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Review Article

Synchrophasor-Driven Machine Learning Application for Enhanced Power System Stability Monitoring: A Comprehensive Review

Kunal Samad[1], Arunkumar Patil[2], Katkar Siddhant Satyapal[3], Santosh Diggikar[4]

[1,2,3,4]*Department of Electrical Engineering, Central University of Karnataka, Karnataka, India.*

[2]*Corresponding Author : arunkumarpatil@cuk.ac.in*

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Abstract *- The continuous increase in complexity and nature of loads in a power system has given rise to unknown inevitable risks hidden from the Power System Operator (PSOs). All the electric equipment in a power grid are assets to a utility whose ultimate goal is to prevent severe damage to these significant electrical components caused by disturbances within a power system. Several utilities are transitioning towards an intelligent grid. Advanced communication technology and the revolution in Artificial Intelligence (AI) have helped PSOs to accurately determine the state of any dynamic power system, providing an observable and comprehensible power grid. First, the paper explores the concept and significance of big data by highlighting some unique characteristics of synchrophasor measurement generated at every interval in conjunction with traditional data. Then, there are challenges in data acquisition and processing techniques while handling these raw data. Also, the methodology and standards are considered for verifying the reliability of synchrophasor data before any online and offline power system study. Secondly, the paper emphasizes the importance of stability analysis for identifying vulnerable points within the network prone to voltage collapse. It will also discuss advancements in simulation studies and control strategies followed by operators to identify critical contingencies and implement corrective measures, enhancing the overall security of a power system using wide-area monitoring systems. Subsequently, the paper focuses on WAMS Enabled Machine Learning Approaches for Power System Stability. This segment comprehensively covers transient and voltage stability assessments, showcasing the innovative intersection of machine learning techniques with WAMS technology. The discussion sheds light on various applications of machine learning in the realm of power system stability.*

Keywords *- Synchrophasor technology, Wide Area Monitoring System (WAMS), Phasor Measurement Unit (PMUs), Synchrophasor technology, Big data, Artificial Intelligence, Machine Learning, Power System Analysis, Transient Stability Analysis and Voltage Stability Analysis.*

1. Introduction

The power system is a complex and vast network comprising generation, transmission, and distribution sectors. The central transmission utility is responsible for developing, planning, and operating the power transmission sector. The Regional Load Dispatch Center (RLDC) monitors and manages the transmission grid. India's transmission system is one the largest in the world and operates at 765 kV, 400 kV, 220 kV, and 132 kV.

The transmission grid is divided into five regional grids, each operated by a RLDC. They coordinate the scheduling and dispatch of electricity from different generating stations and manage grid stability by ensuring the balance between generation and demand. The transmission sector in many countries faces some common challenges, including transmission losses and inadequate grid infrastructure. Various stakeholders are investing in projects to strengthen transmission infrastructure, reduce congestion, and enhance overall grid capacity. Modern power grids' complexity and dynamic nature, exacerbated by the increasing integration of Renewable Energy Sources (RES) and fluctuating demands, necessitate advanced monitoring and analytical solutions.

With the integration of a Wide area monitoring system, the PSOs are now observing real time data and control power system components. The Synchrophasor data, along with other traditional data, helps utilities determine adequate control strategies for enhancing power system security. The data utilization involves the interpretation of spatio-temporal data from each point in the power system. The size of a power system is very large, considering many instrumentation equipment, each having different characteristics and ambiguous occurrence of malfunctions due to multiple reasons. The insufficiency of data handling techniques may cause less than accurate power system stability analysis when considering power system security. The paper highlights the various synchrophasor data utilization techniques, addressing the challenges in data acquisition and pre-processing. This review delves into the innovative intersection of AI techniques with Wide Area Monitoring System technology, focusing on their application in power system stability analysis.

The paper highlights the various synchrophasor-based machine learning algorithms, which mainly focus on real or synthetic Phasor Measurement Units for stability assessments. How the power system analysis gradually shifted from a simple linguistic-based approach used in Fuzzy logic to statistical decision theory to the most advanced deep neural network-based algorithm, which is able to bypass many shortcomings of traditional and classical machine learning-based Power System Analysis (PSA). The advancement in neural networks has also helped data handling processes like data augmentation, labeling and anomaly detection, which further improves the PSA model are also discussed. The goal is to provide a comprehensive overview of these advancements, mostly in the computer science domain, and it is potential to revolutionize power system operations and management.

1.1. Wide Area Monitoring System (WAMS)

The PMUs are high-capacity microprocessor-based relays crucial for measuring electrical values in power systems, predominantly positioned in substations. These units effectively communicate exact values of electrical voltage and current phasors, playing a pivotal role in determining the operating characteristics of power grids. PMUs serve as vital health monitors, offering real-time data for control and optimization of power systems. They are integral in multi-area operations such as monitoring and communication and bolstering power system stability and security. This technology provides crucial information on system dynamics during pre- and post-contingency situations. The data from PMUs assists operators in choosing the most effective algorithms for swift fault detection, identification, and isolation.

The Optimal PMU Placement (OPP) significantly enhances state estimation by supplying real-time dynamic data from key components like generating plants, lines, substations, and protection systems. The goal is to achieve complete observability of electromechanical nodes, especially during events or disturbances that affect multiple locations, leading to correlated changes in measured quantities. Analyzing spatial correlations helps detect patterns, identify anomalies, and improve the prediction or estimation of system behavior. This critical data, timeless and location-specific, is indispensable for monitoring a power grid's Operating Conditions (OC). The diverse electrical data features from PMUs, present at each location, distribute information across multiple dimensions that describe the state of the power grid. This PMU data is essential for Wide Area Monitoring System (WAMS) applications, which mainly focus on protection and control applications. The utilization of PMUs enhances the reliability and efficiency of the grid by providing operators with precise, actionable data in real-time [1].

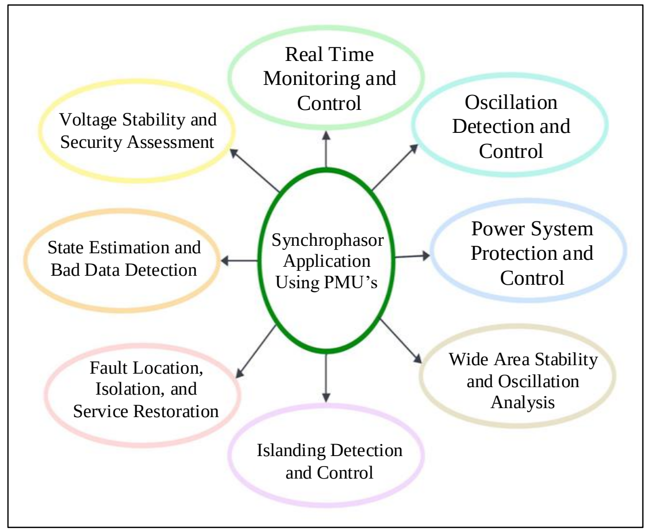

Fig. 1 Various synchrophasor applications using PMUs

The significance of WAMS becomes even more apparent when considering the sensitivity and complexity of wide-area disturbances, which can rapidly cause substantial damage and potentially lead to system collapse. Information regarding the severity of disturbances is essential, providing an accurate real-time snapshot of the system's state and alerting operators to emerging and concealed faults.

The data types required for synchrophasor applications vary, depending on the multilayered nature of the power and energy industries. Essential data such as power system quantities (voltage, current, frequency, ROCOF, and phasor) necessitate real-time transmission to ensure reliable protection and control operations. The accurate and consistent information provided by the synchrophasor is vital for identifying congestion points within the grid, enabling operators to make optimal dispatch changes to ensure reliable power delivery [1].

Synchrophasor technology presents several exciting avenues for research that can further enhance its application and effectiveness in power systems.

1. Algorithm development and testing: Testing of algorithms in real-world conditions as well as simulations ensure bridging of the gap between theoretical research and operational implementation.
2. Open-source platforms: Platforms which provide researchers with a standardized approach for synchrophasor data handling and algorithm testing. It

eventually fosters innovation and fosters adoption of new technology in grid monitoring and control.

3. Anomaly detection: Measurement instruments are susceptible to anomalies due to communication glitches and hardware malfunctions. Research in this area involves developing models that can accurately identify usual patterns in synchrophasor data, preventing false alarms and ensuring the stability of the grid.
4. Integration of RES: Research in this area might focus on developing algorithms that can predict and compensate for fluctuation caused by renewables like solar and wind. Renewables are becoming more prevalent.

Each of the research areas under a wide area monitoring system pushes the boundaries of synchrophasor technology, directly contributing to a more efficient and secure power grid [4].

1.2. Phasor Measurement Units (PMU)

The PMUs are high-capacity microprocessor-based relays crucial for measuring electrical values in power systems, predominantly positioned in substations. These units effectively communicate exact values of electrical voltage and current phasors, playing a pivotal role in determining the operating characteristics of power grids. PMUs serve as vital health monitors, offering real-time data for control and optimization of power systems. They are integral in multi-area operations such as monitoring and communication and bolstering power system stability and security.

This technology provides crucial information on system dynamics during pre- and post-contingency situations. The data from PMUs assists operators in choosing the most effective algorithms for swift fault detection, identification, and isolation. The Optimal PMU Placement (OPP) significantly enhances state estimation by supplying real-time dynamic data from key components like generating plants, lines, substations, and protection systems. The goal is to achieve complete observability of electromechanical nodes, especially during events or disturbances that affect multiple locations, leading to correlated changes in measured quantities.

Analyzing spatial correlations helps detect patterns, identify anomalies, and improve the prediction or estimation of system behavior. This critical data, timeless and location-specific, is indispensable for monitoring a power grid's Operating Conditions (OC). The diverse electrical data features from PMUs, present at each location, distribute information across multiple dimensions that describe the state of the power grid. This PMU data is essential for Wide Area Monitoring System (WAMS) applications, which mainly focus on protection and control applications.

A Phasor Measurement Unit (PMU) typically receives analog inputs from transducers, capturing three-phase electrical values such as voltages, currents, and phasors. This raw data undergoes preprocessing through an anti-aliasing filter to eliminate high-frequency noise or signals that could distort the data. This is followed by converting the analog signals into digital form using an Analog-to-Digital Converter (ADC). The Digital Signal Processor (DSP) then runs a phasor estimation algorithm to estimate signal quantities like frequency, phase angle, and the Rate of Change of Frequency (ROCOF) [4].

The processed phasor data is transmitted to a Phasor Data Concentrator (PDC) via a communication interface for further analysis and control. The phasor estimation algorithm, employing Discrete Fourier Transform (DFT) methods, calculates the positive sequence voltage and current value. This algorithm is crucial for determining the magnitude and phase angle of the phasors, which are essential in calculating the power system's frequency and ROCOF. The PMU data, encompassing local estimates, frequency, and ROCOF, is then relayed to data aggregators for additional analysis and control purposes [2, 3]. Various data-related issues must be addressed at the individual component level of PMU, as shown in Figure 2. The PMU data helps move from power system state estimation to state measurement, enabling real-time system monitoring.

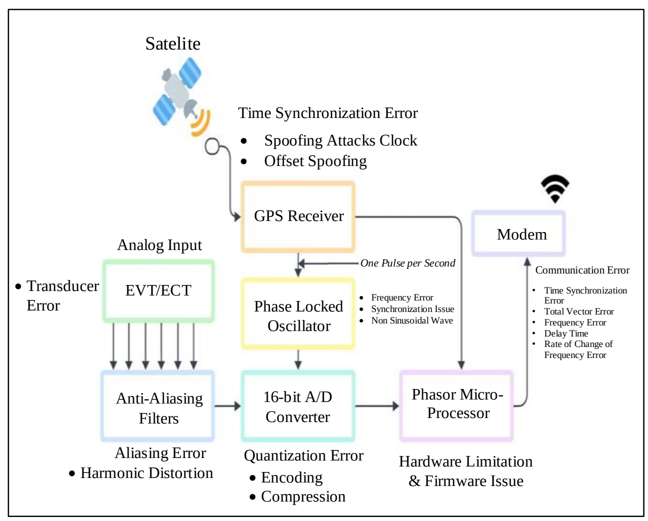

Fig. 2 Block diagram consisting of data-related issues at individual components of PMU

1.3. Motivation for this Review

Machine learning is transforming the power grid using synchrophasor data by enhancing the analysis and prediction of various power grid applications. Machine learning approaches can handle various synchrophasor applications like fault and event (detection and classification, transient stability assessments, voltage stability assessment, Cybersecurity, anomalies detection and oscillation, etc. However, researchers have yet to fully understand several research areas in Artificial intelligence-based power system studies. Sophisticated power system dynamics are modeled using machine learning in conjunction with synchrophasor data, allowing for more accurate and timely assessment, contributing to optimizing power grid operations, and preventing any potential stability and security issues. This paper provides insight into methods of continuous validation and optimization techniques of new algorithms, processes, and tools using synchrophasor data.

All the alternative methods, like Signal analysis, Statistical analysis, and physics-based models, have limitations and challenges and may not be as effective as machine learning. Promoting power system stakeholders to participate in educating and creating awareness of synchrophasor technology among other stakeholders and motivating research institutes to develop WAMS applications so that future blackouts can be avoided.

1.4. Outline of this Review

A Comprehensive Review outlines the organization of the paper following Chapter 1. The integration of Wide-Area Monitoring Systems with Accurate Dynamic Models for Advancing Grid Stability explores the role of power system models in analysis and their integration with WAMS for determining robust control and operation schemes. Later, the paper discusses the future of big data and synchrophasor technology in grid management, challenges in synchrophasor data management, machine learning model incorporation, and data quality issues.

Furthermore, the paper delves into Wide Area Monitoring System (WAMS)-enabled machine learning methodologies for assessing power system stability, encompassing transient and voltage stability evaluations. It also discusses the exclusive use of synchro phasor data in AI-enabled stability studies conducted over the past five years.

The paper summarizes its findings and underscores the pivotal role of artificial intelligence and machine learning in power system stability analysis. Each section meticulously explores distinct facets of power system stability, employing data fusion alongside machine learning techniques, and critically examines the challenges and potential future advancements in this domain.

2. Big Data in WAMS Technology

The core of an efficient power system analysis is the data that satisfies the fundamental dynamic model of the power system. The PS is designed and operated using a mathematical model that illustrates the power system dynamics of the electrical components under steady and during abnormal cases.

Grid modeling tools like production cost modeling, capacity expansion modeling, probabilistic modeling, and network reliability monitoring are some examples of statistical assessments essential for guiding the power industry transition towards clean electricity, and they help power engineers to plan and make informed decisions.

The accuracy of the simulated dynamic response of the power system depends on how precisely the enormous grid is reduced to lower-dimension models. Therefore, the vast grid architecture needs to be partitioned and segregated into zones and further minimized into smaller zones to identify and maintain the adaptation of the grid's operating point. This is necessary to reduce computational burden while performing power system analysis and application of certain parts of the power grid [5].

2.1. Fundamental Need for Accurate Dynamic Model

Wide Area Monitoring Systems (WAMS) technology represents a sophisticated power system monitoring and stability analysis approach. One of the significant challenges in this domain is the vast and sparse nature of synchrophasor measurement and other traditional data, often covering a vast geographical expanse with limited visibility. This scenario necessitates intelligent data fusion and sensor selectivity to handle and accommodate the collected data effectively. The data gathered often presents challenges such as noise, gaps, and various time and space-related patterns, so analyzing incomplete labeled data is essential.

Addressing these challenges is crucial in managing WAMS data, considering their sparse distribution, noise, incompleteness, and the temporal and spatial dependencies inherent in such data. Concerning network reliability analysis, the Development of wide area monitoring equipment has increased the accuracy and resolution of data acquired by the power utilities. The power system behavior can be optimized by analyzing correlations within data spread across the power system in space and time. Both steady state and transient analysis are vital in ensuring a stable power system in power systems.

The Dynamic models help identify potential issues, improve system performance, and provide stable and secure operation. Data fusion strategies combine diverse data types to enhance the understanding and management of complex systems, as shown in Figure 3. High-resolution data from PMUs at various fault locations are merged with traditional data like historical load patterns, maintenance records, and operational data from multiple sensors and systems. The fusion of these two data types enables a more comprehensive analysis, enhancing decision-making.

For example, multi-bus power systems composed of many sub-systems with incompatible defined inputs and outputs might cause port mismatches, which might cause instability. Participation analysis during instability, manipulation of state descriptor, model inversion, connection of sub-systems, and other transformations were performed to validate the state space analysis model to determine the controllability for proper and improper systems.

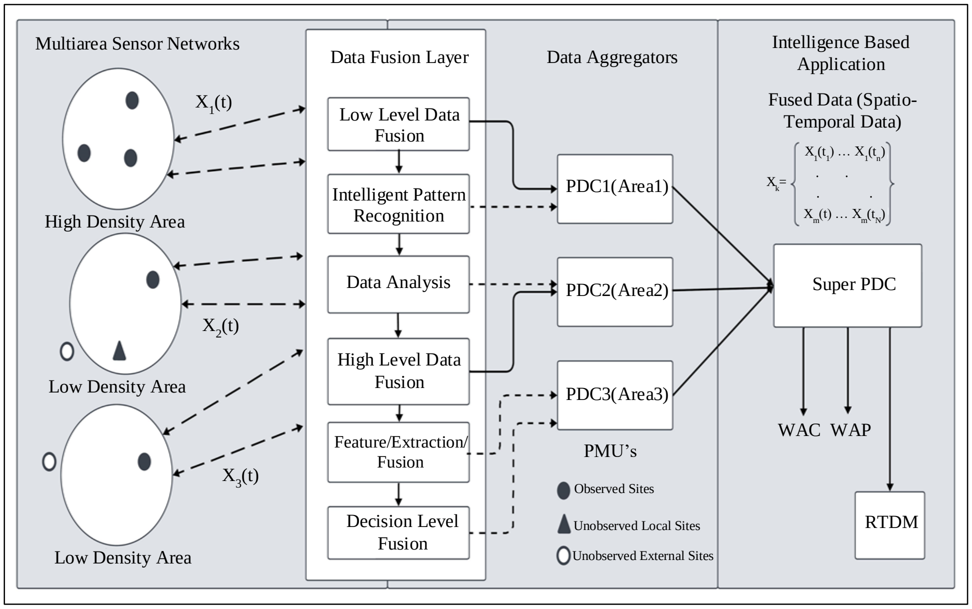

Fig. 3 Conceptual view of data fusion strategy

Table 1. Standard source of data or information in advanced power systems

Instruments	Rate of Sampling	Characteristics
Digital Fault Recorder (DFR)	The sampling rate is 500 Samples per cycle.	Faults and Post-Disturbances investigations.
Transformer Monitoring	Every 10 seconds/ Transmitted at 1200 bits per second.	Control operation and Preventive maintenance of Transformers.
Geographic Information System (GIS)	Based on Geographical Coverage, Infrastructure, Topography and Resolution	Asset mapping and Geographical representation of power grid.
Weather Information	A radar can generate over 50 GB in a day.	Correlation of power consumption and Time of the year and severe weather events.
Seismic Data	Not a direct source of information and day-to-day operations.	Seismic vulnerability of critical infrastructure like power plants, substations, or transmission lines.
Remote Terminal Unit (RTU)	1 sample in every 2-4 Seconds/ Magnitude only	Type of PLC used for System operation status monitoring and control.
Smart Meters	Based on Geographical Coverage, Infrastructure, Topography and Resolution 0.5 million devices can generate more than 120 GB	Demand side management, Power Quality, and Electrical usage and Pricing.
Phasor Measurement Unit (PMU)	One device can collect more than 4.5 GB of phasor data per day	Dynamic Stability of the power grid.
Micro-PMU	100 MB of data per daty	Event Detection, Fault location, Grid optimization, and control.

2.2. Volume and Size of Power Grid Data

For accurate dynamic modeling of power system, a power engineer must have access to critical information about the state of electrical equipment and the various sources of information in the Smart grid-like AMI, SCADA, WAMs, GIS, and other traditional metering data, Shown in Table 1. The operator should be able to merge these various raw data and draw semantic insight from it.

2.3. WAMS Scenarios Currently in India

In India, the initial phase of deploying PMUs began as exploratory projects to assess the capabilities of synchrophasor technology, setting the stage for its broader implementation [6]. In a landmark development in 2012, GE Power's Grid Solutions commissioned an unprecedented WAMS for the Power Grid Corporation of India Ltd (PGCIL), focusing on the Northern Grid.

This initiative termed the Unified Real Time Dynamic State Measurement (URTDSM) system, planned the installation of 1,950 PMUs, aiming to reach a total of 3,000 units across 351 substations, linking 29 State Control Centers, 5 Regional Control Centers, and 2 National Control Centers. The framework requires a substantial bandwidth of 146 Mbps to manage high-speed, synchronous data flow across different grid layers, utilizing complex communication technologies such as Ethernet, TCP/IP, and Web protocols.

This system mandates an annual WAMS data storage capacity of about 500 terabytes. Under the URTDSM project, the implementation and evaluation of new software and substation equipment for the WAMS were conducted. This system significantly enhances the real-time awareness and visualization of the power grid, thereby augmenting operational and planning efficiency.

Recognized as a project of national importance, it receives considerable financial backing, with 70% funding from the Ministry of Power through the Power System Development Fund (PSDF). The system's advanced functionalities include detecting and analyzing low-frequency oscillations, managing islanding operations, and validating dynamic models offline. Moreover, the adoption and calibration of innovative grid technologies in India are underway through pilot projects initiated by various utilities. The Ministry of Power has endorsed 14 smart grid pilot projects nationwide in the distribution sector. The projected expenditure of these initiatives is approximately USD 212 billion, with half of the funding contributed by the Ministry of Power and the remainder by the utilities.

Table 2. PMU installation with optical fiber

Region	Substation		Feeders		PMU		PDC	MPDC	SPDC
	ISTS	STU	ISTS	STU	ISTS	STU			
North	115	618	326	64	251	132	6	9	1
South	73	428	225	58	209	110	6	4	1
West	67	591	303	69	344	178	11	4	1
East	82	544	281	13	50	26	4	5	1
North East	14	93	49	26	71	37	0	3	1
TOTAL	**351**	**2274**	**1186**	**239**	**925**	**483**	**27**	**25**	**5**

Table 3. PMU installation without optical fiber [Report by-POSOCO, "Synchrophasors initiative in India," New Delhi, tech.rep. December 2013]

Region	Substation		Feeders		PMU		PDC	MPDC	SPDC
	ISTS	STU	ISTS	STU	ISTS	STU			
North	83	96	434	435	227	231	6	9	1
South	60	767	520	415	267	216	11	4	1
West	51	44	395	199	202	105	4	5	1
East	60	71	348	289	183	152	6	4	1
North East	18	22	95	69	50	36	0	3	1
TOTAL	272	309	1792	1407	929	740	27	25	5

2.4. The Characteristics of Synchrophasor Data

Synchrophasor data offers high temporal resolution, which traditional data sources lack. The changes in a power system's operating condition play a crucial role in developing accurate dynamic models of the power grid. The size of synchrophasor data generated by PMU is significant.

One PMU device can collect more than 4.5 GB of phasor data daily. There is no exact report on how much WAMS data is produced annually. However, the size can be estimated by considering specific characteristics. Extensive data handling leads to increased power consumption, attributed to the more significant number of data points processed per cycle.

The size of synchrophasor data generated in the power system usually depends on:

1. Types of sensors
2. High-frequency data sampling and preprocessing
3. Data encoding and compression
4. Number of PMUs installed

Time-domain simulation is necessary for creating a dataset of the dynamic changes happening in the power system; creating a database of a small test bus is time-consuming. The limited labeled data is still an active research gap for various power grid applications. In this paper [7], Real-time PMU measurement is replaced by synthetic synchrophasor data, reducing the simulation run-time, which merely accounts for data quality issues. Therefore, it is necessary to have publicly accessible data sources available for the research community. Furthermore, the necessity of a standard benchmark for power system test cases should be openly available to the research community [8, 9].

Table 4. The data generated annually depends on the type of sensors utilized and the number of data streams

		SCADA	**PMU**		**DFR**
Number of Streams	10000	470.2 GB	45.9 TB	4.5 PB	448.5 PB
	100	4.7 GB	470.2 GB	45.9 TB	4.5 PB
	1	48.1 MB	4.7 GB	470.2 GB	45.9 TB
		0.1 Hz	**10 Hz**	**1 KHz**	**100 KHz**
	Sensor's Frequency				

In Table 4, shown above, the volume of data generated annually is highly variable and depends significantly on the nature and quality of the sensors. The various sensors and the sheer number of data streams play a crucial role in determining the total data output, leading to a potentially exponential increase in data volume.

2.5. Data Quality

However, PMUs are not immune to data quality issues, which can be inherent to information and telecommunication limitations and must be accounted for. The data loss issue can be tackled using several advanced data recovery methods. However, there is no standardized method to address data loss, and data are often set to zero by the substitution method. Therefore, a methodology is required to ensure the reliability and authenticity of synchrophasor data. Developments in technology, evaluation procedures, and computational methods are necessary to handle data quality and security interdependency efficiently.

Anomalies in PMU data can cause problems for the protection of the power system, including false and delayed tripping. Bad data anomalies are caused by errors in the synchrophasor data, such as sensor errors, communication errors, or software errors. Figure 4 illustrates that data quality and cybersecurity are deeply interdependent; high-quality data is essential for effective cybersecurity measures, as accurate and reliable information is needed to detect and respond to threats accurately. Conversely, robust cybersecurity is crucial to ensure data reliability; protecting it from unauthorized access and manipulation is essential to maintain its quality. This reciprocal relationship highlights the need for a holistic approach to data management and cybersecurity to maintain the integrity and utility of critical data systems.

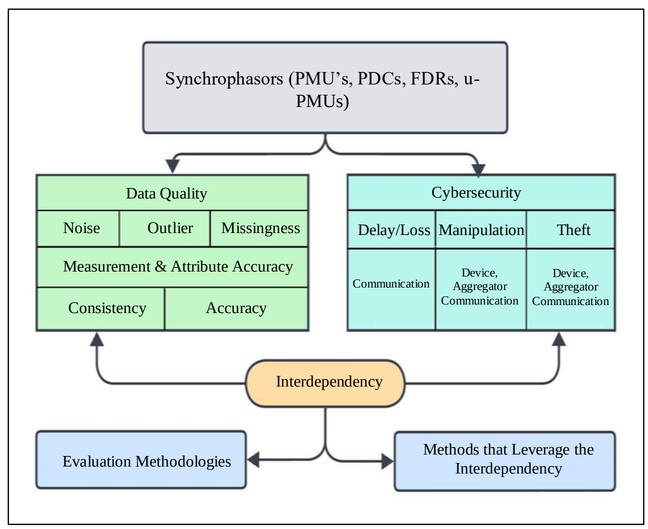

Fig. 4 Synchrophasor data's interdependency based on quality and cybersecurity of various synchrophasor technology

2.5.1. Quantization Error

Continuous data are converted into a limited number of discrete values; this rounding process introduces minor errors, known as quantization errors. PMUs typically capture high-frequency data samples to represent the dynamics of power system phenomena accurately. Low-pass filters, Notch filters, and Kalman filters are some techniques of data preprocessing employed to filter PMU data and accurately capture high-resolution temporal data at every interval [10]. Encoding involves converting raw PMU data into a standard representation that is easy to interpret and that different systems or applications can utilize. PMU data can be stored in various files and structures ranging from well-structured, semi-structured data to quasi-structured data.

Further, processing time, compatibility, and interoperability are some factors that decide a suitable encoding scheme. Compressing large volumes of data into readable structures is crucial for transmission and data storage, real-time processing, and analytics and security [11].

PMU data compression is essential for efficient and effective utilization of data. Still, specific encoding techniques and compression algorithms may sacrifice subtle data variations to maintain high compression ratios.

2.5.2. Time Synchronization Error

The synchronization of multiple PMUs is critical for analyzing the power system state and developing control applications to enhance power grid security. The accuracy and efficiency of PMUs are augmented by the Global Positioning System (GPS).

This synchronization allows for precise correlation of measurements from multiple PMUs, enabling a comprehensive and integrated approach to power system analysis. Sensor error in PMU can introduce clock drift, synchronization delay, and signal latencies in the form of timing deviation [12]. This type of error can arise from communication delays, GPS inaccuracies, network latency, or hardware limitations.

Synchronization errors lead to incorrect identification and misinterpretation of the events. Due to communication delay and signal propagation issues, achieving precise time synchronization across multiple PMUs spread across a vast geographical area is complex.

Adhering to causality principles enables reliable and accurate interpretation of PMU data. The cause-and-effect relationships help identify the root causes of anomalies in PMU data and enhance fault detection, predictive analysis, system control, and data interpretation, contributing to the overall stability of power grids.

Vulnerability in time synchronization, such as spoofing, where an attacker can manipulate and mislead information, potentially causing inaccurate measurements resulting in erroneous detection of system parameters, delayed faults and disturbance identification, and suboptimal control actions [13].

Also, PMU relies on GPS or Precision Time Protocol (PTP) to receive precise time synchronization. It is possible to physically attack the GPS receiver or cause a Denial of Service (DoS) of PTP time synchronization.

Signal obstruction, such as physical barrier and Electromagnetic Interference (EMI), can introduce noise distortion, potentially leading to timing inaccuracies and synchronization errors. Equipment malfunctions, such as faulty antennas and hardware glitches, can impede synchronization signals' proper transmission and reception.

Any discrepancies or errors in the time synchronization among PMUs can lead to Frequency errors since Phase angle errors are closely related to frequency measurement. In Table 2, the IEEE C37.118 standard series specifies a Total Vector Error (TVE) limit of 1%, a phase angle error of 0.5730 degrees, and a time deviation of 31.8μs (50 Hz System). Knowing a small phase angle error can lead to significant frequency estimation discrepancies [14].

2.5.3. Transducer Error

Transformation performance of an Electronic Current Transformer (ECT) and Electronic Voltage Transformer (EVT) on a PMU under steady and dynamic conditions checks for transducer error. Error in the form of harmonic noise may arise and cause anomalies in frequency measurements.

The Rate of Change of Frequency (ROCOF) measurement is sensitive to harmonic noise since the performance of the Electrical Voltage Transformer (EVT) is affected due to deviated input [15]. Sensor errors can cause slight changes in the synchrophasor data, such as random spikes or dips in the measured values. Sensor errors can create biases or noise in the form of impulse noise, which affects the accuracy of state estimation results.

2.5.4. Communication Error

Synchrophasor applications can be categorized into two main classes: online and offline. Synchrophasor applications may become biased and inaccurate due to anomalies in the data. Ensuring data accuracy requires that synchrophasor measurements fall within acceptable error margins and that the data is complete and consistent with acceptable latencies. However, statistical analysis suggests that data quality issues arise randomly, have a small probability of occurrence, and exhibit strong dynamic characteristics [16].

This paper [17] examines the development of special protection and control schemes that consider latencies and optimize the communication architecture to minimize delay within an acceptable range for possible estimation methods, such as substitution and interpolation.

High-speed synchronous data is shared among control centers via various complex communication architectures, including Ethernet, Transmission Control Protocol (TCP)/Internet Protocol (IP), and web applications.

Consequently, this requires a high bandwidth of 146 Mbps and 500 terabytes of WAMS data storage annually. Transmitting high-resolution synchrophasor data demands higher power. Additionally, security issues like third-party tampering with information could cause significant problems for utilities, necessitating data encryption, comprehensive cybersecurity measures, and the incorporation of the latest firewall policies.

Communication requirements for crucial WAMS applications, including generator synchronization, state estimation, and intelligent scheduling, demand higher data rates and tolerance for acceptable delays. WAMS with PMUs offers significantly faster data transmission and lower latency compared to traditional SCADA systems.

Data flow latency in the context of the Indian power grid, particularly between interconnected grids, refers to the time delay experienced as data travels from one part of the grid to another. The exact time can vary, and the approximate time is represented in Figure 5, which includes the average delay in seconds.

This latency can vary depending on the communication infrastructure, the distance between different grid components, and the type of data transmitted. For a vast and complex network like the Indian power grid, which encompasses multiple regional grids, these latencies are critical in real-time monitoring and decision-making processes, affecting the efficiency and reliability of grid operations.

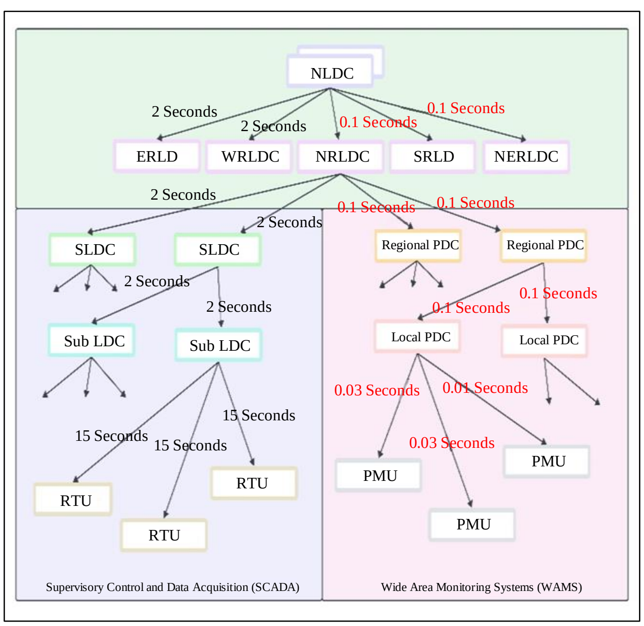

Fig. 5 Shows data flow latency between the intergrids of the entire Indian power grid

2.5.5. Hardware Constraints

The Optimal PMU Placement (OPP) will enhance state estimation by providing real-time dynamic data of key generating plants, lines, substations, protection systems, and FACTS devices. More PMUs are installed in the power grid, which is more likely to increase the size of data, which is not feasible, and network congestion increases. However, to achieve complete observability, one-third of PMUs about the number of buses are sufficiently required.

The OPP is an active research area in the WAMS; Integer Linear programming (ILP) and Genetic algorithms are widely used to determine the power grid's observability range. Also, PMU data requires high bandwidth and low latency communication channels; errors such as missing data points or corrupted data can cause latencies and inconsistency.

Packet loss due to heavy network traffic or congestion can impact the transmission of PMU data. The number of PMUs also depends upon the bandwidth of the channel type to ensure uninterrupted data transmission. Tuning the bandwidth and delays in communication links affects communication characteristics, such as average delay and drop rate, affecting data resolution.

2.5.6. Cyber-Threats

The communication infrastructure must be protected from cyber threats to prevent unauthorized access, data manipulation, or critical power system operations disruption. A bibliographic study of literature on special protection and control schemes shows that developing novel communication schemes, considering the interoperability between varying communication schemes and communication infrastructure, is of utmost importance.

Software-Defined Networking (SDN) architecture is more efficient in managing PMU data congestion than IP network architecture [18]. The need for standards in Wide Area Monitoring Systems (WAMS) technology is critical due to the challenges associated with implementing synchrophasor technology.

These challenges include communication, data quality, cybersecurity, cost, interoperability, standardization, scalability, and regulatory issues. These factors vary from country to country, necessitating a global approach to ensure the effective integration of synchrophasor technology.

Several standards have been derived for the efficient interoperability of PMU technologies within various WAMS markets and stakeholders. The recent intelligent grid standards considering synchrophasor data are updated, and new advancements in operation schemes are taken into account, as shown in Table 5.

Table 5. Some critical and recent intelligent grid standards in consideration to synchrophasor data reliability and interoperability

Functions	Standards	Description
Wide Area Situational Awareness	IEEE C37.118.1-2011	Data contents and format of measured dynamic phasors and frequency measurement.
	IEEE C37.118.2-2011	Proper guide for installation, calibration, Synchronization, and testing of PMUs.
	IEEE C37.244-2013	Proper terminology for the implementation and operation of PDCs was added.
	IEEE C37.247-2013	PDC standards for enhanced data storage capability.
Power System Analysis and Control	CIGRE working group B5.59	Guidelines for synchrophasor application, Voltage stability assessment, oscillation detection, and wide-area monitoring.
	IEEE 61850-90-5	Defines communication network and integration of WAMS technology along with intelligent instruments, switchgear, and other IEDs.
	ISO/IEC 20547	Mechanism of sharing WAMS data between grid operator and stakeholders/customers
Cyber Security	NIST SP 800-82 Rev.2	Guideline to Industrial Control Systems (IC) Security of SCADA and WAMS Components.
	NIST Cybersecurity Framework (CSF)	Guidelines for identifying, protecting, detecting, recovering, and chastising third-party offenses.

2.5.7. Data Storage

Data Storage infrastructure plays a critical role in managing vast amounts of data. It is a significant part of the smart grid; it collects and delivers data for further data analytics. Data storage and retrieval optimization: Implementing distributed computing frameworks for real-time operation requires efficient data partitioning, streamlined data processing pipelines, and optimized algorithms. Techniques such as parallelization frameworks, cloud computing, and distributed data processing platforms contribute to the scalability of PMU data. Distributed File Systems (DFS), such as Google File System (GFS) and Hadoop Distributed File System (HDFS), and NoSQL databases, such as Column databases and Key-value stores, are two types of SQL databases.

Additionally, NoSQL databases, such as Column databases and key-value stores, offer flexible and scalable storage solutions to the smart grid. Big data processing can be accomplished in two ways: Batch processing and Stream processing. The choice between the response times of processing is crucial for timely decision-making in power grid operations.

Furthermore, the effectiveness of data analysis in a smart grid system depends on the class of data analysis employed, such as Descriptive, diagnostic, and predictive analysis, which offers insights into power grid behavior. Each class suits various applications and operations, enabling utilities to detect anomalies, predict future events, and prescribe corrective actions for different power grid applications and operations [19].

2.6. ML Model Life Cycle

The domain of Deep learning and Machine learning, in conjunction with data analytic tools, describes today's AI landscape. For Batch, natural, or hybrid processing for model building of power system applications, data preparation is a crucial step that involves collecting, validating, and pre-processing data. Based on their performance, the data is later fed to a suitable model for a particular power grid application from the pool of nominated models. The model training requires the intuitive and iterative task of tuning hyperparameters that determine the model prediction quality and training time.

Class imbalance is a common challenge in machine learning-based voltage stability assessment using PMUs. Especially when an imbalance in the number of samples associated with one particular contingency is more than other classes, leading to a biased model. However, successful deployment of the selected model and analysis of feedback information from the model decides further possibilities for fine-tuning or retraining the model with newly acquired data. This loop of continuous model training, optimizing, deployment, and feedback summarizes the life cycle of AI model management.

3. WAMS – Enabled Machine Learning Approaches for Power System Transient Stability Assessment

Transient analysis is the most effective approach to determining the power flow limit in the power network during a disturbance. Transient instability can lead to catastrophic cascading failure and widespread blackouts. The transient stability assessment is classified by its characteristics, such as numerical, direct, and machine learning methods. These three classes for transient stability assessments readily provide adaptable solutions to other stability problems in power systems [20]. The necessity of this analysis lies in its role in preventing widespread blackouts and ensuring the stable and secure operation of the power system.

In Figure 6, the time responses of different controls and components are crucial for understanding how a system reacts to disturbances over time. Each component, like generators, transformers, and control systems, has its own characteristic response time, influencing how quickly it can respond to changes or faults in the system. The interaction of these varied response times determines the system's overall stability; fast-acting controls can help stabilize the system quickly, while slower components might delay recovery or exacerbate instability.

The assessment of transient stability involves analyzing the dynamic behavior of the power system following a disturbance. Numerical methods often involve detailed simulations that can capture the system's response over time, providing insights into potential vulnerabilities. Direct methods, on the other hand, offer a more immediate evaluation of stability by analyzing critical parameters and operating conditions without extensive simulations.

Machine learning methods leverage historical data and patterns to predict stability outcomes, offering a modern data-driven approach to stability assessment. By integrating these different methodologies, power system operators can gain a comprehensive understanding of transient stability, enabling them to implement effective mitigation strategies and enhance the resilience of the power grid.

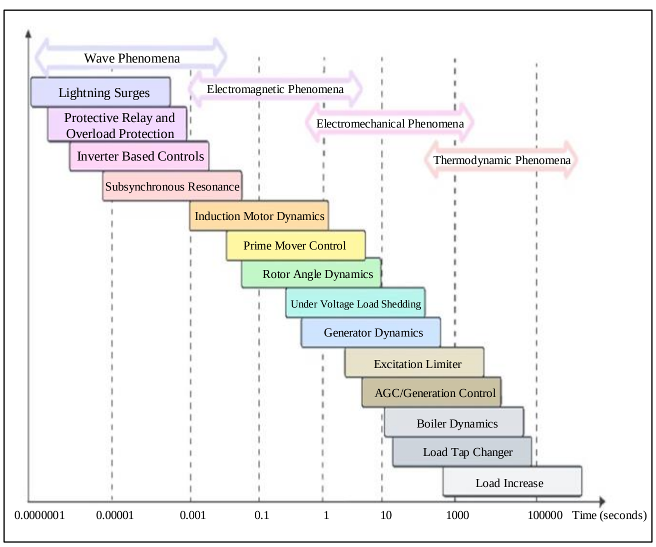

Fig. 6 Time responses of different controls and components for stability analysis

3.1. Overview of TSA Using Machine Learning

Joint studies between power utilities and co-generation were performed to develop possible mitigation strategies. Various sophisticated programs were designed to simulate EMT and electromechanical analysis of transients in multi-phase power systems. Quasi-static phasor simulation is used in multiple applications, including voltage stability analysis, power system planning, and the analysis of power electric and electronic systems in the power system. Quasi-static phasor combined with other methods, such as electromagnetic transient and dynamic phasor simulations, provides a comprehensive understanding of the system's behavior under various conditions.

On the other hand, Electromagnetic Transient Simulation (EMTS) captures detailed, fast dynamic phenomena of inertial response during switching transient, Lighting surges, and the dynamic response of power electronic devices, mostly inverter-based, ranging in order from milliseconds to seconds. Changes in the magnitudes and phasors throughout the network are slow compared to changes in the power system's frequency. Incorporating EMTS enables the assessment of transient phenomena and the evaluation of the effectiveness of protective devices and control systems, thereby enhancing the overall reliability and security of the power system.

The traditional approach is prone to uncertainty in measurement and computation accuracy due to the power grid's rising nonlinearity. It overlooks the security constraints of power system analysis. The variety of contingencies, magnitude of data issues, imbalances in class, and others have severe consequences in training machine learning models and lead to biased model performance. AI techniques, including deep imbalanced learning frameworks, transfer learning, and machine learning approaches, are being utilized to mitigate the impact of class imbalances in transient stability assessment. Time domain: Quasi-Static Phasor (QSP) simulations of steady-state and low-frequency dynamic behavior in the power system can be studied, and discrete changes within steady-state operating conditions of a power grid are represented algebraically for analyzing steady-state stability.

3.2. Fuzzy Logic

In-phase voltage control significantly improves the transient stability margin in power systems, with UPFC methods outperforming quadrature voltage control in reducing swings. The proposed multi-objective optimization method using parallel NSGA-II and fuzzy membership variance provides more scientific and objective solutions for Transient Stability-Constrained Optimal Power Flow (TSCOPF) [21]. Also, nonlinear controllers like Fuzzy Logic Controllers (FLC), Static Nonlinear Controllers (SNC), and ANFIS-based variable resistive fault current limiters effectively improve the transient stability of hybrid power systems in integrated renewable-based power plants [22].

3.3. Decision Tree (DT)

The Decision Tree (DT) algorithm, developed using synchrophasor data, predicts Transient Stability Assessments (TSA) with 95.1% accuracy for post-fault conditions of 39 bus systems in New England [23]. Similarly, the decision tree method achieves 98.5% accuracy immediately after fault clearance and nearly 100% accuracy 2.5 seconds after fault clearance [24]. The proposed method, which utilizes a Characteristic Ellipsoid (CELL) and Decision Tree (DT), classifies power system transient stability after disturbances with high precision and less information [25]. Additionally, an ML method predicts transient stability using Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO). Online Dynamic Security Assessment (DSA) of ever-changing Operating Conditions (OC) is performed in a data mining framework by training decision trees and adaptive Ensemble Decision Trees (EDT) [26].

3.4. Support Vector Machine (SVM)

A combination of Support Vector Regression (SVR) and dragonfly optimization algorithm was proposed. The hybrid DFO-SVR model effectively assesses voltage stability in real-time, providing better performance than the ANFIS model for predicting voltage stability index. [27]. A comparative analysis of this algorithm was conducted where SVMs and ANNs outperformed decision trees regarding accuracy and computation. TSA tasks mainly involve classification and prediction utilizing ML models, which are trained offline, and later, the testing is performed online [28].

3.5. Ensemble Learning (ELM)

Various ensemble learning methods, including bagging, voting, and stacking, are utilized for feature selection in Transient Stability Assessment (TSA). A notable approach involves Java-based feature selection with an Ensemble of OS-Extreme Learning Machines (EOS-ELM), which can reduce features to one-third, enhancing TSA performance [29]. Additionally, the Fisher discriminator is employed to determine the optimal feature subset for transient stability analysis [30]. The maximum relevance minimum redundancy (mRMR) method is designed to identify the most relevant features while minimizing redundancy. This method, combined with Winner-Take-All (WTA) ensemble learning, has been leveraged to improve TSA [31]. Gradient boosting has also been effectively utilized for feature selection, with parallel convolution algorithms addressing input features akin to the data structure of digital images [32].

A case study on the IEEE-39 bus system using the Vision Transformer (ViT) model demonstrates the efficacy of two-stage monitoring for detecting unstable generators. This model outperforms traditional machine learning algorithms in TSA investigations, achieving an accuracy of 98.92% [33]. Furthermore, a novel framework presented in [34] enhances the accuracy of transient instability recognition using imbalanced learning techniques and data from Phasor Measurement Units (PMUs). Addressing data imbalance, the study in [35] introduces a hybrid simulation tool designed to generate realistic datasets, proposing a new method for data organization to enhance the performance of Machine Learning (ML) models in predicting transient stability.

Further exploration into ensemble learning, specifically leveraging synchrophasor data for TSA, is detailed in the comparative analysis of the XGBoost model against other ML models. This analysis highlights how XGBoost addresses limitations inherent in traditional ML approaches [36]. Moreover, an innovative approach to TSA frameworks is introduced, incorporating an improved convolutional neural network augmented by an orthogonal weight modification algorithm. This enhancement significantly boosts the framework's continual learning capabilities. Finally, the study in [37] employs machine learning techniques and grid topology for dynamic stability analysis of power systems, underscoring the advanced methodologies being developed in this domain.

3.6. Deep Learning for TSA

Using a Recurrent Neural Network (RNN) for its Time series data in combination with CNN enhances the spatiotemporal analysis of event signatures. The CNN-LSTM model accurately detects in PS TSA using historical data events (DigSILENT PowerFactory simulation of PMU measurements), with a 99% detection accuracy and Average Computational Time [38]. The LSTM-CNN-based TSA model improves speed and accuracy in transient stability assessment for spatial-temporal analysis, and it was tested on the IEEE 39 bus system [39].

A Deep Belief Network (DBN) for transient stability prediction demonstrates significant improvements in prediction accuracy and computational efficiency [40]. Similarly, [41] developed a model integrating CNN and LSTM for transient stability assessment, achieving high accuracy in predicting system stability under various fault conditions. Another study proposed a Transformer-based model for TSA, which outperformed traditional methods in handling large-scale power systems with complex dynamics [42]. These advancements underscore the potential of deep learning techniques in enhancing the reliability and efficiency of transient stability analysis in power systems.

4. WAMS - Enabled Machine Learning Approaches for Power System Voltage Stability Assessment

Voltage control and stability are a source of concern to every PSO. Since the change in load's nature and pattern are uncertain, it is causing trouble for any power system operator to establish a secure but also an optimally secure power plant. So, coordination information is essential for PSA. The information helps us to understand the mechanism of voltage patterns in existing power systems, allowing the Power

System Operators (PSO) to solve stability problems. The main factors contributing to voltage instability are insufficient reactive power supply, uncertain load characteristics, poor coordination of control, and protective system, which influence the system conditions and characteristics towards voltage collapse. Consideration should be given to possible contingencies, margin, and tolerance for any critical interface, which depends on the load level, active and reactive flow and reactive power reserve.

Generally, power systems are vulnerable to short-term voltage instability due to fast-acting dynamic equipment, which leads to uncertain reactive power demand within the power system. Furthermore, the integration of renewable energy sources, with their variable output, bypasses these stability challenges. Advanced monitoring and control technologies, such as Wide Area Monitoring Systems (WAMS) and Phasor Measurement Units (PMUs), are increasingly being deployed to provide real-time data and enhance the ability of PSOs to predict and mitigate voltage instability.

By leveraging these technologies, operators can implement more sophisticated control strategies to manage reactive power more effectively and improve the overall resilience of the power grid. Continuous research and development in this field are crucial to developing innovative solutions that can adapt to the evolving demands and complexities of modern power systems.

4.1. Overview of VSA Using Machine Learning

The main focus of Power System Operators (PSOs) is to maintain the stability of the power system without resorting to load or generation shedding and to avoid altering control measures that incur operational costs and affect the optimal performance of the power system. The challenges in Voltage Stability Assessment (VSA) include predicting the final state of the network without the need for post-disturbance information and avoiding extensive online simulations to determine important feature sets for VSA. Sensitivity analysis and modal analysis are two methods used to assess voltage stability in a power system.

Traditional methods for voltage stability in power systems have historically relied on statistical model-based approaches. Voltage stability indices estimate the proximity of a bus to instability. However, such simulations do not readily capture sensitivity information and the degree of stability. In steady-state security assessment, computing the voltage margin is required to predict bus voltage magnitudes under different loading scenarios. Developing software tools for real-time VSA is a time-consuming task. An online estimation of voltage magnitudes will help the system operator mitigate the possibility of voltage instability and identify weak areas in the power grid. The solution must be capable of providing the maximum loading margin of the system prior to any voltage collapses. In Figure 7, the categorization of various methods and approaches to evaluate and ensure voltage stability is represented in a taxonomy form. It typically includes steady-state analysis, which examines voltage stability under constant load conditions, and dynamic analysis, which assesses how voltage stability is affected by time-dependent changes in the system, such as rapidly fluctuating loads or line outages. This classification helps identify appropriate tools and techniques for maintaining voltage stability under different scenarios.

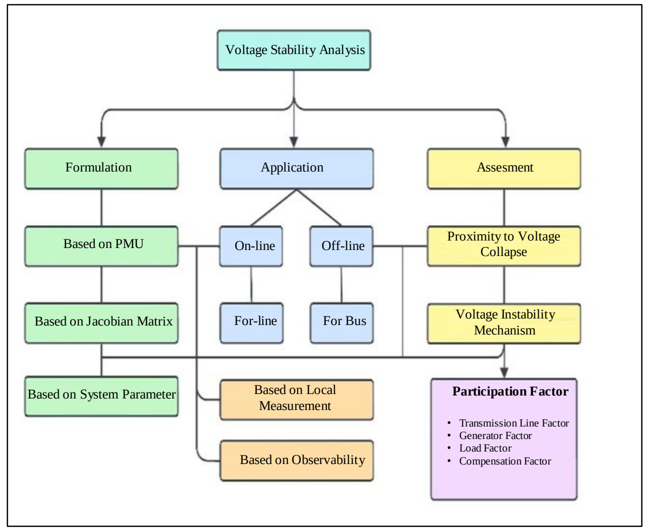

Fig. 7 Taxonomy of Voltage Stability Assessment

Machine learning techniques, including Convolution Neural Networks (CNNs), RNNs, and Reinforcement Learning (RL), have enhanced the accuracy and efficiency of Dynamic Security Assessment (DSA). The fuzzy set theory supplements the traditional mathematical tools in solving power system stability problems. A fuzzy voltage stability index can highlight critical bus bars subjected to standard and contingent operations.

4.2. Traditional Voltage Stability Indices

Among 40 voltage stability indices, they are compared based on their performance, functionality, and applicability. Time domain simulations of the system models capture the chronology of the events. Using the Modern Voltage Stability Index (MVSI) on the IEEE 30-bus system, researchers were able to identify the maximum reactive power load before collapse and rank them in accordance with their vulnerability [43].

Similarly, in [44], the performance of the Bus Voltage Stability Index (BVSI) involved a comparative analysis of BVSI against existing indices, utilizing IEEE 14 and IEEE 30 bus systems and other existing stability indices in predicting voltage collapse were compared under several load conditions while ignoring line resistance partially. The BVSI was found to be more accurate, helping identify critical lines and potential weaknesses in the power grid.

4.3. Artificial Neural Network (ANN)

Fuzzy Logic (FL) techniques have been effectively utilized for voltage and transient stability analysis. However, handling large-scale, uncertain data and identifying complex relationships can be challenging and require expert knowledge to interpret. The identification and adaptive nature of neuro-fuzzy control systems (ANN) combined with linguistic knowledge of fuzzy logic control (fuzzy inference systems), which is known as the ANFIS model, is a widely used tool for power system stability assessment. Once an Artificial Neural Network (ANN) has been adequately trained, it can effectively interpolate any novel pattern covered by its input features.

This paper [45] presents a surrogate control algorithm featuring a Back-Propagation Neural Network (BPNN) aided by NSGA-II, demonstrating computational efficiency in simplified Voltage Stability Margin (VSM) control on a 118-bus system. A compact Artificial Neural Network (ANN) model has been shown to significantly reduce data requirements for efficient voltage stability assessment in power systems (2021) [46].

An ANN-based method is developed to rapidly estimate long-term voltage stability margins, adequate under normal operating conditions and in N-1 contingency scenarios (2022) [47]. An ANN-based voltage stability index (L-index) for Voltage Stability Assessment (VSA) was developed and tested on the IEEE-14 bus system. The method identifies buses with high index values as vulnerable to voltage failures, indicating areas within the power system that require critical reactive support [48]. The proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) based control scheme for Unified Power Quality Conditioner (UPQC) devices significantly enhances compensation capabilities. It effectively regulates serious voltage stability issues like voltage drops and harmonic distortion, thereby improving power quality [49].

4.4. Decision Tree (DT)

The decision tree is reliable in performing extensive contingency simulation for a wide range of operating scenarios, where the objective is to find susceptible regions in multidimensional operating parameter state space. The Decision Trees (DTs) tested on the IEEE 118-Bus system have demonstrated better accuracy by employing adaptive boosting methods. This approach eliminates the need for manual selection of appropriate predictors.

A novel strategy using Fuzzy-based Decision Trees (DTs) was applied to the IEEE 300 Bus test setup. This method effectively determined the power system’s Voltage Stability Index (VSI) [50]. This study utilizes Principal Component Analysis (PCA) for dimensionality reduction of data from various Phasor Measurement Units (PMUs). Correlation analysis is then used to categorize each feature with different stability indices, followed by Decision Trees classifying and assessing the security margin of power systems (2020) [51]. The implementation of the C4.5 algorithm in Decision Trees for real-time voltage stability assessment involves sample acquisition, selection of attributes, and DT construction [52]. Identifying Static Voltage Stability Margin with the Participation Factor Method and Relief-F Algorithm were developed and identified as practical tools for assessing static voltage stability margin [53].

4.5. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised learning method extensively used for Voltage Stability Analysis (VSA) studies. SVM analyzes data for classification and regression tasks, including feature selection, multiclass classification, and time series analysis. Over the last ten years, there have been significant advancements in feature selection and optimization techniques utilizing various dataset types. A novel combination of Support Vector Regression (SVR) and the Dragonfly Optimization algorithm was proposed, enhancing the efficacy of traditional SVR approaches in various applications.

This hybrid Dragonfly Optimization-Support Vector Regression (DFO-SVR) model was found to outperform the Adaptive Neuro-Fuzzy Inference System (ANFIS) model in terms of performance [54]. Furthermore, recent studies have introduced improved versions of support vector machines, namely Aggressive Support Vector Machine (ASVM) and Conservative Support Vector Machine (CSVM). These models aim to enhance real-time transient stability assessment in power systems and reduce the occurrence of false and missed alarms [55].

4.6. Ensemble Learning (ELM)

The study demonstrates that Multi-objective Biogeography-Based Optimization (MOBBO) effectively reduces measurement data needs and misclassification rates in voltage stability assessment of power systems, outperforming other methods like NSBBO [56]. This study utilized the Extreme Gradient Boosting (XGB-CM) framework within ensemble learning-based classification models, yielding a significant improvement in slope stability estimation accuracy over traditional single-learning models [57]. This approach maintains high accuracy in short-term voltage stability assessments, outperforming existing methods even when a significant portion of measurement data is missing.

In this context, the AdaBoost classifier achieved the highest classification accuracy (96.02%), surpassing other classifiers in monitoring voltage instability within electrical power systems [58]. Similarly, the paper [59] investigates the assessment of Short-Term Voltage Stability (STVS) in scenarios where PMU data is incomplete or partially available. By using ensemble learning, the model addresses the issue of class imbalance within limited training samples by employing the Random Under-Sampling Bagging (RUS-Bagging) method, which involves randomly selecting subsets of the majority class samples to balance class distribution before training multiple models [60]. This method focuses on reconstructing PMU data sequences and extracting features using a combination of gated recurrent neural networks and transformer encoders. It aims to emphasize the minority class and balance sample classes through techniques like data augmentation and semi-supervised clustering. This approach performs better than LSTMs, Decision Trees (DTs), and Support Vector Machines (SVMs).

4.7. Deep Learning for VSA

Deep learning has gained preference over traditional machine learning-based stability analysis due to its ability to recognize complex patterns in large, high-dimensional datasets. It can handle temporal dynamics, learn from new data autonomously, and operate in real time. Deep learning requires less manual feature engineering and generally provides more accurate predictions.

In the paper [61], a Long Short-Term Memory (LSTM) based assessment model was built for learning time series of post-fault trajectories. The authors proposed a semi-supervised clustering algorithm to categorize instances of voltage stability. This methodology was validated using the IEEE 39-bus system, confirming its effectiveness. In another study [62], researchers proposed a transferable deep learning-based STVS assessment by constructing physics-aware features such as reactive power flow and grid topology to indicate the voltage stability of the nodes in a power grid. The DL model achieved an accuracy of 99.68% and was tested under various Operating Conditions (OC) on the New England 39-bus system.

Further, in [63], deep learning was utilized alongside techniques such as temporal ensembling for data clustering and the use of the Least Squares Generative Adversarial Network (LSGAN) for data augmentation to leverage limited data with slight differences. This data augmentation also improves the adaptability of the subsequent model to topological changes. The approach of using temporal ensembling and LSGAN provided accurate results when implementing a transformer model for STVS. The effectiveness of the research was compared under different signal-to-noise ratios, topologies, and observation time windows.

Similarly, in [64], an STVS framework was developed based on 1D-CNN to handle data anomalies. The objective was to detect collapse and simultaneously quantify the severity of a power system fault. Data preprocessing included anomaly detection and treatment. An ensemble-based anomaly detector, comprising linear regression, Chebyshev, and DBSCAN base detectors, was used for anomaly detection. The model was tested under IEEE 30 and IEEE 39-bus systems with and without bad data treatment.

5. Advancements in Wide Area Monitoring Systems (WAMS) for Power Grid Stability

With the rise of synchrophasor technology, the future of big data is expected to be characterized by increased data generation, more diverse data sources, and advanced analytics capabilities. As synchrophasor technology continues to evolve, the amount of data created daily and the growth of significant data trends in upcoming years will be influenced by several factors: With the growing need for efficient grid management and system reliability, the amount of data generated by synchrophasor devices and other sources is expected to increase. The global synchrophasor market size and value are projected to reach USD 383.61 million. Several nations began deploying synchrophasor technology in the 2000s. China has invested extensively in synchrophasor systems in conjunction with its high-voltage power grid and Distributed Energy Resources (DERs).

Finally, the challenges associated with synchrophasor technology implementation include communication, data quality, cybersecurity, cost, interoperability, standardization, scalability, and regulatory issues. These challenges vary from country to country and need to ensure the effective integration of synchrophasor technology worldwide. As big data grows, organizations must focus on responsible data collection and management practices, ensuring the privacy and security of customer data AI and ML power automation and analytics. In summary, the future of big data with the rise of synchrophasor technology will be marked by increased data generation, diverse data sources, advanced analytics capabilities, and a focus on data privacy and security. These trends will shape the development and application of synchrophasor data in various industries, including power systems and grid management.

5.1. Outcome of the Review

Dense synchrophasor data provide crucial information on the power grid’s situational awareness. However, Due to practical constraints like communication and hardware malfunction, bad data can influence accuracy during power system analysis. A large amount of generated data is processed before any PSA, including data validation, filtering, aggregation, compression, storage, event detection, state estimation, model analysis, stability assessment, and contingency analysis.

Later, Complex algorithms and computations are often required to extract meaningful insights from the data, which invites processing time and resource allocation challenges. The choice of data compression algorithm defies the trade-off between compression efficiency vs. computational complexity. Computationally intensive algorithms, such as waveform analysis, event detection, and dynamic state estimation, demand substantial processing power to perform complex numerical analyses when considering the operation time.

Hardware limitations and memory constraints are essential in determining the choice of algorithmic models and selecting relevant features from large PMU datasets. The benefits of machine learning in synchrophasor-based power system applications were discussed and compared to other alternative methods developed in the last two decades. From Rule-based systems to machine learning, Utility has been able to interpret power system data better, and the evolution of AI-enabled energy systems. It is to get an insight into interoperability, standards and regulation, and scalability of synchrophasor technology.

5.2. Challenges

Synchrophasor measurement and other traditional data collected across vast geographical expanses are often wide and sparse, offering limited visibility. Effective sensor selectivity and intelligent data fusion are crucial to accommodate the data collected, which is frequently characterized by noise and gaps with various time and space-related patterns. Addressing challenges associated with Wide Area Measurement Systems (WAMS) data involves managing their sparse distribution, noise, incompleteness, and temporal and spatial dependencies. Estimating missing data is essential to prevent biased model estimates while simulating all possible contingencies in a natural power system is computationally challenging.

Incorporating synchrophasor data into machine learning models for stability studies requires overcoming several challenges. The quality of data, feature extraction, and model training demand extensive simulations, data preparation, parameter tuning, and model validation. The wide and sparse nature of synchrophasor data poses a significant challenge for AI applications.

Phasor Measurement Units (PMUs) generate vast amounts of irregular and discontinuous data from various locations across the power grid. Effective data interpolation and alignment techniques are crucial to ensure robust model performance. Managing this influx of data necessitates advanced storage, processing, and retrieval solutions, such as distributed databases and cloud storage, to handle the data load efficiently.

Hardware limitations and memory constraints can hinder the deployment of AI algorithms, requiring high-performance computing resources and optimized algorithms that can operate within these constraints. Additionally, integrating machine learning models into existing power system monitoring frameworks involves ensuring compatibility with current systems and protocols, as well as the adaptability of models to evolving data patterns and system configurations. Continuous monitoring and updating of models are required to maintain their relevance and effectiveness in dynamic operating environments.

6. Conclusion

In conclusion, this comprehensive review article delves into combining synchrophasor technology with machine learning for enhanced power system stability monitoring. The paper has adeptly captured the essence of this evolution, showcasing how the advent of Wide Area Monitoring Systems (WAMS) and machine learning techniques is revolutionizing power system stability analysis.

The challenges of managing, processing, and interpreting the vast data synchrophasors are thoroughly discussed. The paper emphasizes that, despite these challenges, the integration of machine learning models offers promising avenues for various power system analyses. These models can overcome limitations related to data quality, training complexity, and model selection.

The evolution from rule-based systems to machine learning has significantly enhanced utilities' capacity to interpret and utilize power system data more efficiently. Moreover, the paper also acknowledges the challenges that persist. These include the vast and sparse nature of synchrophasor measurements, the need for intelligent data fusion and sensor selectivity, and the necessity of handling data characterized by noise, gaps, and various patterns. The challenges extend to incorporating synchrophasor data into machine learning models for stability studies, including data quality issues, computational demands, and appropriate feature extraction and model training methods.

In summary, However, Deep learning models automate the process of model building by removing system experts. Deep learning, Various Transfer learning, Semi-supervised learning, Ensemble methods, and Active feature selection have been employed throughout the last two decades. The main motive of DL models is to make more efficient use of limited labeled data in power system analysis, enabling improved performance. Further, these results must be verified and warranted with escalated penetration of corrupted data to validate the accuracy of specific AI models used for various power grid applications. Convincing results will aid utilities in mandating these findings and successfully deploying the model in a production environment.

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