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A Review of State Estimation of Power System Dynamic State

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Abstract – The power demand globally has drastically increased. This has led to the recent development of the use of renewable energy sources (RES) in power generation. This surge in energy need and generation has caused decontrol in the power system network, making the power pattern less predictable; therefore, real-time monitoring is critical to have a reliable and stable operation. This paper is a review of the dynamic state estimation process in the Nigerian power system. The paper explains the static, dynamic, tracking and forecasting-aid state estimations. It further provides insight into devices that are used for state estimation such as PMUs and SCADA. The paper concludes that state estimation is a veritable tool for monitoring, controlling and predicting the power system dynamic state for efficient operation of the system. The paper suggests that SCADA and PMUs should be used concurrently in power systems for greater efficiency in the system.

Keywords: state estimation, static state estimation, dynamic state estimation, power system, SCADA/PMUs

I. INTRODUCTION

Power demand globally has drastically increased. This has led to the recent development of the use of renewable energy sources (RES) in power generation. This surge in energy need and generation has caused decontrol in the power system network, making the power pattern less predictable; therefore, real-time monitoring is critical to have a reliable and stable operation.

The operation and control of power systems are in an ordered manner [1]. The increasing advancement and complexity of power systems make real-time monitoring and control important in achieving a dependable operation of the power system. The achievement of monitoring and control in the power system is by Energy Management System (EMS) functions. The mainstay of the energy management system is state estimation (SE). It provides a catalogue of the real-time state of the system for use in other EMS functions [2]. Therefore, state estimation is a requirement for the proficient and correct operation of the power system anywhere in the world.

State estimation determines the crucial assessment of a power system's real operational status as a necessity for a competent and reliable operation. Given the several crucial functions, SE performs in the detection of abnormal situations, generator correction actions, and contingency analysis, its relevance to power systems and the operation of restructured systems is increasing. In a broader sense, SE is divided into three categories: dynamic SE, tracking SE, and static SE (DSE). Based on the measurement set corresponding to that moment, SSE determines the power system status connected to a given time. The SSE algorithm is iterative and starts with a flat initialization. Therefore, SSE utilizes weighty calculations that cannot be done in short intervals. TSE was introduced to carter for the deficiency of SSE. Its estimation starts from the last computed state variables instead of a flat point. SSE and TSE both utilise a single set of measurements to estimate the state of the power system. The DSE, also known as forecasted-aided SE, was created as an improvement over estimators, and it is increasingly relevant in modern energy management systems. DSE can forecast the power system gradually over a short period. Estimation further employs both measurement and prediction data sets at the same time. The estimating error that results from the use of historical-based forecast data during significant changes in the power system state variables is one of the difficult parts of utilising DSE [2]. DSE can capture the dynamics of the system states properly, and it will be crucial for power system control and protection as the complexity of the system grows [2].

The power system dynamic state refers to the changing nature of the power system over time. These changes occur because of changes in frequency, voltage, and current. In practice, power system states may undergo drastic changes during hourly load fluctuations, component outages, or network switching. In such conditions, the inclusion of predicted values could degrade the power system state estimation. With state estimation, power system state could be predicted and can significantly reduce the number of network collapse, therefore increasing the reliability and efficiency of the network.

It is against this background that this work aims to review the state estimation of the power system dynamic state.

II. STATE ESTIMATION

State estimation determines the crucial assessment of a power system's real operational status as a necessity for a competent and reliable operation. Given the several crucial functions SE performs in the detection of abnormal situations, generator correction actions, and contingency analysis, its relevance to power systems and the operation of restructured systems is increasing. In a broader sense, SE is divided into three categories: dynamic SE, tracking SE, and static SE (DSE) [2]. Fig. 1 shows the role of state estimation in the power system. It involves contingency analysis, dynamic security analysis, optimal power flow, control and management, security enhancement and other applications.

Fig 1. Role of state estimation in power system

The following [4] form the foundation of estimating theory:

1) system modelling, measurement, and analysis of all noise traits.
2) a standard for mixing or matching model output and measurements.
3) Using the above task's numerical approach, you can estimate the quantities and determine their uncertainty.
4) If any of the aforementioned steps are inconsistent, an internal consistency check will be performed to see whether they need to be modified.

A. Static State Estimation

A further simplification of the TSE leads to the full disregard of the state transition information and the retention of only the nonlinear measurement

function in the SSE. The states at earlier time steps are therefore unknown to SSE [4]. It is important to note that SSE might function more effectively in the presence of abrupt changes than TSE. Comparatively speaking to DSE, it is unable to track system dynamics. Unlike DSE, it only permits observation of the state vector using the most recent batch of measurements. Performing a FASE when incorporating pseudo-measurements into SSE through state or measurement forecasting [4], [5], [6]. The linear state estimation, which combines voltage and current phasors from PMUs to produce a linear measurement function, is a more recent iteration of SSE (LSE) [7]:

$$zk = Hyk + vk \quad (1)$$

where H is a constant matrix made up of information about the transmission lines in the system. LSE can monitor the online voltage magnitude and angle for each bus at the PMU reporting rate. The real dynamics of the system, such as the shifting loads and machine statuses, are not monitored.

B. Dynamic State Estimation

The dynamic state vector or model parameters of the overall discrete-time state-space model presented in (2) and (3) are estimated using several nonlinear filters created within the Kalman filter architecture [8].

$$xk = f(xk-1, yk-1, uk, p) + wk \quad (2)$$

$$zk = h(xk, uk, p) + vk \quad (3)$$

A prediction step using (2) and a filtering/updating step using (3) are typically involved.

$P_{k-1|k-1}$, a set of points chosen from the probability distribution of (2) or directly from it can be used to construct the predicted state vector given the state estimation at time step in particular $k-1, \dot{x}_{k-1|k-1}$, $\dot{x}_{k-1|k-1}$ which is dependent on the attributed weekly probability distributions. In terms of the filtering step, predictions and measurements from time step k are used to estimate the state vector and its covariance matrix [9].

Depending on how the state statistics are transmitted, various Kalman filters are available, including the extended Kalman filter (EKF), unscented Kalman filter (UKF), ensemble Kalman filter (EnKF), and particle filter (PF) [3], [10]. Given that the computational power is adequate for the magnitude of the problem being addressed and that the equality and inequality criteria are properly enforced, the resulting state space equations (2) and (3) make it possible to rigorously apply DSE to any power system, under any conditions. When system dynamics are truly believed to be absent or negligible and state transitions are only fueled by smooth evolution, it may be misleading to refer to a quasi-steady state operating condition as "dynamic". In reality, we refer to the produced estimators as either FASE or TSE in this circumstance [3], [11].

C. Forecasting-Aided State Estimation

FASE is a precise application of the DSE concept to quasi-steady state settings, where the changing elements of xk are neglected and the state transition model (change in operating point) is only driven by slowly stochastic variations in the power injections (demand and generation). Additionally, the FASE approach presupposes that the state-transition model (4) is linear, in contrast to the earlier DSE formulation. , which results in [7]

$$y_k = Aky_{k-1} + \zeta_{k-1} + w_k$$
$$z_k = h_{(yk,\,p)} + v_k \quad (4)$$

where yk stands for the algebraic state variables, specifically the bus voltage magnitudes and angles; additionally, the necessary transition matrix Ak and the trend vector k1, which is a function of uk, are determined from historical time series data, avoiding the need for nonlinear state-transition models. Exponential smoothing regression or recursive least squares are the often employed methods for that. [8] [12].

Alternatively, without taking into account any further information regarding the problem's structure, the present values are calculated from a weighted average of the most current preceding data, with several weights that are exponentially decreasing. The FASE technique offers satisfactory results, typically better than the more straightforward TSE, when the input or trend vector changes efficiently. However, because the state transition coefficients need some time to adjust to the new environment, results may be obtained that are possibly erroneous when there are sudden changes caused by things like loads, DERs, and system topology, to name a few [13]. To address that, the literature has recommended the skewness test, the normalised innovation vector-based statistical test, and other mitigation measures. However, the Gaussian assumption, which is frequently violated in actuality, is used in these tests, resulting in undependable detection levels. Furthermore, it continues to be quite difficult to distinguish between various oddities. The anticipated state offers helpful information for security analysis and preventive control procedures, which is one of the benefits of FASE that is commonly mentioned. However, to take advantage of the benefits of such a look-ahead or forecasting capacity, there must be enough time for a reaction. This may not be the case in transmission systems with scanning rates of only a few seconds. Readers can consult the two

FASE review publications for more details. [6].

D. Tracking State Estimation

The FASE can be reduced to TSE under the presumption that the state transition matrix Ak is an identity matrix and the change in the state vector is negligibly small [14][15]. The TSE model is formally represented as

$$y_k = Y_{K-1} + w_k,$$
$$z_k = h(y_k, p) + v_k, \quad (5)$$

where the random walk (state change) wk is assumed to be a white Gaussian noise with a known covariance matrix and a zero mean. The lack of a suitable model to reflect the dynamics of the system state is one of the difficulties in developing TSE. The system state remains unaltered, save from an additive Gaussian noise wk, under the quasi-steady state assumption made by TSE. The trend k1 is no longer trivial because of the rising penetration of DERs and flexible loads, and the state change cannot be easily substituted by white Gaussian noises. This situation is made worse by changes in network topology and parameters brought on by the switching of lines, transformers, capacitor banks, or shunt reactors. As a result, it is difficult to adopt TSE for real-world uses.

III. SSE AND DSE COMPARED

While DSE is a new tool for the industry and system operators, SSE has grown to be a frequently utilised tool in modern EMS. As a first byproduct, topological observability analysis delivers a binary response, but it also provides other useful information, such as which buses (islands) are observable or which pseudo-measurements need to be added to restore full observability at the very least. Based on the factorization of the Jacobian or Gain matrices, numerical observability analysis offers a "spectrum" or range of observability solutions, depending on the condition number of the matrix being factorised. Due to aberrant network characteristics or measurement weights, a network may be topologically observable but not algebraically (numerically) observable. In some cases, a network can be numerically observable for a certain combination of weights, but not for others. This is not exactly "binary." It is essential to clarify their implementation and functionality differences and, at the same time, enable a clear path transition from SSE-based EMS to the future DSE-based EMS with power electronics-dominated power systems.

It is possible for a network to be quantitatively visible in some circumstances but not in others, not really "binary." Clarifying the implementation and functional differences is crucial to facilitate a smooth transition from the current SSE-based EMS to the upcoming DSE-based EMS with power electronics-dominated power systems. Differences in implementation in terms of measurements, models, observability, execution rate, outputs, and applications, SSE and DSE have different requirements [8]. Table 1 provides a summary of these variations.

Table 1. Comparing SSE and DSE [8]

Variables	SSE	DSE
Measurement	SCADA reading ranges from 2-10 sec.	PMU/DFR reading ranges from 1/30-1/240 sec.
Observability	Binary (whether observable or not)	Time-varying (Strong/weak/not observable)
Update speed	1 snapshot (every ~ 2-10 sec.)	1 prediction + 1 filtering (every 1/30 ~ 1/240 sec.)
Models	Numerical power flow equations	Differential-numerical equations
Background	largely distributed or centralised	both centralised and decentralised
Outputs	Mathematical variables (voltage magnitudes and angles)	Dynamic variables, including those related to machines, dynamic loads, and DERs
Applications	monitoring and management (operator in the loop)	Control, monitoring (operator in the loop), and adaptive security (operator out of the loop)

To increase redundancy, SSE mostly uses SCADA measurements that are updated every 2–5s and a few PMU measurements. However, since PMU measurements are synchronised while SCADA measurements are not, there is a problem with effectively integrating those two sources of data. In contrast, quick and synchronised measurements for DSE are used, and they may originate from PMUs and digital fault recorders. These measurements have a reporting rate of 30 to 240 samples per second (DFRs). Additionally, the observability theory for SSE and DSE differs significantly from one another [11][8].

The topological, or numerical, based observability analysis for SSE is typically used to decide whether or not the system is observable. Observable islands may be identified if the system cannot be observed [8]. Additionally, the observability analysis can reveal whether or not

there are various solutions to the SSE problem in the presence of ampere readings, where multiple solutions may exist based on the type of remaining measurements and the loading point. When the ampere measurement value is almost zero (an unloaded line), a network may be uniquely visible for severely loaded situations yet "unobservable" (i.e., have an undefined Jacobian) in those cases. This results in indetermination. As a result, although the response is often binary, it depends on the line loading.

In DSE, however, one may speak about strong, weak, or unobservable systems. Calculating the observability matrix's smallest singular value from the Lie derivatives is one technique to put this into numerical form. Stronger (weaker) observability for a specific measurement set is indicated by higher (lower) values of the smallest singular value of the observability matrix [16]. The outcomes of observability are also time-varying because the problem is nonlinear and time-dependent. It is important to note that the system may not be visible but still be detected for DSE in certain circumstances [9].

A little less strong concept than observability is detectability. If all of the unobservable states are stable, a system is detectable. The computing capacity is further challenged because each prediction correction step of the DSE needs to be solved numerically more quickly than the PMUs, DFRs, and MUs scan rate. Decentralized/distributed DSE or parallel computing techniques for centralised DSE are frequently recommended [4] as solutions to this problem.

SSE and DSE produce different results. While DSE gives estimates of the dynamic state variables, such as those connected with generators/dynamic loads/DERs, SSE provides estimates of the algebraic variables, such as bus voltage magnitudes and phase angles. Additionally, a joint DSE is available [4] that simultaneously estimates dynamic and algebraic variables. A linear state estimation (LSE) method that keeps up with the PMU refreshing rate has been devised for some PMU observable networks [4]. It does not, however, follow the system dynamics in practice. The models utilised for SSE and DSE implementation differ. Algebraic equations are employed to represent the system model for SSE since the generators and loads are simply modelled by power injections in SSE. While for DSE, a set of data is used to represent the generators, dynamic loads, DERs, etc., and their controllers. It should be noted that installing PMUs at every generator terminal is not necessary; the DSE can be used if the generator terminal can be observed using a local LSE. A functional diagram between SSE and DSE is shown in Fig. 2.

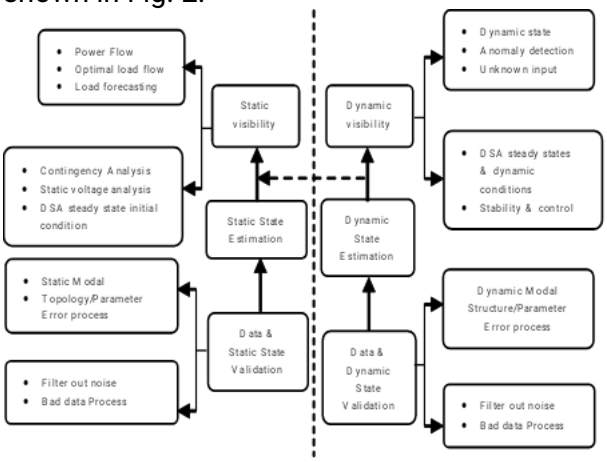

Fig. 2. Functional diagram of the between SSE and DSE [8]

E. Classification of Error

By using observability analysis, you may find out if the specified sample sizes are estimating the state vector. Using the real-time measurements that are now available, typically consisting of real and reactive power, the state estimator calculates the voltage magnitude and phase angles at each bus. Telemetered measurements have been divided into the three categories below based on how serious the inaccuracies that were introduced were [7].

(i) Extreme error: σ is the standard deviation of measurements, and the absolute difference between the measured value and the true value is greater than 20σ.

(ii) Gross error (Bad data): occurs where the variance between the measured value and the true value is between 5σ and 20σ in absolute terms.

(iii) A normal mistake (error): occurs when the discrepancy between the measured and true value is less than 5σ in absolute terms.

Through pre-filtering and measurements, the incredibly inaccurate data are disregarded. Simple verifications of the incoming raw measurement data (such as Limit cheeks) can eliminate some recurrently inaccurate data. However, some significant mistakes will evade this pre-filtering and enter the estimating stage, when their impact on the outcome needs to be reduced or removed. Gross mistakes could be the result of equipment failure or metre malfunction [8].

A faulty data processor can identify measurements that contain bad data (gross inaccuracy). When flawed data is found, it pinpoints which measures are flawed. These are taken out from the list of measurements that will

be used to estimate the state [11].

IV. SE DEVICES USED IN POWER SYSTEMS

A. Phasor Measurement Units (PMUS)

Due to the extensive usage of Phasor Measurement Units (PMUs) and advanced communication infrastructure in power systems, it is now possible to develop a quick and reliable DSE tool. A new generation of power system monitoring systems included in the Wide-Area Measurement System (WAMS) is made possible by expanding the deployment of Phasor Measurement Units (PMUs). PMUs can precisely and directly measure state variables such as bus voltage magnitude and phase angle. They can enhance the resilience and accuracy of the estimation process as a result [1].

The following are some advantages WAMS has over traditional metering infrastructure [9].

1) PMUs are placed following precise instructions, tested during commissioning, and routinely calibrated.

2) Advanced calculation techniques and self-check/self-diagnostic capabilities are built into PMU devices. Additionally, PMUs feature 16-bit or higher A/D converters that offer a very fast sampling rate and extremely precise measurements.

To synchronize the A/D phase-locked loop (sampling clock) and provide the PMU data with the precise time of measurement, a GPS receiver is added to the PMU structure. Additionally, the data's time synchronization quality is transmitted.

B. Synchronized Phasor Measurement Units (PMUs)

State estimation (SE) was introduced long ago as an essential application for managing and maintaining power system stability and control for the operation transmission grid effectively. The state estimation received and processed the measurement of some electrical quantities, which include; voltage, current magnitude, power flow and net power injected. State estimation acted as a locator of contingency or an error in the measurement of the stated quantities in the power system. PMU is a kind of device, which digitally operate in a synchronized way to measure the values of quantities stated above in the power system [1]. PMU provides a solution by evaluating and monitoring a large multi-area power system since their operation is more interdependent. Multi-areas refer to the geographical or based on the voltage level of the system. Synchronize phasor measurements become of highly important technological solver as it provides simple and accurate identification of topo-logical and parameter errors, maintain system observability, and improve statistical and numerical robustness of the estimators.

Moreover, they pave the way for developing estimators with very high scan rates, making it simpler and possible to detect system dynamics that are now neglected by present state estimator [2].

In electrical power system engineering, SE refers to static SE; this computes the condition (state) vector at a particular time instant from measurements captured at the equal time instant, where the process is done several times at K but did not include any physical modelling of the time habit of the system. The DSE method depends on the following general dynamic model, which is in its discrete state transition form as shown in (6) and (7) [3].

$$\hat{X}_K = \hat{X}_K - K_K\left(2k - h(\hat{x}_k - 1)\right) \quad (6)$$

$$k_k = (H_K^T W H_K + M_K^{-1})^{-1}$$
$$\hat{X}_{k+1} = F_K \hat{X} + Uk$$
$$M_{K+1} = F_K\ (H_K^T W H_K + M_K^{-1})^{-1} F_K^T + Q \quad (7)$$

$\hat{X}_K$ *is* the estimated (predicted) state at K time F_K is Jacobian of F calculated at K time, U_K acts as a command coming from linearization, M_K is the covariance matrix of predicted state, Q the covariance matrix of noise ω, assumed to have anormal distribution at zero mean.

C. STATE ESTIMATION IN POWER SYSTEM WITH SCADA, PMUS

Power system monitoring, data collecting, and control tasks are handled by a new generation of equipment. Supervisory Control and Data Acquisition (SCADA) systems are the name given to this group of tools. A SCADA system is an amalgamation of software and hardware technologies that offers a versatile range of functions. The parameters set in the system's database, which allows for future development of the power system network, determine the actual use of a given SCADA system. This is accomplished by the application of sophisticated real-time database techniques, which continuously update the system's database to reflect the current state of the power system [3].

Power system state estimation analyses the received measurements to provide the most accurate approximation of the system's states. Before being passed to other Energy and Management System (EMS) application functions, such as the controllers for the Automatic Generation Control (AGC), contingency analysis, and load analysis, it can be thought of as a filtering channel that processes the raw measurements primarily from the Supervisory Control and Data Acquisition (SCADA) system [18].

A crucial piece of equipment for power

system management and control is the Phasor Measurement Unit (PMU), which can deliver synchronized voltage and current phasors (magnitude and phase angle) within a few cycle time window. PMUs began to play a significant role in many applications due to their accuracy and quick sampling, particularly in large-area monitoring and control [19]. Since measurements of the power system may be obtained using both the SCADA system and PMUs system, the state estimation problem may be divided into two subproblems. A sub-problem first considers measurements from the SCADA system alone, and then improvements are taken into account by supplementing the SCADA readings with PMU measurements [15].

PMU is a Synchrophasor measurement technology (SMT) based device that enables utilities and researchers to learn more about real-time power system monitoring. PMUs make it possible to monitor the actual system state and, in the event of disturbance conditions, to trigger countermeasures [19].

V. CONCLUSION

This paper has reviewed state estimation and its use in the power system. It has been established that state estimation is an estimator used for monitoring, controlling, and predicting errors in the power system for the efficient operation of the system. The static state estimation technique is a traditional state estimation technique used in power systems. It found application in SCADA primarily until the invention of PMUs, which use dynamic state estimation, a more recent estimation technique. Research is ongoing to see how SCADA and PMUs can be used for estimation in power systems to achieve greater efficiency in the system.

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