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RESEARCH ARTICLE

A Review of Machine Learning Approaches in Synchrophasor Technology

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ABSTRACT As power systems (PS) move toward smart grids and microgrids in modern times, complexity eventually rises as a result of integration with various distributed energy resources, demand-side management, and cybersecurity issues. Additionally, frequent PS network blackouts will have an impact on a country's social, economic, and financial position. To ensure the reliability as well as security of the network's smart-driven power system, more advanced monitoring and measurement technology, which is dominated by SCADA systems, is required. This is where synchrophasor-based phasor measurement units (PMUs) come into play, which process and analyze massive amounts of data in real-time more precisely to identify systemic anomalies. Due to their quick response times, high computing speeds, accuracy, and scalability, machine learning (ML)-based techniques are becoming more popular for handling real-time big data. The many ML algorithms used recently in synchrophasor technology, which enhances cybersecurity, fault detection and classification, transient stability assessment, voltage stability assessment, and forced oscillation localization are thoroughly reviewed in this paper. With the help of more than 190 pertinent papers, this work effectively discusses the ML applications in the synchrophasor technology where PMUs and μPMUs are deployed. The article also shows that several concerns have not yet been resolved and are still up for consideration by researchers in the future. One of them is the detection and observation of oscillation and line-tripping occurrences in the distribution area where μPMUs are installed. To address these problems, sophisticated DL approaches are recommended. Future possibilities to decrease bandwidth usage and improve processing delay using edge computing technology are also mentioned in this paper. The research potential for ML and DL approaches also extends to power line communication, wide area monitoring systems, and 5G and 6G network communications.

INDEX TERMS Blackouts, cybersecurity, PMUs, power system stability, synchrophasor, wide area monitoring system.

I. INTRODUCTION

Power systems (PS) are going through a period of major change on a global scale. Decentralized and renewable energy sources (RES) are becoming more and more popular these days [1]. The monitoring and automation of the PS network are redefined as a result of the shift in this generation's portfolio. Power grids are currently running in "load-driven mode" given the current situation. In an advanced system known as "generation-driven mode," where the generation leads and the rest of the system follows, several studies are now being conducted. It is difficult to manage the output power when it comes to distributed energy systems (DES) and smart grids (SG), so more advanced monitoring, as well as automation technologies, are required [2]. A quick review of the development of a few different automation process types is appropriate before discussing PS's advanced technologies. Power generation had become centralized and far from load centres by the middle of the 20th century. Fig. 1 depicts the evolution of monitoring and control mechanisms utilized in the PS network throughout time.

In the early 1880s, monitoring, and control were carried out through operator observation and judgement, and control commands were verbally transmitted [3]. Due to the relatively

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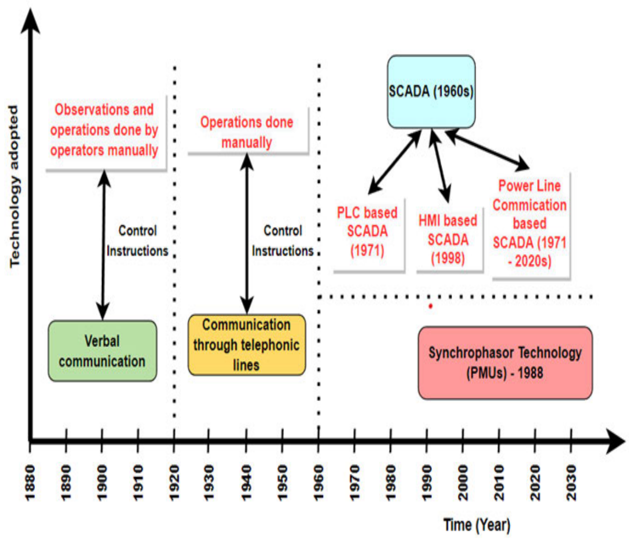

FIGURE 1. Evolution chart of monitoring and control mechanisms in a PS network.

low number of stations at the time, this verbal communication was later transformed into telephone lines, via which data interchange and communication occurred. By the middle of the 20th century, however, the scale and complexity of the PS had grown, and load centres were no longer placed close to the generating stations. As a result, a supervisory control and data acquisition system (SCADA) was developed in the 1960s for data collection, control, and real-time analysis [4]. Eventually, as the electricity demand increased and the distributed networks became more complex, enormous amounts of data were required to be measured at the load centres and simultaneously processed to obtain a true picture of the PS, enabling the operator to take the appropriate control actions. For this reason, Gould Modicon conceived and developed programmable logic controllers (PLCs) [5] in 1971, which increased the utilization of SCADA. The use of PLC in the PS grid was marketed by Allen Bradley in 1977. Since 1990, SCADA has been extensively used for power system control and monitoring. In 1998, PLC manufacturers successfully integrated human-machine interface (HMI) into SCADA systems by adding communication technologies and open protocols with the aid of advanced SCADA research. SCADA systems also incorporate power line connections for communication between stations and control centres.

With the help of power line communication and an HMI system, SCADA is capable of acquiring information such as voltage, current frequency, power flow, the status of circuit breakers as well as isolators etc. from the generating side and transmission side in cycles of every few seconds and send these data to the control centre for continuous monitoring and control. Later on, in many countries, the regional power grids synchronized together to form a national grid and this increased the complexity of the power systems. Moreover, the evolution and involvement of RES and the microgrid concept eventually increase the challenges in measurement as well as monitoring of data from the PS due to their unpredictable nature. As the PS become large and complex, a new technology named 'Synchrophasor technology' (ST) using phasor measurement units (PMUs) was introduced in the early 1980s [6]. PMU was first invented by Dr Arun G Phadke and Dr James S Thorp in 1988 at Virginia Tech. The research was started based on state estimators after the severe blackout of the North-Eastern power grid in North America happened in 1965. Blackouts could be due to several reasons and a detailed list of severe blackouts that occurred globally from 1965-2021 is listed in Table 1.

Along with the population of a country, these extensive blackouts affect its social, economic, and financial aspects. Whether these blackouts are purposeful or unintended, it is essential to have effective monitoring and protection, which includes cybersecurity measures. Due to its inability to perform real-time monitoring and control over such situations, SCADA is unable to solve these issues. Blackouts can be avoided by continuously checking the PS's characteristics, such as voltage and current amplitudes, phase angles, and frequency, to make sure they are within acceptable ranges. This puts the creation of ST using PMUs, a component of the wide area monitoring system (WAMS), into a sharper perspective.

The PS network's protective and measurement devices, such as PMUs and μPMUs, are crucial to achieving the idea of "One Nation, One Grid, One Frequency, One Price," which is a goal shared by all countries. Furthermore, even a minor blackout will result in a significant decline in a country's productivity strategy and cyber-security strategy. Therefore, machine learning-based solutions in synchrophasor technology are becoming more and more in demand to address these issues in contemporary power system assessments. This paper analyses the many blackouts that occurred in various locations and the demand for ML techniques utilized in ST to locate those anomalies in the PS network.

This work offers a critical analysis of several ST applications employing ML techniques in the areas including transient stability analysis (TSA), voltage stability analysis (VSA), fault identification and classification in PS networks, and ultimately the challenges relating to cyber-security. Later, both the limitations of the methodologies that are given and the scope of applications for ML in PMU-based distribution systems are discussed. Finally, the applications of ML algorithms in μPMUs are also well addressed in this paper.

The rest of the paper is structured as follows: The history and development of PMUs, the synchrophasor technology, and the IEEE standards applied to PMU technology are all covered in length in Section II. This section also includes a comparison of ST and SCADA. The stability and security of the power supply as well as the many synchrophasor applications that could be used in PS networks are covered in Section III. The machine learning concept and classifications are highlighted in session IV. The discussion and opinions in the session also serve as a critical examination of various ML applications in synchrophasor technology by

TABLE 1. Major blackouts happen worldwide from 1965-2021.

Major Blackouts (Year wise)	Location and Date	Reason and People affected (millions)	References
North-east blackout (1965)	Canada and USA - November 9, 1965	Failure in the setting of a protective relay on one of the transmission lines of generating station. (~ 30)	[7]
Southern-Brazil blackout (1999)	Brazil - March 11 - June 22, 1999	A lightning strike in the substation. (~ 75-97)	[8]
India blackout (2001)	India - January 2, 2001	Northern India's grid collapsed after a substation in Uttar Pradesh failed to owe inadequate transmission infrastructure. (~ 230)	[8]
Luzon blackout (2001)	Philippines - April 7, 2001	Tripping of the power plant. (~ 35)	[9]
Luzon blackout (2002)	Philippines - May 21, 2002	Flashover of the transmission cable. (~ 40)	[9]
Italy blackout (2003)	Italy, Switzerland - September 28, 2003	Sagging conductor causes transmission line flashover. (~ 56)	[7]
North-east blackout (2003)	Canada and USA - August 14-28, 2003	A software bug in the alarm system of the control room. (~ 55)	[7],[10]
Java-Bali blackout (2005)	Indonesia - August 18, 2005	Cascading transmission line failure caused substation shutdowns. (~ 100)	[8]
Brazil and Paraguay blackout (2009)	Brazil and Paraguay - November 10 -20, 2009	Meteorological events. (~ 60)	[8]
India blackouts (2012)	India – July30 - 31,2012	Weak inter-regional power transmission routes, excessive 400 kV link loading due to faulty protective devices, and poor LDC response. (~ 620)	[10]
Bangladesh blackout (2014)	Bangladesh - November 1, 2014	Substation overloading reduces the frequency to 45 Hertz, causing an electric surge and blackout. (~ 160)	[11]
Pakistan blackout (2015)	Pakistan - January 26, 2015	Due to the breakage of the power transmission line. (~ 140)	[12]
Turkey blackout (2015)	Turkey - March 31, 2015	Overload of power line due to maintenance. (~ 70)	[10], [12]
Sri Lankan blackouts	Sri Lanka - March 13, 2016	Transmission technical failure. (~ 21)	[12]
Java blackout (2019)	Indonesia - August 4-5, 2019	Disruptions in gas turbines of generating stations. (~ 120)	[12]
Argentina, Paraguay and Uruguay blackout (2019)	Argentina, Paraguay and Uruguay - June 16, 2019	Failure in the electrical interconnection system (~ 48)	[13]
Venezuelan blackouts	Venezuela - March 7-July 23, 2019	Mismanagement by using troops instead of electricians to operate substations. (~ 30)	[12]
Pakistan blackout (2021)	Pakistan - January 9, 2021	Cascading effect and shutdown of a power plant. (~ 210 -90% of the population)	[12]

using PMUs and μPMUs. Discussions along with the future research trends in PMUs, μPMUs and communication technologies which employ ML and DL methods are presented in Session V. Finally, conclusions are drawn in Section VI.

II. SYNCHROPHASOR TECHNOLOGY

A. HISTORY OF THE EVOLUTION OF PMU

The research on the symmetrical component distance relay (SCDR), a device that can protect overhead transmission lines by combining symmetrical components of voltages and currents to simplify six fault equations into a single equation, was initiated by Arun G. Phadke and his team at the beginning of the 1970s [14]. Since the positive sequence voltage and current of a PS network form the basis of the majority of power system analysis programmes, including stability, optimum power flow, contingency analysis, state estimation, short circuit studies, load flow studies, and many others, it appears that this invention of measuring symmetrical components of voltages and currents has a wide range of applications. Later, in the 1980s, a global positioning system (GPS) based on GSM-based satellites was established, and time signals from the GPS satellites can be used as inputs to sampling clocks [15]. This is given to the digital relay measurement system, which acts as a measurement tool, providing an instantaneous picture of the actual state of the PS network. With this technology, the PMU uses GPS signals to synchronize the sampling clock so that the phasors can be calculated from a single point of reference. So, in 1988, the Power System Research Laboratory at Virginia Tech made the first PMU [16]. Later in 1992, Macrodyne made the first PMU model that was sold to the public.

B. BASIC PRINCIPLE OF PHASORS

Charles Steinmetz introduced the concept of a phasor being the complex equivalent of a sinusoidal wave quantity [17], where the complex modulus corresponds to the cosine wave's amplitude and the complex angle to its phase angle. He asserts that the representation of a sinusoidal waveform is as follows:

$$X(t) = X_m \cos(\omega(t) + \emptyset) \tag{1}$$

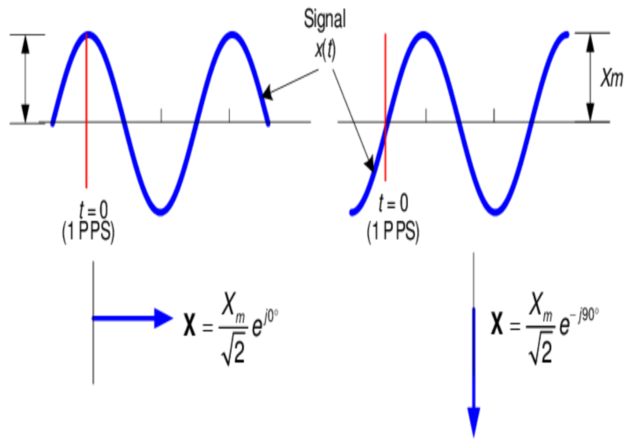

FIGURE 2. **Graphical representation of a conventional synchrophasor.**

Refer to "(1)" the phasor form can be rewritten as:

$$X = \frac{X_m}{\sqrt{2}} e^{j\emptyset} = \frac{X_m}{\sqrt{2}} (\cos \emptyset + j \sin \emptyset) = X_r + jX_i \qquad (2)$$

where $\frac{X_m}{\sqrt{2}}$ is the waveform's RMS magnitude and X_r and X_i are the complex number's corresponding real as well as imaginary components. With time, the phase angle Ø changes especially when t=0.

The IEEE standard C37.188.1-2011 begins with this concept, stating that the representation of the synchrophasor signal is mainly represented by X_t which is given in (1). This is synchronised with the help of coordinated universal time (UTC).

The "synchrophasor" term is defined in [17] as "the magnitude as well as the phase angle of the cosine signal of both voltages and currents which is related to the ultimate point of time". Fig, 2 depicts the traditional synchrophasor representation.

C. PHASOR MEASUREMENT UNITS (PMU)

A phasor measurement unit (PMU) is an instrument used in a power system network to measure the amplitude as well as phase angle of an electrical phasor quantity (voltage and current). It is also capable to measure the frequency as well as the rate of change of frequency (ROCOF) of a PS network effectively. PMUs can offer extremely precise timestamped data. A measurement known as a synchrophasor is obtained by fast sampling a waveform, reconstructing the phasor quantity, and then taking the final reading. A common time reference is required for phasor measurements across a connected grid, and this must be provided by the synchronizing source. The signal from the synchronizing source needs to be referenced to UTC. The signal needs to be accurate enough for the phasor measurement equipment to keep up with the local receiving error and the synchronizing source within 1 μs of UTC.

The block diagram of a PMU is shown in Fig. 3. At the substation, current transformers (CTs) and potential transformers (PTs) are used to measure current and voltage. The analogue inputs of the PMU are voltage and current measured from the

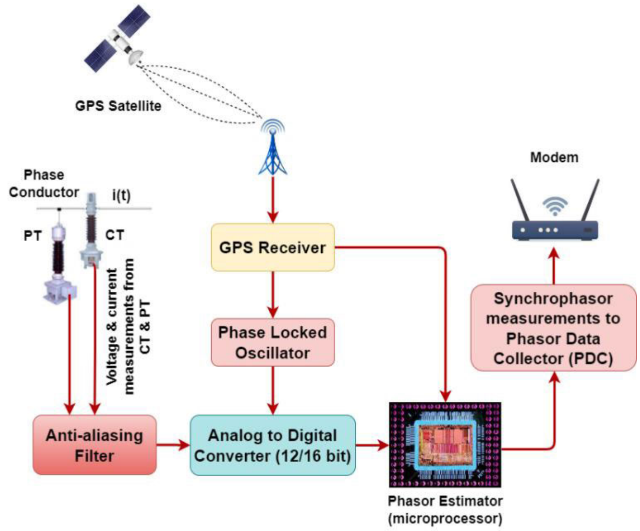

FIGURE 3. **Functional block diagram of PMU.**

secondary winding of the CTs and PTs. An anti-aliasing filter, also known as an analogue low pass filter, is used to filter out actual signal components whose frequencies are greater than or equal to half of the Nyquist Rate to obtain the sampled waveform. It is important to keep in mind that the Nyquist Rate is equal to the highest frequency component of the input analogue signal multiplied by two. If an anti-aliasing filer is not employed, phasor estimations will be incorrect.

The pulse signals from the GPS satellites are phase-locked with the sampling clock. For this, a phase-locked oscillator is used. A phase-locked oscillator and a GPS reference source provide the necessary high-speed synchronized sampling. An analogue-to-digital converter (ADC) is a component of the PMU that converts analogue signals into digital signals. To deliver synchronized time, the GPS relies on a high-accuracy clock that is dependent on satellites. Without GPS, it is difficult to simultaneously monitor the entire grid. The phase estimator, which is effectively a microprocessor, computes positive sequence estimates for each voltage and current value using DFT methods. Local estimates and monitoring of the frequency and ROCOF are both included in the PMU output. The phasor data concentrator (PDC) is the primary component of WAMS [18]. A PDC can be used as a stand-alone unit to gather data and distribute it to other programmes. PDC features can be incorporated into other systems, including monitoring and control systems. The key duties of PDCs are real-time data exchange as well as data processing, data storage and data visualization.

The PDCs' synchrophasor readings are received via modems. Table 2 displays the various international IEEE standards utilized for the PMU and the test for conformity [19].

D. COMPARISON OF PMU WITH SCADA

Before the development of synchrophasors, the PS was monitored using SCADA, but SCADA measurements have

TABLE 2. IEEE international standards for PMU test and compliance.

IEEE Standards	Contribution	Key Features
1344-1995	First synchrophasor standard	Focus on the messaging format for each report and form the time stampings of reports.
37.118-2005	Replaced IEEE 1344	The requirements for the performance measurement as well as communication are added which is adaptable to the PS network.
C37.118.1-2011	Synchrophasor data transfer	The messages, data as well as contents and formats are added along with their usages.
C37.118.2-2011	Guide for synchronisation	Proper guidance is provided for the calibration and testing as well as installation and synchronization of the PMUs are added.
C37.244-2013	PDC guide	Proper guidance and terminology for the PDCs' operation were added.
C37.247-2013	PDC standard	PDC standards are enhanced by adopting concepts from C37.244

TABLE 3. Comparison of SCADA and PMU.

Attribute	SCADA	PMU
Measurement	Analogue	Digital
Resolution	1 sample in every 2 - 4 sec.	10 – 60 samples per sec.
Observability	Steady-state	Dynamic / Transient
Measured quantities	Magnitude only	Magnitude & Phase angle
Monitoring	Local	Wide – Area
Time Synchronization	No	Yes
Total Input / Output Channels	100+ Analog & Digital	~10 phasors 16+ Analog 16+ Digital

historically been focused on steady-state power flow analysis and were unable to examine the dynamic properties of the PS. Table 3 displays the key variations between SCADA and PMUs.

III. POWER SYSTEM STABILITY AND SECURITY

Due to the development of RES and electric vehicles, the power system network and its operations have advanced and become more complex. A difficult problem is managing the RES-based PS network's complexity and security concerns [20]. The PS network's stability and security were greatly improved when WAMS-based synchrophasor technology replaced SCADA. State estimation (SE), SCADA systems and PMUs are examples of modern PS applications that rely too much upon the technology of communication such as the internet which in results the network being open to many dangers [21]. Governments and utility stakeholders typically give the safe and stable operation of the country's power system the ultimate relevance because of the strong linkages between the power system and the numerous social, political, and economic activities. The failure of the PS network of a county due to blackouts not only will lead the nation to financial losses but also will put national security at risk. Several pieces of literature are carried out in [22], [23], and [24] to address these issues of false data injections and suggestions are also proposed to modify the security measures to prevent such events.

The primary task for energy stakeholders nowadays is to maintain the PS network stably and securely after being subjected to a fault in the network. The event classification as well as the location finding is also a real challenge in modern PS networks, especially in transmission as well as distribution sectors are taken into account. The globally scattered electricity system is currently suffering from a multitude of security and stability challenges, demanding considerable protective and preventive measures, as recent events around the world have shown in [25], and [26]. It has historically been challenging to ensure the security and dependability of the energy supply. It was challenging for the operators to adequately monitor the network in the previous power system. Users often anticipate reporting issues and excursions to operators. The modern electricity system is today facing increasing security and stability difficulties on a global scale, despite the numerous improvements that have come to define it in recent years, according to several shreds of evidence and publications. Moreover, the protocols and standards adopted for present PS protection are so vulnerable to hacking and chances are high for the hackers to intrude on the networks will lead to grid collapse. As a solution for this, numerous internet of things (IoT) technologies and modern measuring, as well as protective devices, are installed in the PS network to enhance the stability as well as security of the system [27]. A rise in unhealthy energy demand is also being fueled by the continuous industrialization drive and the development of smart cities. A few unpleasant nonlinear loads were also added to the energy system as a result of industrialization. The rise in energy demand causes generating and transmission infrastructure to approach and pass operational stability restrictions, which leads to the failure of equipment, power quality disturbances (PQDs) [28], inaccurate transient stability analysis (TSA) [29] and imprecise voltage stability analysis (VSA) [30]. Due to the time-synchronized phasor measurements that PMU devices provide, modern power systems have significantly improved the efficiency of measurement documentation. This has paved the way for the implementation of more effective as well as accurate dynamic security analysis (DSA). Moreover, it helps to speed up decision-making as well as control actions more effectively [31]. A comprehensive review is carried out in [32] which covers the PS security as well as stability using ML approaches. The classifier design, dataset creation, preprocessing approaches, optimization strategies, as well as the test systems implemented, were all thoroughly reviewed by the authors in connection to PS security and PS stability issues.

The non-linear behaviour and the complex features of the present, as well as future PS operations along with other factors like dealing with a vast amount of data from the PMU devices, the anomalies due to error in measurements,

TABLE 4. Synchrophasor applications and constraints.

Applications	Contribution/Constraints	References
Monitoring and stability of the voltage	• PMU data generates VSI numerical instability indicators. PMU data predicts short- and long-term voltage stability.	[36]
	• Nonlinear optimal power flow, D' matrix, and Monte Carlo simulation can monitor voltage stability probabilistically.	[37]
	• Thevenin-based VSI.	[38]
	• A GA and decision tree-based voltage stability technique uses PMUs to identify a pre-determined rate.	[39], [40]
Oscillation monitoring and detection	• PMU data is denoised via wavelet shrinkage. In denoised data, Hilbert's approach identifies nonlinear trends. Anti-aliasing frequencies are eliminated by its low-pass filter-based PMU.	[41]
	• Stationary and non-stationary data highlight probability-based analysis and Hilbert method constraints. Both methods can identify signals but not modes with slight frequency and damping ratio fluctuations.	[42]
	• Robust LSE-ARMAX models find electromechanical modes. Robust objectives reduce outliers and data loss.	[43]
	• PMU oscillations are monitored using rotational invariance techniques with total LSE of signal parameters. Synchrophasor data noises make mode identification difficult.	[44]
State estimation	• The tracking of three-phase SE uses a LAV estimation approach against intentional or random poor data. PMUs help LAVs compete with WLSE and eliminate leverage measures smartly.	[45]
	• PMU data is used to create a large-scale phasor-only state estimator, and detrended fluctuation analysis is used to identify transients and suggest the need to reperform SE if transients and poor data are found.	[46]
Fault location identification and protective relaying	• This study suggests two supervisory safeguards. Supervisory layers verify relay functioning and notify operators of PMU-identified incidents. PMUs detect signal interruptions. Modules delete poor PMU data and determine the optimal data stream.	[47], [48]
	• An adaptive-based PMU protection solution is suggested for transposed and un-transposed parallel transmission lines. Distributed line modelling and PMU measurements at both ends are used in this strategy.	[49]
	• Adaptive wide-area backup protection in transmission lines uses PMU measurements and network topologies. Identifying the trouble source helps resolve difficulties with defective lines without iteration.	[50], [51], [52]

potential cyber-attacks to PMU-based transmission systems and so on, have revealed the shortcomings of traditional ways of stability and security measures in a PS network. Energy companies in the market, therefore, realized the significance of proactive, timely, dependable as well as cutting-edge stability and security solutions for modern PS to address blackouts and other threats. Over the past three decades, investigations of power systems have demonstrated the incredible effectiveness of machine learning (ML) algorithms. ML techniques have been widely suggested in studies of the power system that involve tracking and categorizing various hazards to the power system and thereby enhance the overall stability of the network as discussed in [33], [34], and [35].

A. SYNCHROPHASOR APPLICATIONS IN POWER SYSTEM NETWORK

Synchrophasor technology has a wide range of applications in the transmission area of the power system network. The major applications are voltage stability and monitoring, oscillation monitoring and detection, state estimation and fault location identification and protective relaying. Table 4 contains a listing of the primary applications of synchrophasors in power systems, as well as the constraints and contributions imposed by their use. According to the findings of this study, PMUs are not only significant but also indispensable to the stability and safety of power systems.

IV. MACHINE LEARNING CONCEPTS AND CLASSIFICATIONS

Through the use of data analytics, machine learning (ML) aims to teach computers to perform tasks that people and animals do without any assistance. Instead of relying on predetermined equations, ML algorithms use computer techniques to "learn" information directly from data. They may also become more adaptable as more data becomes available. In practice, ML uses a variety of algorithms under a set of rules to analyze data and produce conclusions and/or predictions [53]. Several algorithms are designed and programmed for ML to carry out a variety of tasks like classification, clustering as well as regression. Data mining [54], communication area [55], medical imaging [56], real-time tracking of objects [57], geoscience [58], multimedia applications [59], remote sensing classifications [60], computer vision-based fault location [61], and many more fields have all shown promise for ML as well as deep learning (DL) in particular, over the past ten years. One of the most important steps in the process of developing a smart grid is the integration of modern information and communication technologies, most notably the internet of things (IoT), into the infrastructure of the electrical grid. A large quantity of data is made accessible at the control centres because it is necessary for IoT devices to be able to communicate with and transmit data to other devices on a larger scale. It is necessary to make use of tools and solutions that are based on ML in order to process and analyze data in an efficient manner, as well as to provide support for operational management and decision-making for the system. This is because of the significantly increased system condition awareness and data availability.

The evolution of smart grids as well as microgrids, which are advanced cyber-physical systems, includes distributed energy resources and complicated networks which underlie complex information and communication infrastructures. The real-time monitoring of the PS operation and efficient big data analysis made possible by the ST and WAMS eventually improve the system enhancement as well as management in many areas such as identification of bad data injection using PMUs [62], assurance of the safety of operations [63], detection of anomalies in the system [64], diagnosis of faults [65], effective management of power generation as well as load demands [66], and many more.

Traditional computational, as well as monitoring techniques, are not capable to handle the huge amount of data from the modern PS network, especially from the microgrid, smart grid and DES. As a solution for this ML technologies are adopted and have attracted a lot of attention in recent years. Numerous studies are reported in the field of ML-based technologies in PS monitoring, protection and stability assessments which are commonly observed in PS generation, transmission and distribution addressed in [67], [68], and [69]. As illustrated in Fig. 4, the ML methodologies can be loosely divided into four main groupings, each of which is characterized as follows. Since ML approaches employ the available data to perform a variety of tasks, they are data-driven.

i. A subset of ML named supervised learning [70] mainly aims to learn the mapping of input to output from a set of labelled input or output pairs and a huge amount of training data.
ii. Unsupervised learning is a type of ML classification where the input without classifications or labels is used for the training of an algorithm and to categorise the data based on similarity or difference [71]. When compared with supervised learning algorithms, unsupervised learning algorithms are used to handle complex processing tasks. One of the common unsupervised learning is cluster analysis which is commonly used to perform the exploratory analysis of data to identify the hidden patterns or the grouping in data.
iii. The third classification is reinforcement learning (RL) which involves an agent interacting process with its surroundings and its behaviour is changed according to the response of the external stimuli [72]. The main difference between RL and supervised learning is that it rewards or punishes the agent according to how it behaves in the environment rather than the required tagged input or output pairs. Thus, RL allows the agent to independently choose the behaviours which is the potential advantage of RL when compared with other methods. Thus RL operates identically to humans and animals as feasible [73].
iv. If a single ML algorithm outperforms, the fourth type of classification named the ensemble approach comes into the picture which employs numerous ML algorithms. In the ensemble method, a group of hypotheses is created by numerous base learners and then it is merged to provide a solution to a single problem with the aid of ensemble learning. This method provides better generalizability when compared with individual ML algorithms [74].

A. APPLICATIONS OF MACHINE LEARNING IN SYNCHROPHASOR TECHNOLOGY

There is a wide range of applications of ML in synchrophasor technology (ST) which is shown in Fig. 5.

This section discusses a few applications of the ML techniques and trends used in ST based on the literature review available in the modern PS network.

1. Transient stability analysis (TSA)
2. Voltage stability analysis (VSA)
3. Cybersecurity applications
4. PS fault identification and classification
5. Forced oscillation localization

1) MACHINE LEARNING IN SYNCHROPHASOR FOR TRANSIENT STABILITY ANALYSIS

As indicated in Table 1, some blackouts that have occurred globally over time can affect power systems. The PS's stability, which is mostly evaluated by the transient stability analysis (TSA), will be impacted by these blackouts. From [75], transient stability can be defined as the ability of the generators to maintain synchronization, when a significant disruption occurs in the PS network. The common disruptions are failure as well as the unexpected loss of the generator or load. In short, any faulty components in a PS network will lead to transient instability. For example, the blackouts happening in the PS will lead to temporary instability as addressed in [76]. So the system operators must be capable to evaluate the stability state of the PS and to take necessary corrective actions by monitoring the transient stability limits and thereby identifying the anomalies and avoiding power blackouts. Traditional TSA technologies like extended equal-area criterion (EEAC) [77], and transient energy function methodologies [78] are simply outdated. Time domain

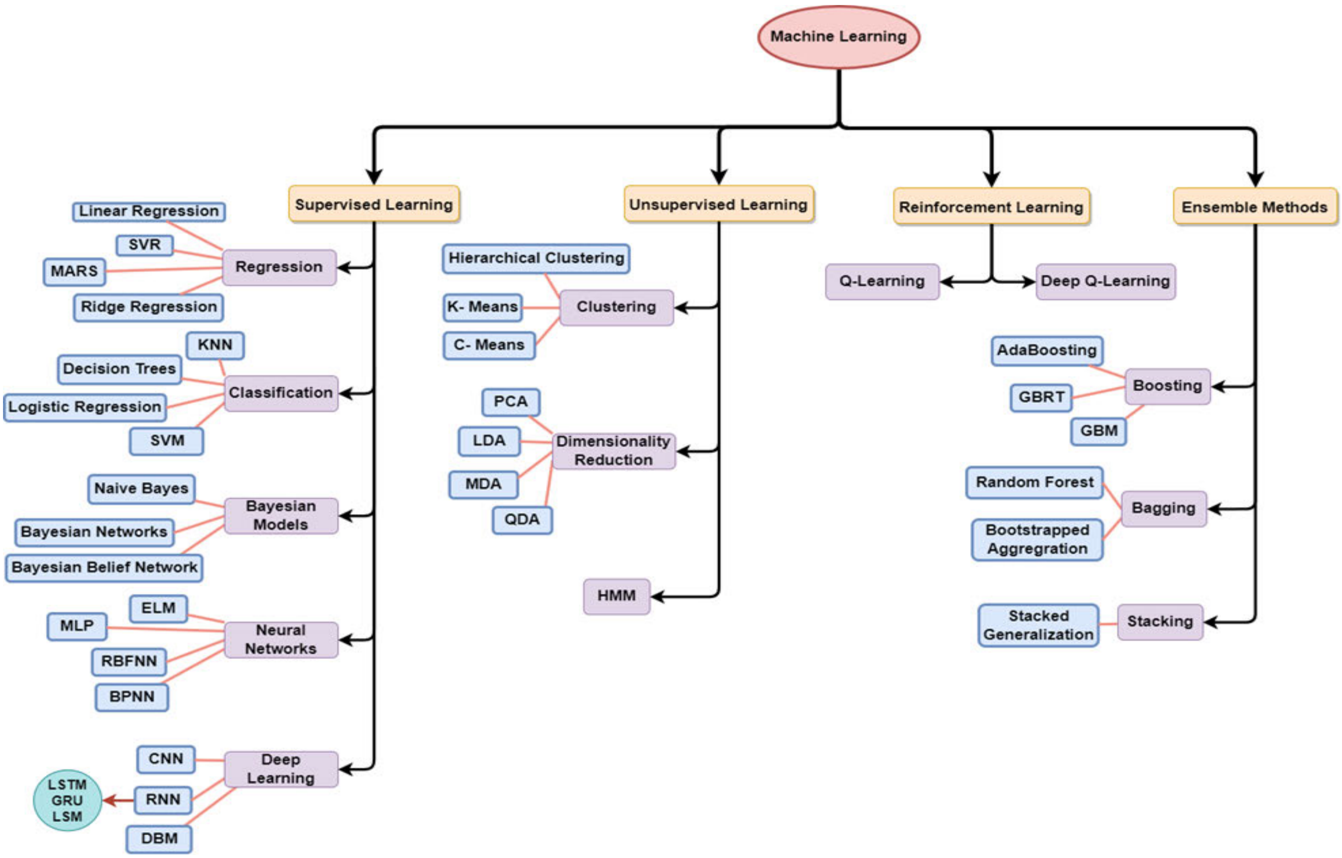

FIGURE 4. Classification of various machine learning techniques.

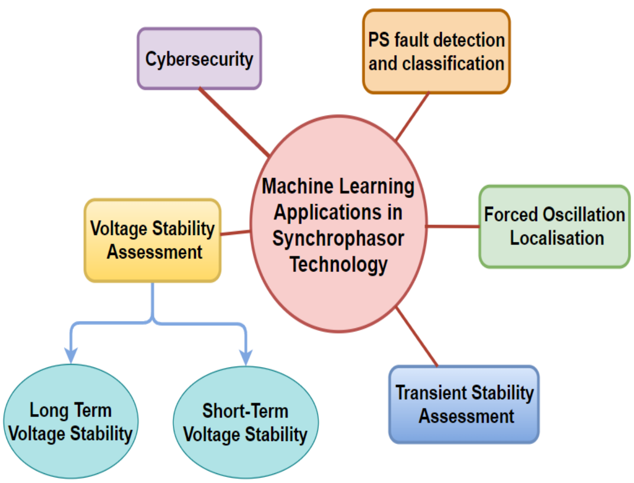

FIGURE 5. Machine learning applications in synchrophasor technology.

simulation (TDS) methodology [79] as well as the Lyapunov exponents' method [80] used for the optimal placement of PMUs also have potential disadvantages. The swing curves for each generation at varying load levels, fault densities, and clearing periods must be calculated with a lot of computation, which is generally seen as the fundamental disadvantage of these systems. The requirements of the contemporary power system cannot be met by the traditional TSA approaches. Additionally, SCADA systems are better adapted to these conventional TSA methods. Due to the evolution of PMU devices to modern PS, a significant amount of time-synchronized phasor measurement data must be processed and stored for the TSA research. Therefore, while managing such massive data analysis, these old methodologies display uncertainty, which causes measurement errors, computation complexity, increased non-linearity, and cyber-security concerns [81], [82]. In order to get beyond these limitations and subsequently create well-calibrated, rapid, and stable solutions that would ultimately boost the security of the current PS network, machine learning-based techniques have been widely endorsed. The sessions that follow describe the various ML techniques used by TSA.

As was discussed in the session above, traditional TSA techniques are unable to handle the massive volumes of data present in a modern PS network, especially when PMUs, WAMS, DERs, microgrids, and smart grids are taken into account. The complexity and risk of the system are also increased by the use of time-synchronized data by PMUs. Therefore, research is focusing on cutting-edge machine learning (ML), deep learning (DL) and artificial intelligence (AI) techniques for TSA. The main advantages of these techniques include the capacity to manage huge amounts of data, quick detection and classification of anomalies, and quick response to unstable and fault conditions [83] and [84]. The creation of the input vector sets, as described in [83], is the first stage in the TSA process. Time-synchronized data are used by PMU-based WAMS systems during pre-fault and post-fault conditions, and these data samples are used as the data samples for TSA investigations as explained in literary works from [84] and [85]. TDS is used in the majority of ML techniques to generate and retrieve sample data [84]. After the samples are extracted, the data must be pre-processed and optimised to eliminate redundant information and enhance the categorization and prediction of transient instabilities [86]. The selection and optimization strategies, the kind of dataset used, and the classification algorithms are explained in literature papers from [84], [85], [86], and [87]. From [88], it is clear that the features of the dataset of post-fault of PMU are reduced to one-third for TSA investigations by utilising a selection approach known as the binary java feature. A better ant-miner technique called extreme learning machines (ELM) is proposed in [89] to extract the feature selection and for pre-processing for TSA research. It is based on kernelized fuzzy rough sets (KFRS). An improved ML method is put out in [85] to predict transient stability using particle swarm optimization (PSO), and it may have the advantage of being more effective at searching than existing optimization techniques for TSA investigations. According to [90] and [91], offline training and online applications make up the majority of the classification and prediction utilising ML approaches in TSA studies. In TSA, the testing is performed online mode while the training model is performed in offline mode. The model classification is carried out as weighted voting of different decision trees (DTs) with the aid of an adaptive ensemble decision tree (EDT) training proposed in [91].

A method based on artificial neural networks (ANNs) that can identify faults as well as classify TSAs is discussed well in [92]. For the TSA classification, an improved support vector machines (SVM) approach is suggested in [90]. Using the Bayesian approach [86], the DT [87], and the k-nearest neighbours (KNN) [93], provide categorization and prediction of TSA data, respectively. According to research, the ensemble of SVMs with the New England 68 bus [90] exhibits 100% accuracy, with minimum-maximum normalisation being used as an optimization strategy. The extreme learning machines (ELM) algorithm, which is based on ANN, is suggested in [89] and is tested in the New England 39-bus system, with a 95.2% accuracy rate. A CNN built on a deep neural network called transudative support vector machine neural network (TSVMNN) was developed in [94] and tested using an IEEE 24-bus system to achieve an accuracy level of 86.27%. According to [86], the PMU data from the New England 39 bus should be processed using the Bayesian multiple kernel learning technique, with an accuracy level of 98.19%. Finally, using the DT algorithm and the PMU data set with post-fault conditions from [88], the New England 39 bus system is classified with an accuracy of 95.1%.

TABLE 5. ML classifications and methodologies in PMUs for TSA studies.

Event	Type of Machine Learning Classification	Proposed Methodology	References
Transient Stability Assessment (TSA)	Supervised Learning	Decision Trees	[87], [88], [91]
		Bayesian multiple kernel learning	[86]
		SVM	[90]
		KNN	[93]
	Deep Learning	ELM - ANN	[89], [92]
		CNN - TSVMNN	[94]
	Reinforcement Learning	-	[95], [97] [98], [99], [100], [101], [102]
	Deep Reinforcement Learning	-	[96], [97] [103], [104]
	Multi-agent Deep Reinforcement Learning	-	[97]
	Vision Transformer Model (ViT)	-	[105]

These results clearly show that TSA studies in a PS network are better suited for ML algorithms with SVM, Bayesian, and DT.

More research is being done in the field of PS networks with the aid of reinforcement learning (RL) [95] as well as deep reinforcement learning (DRL) [96] from recent literature. Reference [97] provides a detailed review of the optimization and control of modern power and energy systems using RL, DRL, and multi-agent DRL (MADRL) based algorithms. It also discusses the various applications of PS networks in the energy market, such as optimization of distribution-based networks and a microgrid, demand response, energy management, and operational control. Finally, the potential applications of MADRL are discussed, including independent as well as centralised learning, and decentralised execution. These works can be extended in the research of TSA studies since RL is a branch of machine learning that studies how intelligent entities should act in a setting to maximize benefits over time, especially in the WAMS technology where synchrophasors are deployed (PMUs and μPMUs). Resistive brake controllers (RBC) [98] and power system stabilisers (PSS) [99] are two examples of PS stability and security-based devices that may be developed and modelled with the help of RL algorithms. Learning and execution are the two key components of RL studies in PS. The implementation of RL will take place during the learning stage, and the knowledge gathered during the learning stage will be used to inform decision-making during the execution stage. As mentioned in [100] and [101], RL algorithms are also employed in the analysis of the power system for automatic generation control (AGC) and the economic dispatch problem (EDP). The work carried out in [102] mentions how the RL algorithm can successfully control the real-time as well as wide-area PS stability margin. Due to scaling issues, RL algorithms frequently encounter difficulties in large-scale PS, especially when the smart grid and microgrid are involved. To get around this, RL and DL are combined to create DRL-based algorithms, which are capable of handling large-scale input and control schemes [103]. The literature on WAMS uses RL, DRL and DNN-based algorithms to improve transient stability which is shown in the works [96] and [104].

The Vision Transformer (ViT) model, a CNN substitute that may be applied to image recognition applications, is introduced in [105]. When PMUs are installed in the generating and transmission sides of the PS network, continuous TSA monitoring is carried out using this paradigm. With this approach, relay failure situations in the PS network are identified and applications such as system instability alarms during relay failures in RES are discussed. Under different SNR levels (40 dB, 20 dB, and 10 dB), the suggested ViT technique provides superior accuracy for TSA at 97.89%, 97.42%, and 96.78%, respectively. It also outperforms standard ML and DL algorithms in TSA investigations with 98.92% accuracy. Table 5 shows the types of ML classifications and methodologies adopted in PMUs for TSA studies.

2) MACHINE LEARNING IN SYNCHROPHASORS FOR VOLTAGE STABILITY ANALYSIS

Voltage instability is caused by an inadequate reactive power supply from transmission lines and generator lines, which has led to several significant system failures around the globe. The capacity of the PS to sustain the bus voltages at their acceptable values following a disruption or fault from normal operating conditions is referred to as the voltage stability analysis (VSA). Modern power systems that use PMU measurements are sensitive to these voltage instabilities and place a strong emphasis on reactive power management and load dynamics [106]. Voltage instability is mostly caused by power blackouts [7], the hasty removal of generators, transformers, transmission lines, and low supply voltage [12]. Short-term voltage stability (STVS) and long-term voltage stability (LTVS) are the two basic categories of voltage stability. The components which are fast-acting for STVS are dynamic in nature. Loads controlled electronically, induction motor loads, as well as the converters for HVDC, are the common components which are dynamic. Normally the duration of STVS is measured in seconds. Meanwhile, LTVS lasts for many minutes (0.5–30 minutes) and is brought on by transformer tap changes, thermostatically controlled loads, and generator current limiters(s). Fig. 6 displays the time-response characteristics of voltage stability.

Since voltage instability can cause a country's grid to fail, proper VSA is one of the most talked about topics in the world of modern power system research. VSA is mostly about keeping an eye on and controlling the power system and its important safety devices, such as PMUs, isolators, CBs, and generator and load dynamics. In VSA studies, the way reactive power is used is also very important [107]. More [108] and [109] talk about the typical VSA methods used in PS networks and PMUs. In [108], the modal analysis method and the continuation power flow method are used. In [109],

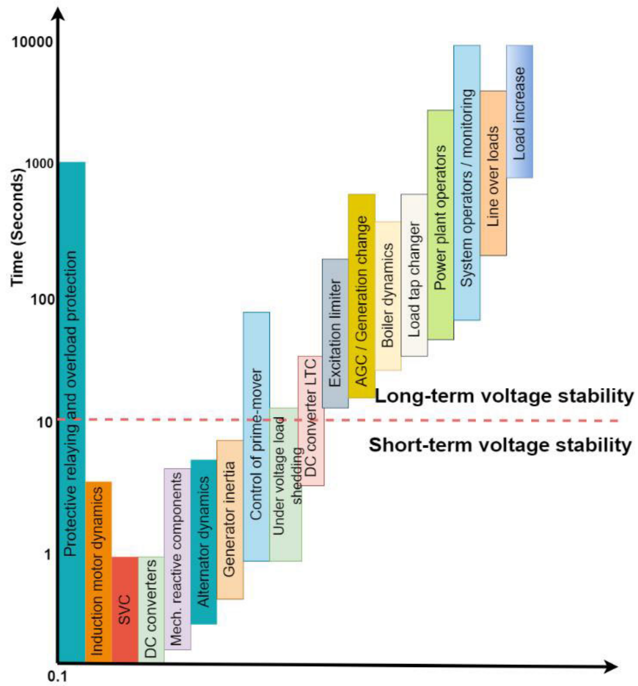

FIGURE 6. **Time-response characteristics of VSA.**

ANN is suggested as a way to monitor the voltage stability margin online. Traditional VSA methods for calculating P-V and Q-V curves at specific load buses with a large number of load flows have been shown to have several flaws [110].

The complex mathematical modelling that went into making the software tools for real-time VSA for modern PS networks takes a lot of time. This can be fixed by using both old ML techniques like fuzzy logic (FL) and ANNs and new ML techniques like adaptive neuro-fuzzy logic interference systems (ANFIS), DTs, and SVMs. This paper talks about real-time PS VSA because PMUs are mostly used to process online data in transmission and distribution networks. AI and ML have been using FL for a long time. FL is an extension of traditional Boolean logic that can handle partial truth or truth values that are not "completely true" or "completely false." FL was first shown to the public by Zadeh in 1985 () [111]. FL is often used for VSA studies. The authors of [112] came up with a good fuzzy-based method for estimating online bus voltages during a power outage and expected changes in load. A fuzzy-based model is utilized in this work for each load bus for the possible scenarios and the voltage at each load bus was predicted separately. Lie et al. [113] have suggested that PMUs be used to extract criteria for voltage security and monitoring. In the suggested method, a two-layer fuzzy-based hyper-rectangular CNN is built using an IEEE 20-bus system that works in different operational situations. The results of the simulation clearly show how to estimate the voltage security margin, which opens up new ways to protect and manage the electric grid. In [114], a unique voltage stability index (VSI) based on FL was made. This index can find important buses in both normal and emergencies based on the FL power flow algorithm which is an alternative to traditional FL and enhances the continuation technique. The way that was suggested is a good way to find key buses in both normal and emergencies.

In 1987 [115], a group of researchers use ANNs to make an advanced model for VSA studies. In the literature, many different ANN architectures and neural network combinations were talked about as ways to measure online voltage stability. In [116] and [117] the multi-layered perceptron (MLP) based neural network is first introduced as a way to figure out the VSM using the energy method. Joya et al. [118] built a single feed-forward back-propagation model using sequential learning to predict the line VSI for different load scenarios. Reference [119] shows how to use regression to choose which features to use when training individual ANNs to measure voltage stability while taking into account many different factors. Chen et al. [120] came up with a new way to figure out how dangerous low voltage is in a PS network by putting together a group of neural networks. In this study, the neural network ensemble (NNE) system is made by first making a model that predicts system instability and a model that shows how low voltage affects the system. After that, the right risk index is made. In [121], the ELM method was proposed for use in online voltage stability assessments for several different situations. For reliable contingencies, a single ELM model has been made so that the VSA under different loading scenarios can be predicted quickly and accurately.

Because of the potential benefits of ANNs' ability to learn from processes and the fuzzy interpretation provided by FL systems, the ANFIS model is frequently employed in VSA studies. ANFIS model is widely used as a powerful tool for almost all PS applications like power system stability [122], power quality [123], faults in transmission lines [124] and frequency control [125]. The power system VSI can be predicted with the aid of a novel architecture which relies on neuro-fuzzy with the help of voltage, active power as well as reactive power measurements with dimensional surfaces is proposed well in [126]. The proposed strategy proved to be quite successful, with the system making accurate voltage collapse predictions in a variety of scenarios. To assess the actual security margins of the power system, a fuzzy inference algorithm is created and optimised using two alternative methods via NN and GA [127]. The outcomes of the work give evidence that the proposed method is efficient for the accurate calculation of the voltage stability margin (VSM) with a high degree of dependability, precision as well as robustness. Amroune et.al. [128] suggested using an ANFIS model to predict the VSM from the data acquired from PMUs on the transmission side.

DT which is a tree-like supervised ML-based model is used widely in PS for the VSA for classification as well as security assessment. Recently, DT-based research has been applied in online VSA incorporating with PMUs and WAMS were explained in [129] and [130]. Beiraghi et Ranjbar [129], using wide-area measurements and a DT algorithm, came up with a new way to check the security of voltages in real-time. With the help of WAMS technology, the proposed method used an adaptive boosting technique which creates a combined model that helps to forecast the voltage security of a PS network. Based on a novel approach to grouping scenarios, Krishnan et McCalley [131] suggested a process for determining DT for PS security assessments of multiple contingencies. The classification of the contingencies is based on a graphical metric, which is a progressive entropy which determines the intersection of the class border progression by comparing it with a set of contingency training datasets. The suggested approach was shown using the French power system in the Brittany region to construct decision rules for five important contingencies against voltage stability issues. The accuracy of DT's identification was improved by [130]using the voltage amplitude and phase difference produced by PMUs. A novel strategy which utilizes the fuzzy-based DTs was put forward in [132] to evaluate the VSI of the PS network. The main goal of the work is to analyse power system data and identify potential areas where voltage collapse may occur. For the forecasting of real-time voltage stability, DTs integrated with other algorithms like FL as well as principal component analysis (PCA). Such a combined approach for online voltage security evaluation that is proposed in [133] reduces the dimension of the credential data from PMUs using PCA. Reference [134] combines the DT-based PCA method with the invasive weed optimization algorithm and the bio geography-based optimization algorithm to figure out how stable the voltage is in PS. In the suggested method, which starts by using PCA to reduce the size of the training data, and further two optimization techniques are implemented to find the best dimensions for the PMU data and thereby reduce the prediction erros of the security assessment.

SVM is a classification-based supervised learning technique used widely in modern PS for classification and regression. In recent times, SVM has become an effective computational method in PS networks due to its wide range of applications to handle big data analysis. Carmona et al. [135] used an SVM-based Bayesian rule to figure out whether a power system was safe, on alert, or in an emergency. This method has been used in a way that is similar to how the multi-class SVM proposed in [136] is used to evaluate security. In the proposed method, four different system security states are taken into account: normal, alert, emergency 1, and emergency 2. Sajan et al. [137] came up with a hybrid model for monitoring voltage stability that combines GA with support vector regression (SVR). There is an opinion that the recommended GA-SVR concept works better than the MLP NN [138]. But GA doesn't work perfectly because it involves a series of steps, such as coding, classification, selection, and mutation, which might slow down or change the performance of the optimization algorithms. Also, the size of population and cross over rate also increases the computation period. In [128] as well as [139] the best parameters of

TABLE 6. ML classifications and methodologies in PMUs for VSA studies.

Application	Type of Machine Learning Classification	Proposed Methodology	References
Voltage Stability Assessment (VSA)	Traditional Boolean logic	FL	[111], [112], [113], [114]
		ANFIS	[127], [128]
	Supervised Learning (Neural Networks)	ANN	[109], [119]
		MLP-NN	[116], [117]
		ELM	[121]
		DT	[129], [130], [131], [132]
	Supervised Learning (Deep Learning Neural Network)	NNE	[120]
	Supervised Learning (Classification)	SVM	[135], [136]
		GA-SVR	[137], [138], [139], [140]

TABLE 7. Cyber threat classification and ML classification.

Threat	Type of Machine Learning Classification	Proposed Methodology	References
False Data Injection Attacks (FDIA)	Supervised Learning	Bayesian model	[141]
	Deep Learning	CNN	[64]
	Neural Networks	ANN	[142]
	Neural Networks	ELM	[143]
	Classification	Margin Setting Algorithm	[144]
Anomaly detection	Deep Learning	Wavelet packet decomposition-based techniques	[145]
	Classification	SVM	[146]
	Deep Learning	LSTM	[147]
Other potential threats	Ensemble Method	Multi-Grained Cascade Forest Algorithm	[148]
	Neural Networks	Deep Auto Encoder	[149]
	Neural Networks	ELM and Deep Auto Encoder	[150]

the SVR model were found with the help of two algorithms namely ant-ion optimization (ALO) and dragonfly algorithm (DA). These algorithms are developed from inspiration by nature. The results of two models namely ALO-SVR and DA-SVR are used for the forecasting of voltage reliability. Later on, Yang et al. [140] put forward a novel method to estimate the voltage stability from PMU measurements by using least-square based SVM model with real-time data. The proposed system is tested in new england 39 bus system to ensure the efficacy of the method. Table 6 shows the ML classifications and methodologies in PMUs for VSA studies.

3) MACHINE LEARNING IN SYNCHROPHASOR-BASED CYBERSECURITY APPLICATIONS

WAMS-based PMUs are used to store and analyse vast amounts of data in the power system network, which is a complicated infrastructure. But fake data injection attacks (FDIA) could lead to the corruption of these PMU measurements. This can also be categorised as intentional fake data attacks (IFDA), where the attack is the result of cyberattacks that may eventually cause the power system to fail and cause blackouts. Unintentional false data corruption (UFDC), the second classification, can also happen as a result of processing, storing, or retrieval problems in data.

Many prospective researchers have looked into these IFDA and UFDC and have suggested ML-based solutions to deal with these problems. When there is a high likelihood that the data is corrupted, a Bayesian-based approximation filter is proposed in [141] supervised ML to detect the FDA. To identify PMU measurement abnormalities, the authors of [145] presented wavelet packet decomposition-based approaches. Reference [62] discusses the smart grid, PMU data assault detection, and the advantages of ML algorithms over state vector estimate methods. The FDIA in which SVM [146] is suggested features a discussion on classification-based supervised learning. Additionally, approaches leveraging ML techniques such as CNN [64], ANN [142], ELM [143], and margin setting algorithm [144] were proposed for FDIA identification and mitigation procedures in the PS network. Studies based on anomaly detection have been proposed in [147] employing RNNs based on DL in which LSTM techniques are employed to identify customer behaviour in a PS network. The literature has addressed a variety of cyber security assaults on power systems, including synchrophasor-based spoofing attacks [148], PMU data manipulation attacks [149], and denial of service (DoS) attacks [150]. The entire breakdown of ML-based cyberattacks and the classifications suggested in this paper is provided in Table 7.

4) MACHINE LEARNING-BASED FAULT DETECTION AND CLASSIFICATION USING SYNCHROPHASOR

The identification and classification of faults in a PS network are one of the potential uses of ML in synchrophasor and WAMS technologies. PMUs guarantee the PDCs' real-time, time-stamped data. Network voltages, currents, phase angles, and ROCOF must be observed and compared with this very accurate and synchronised time-stamped large data from the PMUs to depict the real system state at the measurement time. However, the operators face a difficult task because of this enormous amount of data. This problem can be solved using ML approaches, which can handle huge data processing and data mining.

A lot of research is happening worldwide to find the possibility of ML applications for PMU in fault finding as well as classification. The various ML methods utilised in PS fault detection and classification are discussed in this study. An ML-based categorization approach using decision trees is proposed at the outset of the review [151]. The discernible impact that happens in the signals of numerous PMUs put in the area around the fault point is one potential benefit of this technology. This finally improved the location, timing, and fault type of the defect as well as its precision

TABLE 8. ML techniques and methodology for PS fault detection and classification.

Event	Type of Machine Learning Classification	Proposed Methodology	References
Fault Detection and Classification	Supervised Learning	Decision Trees	[151]
		Regression Trees	[152]
		ANN	[153]
		Ruled-based Fuzzy	[155]
		SVM	[156]
		KNN	[157]

and accuracy. The investigation performed by the authors using real-time PMU data demonstrates the viability of the suggested approach. The state estimator is also established in [152], which uses classification based on regression trees to replicate the voltage phasors of a PS transmission network. Fault detection in transmission lines can be accurately recognised using the ANN methods suggested in [153]. The failure of one or more PMUs, which results in inaccurate or outdated information, is the fundamental flaw of the above-mentioned system. Therefore, to resolve this problem, appropriate communication techniques must be used.

The use of PMUs and AI-based ML algorithms to detect changes in voltage and current phasors during faults is proposed in [154]. Reference [153] proposes an ANN-based fault detection and categorization of PS networks. The rule-based approach using a fuzzy decision system is proposed in [155] for fault detection, categorization, and identification of the fault location. The PS operators will be able to address the issue more skilfully as a result. In [156], a precise method utilising SVM is suggested for locating the bus connected to the problematic PS network branch. This improves the process of pinpointing the fault's location. Additionally, this SVM-based approach contributes to the system's increased stability. In [157], the k-Nearest Neighbours (KNN)-based technique is suggested to locate all fault types in a parallel line using single-end measurements. This method's primary benefit is that it only uses single-end voltage and current measurements. Table 8 shows the ML techniques and the corresponding methodologies adopted in a power system network for the detection and classification of fault events.

5) MACHINE LEARNING APPLICATIONS IN FORCED OSCILLATION LOCALIZATION

In modern power systems, especially in interconnected power systems, forced oscillations (FOs) have become a major problem that threatens stability and safety [158]. FOs can be caused by unusual grid conditions like cyclical loads, broken equipment, periodic system disturbances, controller problems, and power systems that do not have enough damping. FOs will lead to PS failure and will lead to PS issues like a drop in the amount of power that can be transferred, possible damage to equipment, issues related to power quality, system failure, or even widespread blackouts [159]. With the evolution of PMUs and synchrophasor technology, the monitoring of FOs becomes easier due to the high sampling rates of PMUs when compared with traditional SCADA systems. The common methods adopted to monitor the PMU data having FOs and to localise and mitigate the causes are well explained in [159] and [160]. As a result, the methods are classified into the analysis of travelling waves, estimation of mode shape, damping torque analysis, energy-based analysis, machine learning as well as deep learning analysis. Even these dissipating energy flow (DEF) methods among them exhibit consistent performance but are unable to distinguish between the real source bus and the one with a large negative damping contribution [161]. Furthermore, these techniques still require speed enhancement as they were unable to handle several scenarios in the IEEE-NASPI Oscillation Source Location Contest that was held in 2021 [162]. The competition suggests a lengthy window of opportunity to deal with such situations.

In localising FOs where PMUs and μPMUs are deployed, ML and DL algorithms function admirably. Reference [163] proposes ensemble learning, a data mining-based ML approach that improves the localization of fault identification. One of the method's possible downsides is that it requires complete system observability. In [164], a time series-based classification ML approach is given that locates the FO sources quickly by removing disturbances using PMU data. The Mahalanobis matrix is trained using multivariate time series (MTS), dynamic time warping (DTW), and an enhanced k-NN method. The Mahalanobis matrix is used to calculate and compare the separation between the MTS. This method has a classification accuracy of 95%+ and is robust in handling data out of synchronous issues for up to 5 seconds, despite being able to cut calculation time to a few seconds. Yet, this approach not only ignores the identification and detection of force oscillations but also the corrective measures for reducing the effects in a PS network. Multivariate classification, an advanced time series technique, is suggested in [165] and is capable of localising the FOs. Nevertheless, it demonstrates some possible drawbacks of rotor angle and rotor angle speed detail information being omitted.

DL techniques, which have proven to be an effective tool for PS-based applications, can also be used in networks to locate and categorise FOs. The LSTM method is used by a DL method described in [166] to locate the source of low-frequency FOs in PS networks. This approach connects all potential source data to the model and displays more accuracy. This model's fundamental flaw is that it requires enormous amounts of input data for both testing and training, and it is impracticable to install PMUs on every source bus conceivable. Using a two-stage deep transfer learning (DTL) method, the authors of [167] suggested localising the FO localization problem by converting it to an image recognition problem. This approach is reliant on a fixed topology and only functions with it; as a result, it cannot be used for slight or substantial alterations in topologies without having to recon-

TABLE 9. Machine learning applications in forced oscillation localization.

Event	Type of Machine Learning / Deep Learning Classification	Proposed Methodology	References
Forced Oscillation Localization	Machine Leaning	Ensemble learning	[163]
		MTS, DTW, k-NN	[164]
		Multivariate classification	[165]
	Deep Learning	LSTM	[166]
		Two-stage deep transfer learning	[167]
		Transformer-based DL approach	[168]
		CNN models	[169]

struct and recreate the code from scratch. Another problem of this approach is the massive PS network's scalability. A transformer-based DL approach for FO localisation was suggested in the work in [168]. The technique is quick and robust, and it doesn't require retraining to function in the presence of modest or even substantial topology modifications. Even when non-gaussian noise is present, the approach still performs well in terms of localization at a high speed. Also, it can pinpoint the various FOs sources. Nevertheless, the controller type of the oscillatory sources cannot be determined using this method. For the parameter calibration of power plant models utilising the event playback approach, a DL-based framework is proposed in [169]. The system implements and tests both non-residual and residual CNN architectures. When compared to traditional CNN, the suggested residual CNN model (wavnet) exhibits a very significant improvement in the calibration of the model parameters. The results of the calibration show an average inaccuracy of 1.43%. This research can be expanded to calibrate more intricate models in DGs and renewable power plants. Table 9 shows the ML applications in forced oscillation localization of PS network.

B. APPLICATIONS OF MACHINE LEARNING IN MICRO SYNCHROPHASOR (μPMU) TECHNOLOGY

Modern PS uses distributed generation (DG) with RES, unconventional generations, electric vehicles (EVs), as well as controllable loads. This has led to the development of microgrids and smart grids, which can handle a huge amount of data on the power distribution side. The distribution system needs high-resolution monitoring technology and devices to find faults so that the right protective devices can be put in place. This makes the system more stable and secure. Even though PMUs are placed mostly on the transmission side of a PS, they cannot handle the big data that occurs on the distribution side. In this context, μPMUs are put in place on the distribution side of the PS network to measure, monitor, and find faults [170]. All μPMU measurements have been GPS time-stamped so that they can be seen at the same time. Also, cyberattacks on the power network discussed in Section I make researchers more interested in finding and classifying faults in the distribution system with the help of μPMUs. A man-in-the-middle attack, a playback attack, and a denial-of-service attack are the major types of cyber-attacks that the authors of [171] talked about. In man in a middle attack, the attackers will inject malicious content into the communications infrastructure between both the sensors and the control centres or between the control centres and the operators. In the playback attack, hackers send information from the previous period to make it hard for the control centre device and operators to figure out what the real normal and fault conditions are. Lastly, the denial-of-service attack is the most dangerous. In this attack, hackers restrict the communication channel by flooding the targeted network with useless data to which the receiver will be unable to respond and leads to network crashes. This makes it hard for legitimate operators to get in, which can cause a blackout.

μPMUs, which were created specifically for the distributed PS network, were made available by the University of California in association with the Power Standards Lab as well as Lawrence Berkeley National Lab [172]. These μPMUs adhere to IEEE standard C37.118, which guarantees the device's standardisation. When compared to PMUs on the transmission side, the micro-PMUs offer the potential advantages of higher measurement resolution, high accuracy level in the phase angle measurements, and the ability to store and process big data [173]. The μPMUs are capable of millidegree accuracy and microsecond resolution than conventional transmission-type PMUs. The major potential applications of μPMUs are listed in Fig. 7.

The distribution side of a PS network with deployed μPMUs can also benefit greatly from the ML methods that are becoming more popular in PMUs on the transmission side. All of the applications shown in Fig. 7 can be used successfully with ML techniques. A lot of research is happening in this field where big data is involved. In [174] and [175], the fuzzy logic method, a knowledge-based approach which is considered one of the earliest ML techniques is used to pinpoint the defect and categorise it in the context of an unbalanced radial power distribution as well as a transmission line system where μPMUs are deployed. The technique has a very high level of precision and is not at all reliant on the kinds of transients that occur during the fault. Over a wide variety of pre-fault power levels, system configurations, fault resistance, and fault inception angles, the method is extremely effective. To set the fuzzy rule set and tune the approach, more expertise is required.

In [176], it is suggested to use CNN to categorise faults in PS distribution networks with DGs. The proposed method's advantages are that it requires only loop grids and it does not require the line parameters, load values or the type of fault. However, this approach necessitates high sampling rates and a well-processed data source. The measurement device needs

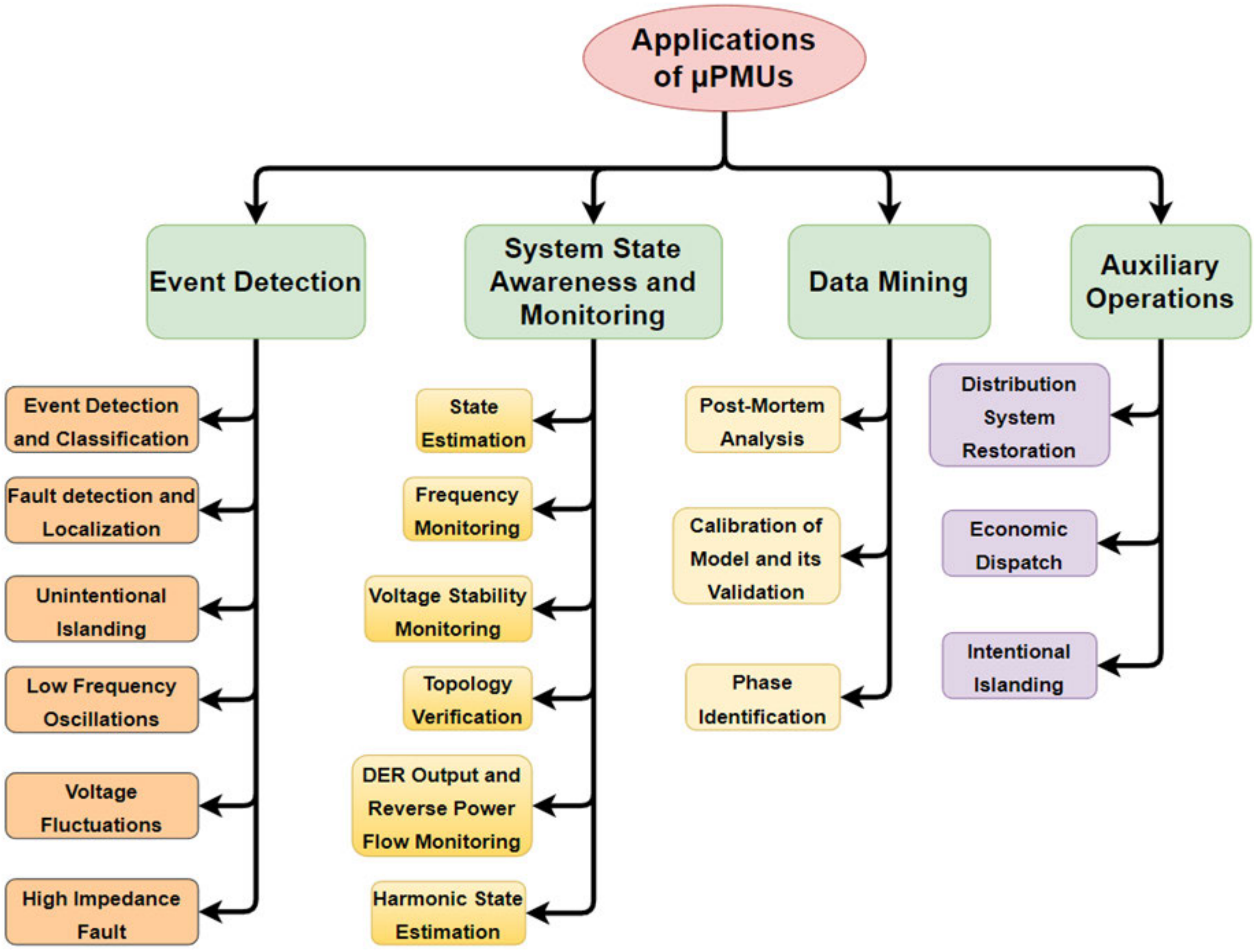

FIGURE 7. Applications of μPMUs.

to be installed in each node as a result, which places a heavy computational burden on the system. Based on the fault current analysis (FCA), it is suggested in [177] to use ANN to locate the problem in the distribution network. Measurements are obtained from the μPMUs deployed in the substation and are taken into account when using the distributed line model. No load values and line arguments are required for processing using this method. But because of its complicated structure, the suggested method cannot be used without a trained data set and sensors with high sampling rates. Additionally, loop grids, which have a significant computational cost, are not covered by this approach. Another drawback is that the proposed method would only work with a current signal. In [178], a back propagation-based ANN approach for high impedance fault (HIF) detection and the location in DG systems where μPMUs were installed is proposed. Although less heuristic than other algorithms, this one requires more software to function properly. Deep graph convolutional networks (GCN) have been suggested by [179] to discover distributed network faults without identifying the problem type or load values. The suggested method performs admirably when dealing with unbalanced loads and is effective with loop grids. By using phasor readings from the μPMUs, the phase angle investigations will improve the system's accuracy. The suggested method, however, is challenging due to the high penetration level, and as a result, it is unable to identify the precise fault position. This approach has a very considerable level of computational complexity. To accurately identify the kind and location of defects in DG systems, an MLP-based NN is also suggested in [180]. Additionally, this technique requires more hardware and software components to support it. As suggested in [181], SVM can be utilised on the distribution side, where μPMUs are located, to detect faults in distribution lines with accuracy and precision. The use of spectral kurtosis (SK) with random forest (RF) in the μPMU is suggested in [182] for intelligent-based island detection. This technique contributes to improving the microgrid's resilience to defects that are not intentional. The suggested programme, however, employs complex algorithm techniques to manage large datasets in the microgrid. An efficient ML technique based on RF in the renewable-based smart grid is proposed in [183] which is a sustainable solution to cyber-based attacks resiliency in DG systems. The proposed method is noise resistant as well as cyber-attack resistance with a detection

TABLE 10. Overview of micro PMU applications and machine learning approaches in distribution networks and DGs.

Event	Proposed ML Algorithm	References
Fault Detection and Classification in Distributed Lines	FL	[174], [175]
Fault Classification in Distribution networks with DGs	CNN, GCN	[176], [179]
Fault Location Identification	ANN, BP-ANN, MLP-NN	[177], [178], [180]
Fault Detection	SVM	[181]
Intelligent-Based Island Detection	SK-RF	[182]
Cyber-attacks in Renewable based DGS	RF	[183]
Detection and Classification of Microgrid Faults	NBC-SVM-ELM	[184]

time of 8.5 ms and shows a precision of 99.89% with 98.91% accuracy. Since a PMU is used to operate the fault detection algorithm, the method is cost-effective because it does not need any extra hardware or software. But this method has a few minor flaws, such as the fact that it takes a lot of time to pre-process the data and has a heavy computational structure.

In [184], three ML techniques namely naive bayes classifier (NBC), support vector machine (SVM), and extreme learning machines (ELM) are presented for the detection and classification of microgrid faults relying on the Hilbert-Huang transform (HHT). Neither line arguments nor load values are required for computation with this method. Comparing this structure to other ML methods stated in the literature, the computational load is quite minimal, and it also works well with loop grids. However, this method is limited to only the present signal and is unable to pinpoint the precise problem location. All nodes must also have measuring equipment. Table 10 provides an overview of μPMU applications and ML approaches used in PS distribution networks and DGs.

V. DISCUSSION AND FUTURE TRENDS

The extensive literature review in synchrophasor technology is carried out in this work by using PMUs and μPMUs combined with ML techniques to aid in the resolution of major PS issues such as fault detection and classification, TSA, VSA, and cyber security challenges. Because of the high sampling rate and time-synchronized measurements from the PMUs, it is capable of doing so, paving the way for significant advancements in the areas of power grid protection, estimation, and control. This paper thoroughly discusses the issues associated with PS networks and how ML techniques can assist in addressing and correcting such issues. Based on a thorough review of the literature, the following observations as well as insights are summarised.

i. Due to the development of DERs, EVs, microgrids, and smart-grid in contemporary PS, synchrophasor technology (ST), utilizing PMUs on the transmission side as well as μPMUs on the distribution side, is currently in huge demand. A country's productivity plan and cyber-security policy will suffer significantly if a slight PS blackout occurs. This paper provides a thorough analysis of the significant blackouts that occurred worldwide between 1965 to 2021 in the introduction.

ii. Several potential benefits of PMUs over SCADA in a PS network led to the evolution of advanced measurement and monitoring technology known as synchrophasor and WAMS technology. PMUs and μPMUs can measure the ROCOF in addition to the amplitude and phase angles of voltage and current. One possible benefit of ST highlighted in Section II of this paper is that it can provide highly accurate time-stamped data using GPS, which aids in dealing with PS stability and security issues. Furthermore, using synchrophasor as well as WAMS technology allows for accurate state estimation, fault classification and identification fault location identification, and efficient real-time tracking of PS events as mentioned in Section III.

iii. ST successfully assesses transient stability using ML techniques and algorithms. SVM and KNN perform better than other supervised learning techniques when using DTs, Bayesian multiple k-learning, SVM, and KNN. For TSA research with better accuracy and precision, a cutting-edge method called DL is also mentioned that makes use of ELM-ANN and CNN-TSVMNN-based works. This work also discusses RL as well as DRL-based works that can handle more difficult computational tasks.

iv. Voltage stability assessment (VSA) can also be performed effectively in a PMU-installed PS network by using ML algorithms. According to the literature, supervised learning methods such as ANN, MLP-NN, ELM, and DT improve voltage stability assessments while requiring less computational effort. Advanced supervised learning techniques such as NNE, SVM, and GA-based SVR produce better results in terms of precision and accuracy.

v. Cybersecurity is the most important concern in sophisticated PS networks because of their scalability and excellent classification accuracy. ML-based cyber-attack detection techniques have shown promising performance. The review reveals a noticeable increase in supervisory ML algorithms used for cybersecurity-related concerns in the PS network in which PMUs were installed. The literature also identifies FDIAs as well as anomaly detection in PS networks as major cybersecurity issues.

vi. It has been observed that fault detection and classification using ML in PS where PMUs are deployed primarily employ supervised learning techniques such as DTs, RTs, ANN, SVM, KNN, and so on. Almost all methods produce good fault detection and classification results.

vii. Moreover, the ML and DL methods reveal a focus on forced oscillation localization research where

PMUs and μPMUs can be deployed. According to a review, advanced k-NN, multivariate approaches, LSTM, CNN, the ensemble, and transformer-based DL techniques produce better results when used to study the localisation of FOs and calibrate model parameters in PS networks.

viii. The rapid increase in renewable-based DGs, EVs, and controllable loads will increase demand for ML applications in distribution PS networks where μPMUs have been deployed. ML techniques have a broad research application in event detection, system state awareness and monitoring, data mining, and auxiliary operations where large amounts of data and complex computational algorithms are required.

Because of the need to improve the monitoring and control of electric power systems, PMU devices became more common in the power generation and transmission sectors. As a result, a large amount of data is generated and sent to control centres, which are eager to find new ways to use this type and quantity of data. Because of the evolution of μPMUs [185], ML and DL-based big data analysis with new and advanced algorithms are essential not only on the generation and transmission sides but also on the distribution side. Traditional and analytical methods are incapable of dealing with such massive amounts of raw data as these are. Because of their high sampling rate, PMU-based WAMS can monitor dynamic behaviours that traditional SCADA acquisition devices cannot. Aside from real-time applications, having synchronized measurements is critical for things like a post-mortem analysis, which is difficult or impossible to perform in real-time. The system's security is dependent on how well this procedure works, which can be greatly improved by using PMU data. To precisely identify line-tripping and oscillation events on the distribution side, where μPMUs are installed, a larger dataset is required. For such events, a whole data set training should be performed, followed by the use of real-time data events to validate and test the algorithm's efficacy. By shifting from an offline to an online environment, DL techniques such as autoencoder-based neural networks [186], generative adversarial networks (GAN) [187], and one-class support vector machines (OCSVMs) [188] can forecast the occurrence and type of fault. Moreover, a lot of the applications listed in [189] essentially evaluated the DL techniques used in electrical PS as a whole, but they may also be used successfully to investigate PS transmission as well as the side of distribution where PMUs and μPMUs are installed.

Synchrophasor-based smart grid networks are primarily IoT and cloud-based networks, with data processing and storage occurring primarily on cloud servers. Even though cloud-based computation has the potential benefits of high storage capacity, reducing complex computational issues with an efficient computation rate, it has limitations such as high delay, which impedes real-time applications in smart grids. This eventually leads to an increase in bandwidth utilization. Furthermore, mobility support is a hindrance to the cloud computing framework. To address the aforementioned issue and speed up synchrophasor data processing, an intermediate and storage-based system known as edge computing [190] can be introduced. Edge computing is a cloud-based solution that provides computing and storage resources at the 'edge' of a network. While also reducing latency and bandwidth utilization, which results in fewer network delays and congestion issues. PMU measurements and WAMS technology necessitate extremely secure communication networks, such as power line communication [191], as well as 5 G and 6 G technologies [192] that employ novel concepts such as virtualization, grid monitoring, and grid stability control. The 5 G and 6 G have high communication speeds, low energy consumption, and enhanced security features, and can thus provide a better communications network for WAMS technology. Machine learning techniques, due to their excellent forecasting capabilities, can be employed to improve radio resource allocation according to demand in 5 G and 6 G-enabled synchrophasor technology [193].

VI. CONCLUSION

This survey provided a critical examination of current research trends and machine learning applications in synchrophasor technology. As the power system transitions to a smart grid, more sophisticated measurement and monitoring technologies must be implemented for better estimation, monitoring stability, and protection. Blackouts in the PS network can be identified and reported more quickly with the help of PMUs as well as μPMUs using the ML and DL methods discussed in this paper. This increases the stability and security of the power system. This paper critically reviewed various ML and DL approaches in synchrophasor technology such as cybersecurity, fault detection and classification, transient stability assessment, and voltage stability assessment. The ML/DL classifications and methodologies used are also well described. The DL methods also address future trends in identifying line-tripping and oscillation events that require a large amount of data. Edge computing is also proposed as a future scope in this paper to improve processing latency while also reducing bandwidth utilization. Powerline communication research trends, 5 G and 6 G network communications in synchrophasor technology with ML and DL techniques are also discussed.

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