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POWER SYSTEM DYNAMIC STATE ESTIMATION BASED ON SYNCHROPHASOR MEASUREMENT USING MACHINE LEARNING

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ABSTRACT: Dynamic State Estimation (DSE) is a very important control center application used in the dynamic monitoring of state variables. With emerging synchronized phasor measurement technology, estimating dynamic state in real time (post fault) for the grid operation become feasible. Phasor Measurement Unit (PMU) is the device which measures bus voltage phasor at the bus to which it is connected and current phasors through the lines connected to that bus. However, PMU measurements undergo random errors and bad data unavoidably caused by the sensor errors, disturbances, etc. In this paper, a framework of power system Dynamic State Estimation based on synchrophasor measurement with machine learning method is proposed. In this DSE of synchronized phasor measurements is performed for a virtual node using the measurements from the other nodes in the network by undertaking a separate DSE at each generator and substation level. This system uses two supervised machine learning approaches namely, Generalized Linear Models and Artificial Neural Networks to provide estimates. This paper illustrates Power system DSE on an IEEE 14-bus test system using proposed method with measurements obtained from PMU. The simulation result shows the increased accuracy of the dynamic generator state estimation and a better performance of the applied method indicate very low error rates; the average error for voltage magnitude was approx for the overall system distributed state estimator.

KEYWORDS: **Phasor Measurement Unit (PMU), Dynamic State Estimation (DSE), Machine learning, synchronized phasor measurement**

I. INTRODUCTION

In very simple words, the state estimation is defined as the procedure of estimating the power system state variables, which knowledge of them is highly important for a wide variety of applications such as contingency assessment, correcting thegenerator operation, etc. Roughly speaking, the state estimation (SE) may be categorized into the static SE, tracking SE, and dynamic SE [1]. The static SE is characterized by extracting the power system state variable within a particular amount of time. In this case, the state estimation algorithm has an iterative nature with a flat start initialization. This results in a very high computational burden which may not be concluded in a short period. To deal with this issue, tracking state estimation was developed based on the last computed state variables [2]. However, in static and tracking SE, state variables are estimated Uusing a single set of measurements. Accordingly, dynamic state estimation is developed, which possesses the ability to extract the power system state variables within a short period of time. Conventionally, distribution networks transported electricity from the transmission substations to the end consumers. The one way flow of electricity and radial topology meant that conservative dimensioning of the network was sufficient to ensure the correct operation, without too many real-time measuring points. However, over the last decade, more consumers, communities and businesses have installed distributed generators. The integration of the electricity system with the transport (e.g. electric vehicles) and heating (e.g. fuel cell cogeneration units) infrastructures is also taking place at the medium and low voltage levels of the electricity grid. With these technologies come a series of challenges which require the network operators to have complete network observability, similar to the transmission system operators. However the distribution network requires significantly more measuring devices than the transmission network to achieve this. In this paper, we investigate the performance of a machine learning (ML) driven engine to replace physical measurement devices on the electricity networks. A dataset of real measurements from the same network are utilized to train models for estimating measurements. These trained models are capable of providing pseudo measurements based only on the real measurements from the other nodes. The applications for the ML engine include the reduction of the number of physical measurement devices installed or, in case of a temporary failure of the measurement device, fill in for the lack of measurements [3].

II. LITERATURE SURVEY

State estimation plays a crucial role in monitoring the operating state of the power system [4]. It is the method used for finding the voltage and phase angle at each bus from the available measurements to recognize the existing operating state. It requires measured values to make the system precise and monitor efficiently. The state estimation of a power system includes collecting the real time measurement data, which includes active & reactive power flows through the lines, power injections at the buses and voltage measurements and calculating the state vector using a predefined state estimation algorithm [5]. Power system state estimation is generally classified into three types: static state estimation, dynamic state estimation and tracking state estimation [6].

Static state estimator will not provide true dynamic state because the measurements are not time synchronized. In tracking state estimation, the state once estimated is updated again and again with new set of measurements for the next time period. The state estimation algorithm is not run completely every time. So tracking state estimation also will not provide true dynamic state of the power system and it is not reliable for real time monitoring of power system. Among the three, dynamic state estimation ensures real time monitoring of the power system by estimating the state one step ahead [5]. Many DSE algorithms are available in literature for which filtering requirement is essential. In case of DSE based on exponential smoothing techniques, filtering is seldom required.

The SEs that uses RTU-SCADA and PMU measurements are defined as combined state estimators (CSEs). These may consist of one-stage process and in which both kinds of measurements are used on a hybrid algorithm (HSE), or may consist of two-stage process. Some authors propose hybrid onestage CSEs which run at SCADA speed and therefore are unable to estimate the dynamic of the state in the presence of disturbances. PMU measurements are used in order to coordinate angles between areas when dealing with distributed estimators, or increase the number of measurements and thus the estimation accuracy [7].

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Furthermore, twostage CSEs at PMU speed are proposed, which can be both static type (SSE) and dynamic type (DSE). The SSEs use present measurements in order to estimate the state in the same time instant. The DSEs use present measurements as well as past measurements [8].

In [9] DSEs that operate at PMU speed and are based on Kalman filter are proposed. These methods adopt dynamic models only to represent the slow evolution of the system. In [10] it is proposed a two-stage SSE that runs at PMU speed and capable of estimating the dynamic behavior of the system state in the presence of fast phenomena. The first stage consists of an iterative HSE based on the WLS technique and the second stage is a linear estimator (LSE) based only on PMU measurements. Because it is a partially observed system by PMU measurements, current pseudo-measurements from estimation at the previous instant are added. This method could generate errors mainly in the presence of sudden changes in the system. Besides, it presents limitations when the electrical distance between PMU measurements and non-observed buses is greater than two buses [10].

III. PROPOSED ARCHITECTURE

The proposed method can be used as a solution to the multi-stage optimal PMU placement problem in which a gradual deployment of PMUs across the distribution network is required because of the high number of nodes. The distributed state estimation, carrying out state estimation process in the power plant and substation respectively, uploading the results and circuit breaker actual status to the control center, then conducting the overall system state estimation, as shown in Fig.1. Our ML engine can create virtual nodes capable of providing estimates until the physical equipment is installed. Further, when they are installed and network observability is achieved, the ML algorithm can offer redundancy and reliability of the solution in the case of failures in measurement devices.

For generator block, the input variables including the previous estimation result (such as the absolute rotor angle 0, electrical angular velocity wand the transient electromotive force) and the PMU direct measurement (such as the generator terminal voltage Ut and phase angle Ot).

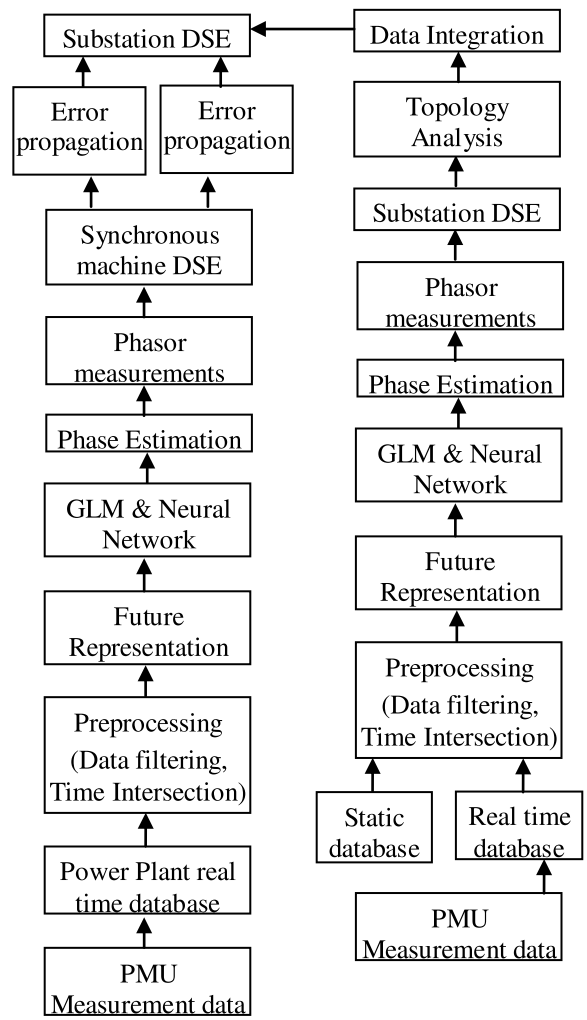

Fig 1: FRAME WORK OF PHASOR MEASUREMENTS ESTIMATION ASED DSE USING ML

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As can be seen in Figure (1) phasor measurements are initially pre-processed. In this step, pre-processing techniques such as data interpolation for missing data or filters for noisy measurements can be used. For evaluation purposes, we extract an intersection of timestamps where data from all the nodes is available. This can be utilized at the training phase only where synchronized data is required to train such a framework. This step results in a processed data of nodes within a network with measurements from the same timestamps. This data is then used for establishing features to train for estimating target variables. In our feature representation stage, synchronized raw measurements are directly used with minimal addition of extra features. Due to this, the feature extraction stage is significantly faster than traditional approaches where several statistical or geometric features are extracted over a time window of measurements. They also have a significant limitation for this application as the output target in such scenarios is an aggregated estimate whereas the proposed system has the capability of producing estimates for a given time stamp based on the real direct measurements.

Feature data from the previous step is then used to train individual models for separate target variables. In this work, we utilize a supervised machine learning framework in which labeled data is provided in the form of true measurements at the training stage. In particular, we use regression models that are appropriate for estimating numeric measurements (as opposed to using classification models in which the target is categorical in nature).

a) Generalized Linear Model (GLM): Input features f are used to fit GLMs for estimating the target data individually. The GLM model assigns coefficients to each of the input feature in the form of a linear equation capable of estimating the target variable. This linear model is of the form:

$$y_p^p \sim 1 + \left[f_{r_1}^{k_1} + f_{r_1}^{k_2} + \cdots + f_R^K\right] \text{ ---- (1)}$$

Where, $M = \{k_1, k_2, \cdots, K\}$, $N = \{n_1, n_2, \cdots, L\}$, q $\in$ M, p $\in$ N, $r = \{\{r_1, r_2, \cdots, R\}: r \in N \text{ and } r \notin p\}$

b) Neural Network (NN): We also use the same set of input features to train multiple Neural Networks for all of the target variables. In particular, we use Bayesian regularization for training the models with 100 nodes.

After the data uploading process, the generator-network interface will be used to convert the generator DSE result to the pseudo measurement of network node voltage phasors (from d-p to x-y axes). Then, combined the generated pseudo measurement error variance, those will finally contribute to the system side linear DSE. Similarly for the substation block, the PMU measurement including the node voltage, phasor current flowing through the circuit-breaker, input and output line current of the substation are taken as an input (with redundancy) for the following substation state estimation with related boundary conditions. The output of the node voltage phasor, the circuit-breaker status, and the estimation error will be up loaded to the dispatch center for the use of network topology analysis and further overall system DSE. The system level DSE starts with the initial network topology analysis, the integration of the substation state estimation result and the generator DSE result through the generator-network interface. When the network node voltage estimation error variance (estimation error propagate from local to the system level) is derived, the weighted Linear Least Squares method is

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applicable to carry on the system level DSE (because the 2 measurement for the system level DSE only including the node voltage and branch current vectors).

IV. RESULTS

The IEEE 13-bus testing system as shown in Fig.2 is used for the verification of the DSE for generators considering the machine learning approach and the entire system respectively. Node 1 is set to be the slack bus. Syncronised voltage phasor measurements are collected using PMUs installed. Apart from the loads, the feeder connects photovoltaic (PV) panels and a co-generation unit therefore reverse power flow is common. The feeders are part of a new strong network with underground cabling. The PMUs take 3 phase measurements from the secondary side of the 20/0.4kV transformers. The measurements are sent securely to a Mongodb database and form part of the input of a distribution state estimation application developed. The proposed framework is evaluated using the nodes within the same network which are filtered out and an intersection of timestamps is established.

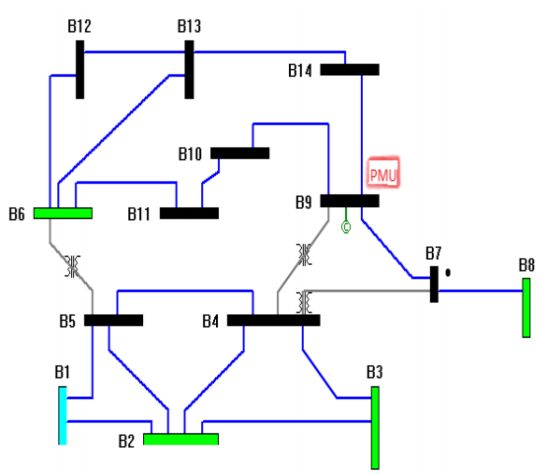
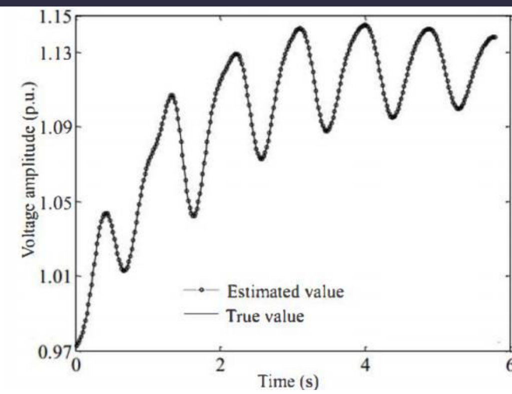
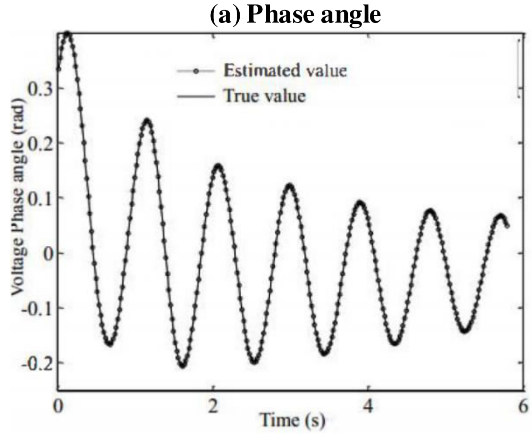


Fig. 2: IEEE 14 BUS SYSTEMS



(a) Phase angle



(b) At node B8 for the system

Fig. 3: THE STATE ESTIMATION RESULT OF VOLTAGE AMPLITUDE

As can be seen in Fig.4, the areas including the nodes directly connected to the transformers and the bus bars on the transmission lines (node B5, B7, B9) are regarded as substations. Undertaking the DSE process at the generators and substations respectively, the system level DSE then can be progressed with their converted pseudo measurements and measurement error variances based on the weighted Linear Least Squares method. Taking node B8 as an example, the DSE result about the voltage amplitude and phase angle at node B8 are shown in Fig.3. Also, the estimation variance of voltage amplitude and angles at each bus is all under the value of 0.15e-6 p.u. and 0.4ge-6 rads respectively. Those above indicate that the applied power system distributed DSE can

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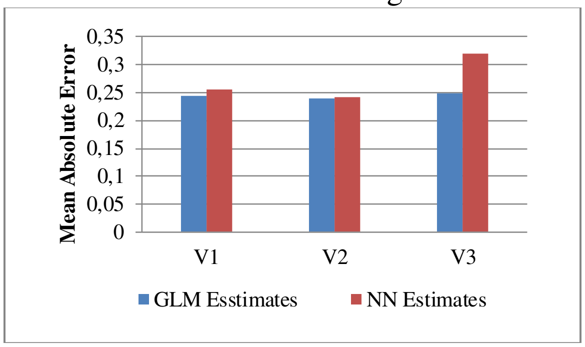
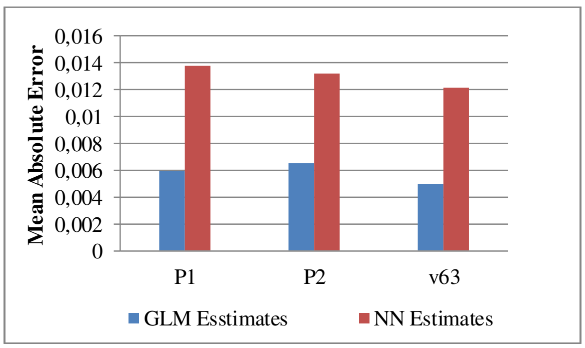
remove the random error effectively from the PMU measurement and obtain accurate estimation value of node voltage.



(a) Voltage Estimation



(b) Phase Estimation

Fig, 4: ESTIMATION RESULTS USING GLM AND NN REGRESSION MODELS AT B8 NODE

Figure 4 (a) shows the voltage estimation results using both GLM and NN. Baseline of 2.30V is used. It can be seen that in all cases, the estimation results have low errors compared against the baseline. In general GLM estimation performs better compared against the NN estimation. Similarly in Figure 4 (b), phase estimation results are shown using both GLM and NN. A baseline of 10mrad is used. In this case, GLM outperforms both the baseline and the NN estimation results. NN estimation on average has a higher error rate compared against the baseline. Based on these results, it can be inferred that a certain linear relationship exists between phasor measurements from different nodes and therefore can be more accurately modeled using a linear model. However, with more training data and higher complexity neural networks (such as deep learning methods), these results can further be improved.

V. CONCLUSION

The framework for the dynamic state estimation of the overall power system proposed in this paper is based on the generator-network interface, converting the generator DSE result into the error variance about the network node voltage pseudo measurement, leading to build to system estimation method involving the generator dynamic constraint, and as a result, to improve the accuracy of the node voltage vector state estimation of the network. The generator DSE proposed in this paper is based on the machine learning algorithm, considered machine learning to estimate synchronized phasor measurements. The simulation results for the generator DSE considering the machine learning and network node voltage vector estimation indicate the improvement of the state estimation accuracy for the generator and the network respectively. In particular, GLMs performed better than the NN model and the baseline. The estimation error decreased with the increase in the total number of nodes considered for training, however we found that the rate of decrease is dependent on the type of measurement.

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