden layer applies a nonlinear activation function to its input, and the output of each neuron is passed on to the next layer until the final output layer produces the predicted target value. During training, the network adjusts its weights and biases to minimize the discrepancy between the predicted target values and the actual target values in the training dataset. This process is typically done using optimizers such as gradient descent and Adam. The capability of ANN regression to represent intricate and non-linear relationships between target variables and features is well known. Fig. 1 portrays the structure of a typical ANN for a regression problem.

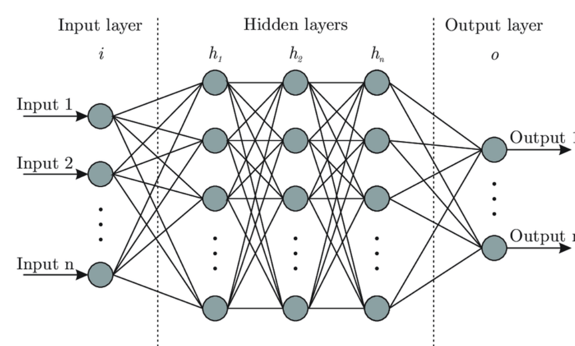

Fig. 1. The structure of ANN.

B. Random Forest

Random Forest is an ensemble learning approach that merges numerous decision trees to generate predictions with greater precision [15]. This algorithm builds a forest of decision trees, in which every tree is trained on a random subset of the training data and a random subset of the features. By using this strategy, overfitting can be reduced, and the ability of the model to generalize can be enhanced. When making a prediction, each decision tree in the forest generates an independent prediction, and the final prediction is obtained by averaging the predictions of all the trees. This approach results in a more resilient and precise forecast than relying on a single decision tree. Random Forest regression is particularly useful for handling high-dimensional data and nonlinear relationships between features and target variables. The structure of a Random Forest is presented in Fig. 2. The mathematical equation of the Random Forest algorithm is defined as follows:

$$\hat{f}_{RF}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{7}$$

where B is the number of trees, x is the vector of input variables, and T_b is a single regression tree formed based on a subset of bootstrap samples and input variables.

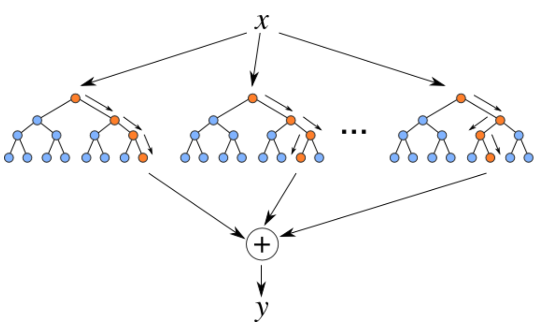

Fig. 2. The structure of Random Forest.

C. XGBoost

XGBoost is a type of gradient-boosting algorithm that combines multiple weak learners (decision trees) to make more accurate predictions [16]. XGBoost creates a set of decision trees iteratively, in which each tree is trained on the residuals of the previous tree. This approach helps to reduce the bias and variance of the model and improves its generalization ability. XGBoost also uses a technique called gradient boosting, which involves calculating the gradient of the loss function for the predicted values and using it to update the model parameters in each iteration. This helps to optimize the objective function and improve the model's performance. The general formula of the XGBoost algorithm can be given as follows:

$$f(\theta) = L(\theta) + \alpha(\theta) \tag{8}$$

$$L(\theta) = l(\hat{x}_i, x_i) \tag{9}$$

$$\alpha(\theta) = \gamma T + \frac{1}{2}\|\omega\|^2\lambda \tag{10}$$

where $f(\theta)$ is the objective function, $L(\theta)$ is the loss function between the predicted value $\hat{x}_i$ and the actual value x_i, $\alpha(\theta)$ is the regularization term, λ is the regulating parameter, ω is the weight of leaves, T is the number of leaves of the tree, and γ is the learning rate.

IV. Simulation Results

A. Simulation Setup

Simulation data is created for the IEEE 14-bus and 30-bus systems. The 14-bus system comprises 4 generators and 9 loads, while the 30-bus system has 6 generators and 24 loads. Dataset generation is referenced as [8], wherein the actual load demand at each bus is multiplied by the normalized load profile in [17] to achieve the load demand at each bus at each time. Subsequently, AC power flow computation is performed for load data at each time using MATPOWER 6.0 to obtain power flow results, including active power injection at the reference bus, reactive power injections at buses, voltage magnitude and phase angles at buses, and line flows at branches. The obtained power flow results at each time are used to form the measurement and state data. For the 14-bus and 30-bus systems, 64 and 110 measurements were taken, respectively, as proposed in [8]. Meanwhile, the states are represented by the voltage magnitudes and angles at buses, with 28 and 60 states, respectively, wherein the voltage angle of the reference bus is set to zero. The dataset contains 39444 samples, which are divided into two parts: training (76%) and testing (24%). The machine learning models are coded using the Python environment with the TensorFlow library.

B. Performance Evaluation Metrics

Two popular statistical metrics, the mean absolute error (MAE) and the root mean square error (RMSE), are employed to estimate the effectiveness of the machine learning algorithms:

$$MAE = \frac{1}{N_s N_b}\sum_{i=1}^{N_s}\sum_{k=1}^{N_b} |\hat{x}_k - x_k| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N_s N_b}\sum_{i=1}^{N_s}\sum_{k=1}^{N_b} (\hat{x}_k - x_k)^2} \tag{12}$$

where N_s is the total number of samples, N_b is the total number of buses, $\hat{x}_k$ is the predicted state for voltage magnitude or phase angle at the k^{th} bus, and x_k is the actual state for voltage magnitude or phase angle at the k^{th} bus.

C. Results and Discussion

The study examines and contrasts the effectiveness of three machine learning algorithms for state estimation, and these evaluations are conducted on the IEEE 14-bus and 30-bus systems. Fig. 3 and Fig. 4 depict the estimated voltage magnitudes and phase angles by ANN, Random Forest, and XGBoost models at different buses of 14-bus and 30-bus systems from the 5000^{th} to the 5050^{th} testing sample. As shown in Fig. 3 and Fig. 4, the states predicted by three machine learning models closely approximate the actual states. Moreover, the voltage phase angles estimated by the proposed algorithms strongly resemble the actual value of the system state for both systems.

Table I shows a comparison of ANN, Random Forest, and XGBoost models using MAE and RMSE for voltage magnitude estimation for 14-bus and 30-bus systems. Performance comparisons of three models for voltage phase estimation are presented in Table II. The lower values of the MAE and RMSE indicators show a higher accuracy of an algorithm in state estimation. Generally, all three models have low values for MAE and RMSE metrics for voltage magnitude and phase angle estimations.

From Table I, the ANN model yields an MAE of 0.00006 and RMSE of 0.00016 for voltage magnitude predictions for

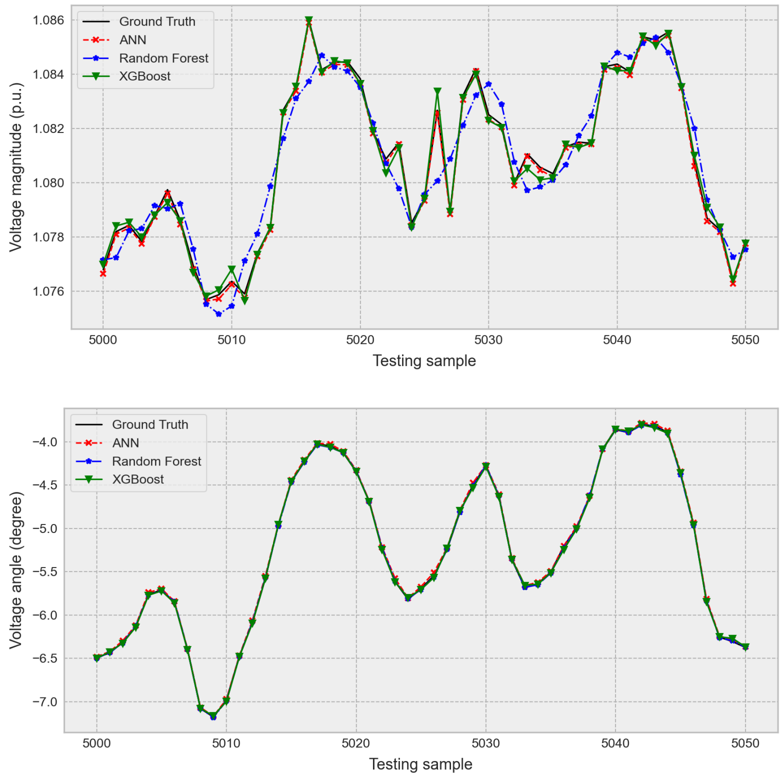

Fig. 3. Voltage magnitudes and phase angles estimated by different algorithms at the 10^{th} bus of 14-bus system for the 5000^{th} to 5050^{th} testing sample.

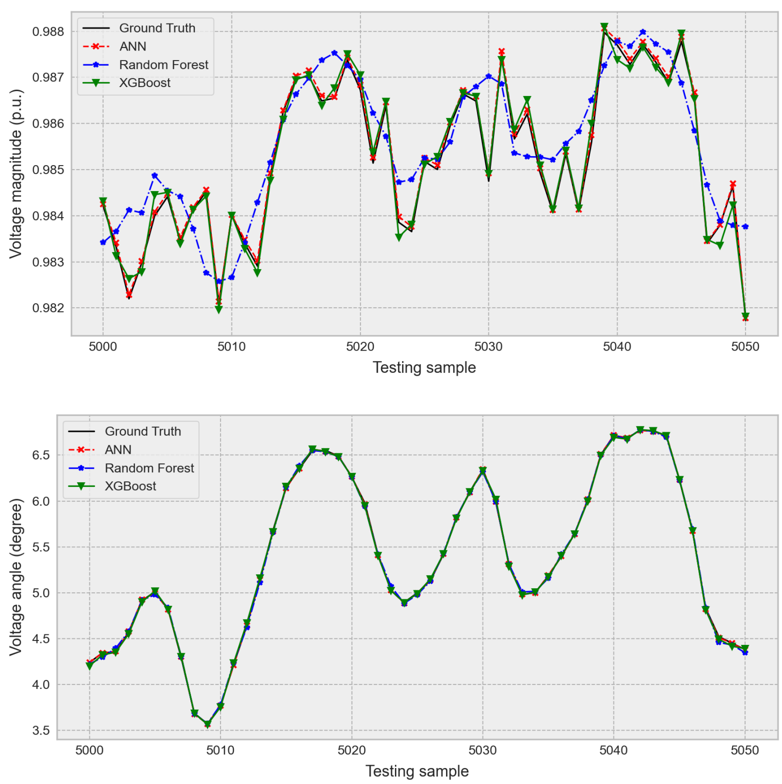

Fig. 4. Voltage magnitudes and phase angles estimated by different algorithms at the 10^{th} bus of 30-bus system for the 5000^{th} to 5050^{th} testing sample.

TABLE I
COMPARISON OF ANN, RANDOM FOREST, AND XGBOOST BASED ON MAE AND RMSE METRICS FOR VOLTAGE MAGNITUDE ESTIMATION

Algorithms	**IEEE 14-bus system**		**IEEE 30-bus system**	
	MAE	***RMSE***	***MAE***	***RMSE***
ANN	0.00006	0.00016	0.00009	0.00016
Random Forest	0.00039	0.00061	0.00083	0.00124
XGBoost	0.00011	0.00016	0.00014	0.00019

TABLE II
COMPARISON OF ANN, RANDOM FOREST, AND XGBOOST BASED ON MAE AND RMSE METRICS FOR VOLTAGE PHASE ESTIMATION

Algorithms	**IEEE 14-bus system**		**IEEE 30-bus system**	
	MAE	***RMSE***	***MAE***	***RMSE***
ANN	0.01351	0.02174	0.01075	0.01669
Random Forest	0.00746	0.01138	0.01632	0.02461
XGBoost	0.00978	0.01657	0.01207	0.01832

the 14-bus system, which is the best performance among the three algorithms. However, with an MAE of 0.00746 and an RMSE of 0.01138, the Random Forest model has lower MAE and RMSE values than other models for voltage phase prediction, as can be seen in Table II. Hence, the ANN model offers the most accurate estimations for voltage magnitudes, while the Random Forest model provides the best estimations for voltage angles for the 14-bus system.

For the 30-bus system, the ANN model outperforms the Random Forest and XGBoost models for both voltage magnitudes and phase angle estimation. Meanwhile, the Random Forest model has the worst performance among the three proposed models. It is worth noting that these highly accurate estimates are obtained without hyperparameter adjustment for the models. Therefore, machine learning models are very efficient and well-suited for state estimation.

V. CONCLUSION

This study proposes three machine learning algorithms, namely ANN, Random Forest, and XGboost algorithms, for power system state estimation. In contrast to traditional techniques that provide a snapshot estimate, machine learning algorithms fully utilize their learning ability to model the temporal correlations between system states. Three distinct machine learning models were trained and evaluated on the IEEE 14-bus and 30-bus systems. From the obtained results, all three machine learning algorithms show high accuracy and robustness in estimating the states of the system. Among the three proposed algorithms, ANN models achieve better results than other algorithms in terms of MAE and RMSE. It can be inferred that the application of machine learning in state estimation holds the potential for implementation in actual control centers.

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