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# Power Flow Parameter Estimation in Power System Using Machine Learning Techniques Under Varying Load Conditions

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**ABSTRACT-** In power transmission network state estimation is more complex and the measurements are critical in nature. Estimation of power flow parameters such as voltage magnitude and phasor angle in a power system is challenging when the loads are varying. The objective of the work is to estimate the voltage magnitude and phase angle using machine learning techniques. Some of the Machine learning techniques are decision trees (DT), support vector machines (SVM), ensemble boost (E-Boost), ensemble bags (E-bag), and artificial neural networks (ANN) are proposed in this work. Among these methods, the best machine learning techniques are selected for this study based on performance metrics. Performance metrics are Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Neural network produces minimum error when compared to other ML Techniques. Among three Performance Metrics MSE provides minimum error and is used to predict the exact model in this work. Therefore, it is concluded that the neural network can predict voltage and angle accurately under various load conditions in the power system effectively. Neural Network (NN) is applied to different load condition, and performance metrics are computed. To validate the proposed work, IEEE 14 and IEEE 30 bus systems are considered. The predicted value is compared to the actual value for all the load variation and residues are measured. The regression learner software in MATLAB is used to implement ML approaches in this work. The Outcome of this proposed work is used in phasor measurement units. The predicted value of voltage and angle using a neural network can be used to minimize the voltage magnitude and phase angle error in phasor Measurement Units (PMU).

**General Terms:** Regression, Power system Parameter estimation, various load condition.

**Keywords:** State estimation, Machine learning, Artificial neural network, Mean square error, Regression.

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## 1. INTRODUCTION

In modern Electric power systems, the determination of voltage and angle is required to calculate real, reactive power flows and line losses in the transmission line. Voltage and angle are measured using the metering device in the power systems to calculate their state variables [1]. Further studies such as voltage regulation, Contingency market, Security analysis, and power system planning are also important areas in power system networks that requires measurement of voltage and angle [2]. The process of calculating power system parameters is called state estimation (SE) also used in power system for monitoring [3]. Power system monitoring and operation estimates the power system state variables based on the available measurements. Active, reactive power, voltage and current measurements are considered in the SE [4]. SE process is difficult when increasing the load above the normal load. So More research required to estimate the power flow parameters in power system.

So many literatures and studies have been reported to solve the state estimation problem in the past. The semidefinite programming model is used to solve the state estimation problem [5]. Convex semidefinite programming model solves state estimation problems more efficiently [6]. State estimation in electric power systems is implemented in many ways. It is one of the exciting researches in the power system to determine the parameters of power flow measurements. To estimate the error in the electric power system [7] co variance matrix method used in real-time measurements. In that, WLS is used for error identification and sensitive analysis. In [8], a technique was implemented using synchro phasor measurements and used in state estimation of parameters. Various methods are implemented in SE problems using residual sensitivity analysis [9].

Weighted least square (WLS) estimation is widely used in the state estimation problem. Modified weighted least square estimation and classical weighted least square approaches have been used in state estimation in the past literature [10]-[11]. In Weighted least square estimation, the difference between the estimated and actual value can be minimized by sum of squares approach. WLS faces issues difficulty error in state estimation, alternative methods are also there to solve this problem [12]-[13]. Dynamic State estimation is the approach to change their behavior with respect to time. Due to sudden changes in load, Dynamic state estimation behaves in two ways to estimate the state in the power systems one is an iterative estimation, and another is a Taylor series expansion [14]. Only the measurement residuals are reduced in WLS. To solve this problem, Kalman filter is proposed and it provide solution by reduction of mean square error.

In nonlinear systems, state estimation is measured using the Kalman filter approach. These are classified into Classical Kalman filter and nonlinear Kalman filter. Nonlinear Kalman filter are further classified into two types, namely extended Kalman filter and unscented Kalman filter [15][16]. A Parallel Kalman filter (PKF) is one of the techniques to solve the state estimation problem. In PKF, states are separated into two vectors, and each is considered as a linear system and its perform based on the game theory approach [17]. State estimation is also implemented using minimizing technique and parallel Kalman filter technique. Maximum likelihood and minimum variables are the other methods of state estimation. In maximum likelihood [18], maximize the probability of the estimated value for the state variable as close to the actual value. Minimum variance [19] is also one of the techniques used in state estimation. In this, the predicted value of the sum of the errors is minimized like the weighted least square method. Despite the fact that there are numerous methods for state estimation, recent research has focused more on machine learning methods for accurate measurement.

Several researchers suggest using a deep learning model trained on the set of examples. A recurrent and feed-forward neural network is used to solve the state estimation problem for given measurement data [20][21][22]. Using graphical neural network (GNN), power flow parameters are estimated. It is used to predict real reactive power injections and voltage, angles are measured and trained through the graph based on the historical data [23][24]. Even though the predicted output value, did not compare GNN with other machine learning techniques and not discussed errors. In the proposed work estimated voltage magnitude and phasor angle using a neural network compared with other ML techniques such as DT, SVM, E-boost, and E-bag with the error measurement of RMSE, MAE, and MSE. Machine learning techniques are used to interpret data to analyze, evaluate, predict, and classify large amounts of information related to assessing essential problems of power system dynamical security in a way that maintains reliability. From the literature studies the conventional approach is not appropriate in state estimation to determine phasor angle and voltage magnitude for various load conditions. Machine learning is suitable for estimating state characteristics under larger varying load scenarios. So, in this study, a machine-learning technique is suggested. The motivation behind this research is artificial intelligence plays a significant role in a power system. In power system protection, large numbers of data are stored in the computer. To start research using these data sets, machine learning models are more useful. Different data sets and different models bring changes in the output. Data forecasting will be used to make intelligent decisions without humans.

### 1.1 Key Contribution

To Summarize, the main features and contributions of this work are described as follows:

- Machine learning techniques are proposed to estimate power flow parameters in a power system network. Neural network is identified the best method compared to decision tree, Support vector machine, Ensembelling boost, and Ensembelling bag techniques.
- Neural Network is applied with different load conditions in IEEE 14 and IEEE 30 bus systems, and performance metrics are measured.
- RMSE, MAE, and MSE are proposed to calculate the residue between the true and predicted value of voltage magnitude and phasor angle.

MSE produce minimum error for IEEE 14 and IEEE 30 bus system among the three-performance metrics.

## 2. MACHINE LEARNING METHODS

This section includes decision tree, Support vector machine, Ensemble boost/bag, and neural networks along with schematic diagram of the proposed work using neural network and its architecture are explained. Process flow diagram that states input and output data sets of power flow parameters, data separation, implementation of machine learning followed by performance metrics are discussed. Performance metrics like RMSE, MAE, and MSE with their formula are presented.

### 2.1 Artificial Neural Network (ANN)

ANN architecture consists of three layers, namely the input layer, hidden layer, and output layer. The input layer receives input values and between the input and output layers that are set of neurons is called the hidden layer. The output layer produces multiple outputs. In ANN, weights are used to obtain the required output. Weights may be positive, negative, or zero based on neurons. The tuning of the weights is called learning or training. The backpropagation method is used in the ANN for training. By adjusting weights and back propagated layers, the desired output is obtained. A set of input data is given to ANN, and the produced output is called training. The desired output value is compared to true data and the error is calculated. Totally 250 and 450 data sets are used for IEEE 14 and IEEE 30 bus respectively. In Artificial neural network (ANN), each node has some weights. The transfer function is used to calculate the weighted sum of the input. Weights, bias and activation function are parameters of neural network. Sigmoid, relu, SoftMax, and tan are typical activation functions. In this

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work, the relu activation function is used in the ANN. Number of hidden layer used in this work is two. Network are tuned with activation function and hidden layers. Weights and bias are tuning parameters and adjusted using the Levenberg algorithm. The neural network consists of an input layer, an Output layer, and a hidden layer connected with nodes. It works in two different modes forward propagation, and back propagation. ANN has many processing units that are called neurons. *Figure 1* and *2* shows the Schematic diagram of the proposed work with an artificial neural network. Here the input is real and reactive power, and the output is voltage magnitude and phasor angle. The input layer has 'n' number of inputs with two hidden layers and two output layers. ANN provides the best performance for the estimation of results. The architecture and parameters are varied based on input and output datasets. Regression learner-based machine learning techniques are implemented in this proposed work. Bias, weights, hidden layers, and activation functions are varied based on the availability of data sets and their functions.

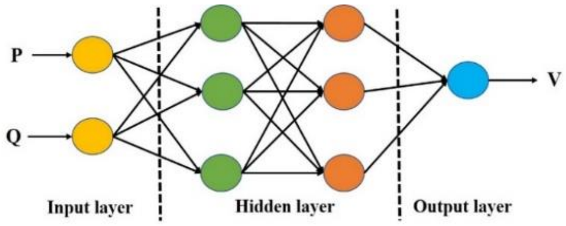


**Figure 1:** Schematic diagram with Voltage Magnitude

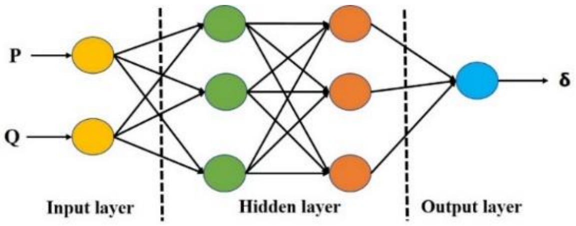


**Figure 2:** Schematic diagram with Phasor angle

## 2.2 Decision tree (DT)

The decision tree is a tree structure and a kind of supervised learning technique mostly used in regression-type problems. Internal nodes, branches, and leaf nodes are part of the decision tree. The decision node and leaf node are two important nodes used in the decision tree. The decision node consists of many branches to make a decision, and the leaf node is the output node there are no branches. It produces output based on decision given by decision node. The operation looks like a tree so it is called decision tree. Root node starts from the decision node.

## 2.3 Support Vector Machine (SVM)

Support vector machine is mostly used in classification problems and regression problems. The primary objective of the sum is to determine hyperplane and decision variables. The dimension of the plane is directly proportional to the number of input parameters. More lines and boundaries are there in n-dimensional space. Clarify the data points to predict the best boundary among them. Finally, the best boundary determined is called a hyperplane of the SVM.

## 2.4 Ensemble boost and bag (E-Boost/E-Bag)

Ensemble learning is one of the machine learning techniques. It has better predictive performance from multiple nodes. The Ensemble is classified into three different types, namely Ensemble bagging, Ensemble boosting, and Ensemble stacking. In Ensemble bagging, learners learn independently in parallel to determine the average model Ensemble boosting learner learn sequentially to improve the model predictions. Boosting and bagging are used in Machine learning to reduce errors, but the way predictions are different. The main objective of bagging and boosting is to decrease the variant, not bias in bagging and decrease bias, not variance in boosting.

# 3. METHODOLOGY

In this work, the Process flow diagram explains the implementation of the machine learning techniques in estimating the power flow parameters in the power system area as shown in *figure 3*.

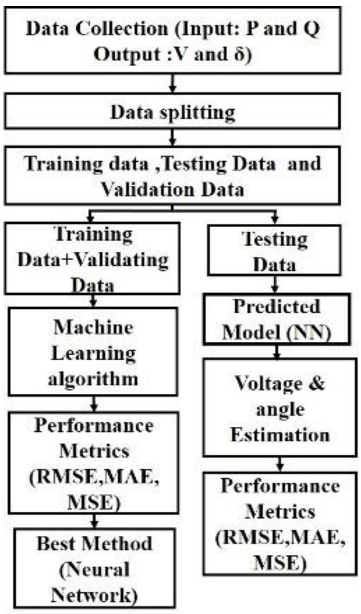


**Figure 3:** Process flow diagram of the proposed work

Data are collected, splitted (Training, testing, and validation), and different machine learning methods are implemented with analysis of performance metrics. Finally, power flow parameters are estimated. Totally five types of ML methods Decision tree, Support vector machine, Ensemble boost/bag, and neural network are used in the proposed work. Among them, the neural network provides better performance, and this analysis is measured using performance metrics. This work estimates voltage magnitude and phasor angle using machine learning techniques. Initially, data sets are generated for real, reactive power, voltage, and angle by metering device for IEEE-14 and IEEE-30 bus system. Data are splitted into three categories: training, testing, and validation with the percentage of training has 70% of data, testing has 15% of data, and validation has 15% of data. Splitting the data can be done in two

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ways manually and automatically by means of machine learning techniques. In data splitting, real (P) and reactive power (Q) are considered input, while voltage (V) and angle (δ) are considered as an output. Once the data splitted then is divided into two one is for training with validation, and another one is testing data. Machine learning techniques such as decision tree (DT), Support vector machine E-boost and E-bag, and neural networks are applied to the data sets. Performance metrics such as RMSE, MAE, and MSE are measured. The neural network is applied to test the data for various load conditions with performance metrics. Where, voltage and angle are estimated for different load conditions.

## 4. PERFORMANCE METRICS

Performance metrics are used to identify which metrics have minimum error among them. Three metrics are introduced, such as RMSE, MAE, and MSE, followed by their formula, discussed in this section.

### 4.1 Root Mean Square error (RMSE)

It is most commonly used to measure for evaluating the quality of predictions. Lower the RMSE means that the data set can fit. Higher the RMSE with greater than 1, the data set is inaccurate. RMSE produces a perfect model for the data and has an average prediction error. It is one error technique that measures the transformation between prediction value and original value. It will be more beneficial to measure the efficiency of the model. Root mean square error can be calculated using the formula given in equation (1)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (1)$$

### 4.2 Mean Average error (MAE)

It is based on the absolute value of error and shows the difference between the magnitude of the actual value and the predicted value. From that, the prediction error is calculated. Prediction error converts to the position by taking absolute of all errors. It is a kind of loss function used for regression analysis. It measures accuracy for continuous variables. Finally, all absolute errors are calculated and are called an MAE. Mean Absolute error can be calculated using the formula given in equation (2)

$$MAE = \frac{\sum_{i=1}^{n}|O_i - P_i|}{n} \quad (2)$$

### 4.3 Mean Square error (MSE)

MSE is one of the commonly used loss functions. It is calculated by taking the average, specifically the mean of errors squared from data related to a function. Mean square error is also called mean squared deviation. It is defined as the average square difference between actual and predicted values. To calculate the MSE true value, subtract with the predicted value, square the difference, and do that for all observations. Finally, the formula will become a squared value divided by the number of observations. The mean square error can be calculated using the formula given in *equation (3)*

$$MSE = \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n} \quad (3)$$

Where,
Σ = Sum which means that sum of all up
n=Total number of observations
$P_i$=Predicted value of $i^{th}$ observation
$O_i$=observed value of $i^{th}$ observation

## 5. RESULTS AND DISCUSSION

Among Many IEEE bus system, IEEE 14 and the 30-bus system is only considered in this work. This machine learning work is used in phasor measurement units of power system networks. Real-time PMU data is available only for IEEE 14 and 30-bus systems, and hence this two-test system is proposed in this work. The results and discussion section explain two case studies with each corresponding tables for the measurement of voltage magnitude and phasor angle for the IEEE 14 and IEEE 30 bus system. Identification of the best machine learning techniques, along with performance metrics.

**Case 1: Estimation of voltage magnitude and Phasor angle for IEEE 14 bus system using ML techniques**

Data preprocessing is done based on the solutions obtained by the holomorphic embedding-based continuation (HEBC) method for IEEE 14 and IEEE 30 bus systems. In that, loads are varied in terms of percentage with the load factor. The initial load will be 10%, and the final load will be 400% are considered. Voltage magnitude and phase angle are obtained by varying the load and based on percentage. This data set is used in the proposed work. *Table 1* shows the voltage magnitude error measurement for IEEE 14 bus system using different machine learning techniques. Five Machine-learning techniques are introduced to validate the results. Validation and testing results are provided in *table 1*.

**Table 1: Voltage Magnitude for IEEE 14 bus system using Different ML techniques**

| Method | RMSE | | MAE | | MSE | |
|---|---|---|---|---|---|---|
| | Valid | Test | Valid | Test | Valid | Test |
| DT | 0.050 | 0.065 | 0.033 | 0.044 | 0.002 | 0.004 |
| SVM | 0.062 | 0.087 | 0.038 | 0.050 | 0.003 | 0.007 |
| E-Boost | 0.066 | 0.067 | 0.058 | 0.058 | 0.004 | 0.004 |
| E-Bag | 0.052 | 0.066 | 0.034 | 0.041 | 0.002 | 0.004 |
| NN | **0.042** | **0.034** | **0.027** | **0.023** | **0.001** | **0.0012** |

Among the five-techniques, neural network gives the least error and hence neural network is identified as the best machine learning technique for the proposed work. Among the three errors, MSE has the lowest error value, and RMSE has the highest error value. The lower the performance metrics imply that the model is good.

*Table 2* presents the, measurements of performance metrics using neural networks by varying load conditions for the IEEE 14 bus system. A different set of loads and factors are given to measure the voltage magnitude. When the load increases linearly, the MAE, MSE, and RMSE errors are also increased.

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Comparing MAE, MSE and RMSE error is observed to the minimum in MSE. Observe from this table, understand that MSE provides least errors. The minimum and maximum values for MSE are 0.0003 and 0.0116.

**Table 2: Voltage Magnitude for IEEE 14 bus system at different load condition using neural network**

| Sl. No | Load (%) | Load factor | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | 10 | 0.1 | 0.0154 | 0.0004 | 0.0195 |
| 2 | 20 | 0.2 | 0.0142 | 0.0003 | 0.0184 |
| 3 | 30 | 0.3 | 0.0157 | 0.0004 | 0.0201 |
| 4 | 40 | 0.4 | 0.0124 | 0.0003 | 0.0169 |
| 5 | 50 | 0.5 | 0.0113 | 0.0003 | 0.0171 |
| 6 | 60 | 0.6 | 0.0123 | 0.0003 | 0.0179 |
| 7 | 70 | 0.7 | 0.0136 | 0.0004 | 0.0191 |
| 8 | 100 | 1.0 | 0.0141 | 0.0005 | 0.0220 |
| 9 | 130 | 1.3 | 0.0177 | 0.0005 | 0.0226 |
| 10 | 160 | 1.6 | 0.0190 | 0.0006 | 0.0257 |
| 11 | 190 | 1.9 | 0.0182 | 0.0006 | 0.0236 |
| 12 | 220 | 2.2 | 0.0225 | 0.0008 | 0.0283 |
| 13 | 250 | 2.5 | 0.0277 | 0.0012 | 0.0347 |
| 14 | 280 | 2.8 | 0.0311 | 0.0017 | 0.0415 |
| 15 | 310 | 3.1 | 0.0348 | 0.0023 | 0.0477 |
| 16 | 340 | 3.4 | 0.0344 | 0.0027 | 0.0520 |
| 17 | 370 | 3.7 | 0.0458 | 0.0049 | 0.0699 |
| 18 | 400 | 4 | 0.0709 | 0.0116 | 0.1076 |

*Table 3* shows the phasor angle error measurement for IEEE 14 bus system using different machine learning techniques. Various machine-learning techniques with their validation and testing results are provided in *table 3*. The neural network has minimum error compared to other machine learning techniques. So Neural network is observed to the more suitable for the proposed work. Compared to RMSE and MAE lowest error value is recorded in MSE. There are two ways to identify the best model for this work: one is which metrics having minimum error value, and another is to verifying which metrics have validation and testing results more similar. In this case, MSE satisfies both methods and hence chosen as the best metrics. In this work, the predicted value is more accurate when compared to the actual value. Machine learning performance is better than the conventional method. If the error value is between 0 to 1, and the model is good. In this work, error values are minimum and within 0 to 1.

**Table 3: Phasor angle for IEEE 14 bus system using Different ML techniques**

| Method | RMSE | | MAE | | MSE | |
|---|---|---|---|---|---|---|
| | Valid | Test | Valid | Test | Test | Valid |
| **DT** | 0.339 | 0.410 | 0.245 | 0.317 | 0.115 | 0.168 |
| **SVM** | 0.387 | 0.471 | 0.259 | 0.329 | 0.150 | 0.222 |
| **E-Boost** | 0.343 | 0.375 | 0.247 | 0.287 | 0.117 | 0.140 |
| **E-Bag** | 0.338 | 0.368 | 0.244 | 0.283 | 0.114 | 0.135 |
| **NN** | **0.311** | **0.312** | **0.210** | **0.236** | **0.097** | **0.097** |

*Table 4* shows the phasor angle measurement for IEEE 14 bus system using different performance metrics. The performance metrics are MAE, MSE, and RMSE.MSE provides the least error value compared to other metrics. The minimum and maximum value of MAE are 0.1023 and 0.7255 respectively. The minimum and maximum value of MSE are 0.0156 and 0.7096. The minimum and maximum value of RMSE is 0.1249 and 0.8424.

**Table 4: Phasor angle for IEEE 14 bus system at different load condition using neural network**

| Sl. No | Load (%) | Load factor | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | 10 | 0.1 | 0.1586 | 0.0264 | 0.1625 |
| 2 | 20 | 0.2 | 0.1567 | 0.0310 | 0.1760 |
| 3 | 30 | 0.3 | 0.1390 | 0.0226 | 0.1503 |
| 4 | 40 | 0.4 | 0.1201 | 0.0166 | 0.1286 |
| 5 | 50 | 0.5 | 0.1063 | 0.0156 | 0.1249 |
| 6 | 60 | 0.6 | 0.1023 | 0.0174 | 0.1318 |
| 7 | 70 | 0.7 | 0.1075 | 0.0217 | 0.1472 |
| 8 | 100 | 1.0 | 0.1272 | 0.0325 | 0.1801 |
| 9 | 130 | 1.3 | 0.1574 | 0.0415 | 0.2038 |
| 10 | 160 | 1.6 | 0.1824 | 0.0495 | 0.2224 |
| 11 | 190 | 1.9 | 0.1981 | 0.0567 | 0.2382 |
| 12 | 220 | 2.2 | 0.2124 | 0.0668 | 0.2584 |
| 13 | 250 | 2.5 | 0.2295 | 0.0836 | 0.2891 |
| 14 | 280 | 2.8 | 0.2544 | 0.1114 | 0.3338 |
| 15 | 310 | 3.1 | 0.3075 | 0.1568 | 0.3959 |
| 16 | 340 | 3.4 | 0.3912 | 0.2311 | 0.4808 |
| 17 | 370 | 3.7 | 0.5028 | 0.3627 | 0.6023 |
| 18 | 400 | 4 | 0.7255 | 0.7096 | 0.8424 |

**Case 2: Estimation of voltage magnitude and Phasor angle for IEEE 30 bus system using ML techniques**

*Table 5* gives the voltage magnitude error measurement for IEEE 30 bus system using different ML techniques and measured performance metrics. To identify the best model for the proposed work, metrics with a minimum error value is chosen. Loads are varied in terms of percentage with the load factor. Neural Network has a minimum value of error compared other four techniques. Therefore, NN is the suitable model for the case 2. MSE has the lowest error value compared to other metrics, followed by MAE, and RMSE.

**Table 5: Voltage Magnitude for IEEE 30 bus system using Different ML techniques**

| Method | RMSE | | MAE | | MSE | |
|---|---|---|---|---|---|---|
| | Valid | Test | Valid | Test | Valid | Test |
| **DT** | 0.079 | 0.067 | 0.057 | 0.050 | 0.0063 | 0.004 |
| **SVM** | 0.081 | 0.083 | 0.057 | 0.064 | 0.0065 | 0.007 |
| **E-Boost** | 0.083 | 0.073 | 0.069 | 0.062 | 0.0070 | 0.005 |
| **E-Bag** | 0.072 | 0.063 | 0.053 | 0.048 | 0.0052 | 0.004 |
| **NN** | **0.069** | **0.060** | **0.049** | **0.043** | **0.0048** | **0.003** |

*Table 6* states the voltage magnitude error measurement using a neural network. The minimum and maximum load variation for IEEE 30 bus system is 10% and 290%. Three performance metrics are used, namely MAE, MSE, and RMSE. Among three metrics, MSE provides minimum error and the minimum and maximum values of MSE is 0.0011 and 0.0188. Similarly, RMSE and MAE also have lower and higher error values based on the load variation provided in *table 6*. All the performance

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metrics provide perfect error measurements to predict a good model.

**Table 6: Voltage magnitude for IEEE 30 bus system at different load condition using neural network**

| Sl. No | Load (%) | Load factor | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | 10 | 0.1 | 0.0388 | 0.0021 | 0.0455 |
| 2 | 30 | 0.3 | 0.0342 | 0.0017 | 0.0409 |
| 3 | 50 | 0.5 | 0.0414 | 0.0030 | 0.0546 |
| 4 | 81 | 0.81 | 0.0391 | 0.0032 | 0.0569 |
| 5 | 100 | 1.0 | 0.0362 | 0.0024 | 0.0489 |
| 6 | 119 | 1.19 | 0.0288 | 0.0017 | 0.0409 |
| 7 | 138 | 1.38 | 0.0259 | 0.0011 | 0.0337 |
| 8 | 157 | 1.57 | 0.0267 | 0.0011 | 0.0338 |
| 9 | 176 | 1.76 | 0.0271 | 0.0011 | 0.0335 |
| 10 | 195 | 1.95 | 0.0291 | 0.0015 | 0.0387 |
| 11 | 214 | 2.14 | 0.0341 | 0.0020 | 0.0445 |
| 12 | 233 | 2.33 | 0.0402 | 0.0029 | 0.0541 |
| 13 | 252 | 2.52 | 0.0516 | 0.0050 | 0.0709 |
| 14 | 271 | 2.71 | 0.0683 | 0.0093 | 0.0965 |
| 15 | 290 | 2.9 | 0.0978 | 0.0188 | 0.1371 |

**Table 7: Phasor angle for IEEE 30 bus system using Different ML techniques**

| Method | RMSE | | MAE | | MSE | |
|---|---|---|---|---|---|---|
| | Valid | Test | Valid | Test | Valid | Test |
| **DT** | 0.305 | 0.237 | 0.242 | 0.193 | 0.093 | 0.056 |
| **SVM** | 0.310 | 0.296 | 0.252 | 0.235 | 0.096 | 0.088 |
| **E-Boost** | 0.283 | 0.221 | 0.230 | 0.179 | 0.080 | 0.049 |
| **E-Bag** | 0.281 | 0.230 | 0.231 | 0.176 | 0.079 | 0.053 |
| **NN** | **0.272** | **0.216** | **0.209** | **0.167** | **0.074** | **0.0469** |

*Table 7* demonstrates the phase angle error measurement for the IEEE 30 bus system using different machine learning techniques. Five machine-learning techniques were introduced to validate the results. The findings of the validation and testing are presented in *table 7*. Among the five techniques, neural network has the lowest error. Thus identified, the best machine learning technique adapted to the proposed network. Among the three errors, the MSE shows the lowest error rate, and the RMSE shows the highest error rate. The lower the efficiency settings, the better your model.

**Table 8: Phasor angle for IEEE 30 bus system at different load condition using neural network**

| Sl. No | Load (%) | Load factor | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1 | 10 | 0.1 | 0.1280 | 0.0393 | 0.1981 |
| 2 | 30 | 0.3 | 0.1622 | 0.0427 | 0.2065 |
| 3 | 50 | 0.5 | 0.1842 | 0.0549 | 0.2343 |
| 4 | 81 | 0.81 | 0.1793 | 0.0542 | 0.2368 |
| 5 | 100 | 1.0 | 0.1522 | 0.0432 | 0.2078 |
| 6 | 119 | 1.19 | 0.1307 | 0.0325 | 0.1802 |
| 7 | 138 | 1.38 | 0.1121 | 0.0249 | 0.1579 |
| 8 | 157 | 1.57 | 0.1103 | 0.0216 | 0.1469 |
| 9 | 176 | 1.76 | 0.1265 | 0.0254 | 0.1594 |
| 10 | 195 | 1.95 | 0.1585 | 0.0340 | 0.1843 |
| 11 | 214 | 2.14 | 0.1602 | 0.0363 | 0.1906 |
| 12 | 233 | 2.33 | 0.2106 | 0.0625 | 0.2500 |
| 13 | 252 | 2.52 | 0.2431 | 0.0838 | 0.2895 |
| 14 | 271 | 2.71 | 0.3041 | 0.1251 | 0.3537 |
| 15 | 290 | 2.9 | 0.4143 | 0.2324 | 0.4821 |

*Table 8* presents the performance metrics measured for phase angle measurement for IEEE 30 bus system using machine-learning techniques. Different loads and load factors are considered to measure the performance metrics. MSE Provides minimum error compared to MAE and RMSE for this case. The minimum and maximum value of MSE is 0.0216 and 0. 2324. Other metrics measured value also provides better results to predict the exact model. In the existing model, traditional techniques such as weighted least square estimation and regularized least square estimation are used to estimate the voltage magnitude and phase angle. In the proposed work machine learning-based parameter estimation is introduced. The data sets used in the manuscript are new, so that compared using different ML models. By comparing different machine learning models, neural network performance is better. This proposed comparison with different machine learning models is shown in *Tables 1, 3, 5,* and *7.*

## 6. CONCLUSION

This paper discusses power flow parameter estimation based on ML methods in a power system. Recently many researchers have various methods for estimating power flow parameters. This paper discusses and compares the ML strategies such as decision trees, support vector machines, ensemble boost, ensemble bags, and neural networks. Based on results obtained using performance metrics, the neural networks provided the best results among those methods with voltage and phasor angle measurement. The neural network is then applied to the IEEE 14 and 30 bus systems to handle various load conditions. Validation and testing results are compared with various machine-learning techniques and measured performance metrics such as RMSE, MAE, and MSE. To identify the best model for the proposed work, metrics should have a minimum error value. Among the three-performance metrics, MSE provides minimum error for IEEE 14 and 30 test systems compared to other metrics. In future work, the predicted data can be used in PMU measurements for estimating voltage and angle. Neural networks require more data for processing. In the proposed work, estimation of phase angle in state estimation, a neural network takes more time to process than the estimation of voltage magnitude, also it takes much more time to train the data. These limitations can be overcome by using deep learning methods. This is to be considered as future work.

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