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Abstract

Power system state estimation has been playing a core part in the energy management system (EMS) utilized by power system operators since its establishment in the 1970s. The state estimator is responsible for providing accurate information (e.g. voltage magnitudes and angles of all buses in the network) for the EMS so that its security assessment functions can be deployed reliably. Recently, the power system is experiencing unprecedented evolution of complexity due to the increasing injection of renewable energy, increasing usage of power electronic devices and the increasing number of HVDC links in the network. One of the solutions to such challenges is to deploy Wide Area Monitoring System (WAMS) supported by the Synchronized Measurement Technology (SMT).

Prior to state estimation, an observability analysis must be performed to make sure the measurements (e.g. power injection and flow measurements) received can support the normal functioning of the state estimator. If the measurements cannot provide full observability of the network, the observability analysis function identifies the observable islands where state estimation can still be performed within the observable islands.

This paper reviews the literature on state estimation (SE) in power systems. While covering works related to SE in transmission systems, the focus of this paper is to review the method of implementing it in the distribution network. The critical topics of distribution systems SE (DSSE), the different state estimation methods, data driven modelling, and cyber – security are discussed. The conventional and recent approaches, including bad data detection and state estimation (SE) based on different kinds of neural networks, have been reviewed. This paper can give a crisp idea about recent achievements, research gaps and future research paths of state estimation in power systems.

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List of Abbreviations

EMS	Energy Management System
WAMS	Wide Area Monitoring System
SMT	Synchronized Measurement Technology
SE	State Estimation
DSSE	Distribution System State Estimation
SCADA	Supervisory Data Acquisition
AGC	Automatic Generation Control
UAV	Unmanned Ariel Vehicle
UD	Upper Diagonal
EKF	Extended Kalman Filter
SPKF	Sigma Point Kalman Filter
UKF	Unscented Kalman Filter
CDFK	Central Difference Kalman Filter
SRUKF	Square Root Unscented Kalman Filter
CKF	Cubature Kalman Filter
GM	Gaussian Mixture
WLS	Weighted Least Square
LAV	Least Absolute Value
IPM	Interior Point Method
DSE	Dynamic State Estimator
DER	Distributed Energy Resource
PMU	Phase Measurement Unit

STATE ESTIMATION IN POWER SYSTEMS

1.1 Introduction

The growth in size and complexity of electric power systems along with increase in power demand has necessitated the use of modern Energy Management Systems (EMS). In the past few decades, major advances in the hardware and software technologies have transformed the power system control from a simple process control to a system of distributed processing capable of supporting several levels of application functions. The supervisory control and data acquisition/automatic generation control (SCADA/AGC) systems have now given way to the full-fledged Energy Management systems. This very large and complex hardware software system is based in utility company's load dispatch or control centers, which perform extensive on-line monitoring, assessment, analysis and optimization functions to ensure economical and secure operation of power system as well as to facilitate the periodic tasks carried out by the operating personnel [1]. Data received at energy control centers through telemetry link contains small random noise due to inaccuracy of the meter through which they have been acquired. This could be in Analog/digital conversion circuit and communication link. Moreover, some of the data may be missing due to communication Failure or meter faults or may contain gross error. Since, the success of all the advanced functions being carried out at energy control centers depend on how accurate the system data are being used to run the software. Thus, the state estimation of an electric power system is a function, which utilizes the statistical criterion to filter out the noise which is usually present in the telemetered measurements acquired through the data acquisition system and which determines the system operating states (complex bus voltages). The output of the state estimator is used as need to various advanced function of the Energy Management. To obtain reliable estimate of the system states, redundant set of measurements are taken and processed [1].

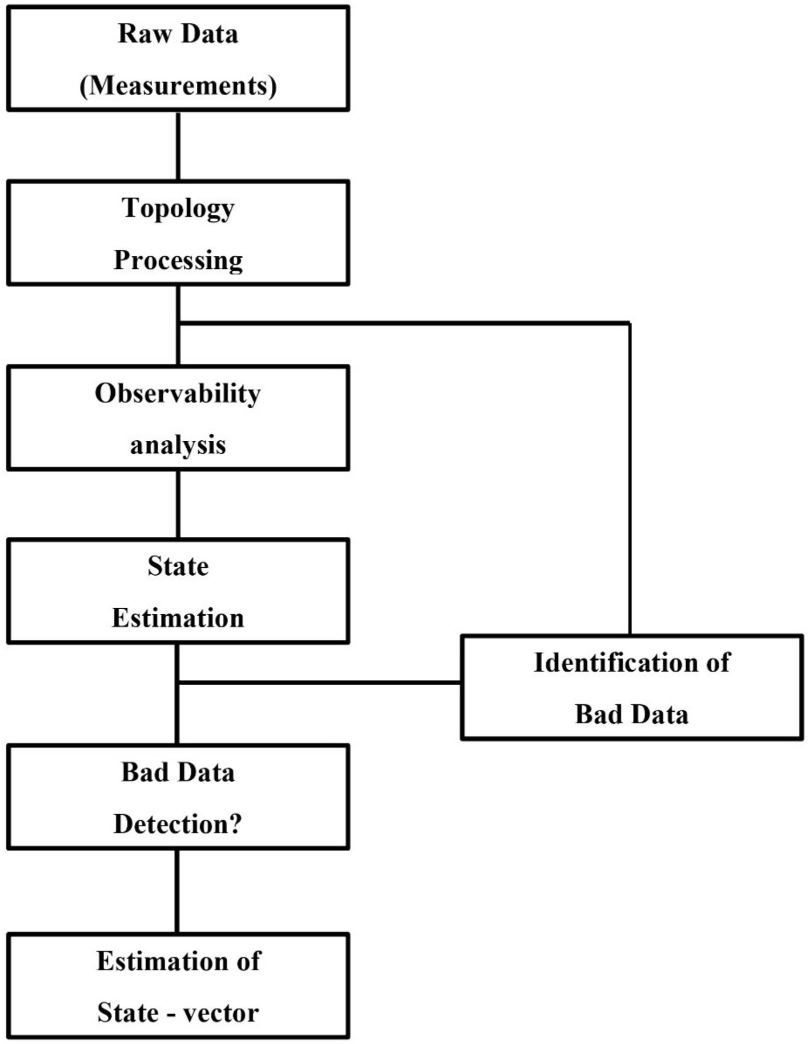

Fig 1. Conventional State Estimators

1.2 Types of State Estimation:

Depending on the time variant or invariant nature of measurements and the static dynamic model of the power system states being utilized, the state estimation can be classified into three categories:

i. Static state estimation

ii. Tracking state estimation

iii. Dynamic state estimation

The static state estimation is defined as the data processing algorithm for converting redundant meter readings and other available information in to an estimate of the vector, while measured data are taken to be time invariant and state model of the power system is considered [1-3].

The tracking state estimation algorithms are based on a simple extension of the static state estimation techniques. They utilize the recent available value of the system states to update their estimated values non iteratively during the subsequent sampling period. This class of estimators has been arisen from the natural need of making static state estimators as efficient as possible in regard to the computational speed making them more suitable for real-time implementation [4].

The dynamic state estimator utilizes, in addition to the present states, the previous estimates of the states. The capability of forecasting the state vector one step ahead is an important advantage of the advantage of the dynamic estimators. State prediction gives a longer decision time to the system operator, because economic dispatching, security assessment and other functions can be performed in advance. In dynamic state estimation, dynamic model for the time behaviour of system states is utilized, whereas tracking and static state estimators do not require any dynamic model of the system states. In the present thesis only static state estimation has been studied [5].

1.2.1 Bad Data Processing

Static-state estimation is related in many ways to conventional load-flow calculations. However, the state estimator is designed to handle the many uncertainties associated with an actual system using meter readings telemetered in real time to a digital computer. Uncertainties arise because of meter and communication errors, incomplete metering, errors in mathematical models, unexpected system changes, etc. The purpose of a static state estimator is to "clean up" the incoming data (actual measurements, system status information, and possibly pseudo measurements) and provide the rest of the control computer or the system operator with a "reliable" set of numbers (the state estimate) which are truly representative of the actual system. Thus, there is a great conceptual and practical difference between static-state estimation as a part of a real-time control system and the usual load-flow studies done the office for system planning.

Static-state estimation is related to conventional load-flow calculations. However, the state estimator is designed to handle the many uncertainties associated with trying to do an on-line load flow for an actual system using meter readings telemetric in real time to a digital computer. Uncertainties arise because of meter and communication errors, incomplete metering, errors in mathematical models, unexpected system changes, etc.
These uncertainties make for large differences between the usual load flow studies done in the office for system planning and on-line estimation done as part of a control system. Three possible approaches for obtaining the crucial database are:

1) Data acquisition with no processing
2) Data acquisition with digital computer used for data logging, limit checking, and simple logic comparisons between redundant measurements of essentially the same variable.
3) Data acquisition with a digital computer used in a systematic way, based on a mathematical model, to clean up the data (by treating small random errors, bad data, modelling errors, and parameter errors), and to compute (estimate) quantities and variables which are not directly measured. The third approach is static state estimation.

1.3 An Exposition on State Estimation

Some of the states in a system cannot be directly measured, or else, some measurements are not accurate enough due to sensor uncertainty. A sensor is a detection device that converts an actual physical quantity (the so-called state) into an electrical signal output and provides measurement data. The conversion process introduces some errors. These errors include drift error and measurement noise. The sensor's correction can eliminate the drift error, but the measurement noise cannot be eliminated fundamentally. Thus, the output of the sensor cannot be completely consistent with the state to be measured.

State estimation is one of the most common methods for estimating the most likely value of a state based on measurements and a system. It is a prerequisite for high-level information extraction and control and has been widely used in mobile robots [6], unmanned aerial vehicles (UAVs) [7], sensor networks [8], smart grids [9], health performance detection and evaluation [10, 11], etc.

State estimation methods have a long history. In 1809, Gauss proposed an optimization method called the least-squares method to determine a celestial body's orbit from measurements [12]. Since the least-squares method does not need to know the signal's prior statistical knowledge when estimating, the least-squares method has a wide range of applications in many fields.

In the 1940s, to control firepower, Wiener et al. [13] designed the Wiener filter in the frequency domain to achieve linear optimal dynamic estimation in a stationary random process system. Through the calculation of the Wiener–Hopf equation, the Wiener filter obtains the analytical solution of the optimal transfer function of the filter, which can suppress or gate signals containing a variety of information. However, because the Wiener filter requires that both the estimated state and the measurement conform to a stationary random process, and the Wiener–Hopf equation needs to be solved in the filtering process, the amount of calculation and the storage space required are extensive. The project is challenging to realize; therefore, it limits the applications of Wiener filters.

To overcome the shortcomings of Wiener filters, in 1960, Rudolf Emil Kalman proposed modern filtering theory [14]. He introduced state space in stochastic estimation theory, used state models to describe the relationship between states and measurements, and estimated states based on measurements using predictions and updates. Kalman filtering does not need to store all historical data. According to the state estimation at the previous moment and the current measurement information, a new estimate can be calculated according to the recursive method, which reduces the computer's storage and calculation capacity requirements and improves real-time processing. Simultaneously, the Kalman filter can estimate one-dimensional, stationary random processes and multidimensional, nonstationary random processes [15].

The Kalman filter has been widely used because of its simplicity and ease of implementation. Because a computer will continue to accumulate and transmit rounding errors and truncation errors during the calculation process, the error covariance matrix loses its positive definiteness and results in unstable filter estimation. Therefore, researchers have successively proposed a series of numerical, robust filtering algorithms, such as square root filtering, UD (Upper-Diagonal) decomposition filtering, and singular value decomposition filtering [16]. These methods effectively improve the Kalman filter's numerical stability while also increasing computational efficiency [17].

On the other hand, the standard Kalman filter requires an accurate model, the known statistical characteristics of the system noise. These requirements are relatively harsh in applications. In actual systems, the system cannot meet these conditions due to some uncertainties, making the Kalman filter lose its optimality, which reduces the estimation accuracy and even leads to divergence. Researchers have introduced the idea of robust control in filtering to solve this problem, thus forming a robust estimation [18].

Moreover, the standard Kalman filtering theory is only applicable to linear systems and requires that the observation equations are linear. Meanwhile, in actual engineering practice, the system is generally nonlinear. Therefore, in the 1970s, Bucy and Sunahara proposed the extended Kalman filter (EKF) [19-20]. The nonlinear system is linearized first and then uses the generalized Kalman filter to estimate the state. However, because the linearization process will introduce errors in the nonlinear system due to calculating the Jacobian matrix, the final state estimation accuracy will decrease. When the Jacobian matrix calculation is inaccurate, the problem of filtering divergence will also occur. The sigma point Kalman filter (SPKF) method is a class of approximate nonlinear filtering methods based on the Gaussian distribution, including the unscented Kalman filter (UKF), central difference Kalman filter

(CDKF), square-root unscented Kalman filter (SRUKF), etc. [21]. The ideas of these methods are roughly the same, of which the UKF is the most famous. It uses several sigma points for nonlinear systems to obtain the accuracy with second order.

With continuous research, the original methods have improved in the Gaussian domain filtering system. Some new methods have been proposed for approximating nonlinear characteristics. In Bayesian filtering's general framework, the filtering process involves predictions and updates, including two integral operations. Under the Gaussian assumptions the integral is a multidimensional integral operation of the product of the equivalent Gaussian function and the system function. A new idea is provided to realize approximate

Gaussian filtering: the nonlinear filtering is realized through an integral calculation. For example, Simon Haykin et al. proposed a new filtering strategy independent of the EKF and UKF, named the cubature Kalman filter (CKF) [22].

The above methods all describe the noise of a system using the Gaussian distribution. Studies have shown that the effectiveness of these methods is only valid for single-mode problems. They assume that the system state and noise are both Gaussian distributions, where one Gaussian component corresponds to one mode. However, many issues faced in the real world are often much more complicated than single-mode problems. A typical example is system noise, including process noise and observation noise, which is not a Gaussian distribution, but a gamma distribution or other complex mixed distributions [23].

Therefore, with the filtering of the above mentioned algorithms based on the Gaussian noise assumption, it is difficult to obtain a satisfactory estimation performance due to the model mismatch. In general, complex noise can be expressed as the sum of multiple Gaussian noises. Then, the EKF, UKF, and CKF are applied to obtain the Gaussian mixture (GM)-EKF, UKF, and CKF [24]

It is necessary to provide the system with the specific expression of the model and the distribution characteristics of noise for the standard Kalman filter, EKF, UKF, CKF, etc., as well as the multimode, complex, approximate Gaussian mixture filtering methods, such as GM-EKF, etc. However, when the system is complex, it is challenging to obtain these system models. Therefore, based on random sampling, another type of filter has appeared, which realizes the state's estimation by calculating the conditional probability of the system state and realizes the conditional probability transfer through Bayes' theorem. Its algorithm is not based on the state function's distribution characteristics, observation function, and noise (such as the mean and variance, etc.), but the state's conditional probability density. Its purpose is to provide the state's probability distribution, not the functional expression of the state. This algorithm is based on Monte Carlo simulation technology and is usually called the sequential Monte Carlo method or particle filter method [25].

In this type of method, a large number of particles are generated by Monte Carlo simulation, and their distribution is used to approximate the probability distribution of the state. Its advantage lies in its strong applicability, and it can be applied to any complex system through calculating particles. Its accuracy can approach optimal estimation. It can overcome the shortcomings of traditional Gaussian filtering algorithms such as the EKF, which are more sensitive to initial value selection. By contrast, particle filters easily capture the actual state within a specific error range due to particles' dispersion, thereby improving the filter system's stability and convergence speed. However, the Monte Carlo simulation method is challenging to realize recursive filtering with, and the calculation amount is much more tremendous than that with the Gaussian approximation method, which affects its real-time application to some extent.

With the development of sensor technology and storage technology, especially in recent years, modern intelligent systems, such as unmanned aerial vehicles (UAVs), autonomous driving systems, etc., have been widely used. We found that there are more and more sensors in the system, and the measurement is also increasing. In the military and civil fields, many processes, such as target monitoring, detection, tracking, and identification, are based on multiple sensors' measurements and are completed by information fusion technology [26]. Therefore, the data-driven learning network has also become an important research direction in state estimation theory.

Compared with model-based methods that require known system information, data- based methods can use big data to obtain system characteristics that cannot be described by the model. However, they abandon the established knowledge of the system and rely too much on data. When the data are insufficient or of low quality, the result is not better than that from traditional model-based estimation methods. Therefore, these two methods have their advantages and disadvantages. It is crucial to effectively combine model-driven and data driven methods to improve the performance of state estimation effectively, i.e. use a hybrid-driven state estimation method.

Estimation methods such as the Kalman filter series, EKF, UKF, CKF, and particle filters have obtained rich published research results. They are widely used in various detection, tracking, and control systems. However, data-driven methods based on shallow networks cannot fundamentally improve the estimation performance, so related research has not been the mainstream part of research into estimation methods. Recently, the rapid development of other artificial intelligence methods was highlighted in recent years [27-28], prompting researchers to reconsider improving estimation performance by the hybrid modeling method. However, related research in this area has just begun, so there are not many related review papers.

Although there are not many, the authors are still willing to recommend the following reviews that are worth reading: Hong et al. [29] provides a survey for estimators that can produce accurate estimations for complex dynamic systems, such as airbag, debris detection, and active blast protection systems. From an application perspective, Dehghan- pour et al. [30] focuses on distribution system state estimation in power systems. A few critical topics are discussed, such as mathematical problem formulation, the application of pseudomeasurements, metering instrument placement, network topology issues, the impacts of renewable penetration, and cybersecurity. It is worth emphasizing that both conventional and modern data-driven methods are reviewed in this survey. Similarly, Jin et al. [31-32] are also based on the applications. Simultaneously, the latter emphasizes the research progress in artificial intelligence in moving objects, which is more general and includes deep learning networks in unmanned autonomous mobile systems.

Unlike the above review papers, this review introduces state estimation methods without emphasizing a specific system or application background. We try to provide the development path of the state estimation method from the perspective of the method and discuss the future development trend under the premise of the current system's universal characteristics.

This review is based on the problem of state estimation, starting with the introduction of classic estimation methods. We analyze the problems of classic estimation methods, the current research progress and problems of model-driven and data-driven methods, and discuss the state based on the combination of data-driven and model-driven methods. [33].

1.4 Static State Estimation

State estimation is an essential tool used by operators for real time analysis. State estimation can provide flexibility to operators in decision-making if an emergency occurs.

Accurate knowledge of state is necessary to avoid system failures and blackouts. State estimation results form basic inputs to various power system operations. Fred Schweppe introduced Weighted Least Squares (WLS) power system state estimation in 1969 in his classic papers [34], [35], [36]. Since then power system state estimation has been a very active research area. The fundamental problem of state estimation can be defined as an over determined system of nonlinear equations solved as an unconstrained weighted least-squares (WLS) problem. The WLS estimator minimizes the weighted sum of the squares of the residuals. Residuals are the error or difference the estimated values and the actual values [37]. Besides the WLS algorithm, other state estimation methods such as decoupled WLS and Least Absolute Value (LAV) estimation were developed, but WLS is dominant in practical implementations. References [38-40] provide detailed account of modifications in technique for improved numerical formation. Various numerical methods have been explored to avoid the problem of ill-conditioning of gain matrices. A performance review of methods like orthogonal transformation, normal equations and hatchels augmentation method is done by Holten et al in [41]. This work reported the orthogonal transformation to be most suitable amongst there's. Aschmoneit et al. extended the concept of power system state estimation to include constraints of some zero injections buses [42]. Such buses do not possess any load or generation. Clements, Davis and Frey solved this problem of constrained state estimation using Interior- Point method (IPM) [43].

Conventional State Estimation is static in nature. Static state estimation kind of takes snap-shots of the system and does not in true sense incorporate the system dynamics. Changes in power system are driven by loads. As the load varies, the generation is expected to change. Hence power flows through line and injections at buses change. This makes system dynamic. Also, the time constants for transient are faster than the rate at which conventional SCADA captures data/measurements. Thus, if static state estimation is to be carried out, it has to be done at much smaller time intervals.This becomes cumbersome and computationally difficult. Requirement of large memory can also be an important issue. Conventional data acquisition provides steady but unsynchronized information and at low sampling density. Thus dispatching and controlling centre cannot know the dynamic operating states of the system exactly. Thus an improvement in the available estimation procedures is of importance. Dynamic State Estimators (DSE) meets this requirement.

1.5 Dynamic State Estimation

Using the information about state vector at time instant k, the Dynamic State Estimation technique can predict the state vector of power system at next time stamp k+1. Due to the prediction ability, it allows security analysis to be carried out in advance and hence the signal operator can have more time during emergencies. Another important aspect of dynamic state estimation is that rather than conventional states like bus voltage and angle, states that truly depict the dynamics of a system like generator rotor angle, speed or generator internal voltages are estimated. Such parameters can be helpful to take predictive actions using generator controls in case of incipient emergencies.

The discussion so far indicates that estimation of the dynamic states of a power system network is necessary. It becomes important that the chosen technique for such estimation must be robust, accurate, efficient, less time consuming and ensuring the result. Extended Kalman Filter (EKF) is a well-known approach for the DSE. However, a brief insight on other available techniques is desirable before establishing the importance of any one technique.

According to [44], dynamic state estimation techniques are broadly classified into Kalman filter-based, Robust dynamic techniques, Square root filter-based and Artificial Intelligence- based techniques. Authors have tried to categorize certain available techniques as mentioned above; however, it necessarily may not sum up all the available techniques.

Majority of DSE techniques are in one or more way variants of Kalman filter technique. The reason why it is so widely-used is the relative ease of implementation over other available techniques. Also, Kalman filter techniques provide advantage that it is possible to predict the state at next instant; in addition to filtering out the noise from the available measurements. The Kalman filter based technique assumes Gaussian distribution of noise. But frequently, the noise distribution deviates from the assumed model. The performance of Kalman filter based technique degrades in the presence of these outliers. For this purpose certain techniquescalled Robust techniques were developed. Authors in [45] have addressed the issue using a statistical approach based on M - estimation technique. However Robust techniques are computationally very complex and mathematical formulation is cumbersome.

Square root filter techniques are similar to Kalman filter. They are meant to overcome numerical errors that may arise while computer implementations of Kalman filter techniques [46, 47]. As the name suggests, it is intended at calculating square roots of covariance matrices rather than using them directly. Square roots are often calculated using special decomposition methods like Cholesky decomposition, etc.

1.5.1 Role of Dynamic State Estimation in Power System Modeling, Monitoring and Operation

Dynamic state estimation (DSE) [48] is going to be very useful for time critical monitoring, control, and protection of future electric power grids. This is largely due to the changes in generation mixes and load compositions, particularly the increasing penetration of intermittent, stochastic and power electronics-interfaced non-synchronous renewable generation and distributed energy resources (DERs) [49]. In this context, where the system operating point changes more often and more rapidly, tracking the system dynamic state variables is of critical importance. Recall that dynamic state variables are the ones associated with the time derivatives in the set of differential-algebraic equations describing power system dynamics [50]. The dynamic state variables of the synchronous generators correspond to their electromagnetic and electromechanical processes, as well as their controllers [51]. As for the non-synchronous generations, the dynamic state variables are associated with the primary source of energy, e.g. solar photovoltaic arrays, batteries and wind turbines, as well as their controllers. Examples include the frequency at the point of common coupling between the power converter and the electric grid, the electric current in the converter, and the pitch angle of wind turbines. Furthermore, there exists an important challenge in the development and maintenance of accurate models for power electronics-interfaced devices. DSE can be developed to validate the models and to estimate unknown or incorrect parameters.

1.6 Comparative overview of SSE and DSE:

Table 1: Comparison between Static State Estimation and Dynamic State Estimation based on different parameters

	SSE	**DSE**
Measurements	From the SCADA (every 2-10 sec)	From PMU/DFR/MU (every 1/30 sec – 1/240 sec)
Observability	Binary (observable or not)	Time –varying (Strong/weak/not observable)
Update Speed	1 snapshot (every 2-10 sec)	1 prediction + 1 filtering step of the Kalman filter (every 1/30 sec)
Models	Algebraic power flow Equations	Differential algebraic equations
Framework	Mostly centralized or distributed	Centralized and distributed/decentralized
Outputs	Algebraic variables (voltage magnitude and angles)	Dynamic variables (machine/dynamic load/DERs dynamic variables)
Applications	Monitoring and control (operator in the loop)	Motoring, control and adaptive protection

1.7 Conclusion

In conclusion, this comprehensive discussion has explored various facets of state estimation in the context of power systems. The examination began with an overview of the types of state estimation, including static, tracking, and dynamic state estimation. Static state estimation, as discussed, involves processing data to estimate the vector of the power system states, assuming time-invariant measurements and a static state model.

The focus then shifted to tracking state estimation, which extends static techniques by updating estimated values non-iteratively during subsequent sampling periods. This enhancement aims to improve computational speed, making the estimator suitable for real-time implementation. Dynamic state estimation, the third category, incorporates both present states and previous estimates, enabling the forecasting of the state vector one-step ahead. The advantage of dynamic estimators lies in providing a longer decision time for system operators, particularly in functions like economic dispatching and security assessment.

The subsequent section delved into the concept of bad data processing in static state estimation, highlighting its role in handling uncertainties associated with meter readings, communication errors, and other sources of discrepancies. The three approaches to obtaining crucial database data acquisition with no processing, data acquisition with basic digital processing, and data acquisition with a mathematical model-based approach were elucidated, with the latter constituting static state estimation.

The exposition on state estimation continued with a discussion of various state estimation methods throughout history. The review encompassed Gauss's least-squares method in 1809, Wiener's frequency domain Wiener filter in the 1940s, and Kalman filtering in 1960. The evolution from standard Kalman filtering to extended Kalman filtering and other robust filtering algorithms, such as square root filtering and particle filtering, was explored. Challenges and advancements in dealing with nonlinear systems and complex noise distributions were addressed.

The narrative then transitioned to the challenges and advancements in state estimation, particularly the emergence of data-driven methods and their integration with model-driven methods. The review emphasized the importance of combining these approaches to leverage the strengths of each, noting that data-driven methods alone may struggle with insufficient or low-quality data.

Further, the discussion touched upon the recent rise of artificial intelligence methods in state estimation, with a focus on the limitations of shallow networks and the potential of hybrid modeling methods. The review acknowledged the nascent stage of research in this area, pointing out the need for effective combinations of model-driven and data-driven techniques for improved state estimation performance.

The section on static state estimation emphasized its crucial role in real-time analysis, providing operators with accurate knowledge to avoid system failures and blackouts. The Weighted Least Squares (WLS) algorithm, introduced by Fred Schweppe in 1969, was highlighted as a dominant method in static state estimation. Various modifications and numerical methods to address ill conditioning of gain matrices were also discussed.

The exploration concluded with a discussion on dynamic state estimation (DSE), outlining its predictive capabilities and significance in predicting dynamic system parameters, especially in the context of modern power grids with diverse generation mixes and rapid changes. The classification of DSE techniques, including Kalman filter-based, robust dynamic techniques, square root filter-based, and artificial intelligence-based methods, was presented. The role of DSE in power system modeling, monitoring, and operation was underscored, particularly in addressing the challenges posed by renewable energy sources and power electronics-interfaced devices.

In summary, this discussion has provided a comprehensive overview of state estimation in power systems, covering static, tracking, and dynamic techniques, historical developments, challenges, advancements, and the evolving landscape of data-driven and artificial intelligence-based methods. The emphasis on the integration of model-driven and data-driven approaches signals a promising direction for future research in the field of state estimation.

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