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Original Article

Dynamic State Estimation of Power Systems Using Deep Learning and PMU Data

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Abstract:

Dynamic State Estimation (DSE) is vital to the real-time and robust operation of the contemporary power systems especially during dynamic operating conditions due to the incorporation of renewable energy sources, variability of load, and network disruptions. The conventional methods of DSE, which are mainly founded on the Kalman filtering and observer-based methods, are highly dependent on proper mathematical models of the development of the system. These models are however, not always easy to get or sustain because of the system nonlinearities, lack of parameters, and changing topologies. Massive application of Phasor Measurement Units (PMUs) has made it possible to make high-resolution time-synchronized measurements, leading to a move away towards data-driven estimation methods. The recent years have witnessed deep learning (DL) as a potent alternative to dynamic state estimation, which provides good nonlinear modeling ability and resistance to uncertainties without explicit models of the system. The paper gives a detailed review of the dynamic state estimation of power systems with emphasis on the deep learning methods inferred on the PMU data. The development of the traditional Kalman filter-based approaches to the modern deep learning based systems is discussed in a systematic way. Different deep learning networks, such as recycling neural network, long short-term memory networks, convolutional neural networks, graph neural networks, and transformer based networks are discussed and compared. The essential issues concerning the PMU data quality, scalability, usability, and real-time implementation are addressed. Lastly, the actual research problems and future outlook are determined as an indicator of further developing deep learning-based dynamic state estimation.

Keywords:

Dynamic State Estimation, Power Systems, Phasor Measurement Units, Deep Learning, Kalman Filters, Smart Grids, Review

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1. Introduction

Timely and minute knowledge of states of power systems is a critical requirement in the reliable functioning of the system. Many important functions take state estimation as their basis, such as stability evaluation, contingency analysis, protection coordination and real-time controller. Conventionally, the state estimation in power systems has been performed by means of the static models and measurements of the Supervisory Control and Data Acquisition (SCADA) systems [1]. Though a successful deployment of static state estimation has been made over decades, it is constrained, per se, by low sampling rates and the incapacity to deal with fast dynamics of the system. Modern power systems have grown complex and dynamic with the growing infiltration of power-source renewability, power-electronic interfaces as well as distributed energy resources. Such transformations have increased the necessity to have the Dynamic State Estimation (DSE) which seeks to provide estimates of the time varying internal states of the power systems when subjected to transient and dynamic operating conditions.

The introduction of Phasor Measurement Unit (PMU) has transformed power system monitoring in that it is synchronized measurements of both voltage and current phasors at a very high rate of sampling [2]. The PMUs can be used to monitor the whole area and increase the observability of the system, which makes them specifically suitable in dynamic analysis. Nevertheless, the use of PMU data to estimate dynamic states creates new issues, such as the volume of data, measurement noise, and communication delays as well as the missing data. The common variants of the Kalman filter used as the basis of conventional DSE strategies include the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Ensemble Kalman Filter (EnKF) [3]. Despite their mathematically sound basis, these approaches require precise system models and parameters in order to work well. Practically, the inaccuracies of the model and unmodeled dynamics, as well as parameter uncertainties, can considerably worsen the accuracy of estimates.

To overcome such constraints, data-oriented and deep learning based methods have become the focus of growing attention. Deep learning models have the advantage of learning complicated nonlinear relations directly out of data, and it is especially well-aligned with modeling temporal dependencies of PMU measurements [4]. Several studies have been conducted on the use of deep learning methods to the dynamic state estimation in the last ten years, as the results have been already promising in its accuracy and robustness.

The given paper is the in-depth overview of dynamic state estimation techniques of power systems specifically focusing on deep learning approaches based on PMU data. Contrary to prior research where emphasis on model based estimation methods is highly considered, the current review critically assesses recent advances in the domain of deep learning based DSE, highlights key trends and demonstrates gaps in research that need to be filled in order to deploy them in real world settings.

2. Fundamentals of Dynamic State Estimation

2.1. Dynamic State Variables in Power Systems

Dynamic state estimation seeks to give estimates of state within the internal system that changes with the passage of time based on the laws of physics. Common dynamic states variables are generator rotor angles, rotor speeds, transient internal voltages and other electromechanical states [5]. The dynamics in these states are governed by nonlinear differential-algebraic equations of generator dynamics, network interactions and control systems. A power system can be generally represented as a continuous-time state-space as follows:

$$\dot{x}(t) = f(x(t), u(t), w(t))$$
$$y(t) = h(x(t), v(t)) \qquad (1)$$

where *x(t)* represents the state vector, u(t)u(t)u(t) denotes control inputs, *y(t)* is the measurement vector, and *w(t)* and *v(t)* represent process and measurement noise, respectively.

2.2. Discrete-Time Representation for DSE

In a pragmatic approach, the continuous-time system is sampled, resulting in a nonlinear state-space model which is a discrete time system. Dynamic state estimation aims at estimating the state at any given moment in time using the historical measurements and dynamics of that system [6]. Orbit stir excessive states in a stream of height discharge may be estimated near real time through PMU measurements as they have a substantial level of temporal resolution.

2.3. Role of PMUs in Dynamic State Estimation

At the PMUs, simultaneously voltage and current phasor measurements are accessed with time stamps that are determined by Global Positioning System (GPS) signals. This synchronization enables measurements at geographically spread locations to be joined coherently and in the process importantly enhances system observability. The PMUs have better sampling rates and less latency as compared to SCADA systems, which is essential in the dynamic state estimation [7].

Although PMU measurements have benefits, they may have noise, communication delays, loss of data, and threats to cyber-security. These are the challenges that should be taken into consideration when developing the dynamic state estimation algorithms.

3. Conventional PMU-Based Dynamic State Estimation Methods

Traditional phasor measurement unit (PMU) based dynamic state estimation (DSE) techniques are an important contribution to the monitoring and control of the contemporary power systems. These techniques use high-resolution, time-matched voltage and current phasor-based measurements offered by PMUs to provide an estimation of dynamic conditions of rotor angles, rotor speeds and internal generator conditions. Advantages PMU-based DSE is aimed to monitor the dynamics of the systems in real time when the system operates in normal situations and the presence of disturbances.

Model-based estimation methods are the most common techniques of traditional approaches with the most commonly used being the Kalman filter (KF) and its variations [8]. Using linearized system models, the standard KF has been implemented and the Extended Kalman Filter (EKF) resolves the nonlinearities, by linearizing the system about operating points. In order to have a better accuracy of the estimates when the nonlinear behavior is stronger, techniques like the Unscented Kalman Filter (UKF) and Ensemble Kalman filter (EnKF) have also been implemented [9]. Although these techniques are effective, the traditional PMU-based DSE approaches pose problems with respect to which are sensitive to noise, modeling inaccuracies, and the use of exact system parameters. These have fuelled continued research into more resilient and adaptive estimation infrastructures of large scale power systems.

3.1. Extended Kalman Filter (EKF)

One of the earliest methodologies, and the most common, is the Extended Kalman Filter of power system dynamic state estimation. EKF performs linearization of the system equations of nonlinear system about the present operating point and uses Kalman filter methods to estimate the states. Although EKF is computationally efficient, it is a linear method that can be highly sensitive to modeling errors and massive nonlinearities.

3.2. Unscented Kalman Filter (UKF)

The Unscented Kalman Filter (UKF) is a nonlinear state estimation method that builds upon the Extended Kalman Filter (EKF) with the aim of eliminating shortcomings by such methods as those caused by linearization errors. The UKF does not attempt to use first-order Taylor series approximations but instead relies on the unscented transformation which makes use of a deterministic set of selective sigma points to represent the mean and covariance of the system state distribution. The propagation of these sigma points using the nonlinear system dynamics makes it possible to better represent nonlinear transformations.

When used in conjunction with PMU based dynamic state estimation, the UKF has shown better estimation accuracy and numerical stability particularly in operating conditions that are highly nonlinear which includes faults, load fluctuations and quick transients. UKF reduces bias and divergence usually experienced in EKF-based methods by retaining higher-order statistical properties of the state distribution [10]. This enhanced performance, however, comes at the cost of more complex computation and additional memory which can restrict its ability to scale to large-scale power systems with large dimensional state vectors.

3.3. Ensemble Kalman Filter (EnKF)

EnKF is a stochastic state estimator that makes use of a Monte Carlo framework to model system uncertainty. EnKF involves the use of an ensemble of state realizations that are used to approximate probability distribution of coupled system states instead of requirement in egocentric propagation of covariance matrices. Each ensemble member is evolved through the observations of PMU are used to apply systems dynamic model, and measurement updates.

Table 1. Conventional pmu based DSE Methods

Method	Description	Key Features	Advantages	Limitations
Extended Kalman Filter (EKF)	Linearizes nonlinear system equations around the current operating point and applies Kalman filtering for state estimation	First-order Taylor series linearization, recursive estimation	Computationally efficient; widely used; suitable for mild nonlinearities	Sensitive to modeling errors and strong nonlinearities; may diverge under severe disturbances
Unscented	Uses the unscented	Captures higher-order	Improved estimation	Higher computational

Kalman Filter (UKF)	transformation with deterministic sigma points to propagate mean and covariance through nonlinear dynamics	statistics; better handles nonlinear transformations	accuracy and numerical stability; robust under rapid transients and load variations	complexity and memory requirements; scalability issues for large-scale systems
Ensemble Kalman Filter (EnKF)	Stochastic Monte Carlo approach using an ensemble of state realizations to approximate probability distributions	Propagates multiple system state realizations; avoids explicit covariance propagation	Handles large-scale and high-dimensional systems; effective under partial observability	Accuracy depends on ensemble size; large ensembles increase computational cost; may suffer sampling errors with small ensembles

EnKF has been used in dynamic state estimation in PMU-based large-scale and high-dimensional power system because it can process large-scale and high-dimensional dynamics of power systems more effectively than conventional variants of the Kalman filter. It is especially useful in complex system dynamics as well as partial observability. The level of accuracy of the estimation by EnKF is however highly correlated to the ensemble size. Small ensemble can cause sampling errors and divergence of the filter whereas large ensemble can raise the cost of computation which can be difficult to implement in the real-time of a wide-area monitoring system.

3.4. Drawbacks of the Model-Based Methods

Despite the wide usage of Kalman filterbased dynamic state estimation techniques, the performance is limited by a number of limitations that are inherent to it. Their heavy reliance on system models that are accurate and adequate values of the parameters that are not always readily available or easy to maintain in the power system environments is a major problem. Inaccuracies in model, uncertainty of parameters, and nonlinear dynamics not modeled, might have a detrimental effect on the accuracy of the estimation and can even cause filter divergence. Also, these methods are computationally expensive and quickly increase in calculation as the size of the system grows, rendering them computationally difficult to implement in real-time large-scale interconnected networks [11]. The other issue is that they are highly critical to the absence, lateness, or corruption of PMU measurements that may occur in a wide-area monitoring system, such as due to communication errors or sensor failures. All these issues have collectively contributed to growing interest in methods of data-driven and hybrid estimation that are more likely to respond to the uncertainties in the system and measurement imperfections.

4. Machine Learning in Power System State Estimation

Machine learning (ML) methods have become a new hope to replace traditional model-based methods of power system state estimation in the last few years. Unlike traditional techniques: emphasize heavily on using proper mathematical models and system parameters of the system being studied, ML-based methods learn how the complex system acts on the basis of historical and real-time measurements of the system. Such data-based capability enables ML models to learn nonlinear correlation and dynamical patterns which would be hard to present with the help of analytical models only. Such techniques as neural networks, support vector machines and deep learning architectures have been investigated to estimate both static and dynamic state, usually with better resistance to noise, convergence errors, and incomplete measurements [12]. ML methods can be successfully applied in PMU-enabled setup to act on large quantities of high-resolution information and make speedy state forecasts that could be incorporated into real-time monitoring. Nevertheless, some issues revolve around availability of data, generalization where the operating conditions are not seen and interpretation of the learned models. The solution to these problems is needed to enable credible use of machine learning methods to become viable building blocks of a real-world state estimation in a power system.

4.1. Ancient Methods of Machine Learning.

Before deep learning emerged as commonly used, initial methods of machine learning had been explored as data-driven methods of state estimation in the power system. Artificial neural networks (ANNs) were considered one of the earliest methods studied, due to their capability to estimate nonlinear maps between measurements and system states [13]. On the same note, support vector machines (SVMs) and classical regression-based models were used to predict the magnitudes of the voltage, the phase, and other variables of the state at past measurement data points. The methods showed that the reasonable accuracy of estimation was possible without the explicit use of detailed physical system models. Nevertheless, their performance was limited by the weak network structure, as well as a small representational capacity. More importantly, early ML techniques considered measurements mostly as independent constituents making them not suitable to reflect the temporal correlations and dynamics that define a power system. Consequently, they failed to perform well in an environment of fast operating conditions or disruptions.

4.2. Transition to Deep Learning

The shift to deep learning was a breakthrough in data-driven estimates of the state of the power system. Hierarchical learning of features and significantly better nonlinear approximation abilities are made possible by deep learning models including deep neural networks and recurrent architectures [14]. It has been facilitated by the growing accessibility of high-resolution PMU data, and by progress in parallel computing and graphics processing units. In contrast to more traditional model based methods, deep learning methods do not need to know the explicit system equations or identify parameters and instead learn the complex behavior of a system directly only using data. In addition, deep architectures are also capable of highly capturing temporality and changing system dynamics, thus highly suitable in dynamic state estimation due to the changing operating conditions. Although the issues associated with training the data needs and interpretation of the model still persist, it is evident that deep learning has become an invaluable resource when aiming to increase the accuracy and resilience of estimations in the contemporary power systems.

5. Deep Learning Based Dynamic State Estimation

Dynamics state estimation based on deep learning has received substantial attention to be a valid alternative available to traditional model-based approaches in the current power systems. Through the implementation of deep neural networks, the approaches have the advantage of learning the intricate nonlinear relationships directly with time-synchronized PMU measurements. Deep learning approaches estimate the dynamics of a system using data, unlike the traditional estimators, which use the explicit system model and parameters, which makes them less susceptible to modeling errors and parameter changes.

Recurrent architectures like Long Short-term memory (LSTM) networks and Gated Recurrent Units (GRUs) have received significant interest as these network types attribute temporal effects and dynamic behavior to successively time-separated data streams. Besides, convolutional neural networks (CNNs) have been used to derive spatial information on wide-area PMU measurements, which has improved the accuracy of estimation even more. It is shown that in cases of noisy measurements, missing data and highly changing operating conditions, deep learning based estimators showed enhanced robustness [15]. Nevertheless, both the quality of the available training data and cautious model design is critical to their performance. Nonetheless, deep learning still demonstrates high prospects of real-time dynamic state estimation in big-scale electrical systems.

5.1. Motivation for Deep Learning in DSE

Deep learning is particularly attractive for dynamic state estimation due to its ability to:

- Capture nonlinear system dynamics
- Model temporal dependencies in PMU data
- Handle high-dimensional input spaces
- Provide robustness to noise and uncertainties

These advantages have led to a growing body of research on deep learning-based DSE.

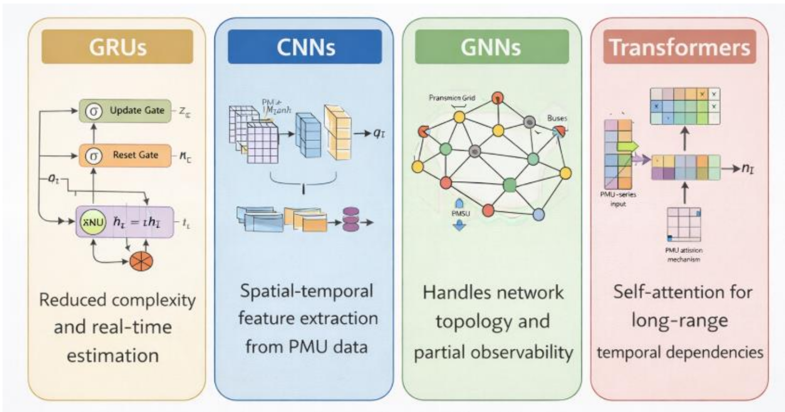

Figure 1. Deep Learning Approaches for Dynamic State Estimation

5.2. Recurrent Neural Networks (RNNs)

The Recurrent Neural Networks (RNNs) are set up to deal with time-dependent and sequential data by additional connections that enable information to carry over through the time sets. This time-warping memory property renders RNNs appropriate to perform modelling of the time-varying to characterize the state of the power system with a sequential recording of PMU measurements. RNNs can be applied in dynamic state estimation by training on the relationship between previous observations and the current system states such that short-term dynamic tracking can be done without the explicit physical model [16].

Mathematically, the equation of updating the hidden state of a standard RNN will be:

$$\mathbf{h}_t = f(\mathbf{W}_h \mathbf{h}_{t-1} + \mathbf{W}_x \mathbf{x}_t + \mathbf{b})$$
$$\mathbf{y}_t = g(\mathbf{W}_y \mathbf{h}_t) \quad (2)$$

And where xt is the PMU input at time t, ht the hidden state and yt the estimated system state. The traditional RNNs though simple in their concept have disappearance and explosion gradient issues during the training process preventing the sequence of such long-term dependencies of the training process especially when dealing with extended transient events in power systems.

5.3. Long Short Term Memory (LSTM) Networks.

To address the problem of limited training of RNNs, an enhancement of LSTM networks was offered, which includes the use of gated memory cells that explicitly regulate information flow. These gating processes allow LSTMs to memorize access to the relevant information during long time spans ignoring the irrelevant information and thus are quite appropriate in PMU-based dynamical but estimations of state during steady-state and transient scenarios.

LSTMs can provide appropriate long-term temporal dependence and nonlinear dynamics of the complexities that these mechanisms enable. Consequently, the LSTM-based estimators have always been found to be more accurate, stable, and robust than conventional RNNs especially in fault cases, load variations and other dynamic variations in the power system.

5.4. Gated Recurrent Units (GRUs)

Gated Recurrent Units (GRUs) are proposed as a very simple variant of the Long Short-Term Memory networks in order to make them simpler and still be able to capture the ability to model temporal dependencies. GRUs do this by merging the input and forget gates of LSTMs in a single update gate to reduce the number of trainable parameters as well as computational costs [17]. This simplicity of structure is what makes GRUs especially appealing to the case of real-time dynamic state estimation, in which speed of inference and low latency are important.

GRUs have been demonstrated to be effective in the estimation of time-varying system states in PMU based dynamic state estimation in both regular and disturbed operational environments. Their relatively low complexity makes stable training with small amounts of data feasible and their implementation in large-scale power systems becomes cheap enough to deploy. A number of works indicate that GRU-based estimators are as accurate in estimation as LSTM-based models and have a better training efficiency and robustness, implying their use in the context of a wide-area monitoring system.

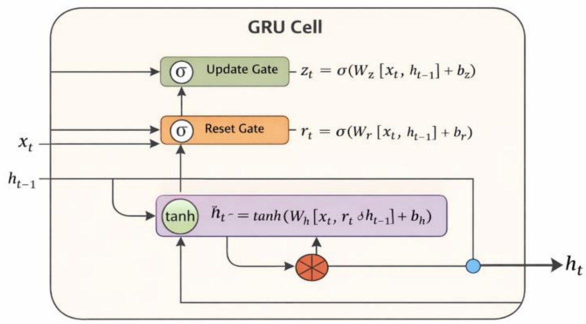

Figure 2. An example GRU cell

5.5. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have found more and more applications with power system state estimation since the algorithms have a high potential of automated feature identification. CNNs are found to be especially efficient in working with PMU-based measurements, in order to identify spatial correlation of geographically dispersed PMUs. CNNs have the capability to learn local structure and localized pattern within synchronized voltage and current measurements, which are hard to capture with other standard methods due to convolutional filters.

CNNs can also be used with recurrent models like LSTMs or GRUs when they are further extended to dynamic state estimation. This is the type of hybrid architecture found in a CNNs which extracts spatial features of PMU data, and recurrent layers which represents time-based dependencies between the successive time steps [18]. This mixture allows simultaneous teaching of the spatial and time stability, and with higher accuracy of estimations in the transit of events, faults and variations in loads. Consequently, the CNN-based hybrid models are now a common tool of large scale and high-resolution sensor data processing of PMU.

5.6. Graph Neural Networks (GNNs)

GNNs offer a graphical and physically intuitive way of learning power system state, directly using the network topology as a component of the learning. The influence system in GNN-based methods indicates that the power system is modelled as a graph with the bus being nodes and the transmission lines being edges. This embodiment enables the model to directly obtain the interaction of electrical connected components, as opposed to the use of the sole method of measurement correlations [19].

To on-the-fly estimate dynamic states, GNNs facilitate local information passing throughout the network in such a way that they are significantly more robust when regions of the system are affected by partial observability and absent measurements by PMUs. Moreover, the GNN based estimators exhibit great sensitivity to changes in topology, which can be caused by line outage or network reconfigurations, something that several more traditional and data-driven estimators fail to achieve. GNNs help fill the data-driven learning architecture, physics of power systems, and enable scalable and resilient state estimation by introducing physical connectivity in the learning architecture, which makes them a promising direction of scalable and resilient dynamic state estimation.

5.7. Transformer-Based Models

Transformer-based models, that were initially designed to work in natural language processing, have been widely used in power systems recently because their self-attention mechanisms are potent. Transformers, unlike recurrent networks, can simultaneously process time-series data in parallel and apply attention mechanisms to extract a set of significant dependencies between time steps. This allows them to better capture long range temporal relationship especially where there is a delay in responsiveness of the system, or where responses to momentary behavior are long lived.

Transformer architectures in dynamic state estimation do not exhibit any gradient degradation pathologies of recurrent models because the temporal correlations directly emerge in the model (when supplied with PMU data). Initial studies have shown that the accuracy of Transformer-based estimators in complicated dynamic conditions is great, and they are highly robust to noise and measurement anomalies [20]. Transformers also have higher calculation and data demands than conventional recurrent models but recent studies indicated Transformers have a bright future as an emerging paradigm of next-generation dynamic state estimation in large-scale power systems.

6. PMU Data Handling in Deep Learning Based DSE

Phasor Measurement Unit (PMUs) generate data that are based on dynamic state estimation through the generation of time-synchronized and voltage, current and frequency phased measurements on the power system. PMU data: PMU data is to be dealt with in deep learning-based DSE, as the quality of its measurements, along with completeness and consistency directly affect the quality of models. Noisy and missing PMU data may exist, and prior to any analysis is possible, the preprocessing phase comprises the identification of outliers, interpolation and normalization of the raw PMU data.

In spatial distributed PMUs, data structure becomes important so as to preserve the network topology and inter-bus correlation. These techniques are the response methods responding to models cast on graph representations, adjacency matrices or structured tensors, such as Graph Neural Networks (GNNs) or CNN-RNN hybrids [21]. In addition, sequential PMU measurements should have the capability of being subject to time as a result of the repetitive or attention-based structures, in which the models can represent the emergent transformation of system states. Quality model training, mitigation of the impact of measurement error and expansion in capacity to perform real-time estimation of large-scale power systems are some of the guarantees of proper data management.

6.1. Data Preprocessing

Preprocessing raw PMU readings is among the most crucial elements of deep learning based dynamic state estimation because the results of the analysis could be anomalies, noise, or offsets in raw PMU measurements that negatively affect model performance. Here, preprocessing usually begins with time synchronization by therefore making the readings of measurements by geographically distinct PMUs synchronized with a common time generator generally through GPS cues. It is done by normalization or scaling of the features so that all parts are like most likely converged in training in the model. Methods, such as noise filtering (moving averages, wavelet-based denoising, Kalman smoothing, etc.), are typically applied to remove variations in measurements, but not other important transient information. Finally, PMU data may be generated in both time windows or sequence and distinguished according to the needs of the input sequence models of RNNs, LSTMs, GRUs, or Transformer-based architectures. Such tasks as preprocessing and proper preprocessing could be regarded to deliver clean structured, and time consistent input in deep learning models both of which are vital in dynamic state estimation in both normal and disturbed system states.

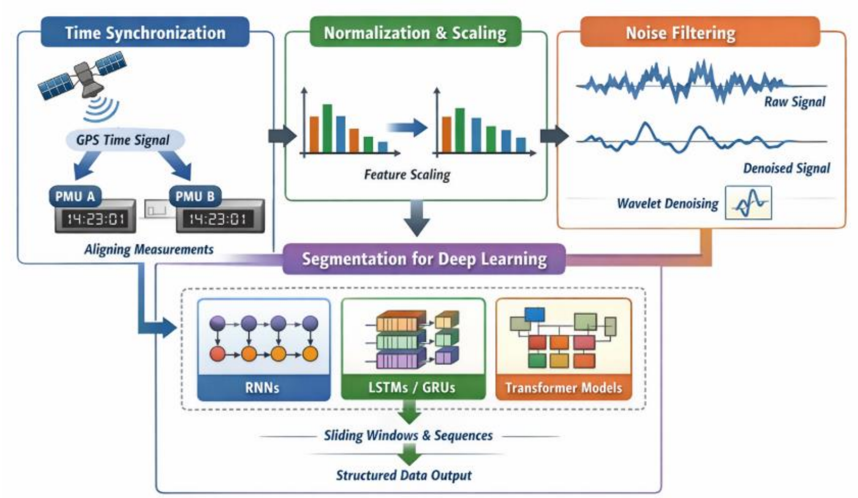

Figure 3. Data Preprocessing for PMU Based Dynamic State Estimation

6.2. Working with Lost and Damaged Data.

An other issue with wide-area monitoring systems is that data in PMU is not incomplete (or corrupted). Measurements would be lost due to the absence of communication, packet loss or sensor failures may also all result in a measurement error which would give an outlier or corrupted measurement. In order to overcome these issues, data-driven DSE approaches have employed data augmentation in which artificial instances of unavailable data are added to the training sets in order to make the model resistant. These missing data may undergo the imputation processes of linear interpolation, Nearest Neighbors or model-based statistical estimation processes to fill in the missing data before feeding it into the network. Higher-order deep learning architectures, such as auto-encoders or which use the GAN technology, may be trained to present missing or damaged data by encoding latent representations to restore the original data without time or local innuendo inferential links to the original position. Even with incomplete or noisy power system stream outages, deep learning based estimators are able to reach high accuracy and stability, making them suitable to work well in a realistic environment, implying that their implementation can be applied to real-time in real power systems monitoring.

6.3. Cyber-Security Considerations

The increasing application of PMU-based measurements is that the state is exposed to cybersecurity threats, in particular, false data injection (FDI) attacks, which have the capability to also poison the state estimations algorithms with no normal alarms. Combination of deeper learning and anomaly detection frameworks based on DSEs is also actively being applied to resiliency to such attacks. Adversarial training is one of the methods that trains the networks with normal and malicious data and utilizes the hybrid structures that combine the statistical detection features with the neural networks to identify differences between measurements. In addition, the graph-based and attention mechanisms can be used to detect anomalies in relation to the topology of the physical system and temporal correlation. It has been demonstrated that transforming DSE into cyber-resilient results in a higher resiliency to an attack and also greater reliability in case of data loss, noise, or other failures in its functionality [22]. Afterwards, safe data processing has become the essential aspect of modern PMU-based deep network architecture of real-time power systems surveillance.

Table 2. Deep Learning Based DSE Methods

Category	Description	Techniques / Methods	Research Implications
Data Preprocessing	Preparation of raw PMU measurements for deep learning models	Time synchronization, normalization, noise filtering (moving average, wavelet denoising, Kalman smoothing), sequence/window segmentation	Ensures temporal consistency and clean inputs; improves model convergence and estimation accuracy
Handling Missing and Corrupted Data	Addressing incomplete or faulty PMU data due to communication failures or sensor malfunctions	Linear interpolation, K-nearest neighbors imputation, autoencoder-based reconstruction, data augmentation	Enhances robustness of deep learning estimators under missing data and improves reliability during real-time operation
Cyber-Security Considerations	Protecting DSE against malicious attacks and anomalous data	False data injection detection, adversarial training, anomaly detection, graph-based or attention-based anomaly models	Strengthens resilience against cyber threats and ensures reliable dynamic state estimation under adversarial conditions

7. Comparative Analysis of Existing Studies

An overview of the current literature on deep learning-based dynamic state estimation (DSE) reveals some significant trends in the methodology, choice of models, and scenarios of application. Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) represent two of the most common sequential models in the literature since they were shown to address temporal dependencies of PMU measurement streams. LSTMs, which have gating features, are better at long-term correlation learning, but GRUs deliver similar with a smaller number of parameters, which is useful in real time and large scale.

Some papers have investigated hybrid CNNRNN structures that fuse the strengths of convolutional neural networks (CNNs) in extracting spatial information with the strength that recurrent networks have in extracting temporal information. Such hybrid models enhance the accuracy of the estimation and are especially helpful in a large-scale power system that has a lot of spatial correlation between PMU locations.

Graph Neural Networks (GNNs) can be viewed as a more recent paradigm, and they directly consider the topology of the system in the process of learning. GNN-based DSE can get around the drawbacks of purely sequential models by modeling buses and transmission lines as nodes and edges, which show strong performance in changes to topology, partial observability, and missing PMU data.

According to the architecture based on transformers, taking advantage of self-attention mechanisms, are becoming a promising option in promoting long-range dependencies and parallel computation. Their utilization to power system DSE is, however, still sparse with few exploratory studies that have been only done on small- to medium-scale systems that are based on the IEEE benchmark. The vast majority of research works prove their methods on the example of standard test cases including the IEEE 14-bus, 39-bus, and 118-bus system as these test cases allow to get consistent performance appraisals. Although these studies can set the baseline performance, it is a research open question how to generalize models to large-scale realistic power grids and scenarios where there is a large share of renewable generation.

8. Performance Evaluation Metrics

The performance of the dynamic state estimation (DSE) methods should be evaluated by the set of both quantitative and qualitative measures that reflect both the accuracy and the efficiency of the calculations. Some of the popular measures are mentioned below.

8.1. Root Mean Square Error (RMSE)

RMSE is used to measure the mean magnitude of the errors in the estimation process with more weight being assigned to greater deviations. It is usually utilized in order to measure the quality of estimated system states with respect to actual states. In the case of NNN states in TTT time, RMSE is given by:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\frac{1}{N}\sum_{i=1}^{N}\left(x_{i,t}^{\text{true}} - x_{i,t}^{\text{est}}\right)^2} \quad (3)$$

Where $x_{i,t}^{true}$ and $x_{i,t}^{est}$ represent the true and estimated states of the i^{th} variable at time t, respectively. Lower RMSE values indicate better estimation accuracy.

8.2. Mean Absolute Error (MAE)

MAE computes the average absolute difference between estimated and true states. Unlike RMSE, MAE is less sensitive to outliers and provides a straightforward measure of average error:

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N}\sum_{i=1}^{N}\left|x_{i,t}^{\text{true}} - x_{i,t}^{\text{est}}\right| \quad (4)$$

MAE complements RMSE by highlighting consistent small deviations rather than extreme errors.

8.3. Convergence Time

Convergence time refers to the duration required by an estimator to stabilize and produce reliable state estimates after system disturbances or initialization. Formally, it can be defined as the time t_c at which the estimation error falls below a predefined threshold ϵ:

$$t_c = \min\{t \,|\, \text{RMSE}_t \le \epsilon\} \quad (5)$$

Shorter convergence times indicate faster responsiveness, which is critical for real-time monitoring and control.

8.4. Robustness under Noise and Missing Data

Robustness measures the estimator's ability to maintain accuracy under noisy measurements or incomplete PMU data. It is often quantified by evaluating RMSE or MAE under perturbed conditions:

$$\text{Robustness} = \frac{\text{Performance}_{\text{noisy/missing}}}{\text{Performance}_{\text{ideal}}} \times 100\% \quad (6)$$

There is an assumption that the less the degradation percentage, the more the resilience to imperfections in the measurements. It has once again been shown in the systematic literature that deep learning-based DSE schemes, e.g., LSTM, GRU, CNN-RNN and GNN, are superior compared to the conventional Kalman filter-driven ones at nonlinear and uncertain operating regimes. This advantage is even greater at the events at moments in time, load variations and partial observability of PMUs that can limit the real dynamics of an intricate system to be precisely modeled by conventional linear or linearized approximators.

9. Challenges and Future Research Directions

Though deep learning based dynamic state estimation (DSE) has shown its great benefits over traditional approaches, there exist a number of research challenges that still constrain its usage. One of the greatest drawbacks is that there are not many datasets on real PMU. The vast majority of literature uses synthetic data produced by one of the standard test systems (IEEE 14-bus or 118-bus networks) that might not reflect the dynamics of a real power system. Such limited data prevents the generalization and validation of the model and performance in different operating conditions.

The other severe issue is the extrapolation to invisible operating conditions. The deep learning models developed using historical or simulated data might not ensure the accurate prediction of the states of the system in the occurrence of a rare event, extreme disturbances, or unusual load/generation patterns. Besides, the issue of interpretability of deep learning models still exists. Whilst true, black-box models can give very little information about the underlying physical relationships, which is important to operator trust and compliance with regulators.

Practical limitations are also those of real time deployment. The large dimensionality of systems and large PMU datasets, as well as complicated network structures, can lead to high computational and memory demands thus slowing down real-time state estimation in a practice setting.

In order to overcome these issues, a number of future directions in research have developed. Physics-informed deep learning is a neural network that integrates physical systems modeling with data learning to enhance overall generalization and trustworthiness. The hybrid model-based/data-driven methods are the approaches that utilize the advantages of the two paradigms with the goal of balancing accuracy and strength. Lastly, explainable artificial intelligence (XAI) methods are also being explored so that state estimates can be present as explainable, transparent, and trustworthy states and that operators can use these estimates to make informed decisions when the system is dynamic. Such guidelines should contribute to the applicability, resilience, and uptake of deep learning-based DSE in the contemporary power systems.

10. Conclusion

The review has given a general description of dynamic state estimation methods of power systems as well as the deep learning methods based on PMU data. The transition to the data-driven approach in contrast to the model-based approaches would indicate the increased complexity of the modern power system and the requirements of the reasonable and scalable estimation tool. It is necessary to mention that even though the potential of the deep learning-based DSE has been identified, further researchers are required to address the challenges of the interpretability, data availability, and real-time application. The conclusions, offered at this review, are intended to guide the further research and to help to implement the deep learning-based dynamic state estimations in the functioning of the power systems in the practical case.

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