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Frequency Event Detection and Mitigation in Power Systems: A Systematic Literature Review

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ABSTRACT Modern power systems characterized by complex topologies require accurate situational awareness to maintain an adequate level of reliability. Since they are large and spread over wide geographical areas, it is inevitable that failures will occur. Various generation and transmission disturbances, such as generator and transmission line tripping and load disconnection, give rise to a mismatch between generation and demand, which manifest as frequency events. These events can take the form of negligible frequency deviations or more severe emergencies that can precipitate cascading outages, depending on the severity of the disturbance and efficacy of remedial action schema. The impacts of such events have become more critical recently due to increased levels of renewable penetration and distributed energy resources, which have caused a decline in system synchronous inertia. Due to the repercussions, it is indispensable to arrest such disturbances on time by activating primary frequency control measures. In this paper, a comprehensive systematic literature review is presented on the techniques used for event detection in power systems and the methods of primary frequency response in modern power systems. The paper also highlights the impacts of severe frequency events within power systems.

INDEX TERMS Power system disturbance, power blackouts, low inertia power systems, event detection, frequency control, systematic literature review.

ACRONYMS

SLR	Systematic Literature Review
PMU	Phasor Measurement Unit
PFR	Primary Frequency Response
ROCOF	Rate of Change of Frequency
WAMS	Wide Area Measurement System
UFLS	Under-Frequency Load Shedding
RES	Renewable Energy Source
DER	Distributed Energy Resource
BESS	Battery Energy Storage Systems
EV	Electric Vehicles
DLC	Direct Load Control
GEL	Grid-Enabled Load
WT	Wind Turbine
WPP	Wind Power Plant
IBR	Inverter-based Resource
DFIG	Doubly-fed Induction Generator
PV	Photovoltaic
GRC	Generation Rate Constraint
DG	Distributed Generation
MG	Microgrid
VI	virtual inertia
FFR	Fast Frequency Response
GFC	Grid-following Control
SCADA	Supervisory Control and Data Acquisition
VSM	Virtual Synchronous Machine
AEMO	Australian Energy Market Operator
EI	Eastern Interconnection
TKEO	Teager-Kaiser energy operator
PCA	Principal Component Analysis
SVM	Support Vector Machines
FDR	Frequency Disturbance Recorder
DFA	Detrended Fluctuation Analysis
CNN	Convolution Neural Networks
LSTM	Long Short-term Memory
NERC	North American Electric Reliability Corporation
FFT	Fast Fourier Transform
ESS	Energy Storage Systems
PEV	plug-in EV
SOC	stage of charge
TCL	Thermostatically controlled load

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VSWT	Variable-speed Wind Turbine (WT)
MGCC	microgrid central controller
DFT	Discrete Fourier Transform
DWT	Discrete Wavelet Transform

PREFACE TO THE READER

This manuscript presents a Systematic Literature Review (SLR) of frequency as an indicator of system reliability by investigating the impacts of frequency events in power systems, contemporary event detection techniques, and methods of frequency control in power systems. The authors gathered a set of documents from academic literature and technical reports, and applied an inclusion criteria for choosing the documents to be reviewed for this paper. Over the course of developing this manuscript, the authors came across other documents that were not discovered through the SLR, but were important to the topic. Those documents are labeled with an '*' following the in-text citation. All other references which were discovered through the SLR are cited without the '*'.

I. INTRODUCTION

The primary goal of system operators has always been to operate the power system with an adequate degree of reliability and security to ensure continuity of supply to consumers [1]*. The imbalance between supply and demand in a power system, which is commonly caused by loss of generation and/or transmission line tripping, is the most dangerous condition for reliable operations. Every imbalance should be efficiently arrested and counteracted to prevent unforeseen collapse. For reliable operation of power systems, frequency should be maintained within a permissible band around a nominal value, typically 50 Hz or 60 Hz. Frequency, therefore, is an indicator of the system reliability and failure to maintain it within a permissible band may lead to equipment failure, cascaded tripping of power plants, and possibly loss of service [2]*.

A modern power system with high penetration of Renewable Energy Source (RES) present unprecedented challenges for power system operators. The salient technological problem of these systems is the ability to maintain frequency stability due to a reduced amount of reserve power, specifically rotational inertia. System inertia has decreased considerably with the rise of inverter-based generators; which do not have rotational inertia [3]*. Modern power systems require advanced situational awareness to assess system conditions in real time and take protective measures in a timely manner. Modern engineers and researchers use state-of-the-art communication technologies, signal processing, and data analysis techniques to offer operators enhanced system insight, including detection of sudden frequency deviations. Figure 1 depicts an example of such a frequency deviation.

Steady-state and transient stability of power systems have been a topic of study for researchers for over a century [4]*. Numerous techniques have been reported in literature for power system disturbance detection. These can be categorized into 1) model based, 2) signal based, 3) knowledge based, 4) hybrid techniques [5]*, [6]*. Model based approaches use a system or process model to evaluate the uniformity between predicted and actual output. These can be further classified into stochastic (using Kalman filters, etc.) and deterministic (e.g., can be solved with linear matrix theory) methods. Signal-based approaches detect disturbances based on features extracted in the time domain, for example using standard deviation, root mean square, peak, average, or, in the frequency domain, spectrum analysis. Knowledge based techniques use an historical data-set to perceive system behavior. They can be classified as Qualitative, e.g. expert systems, and Quantitative, e.g. Principal Component Analysis (PCA), Support Vector Machines (SVM), neural networks, or fuzzy logic. Hybrid techniques use a combination of any of the above methods for event detection [7].

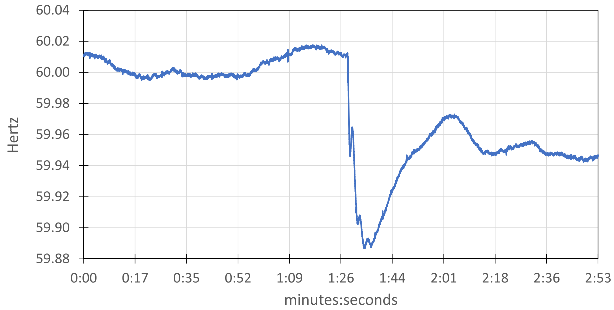

FIGURE 1. A frequency deviation measured within the U.S. Western Interconnection on January 20, 2020 at 0658. Frequency decreased from 60.01 Hz to 59.89 Hz (0.2%) in 5.9 seconds, then recovered to 59.95 Hz around 40 seconds later. Data sample rate is 60 frames per second.

The advent of Phasor Measurement Units (PMUs) and their recent deployment on a large scale have enabled real-time state monitoring with high temporal resolution. We note that the PMU-based event detection methods can be classified into 1) signal analysis and 2) machine learning. Signal analysis technique use signal processing methods, such as Wavelet Transform [8], and Swinging Door Trending [9]. Signal analysis techniques can detect events but are unable to accurately identify fault type and location. Many machine learning methods for PMU-based event detection focus on statistical feature extraction approaches, which are non-robust and inefficient [10]. Other machine learning techniques use large historical data sets for supervised learning, such as SVM [11], Decision Tree [11], Artificial Neural Networks [12] and Long Short-term Memory (LSTM) [13]. However, supervised learning techniques can be negatively affected by inappropriate and insufficient data selection [14].

The frequency response capabilities of a power system are crucial reliability assets and have lately been garnering substantial attention, especially with the recent large-scale penetration of renewable generation in power systems. Traditionally, frequency control in power systems was exerted by conventional generators through their inertial response and their governor actions. However, with the replacement of conventional generators by RESs in modern power systems, new methods must be deployed. With the loss of system inertia caused by large-scale penetration of RESs, frequency control is becoming a critical grid service.

This paper focuses primarily on the ongoing research on advanced system monitoring tools for frequency event detection and responsive frequency control assets to ensure security and reliability of the future low inertia electric grid. It aims to give a broad survey of the topic by investigating the problems associated with future power systems and then extending the study to focus on the solutions proposed so far. We reviewed relevant literature, put them into context, and formulated three logical questions to broadly cover various aspects of the topic; impacts, detection, and remedy. It is important to clarify that the scope of this article is not intended to be comprehensive, nor does it cover all facets. Our literature study is characterized by a systematic process for gathering relevant literature and applying an inclusion criteria. In particular, we focus on three aspects of the topic: impacts of events, current detection methods, and modern sources of frequency control.

Numerous studies and surveys have been carried out on power blackouts [15], [16], and frequency control in low inertia systems [17]–[20]. However, no extensive systematic literature study is available on the topic that broadly covers various aspects of the topic - impacts of events, modern detection methods, and remedies - which distinguishes this approach from other studies reported in the literature.

The remainder of the article is organized as follows. Section II focuses on the challenges in low inertia systems and the potential of using RESs and demand response technologies in providing frequency control support. Section III presents the methodology, search criteria, and inclusion criteria for conducting this systematic literature review. Section IV reviews the literature and presents solutions available for event detection and frequency response in future power systems. Section V concludes the discussion.

II. FREQUENCY CONTROL IN LOW INERTIA SYSTEMS

Currently, the electric power system is experiencing an era of unprecedented changes. Concerns about the environment and sustainability have led to the replacement of a large number of conventional power units with RESs. As a result, in the last decade, total global installed capacity have expanded by a factor of 40 for solar power [21]* and a factor of around 6 for wind [22]*. The fundamental challenge paired with this transition is the substitution of synchronous machines and their well-known properties with inverter-based generation, whose dynamics are yet to be fully explored [17]*. Figure 2 presents an energy conversion model of synchronous generator and Inverter-based Resource (IBR). The mechanical power coming from turbine and the rotating mass in a synchronous generator act as energy source and energy storage, respectively. Converter, effectively, is a controllable DC to AC transformer, which requires an energy source and an energy storage to behave like a synchronous generator [17]*.

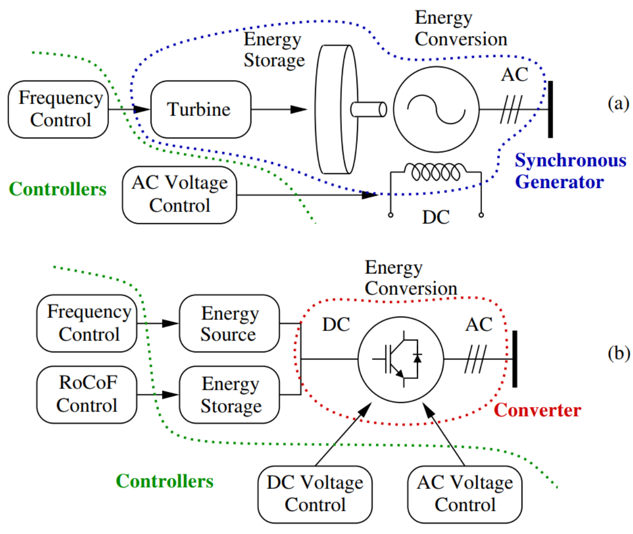

FIGURE 2. Energy conversion of a) Synchronous machine b) IBR [17]*.

The interaction of these resources with the grid differs significantly from that of conventional plants, owing to their physical characteristics and power electronics-based interface. Unlike synchronous generators that provide inertia to the system, IBRs do not possess inherent inertia capabilities. Synchronous inertia decelerates the natural response of the system during supply/demand imbalances, giving power systems operators more time to react. Consequently, a reduction in synchronous inertia has caused frequency events to exhibit larger frequency deviations and higher Rate of Change of Frequency (ROCOF) in low inertia systems. Figure 3 shows the increase in ROCOF and frequency response with a decline in inertia of a simulated Great Britain power grid with 20 GW demand [23]*. Severity of these frequency events is expected to pronounce based on the projected replacement of conventional units with IBRs. The stochastic nature of RESs further aggravates the problems of load-power balancing and frequency control [24]*.

The frequency dynamics of a power grid are defined by the expression [25]*:

$$\frac{df_{grid}}{dt} = \frac{P_G - P_D}{M} = \frac{\Delta P}{M} \tag{1}$$

where f_{grid} is the synchronous frequency, df_{grid}/dt is the ROCOF, and M is effective inertia constant of the system. M reflects the sum of normalized inertia constant of all rotation-based generators. Equation 1 depicts the inverse relation of ROCOF with M.

In future low inertia systems, a series of events may occur before primary response comes into play. This necessitates responsive frequency control assets to act before conventional frequency support. Additionally, advance system monitoring tools may be required for enhanced supervision. For instance, during low inertia conditions, existing Under-Frequency Load Shedding (UFLS) limits may result in unwarranted and excessive demand disconnections. This can engender an

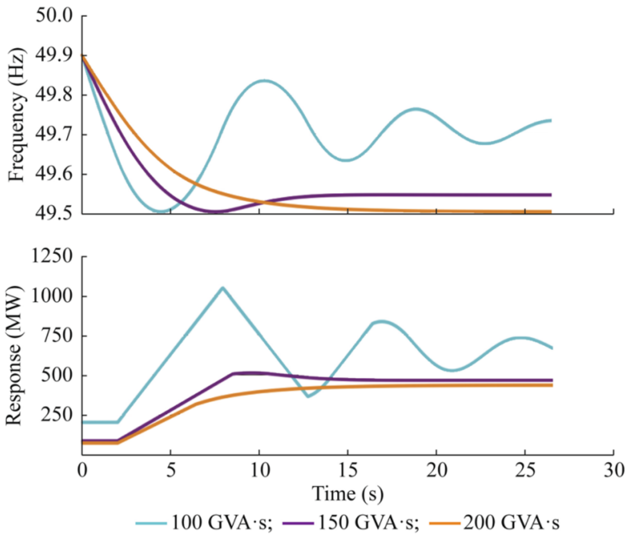

FIGURE 3. Frequency containment simulation of 600 MW generation loss showing impact of inertia reduction [23]*.

over-frequency event following an under-frequency disturbance and ultimately precipitate cascading tripping.

A. PRE-EVENT CONCERNS

With further decommissioning of synchronous generators, future power systems are expected to be more oscillatory in nature during and after disturbance [26]* (Figure 3). Large-scale Electric Vehicles (EV) adoption could result in abrupt demand variation, which also entails a fast frequency response [27]*. This necessitates a revision of existing frequency monitoring and frequency response methods.

Wide-area disturbances can be avoided or mitigated by monitoring power system dynamics in real-time. High resolution phasor measurements can be coalesced in a central unit to enable real-time monitoring and control of power systems. Conventional Supervisory Control and Data Acquisition (SCADA) systems, with a temporal resolution of 1-10 seconds, are not suited for current power systems. Wide Area Measurement Systems (WAMSs), with temporal resolution in milliseconds, are considered an effective tool for accurate state estimation and control in modern power systems [28]–[30]*. Great Britain has deployed WAMS under the Visualization of Real-Time System Dynamics Using Enhanced Monitoring (VISOR) Project for enhanced situational awareness during pre-event period [31]*. The VISOR system allows risk identification with frequency, voltage, and angle monitoring. Similarly, the U.S. western electricity coordinating council (WECC) used WAMS to perform three major tests of system dynamics during 2005 and 2006 [30]*. These probing tests represent the most extensive applications of PMUs to assess dynamic security. High resolution PMU data allowed monitoring of sharp dynamic information throughout the network.

B. POST-EVENT CONCERNS

To keep abreast of technological advancement, some major challenges, such as dynamic modeling, security constraints, and adjustments to the frequency control requirements, have been explored [32]–[34]*. Studies on Generation Rate Constraint (GRC), one of the significant constraints in frequency response and modeling analysis, began in 1983 [35]*. Numerous research studies have reported on non-linear dynamics of the system [36]–[38]*. Some studies have focused on load dynamics [39]*, [40], and active power/frequency and reactive power/voltage relation [41], [42]*. Several studies have considered the effects of uncertainty of system dynamics on frequency control [43], [44]*.

Effects of stochastic nature of Microgrids (MGs), Distributed Generations (DGs), and large-scale integration of RESs have been widely studied! [17]–[20]*. Numerous research works have focused on controllable load and smart load technologies for providing frequency control [45]–[47].

Synchronous Condensers, virtual inertia (VI), and Fast Frequency Response (FFR) are three relevant techniques worth mentioning. Synchronous condensers are basically unloaded synchronous machines that normally operate as motors without providing active power, but can act as a generator when needed. They have been in use for reactive power support for decades [48]*. They have inherent inertia capabilities and respond instantaneously to power imbalances [49]*.

Recent research has revealed that VI-enabled IBRs (less than 20 ms response time) can increase frequency stability [24], [50]–[52]. However, apart from inadequate inertia, its heterogeneous distribution might also cause rapid frequency dynamics, which makes optimal placement of VI an important consideration [53], [54]*. Several control algorithms have been developed for VI. Grid-following Control (GFC) has been a widely used topology that relies on frequency deviation and ROCOF estimation via a phase-locked loop (PLL) for active power injection [55]*. Virtual Synchronous Machines (VSMs), a series of grid-forming converter technologies, are an alternative to GFC for VI [56], [57]*. During disturbances, VSMs can simulate synchronous generator behavior to provide reactive support in addition to inertial response.

Frequency control schemes that offer faster responses than synchronous generators are referred to as FFR; response times for these assets are in the range of hundreds of milliseconds, sufficient to provide Primary Frequency Response (PFR) in place of rotational inertia. Requirements for PFR vary by jurisdiction. In Great Britain, PFR needs to activate within two seconds of the triggering event, with full provision of the requisite power within ten seconds [58]*. Australian Energy Market Operator (AEMO) mandates a 5% increase in active power achieved within ten seconds of the frequency deviation from PFR deadband, which is ±1.5 Hz around the nominal value [59]*. Currently, FFR is not subject to a commonly established criteria. However, considering PFR requirements, FFR should be provided by IBRs [27], [60]*.

IBRs offer faster response than conventional systems for both active and reactive power support [17]*. Non-synchronous devices need to take on system control functions that were formerly performed by synchronous generators, such as voltage support and oscillation damping. The rapid switching capability of electronic components on the demand side ensures a faster response for frequency support than synchronous generators. Therefore, IBRs and load-side resources are promising alternatives for frequency control owing to their fast response as well as recent developments in measuring, processing, and communication technology.

During transients, neither frequency nor ROCOF are uniform across the system. Decline in rotational inertia will increase regional variations in these quantities, which demands locational event detection and frequency response [54], [61], [62]*. Therefore, it is critical to leverage the advance computational tools with the remarkable potential of RESs and demand response technologies in providing frequency control supports to ensure a secure and reliable electric grid with a large-scale penetration of RESs.

Table 1 presents a comparison of frequency control capabilities of various techniques for future low inertia power systems. Synchronous condensers appear to be a costly approach, as these systems require conversion of decommissioned synchronous generators or installation of new units to provide requisite and reserve capacity [26]*.

TABLE 1. Comparison of various frequency control techniques for low inertia systems [26]*.

Solution	Cost	Frequency Control Capabilities		
		Limit ROCOF	Frequency nadir	Rapid demand change
Synchronous Condenser	High	Strong	Weak	Medium
VI with GCF	Low	Strong	Medium	Strong
VI with VSM	Low	Strong	Medium	Strong
FFR	Low	Medium	Strong	Strong

III. METHODOLOGY

To conduct a useful survey on a research topic, it is of prime importance to follow a specific and repeatable method. A systematic literature review is a method which uses repeatable processes to aggregate published materials for conducting a survey. The first step in conducting an SLR is to formulate research questions specific to a topic. In the second step, a collection of relevant research material is formed by conducting a search. The authors of this document have focused on online published literature such as journal articles, conference papers, scientific books, and regulatory materials. In the third step, the pool of documents grows smaller after application of inclusion criteria, which leaves only those documents that meet the inclusion criteria, with the rest of documents excluded.

The authors formulated the following three research questions (RQ):

- What are the impacts of frequency events in power systems?
- What are the current methods used for event detection in power systems?
- What are the modern dispatchable sources of PFR in power systems?

A. SEARCH CRITERIA

As a first step, the authors used the following databases for this review to gather a large set of material while keeping track of the database names, search keywords and search criteria for repeatability. It is pertinent to mention here that future searches of the same databases could yield different results that meet the inclusion criteria because databases change over time.

1) GOOGLE SCHOLAR

Google Scholar filters search results to show only those publications that are open access or to which the academic institution subscribe. The two searches from Google Scholar gave the following results:

Search 1 used the keyword "frequency event detection in power system." The authors included the first 220 results from this search in the pool of material. Search 2 used the keyword "primary frequency response in power system." The first 50 results from this search were included.

2) INSPEC

The authors confined the Inspec search to journal and conference papers only. The two searches from Inspec gave the following results:

Search 1 used the term "event detection in power system," searched in all fields. Articles with the following controlled vocabulary were excluded: *power supply quality*, *domestic appliances*, *power consumption*, *smart meters*, *energy conservation*, *energy consumption*, *load management*, *optimization*, *power system harmonics*, *inverters*. This yielded 85 non-duplicate results.

Search 2 used the term "primary frequency response in power system" searched in all fields. Articles with the following controlled vocabulary were excluded: *power generation dispatch*, *voltage control*, *power generation economics*, *power system simulation*, *stochastic processes*, *rotors*, *damping*, *high voltage direct current* (HVDC) *power transmission*, *power generation faults*, *control system synthesis*, *power transmission control*, *HVDC power converters*, *power system faults*. This yielded 77 non-duplicate results.

B. INCLUSION CRITERIA

After having gathered a large set of articles, the next step was to develop inclusion criteria to include only relevant and useful material in this review. The inclusion criteria focused on frequency events and sources of PFR in power systems, and excluded voltage/PQ events, as well as secondary and tertiary frequency response. The authors did not confine this review only to the U.S.A.; international studies were also included. The inclusion criteria used by the authors for this SLR are presented in Table 2.

TABLE 2. Systematic Literature Review inclusion and exception criteria.

Source	Inclusion Criteria	Exception Criteria
Journal, Conference & White Papers	Discuss the adverse impacts of frequency events in Power systems	Economic impacts
Journal & Conference Papers	Discuss event detection methods in power systems	Power load event detection for non-intrusive load monitoring, PQ assessment in power systems, wind power ramp event detection
Journal & Conference Papers	Provide comparison analysis of various event detection methods	Power load event detection for non-intrusive load monitoring, PQ assessment in power systems
Journal & Conference Papers	Discuss challenges of low inertia systems and existing dispatchable sources of frequency response in power systems	Secondary and Tertiary response, economic analysis

C. APPLYING INCLUSION CRITERIA

The Google Scholar searches yielded 270 non-duplicate results, of which 179 documents were excluded based on title and abstract. One document could not be found. Eight documents were excluded further after reading the remaining documents in full. The Inspec searches yielded 162 non-duplicate results, of which 105 were not included based on title and abstract. The remaining documents were read and six of these documents were excluded. In total, 133 documents were included in this review as shown in Table 3. Figure 4 depicts the flowchart of the review process adopted for this study.

TABLE 3. Number of documents used in the review.

Database	Included	Excluded
Google Scholar	82	187
Inspec	51	111
Total	133	298

IV. RESEARCH QUESTIONS

A. RQ1: WHAT ARE THE IMPACTS OF FREQUENCY EVENTS IN POWER SYSTEMS?

Protection systems at the transmission level are required to clear faults within 140 ms [23], [63]*. This might result in a loss of generation/load and a subsequent loss of Distributed Energy Resources (DERs), depending on ROCOF settings, causing a power imbalance post fault clearance. Conventionally, synchronous generators have been the source of Primary Frequency Response to contain frequency disturbance within a few seconds after the onset of an event, followed by secondary and tertiary responses. If PFR is rendered ineffective at containing the disturbance, a load-shedding scheme could be triggered. Otherwise, the disturbance could possibly be followed by a cascade of events leading to a blackout.

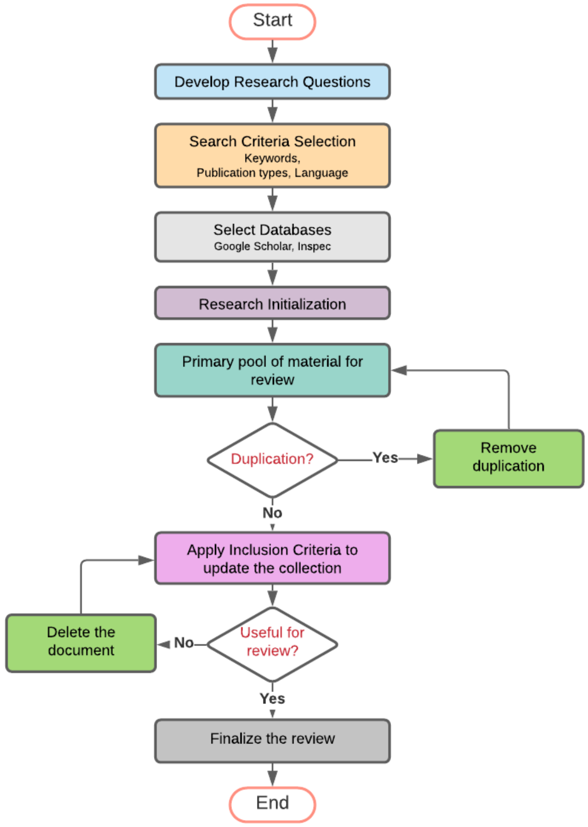

FIGURE 4. Flow chart of the systematic literature review process.

The authors examined multiple reports analysing causes of major disturbances in power systems across the globe. Many disturbance reports are available online. This review included a few of them to emphasize the impacts of events in a power system. Power system events can be caused by generator loss, transmission line loss, lightning strike, equipment failure, human error, substandard maintenance, among others [25]*.

The Nordic power system experienced a severe blackout on September 23, 2003, which affected southern Sweden and eastern Denmark [64]*. Prior to the disturbance, the system was operating under normal conditions. However, two 400 kV transmission lines and one HVDC link to Germany and Poland were out of service for scheduled maintenance. Initially, a 1235 MW nuclear unit tripped due to an internal fault in a valve. The system recovered within less than a minute. After a few minutes, a busbar fault occurred at one of the substations, which caused the loss of 1750 MW and all the transmission lines connected to that busbar. This led to overloading, oscillations, and voltage stress conditions. The system was eventually split into two parts. This blackout caused a loss of 6350 MW in both countries and affected almost 4 million people [64]*.

On September 24, 2006, the national grid of Pakistan faced one of its worse blackouts [65]*. Before the occurrence of the disturbance, the system was operating normally, but close to stability limits with one 500 kV transmission line out of service for maintenance. The failure was initiated when a

TABLE 4. Major power outages across the globe from 2011 to 2018 [15]*.

Region	Date	Duration (hours)	People Affected (millions)	Causes
Mexico & U.S.	8 Sept 2011	12	2.7	Transmission line tripping
Brazil	4 Feb 2011	16	53	Transmission line fault, fluctuated power
India	30 July 2012	15	620	Transmission line overload
Bangladesh	1 Nov 2014	24	150	HVDC station outage
Pakistan	26 Jan 2015	2	140	Plant technical fault
Holland	27 March 2015	1.5	1	Bad weather
Turkey	31 March 2015	4	70	Power system failure
Ukraine	23 Dec 2015	6	230	Cyber-attack
Kenya	7 June 2016	4	10	Animal shorted the transformer
South Australia	28 Sept 2016	6.1	1.7	Storm and bad weather
U.S. (NY)	1 March 2017	11	21	Cascading tripping of transmission system
U.S. (Southeast)	10 Sept 2017	5	7.6	Cascading tripping of transmission system
Brazil	21 March 2018	1	10	Transmission line failure
Canada (BC)	20 Dec 2018	4	0.6	Heavy wind

500/220 kV transformer tripped due to indiscriminate operation of a relay, which then caused the tripping of the parallel 500/220 kV transformer. A cross-trip scheme was triggered as a result of this tripping, which isolated the north region with excessive generation and left the rest of the system with voltage collapse. Consequently, the system faced a major blackout after cascading under-voltage/under-frequency tripping in the generation-deficit area and over-voltage/over-frequency tripping in the generation-excess area, which affected almost 75% of the country [65]*. Table 4 summarizes major cascading events and major blackouts that occurred globally from 2011 to 2018 [15]*.

The most severe major blackout in the U.S.-Canadian grid occurred on August 14, 2003 [66]*. It affected eight U.S. states, two Canadian provinces and at least 50 million people. Reports published on the blackout revealed the tripping of 400 transmission lines and 531 generators. Before the occurrence of the event, the system was operating normally. However, due to tripping of the Eastlake 5 generator, the Cleveland-Akron area was facing voltage stress conditions. The situation exacerbated the limited visibility of the ongoing situation due to maloperation of the Midwest ISO state estimator and real-time contingency analysis tools. The coincident tripping of three 345 kV transmission lines further aggravated the situation and the system faced cascaded tripping, which led to a major power blackout [66]*. With the beginning of the cascade, the frequency oscillations served as the medium for the blackout expansion over a wide area. Table 5 shows the total number of recorded power outages in the U.S.A. from 2008 to 2017 [67]*.

TABLE 5. Total number of recorded power outages in the U.S. from 2008 to 2017 [67]*.

Year	Number of Outages	Affected People (millions)
2008	2169	25.8
2009	2840	13.5
2010	3149	17.5
2011	3071	41.8
2012	2808	25.0
2013	3236	14.0
2014	3634	14.2
2015	3571	13.2
2016	3879	17.9
2017	3526	36.1

B. RQ2: WHAT ARE THE CURRENT METHODS USED FOR EVENT DETECTION IN POWER SYSTEMS?

The North American Electric Reliability Corporation (NERC) has published disturbance monitoring and reporting requirements [68]* wherein trigger thresholds are established for various disturbances. However, these thresholds are observed to be too conservative and some events may go undetected [69]. The existing work on event detection in power systems collected for this review is divided into four categories: Signal Processing based methods, Statistical Analysis based methods, Machine Learning/Deep Learning based methods, and Hybrid methods, which uses a combination of the other three.

1) SIGNAL PROCESSING BASED METHODS

Complexity and speed of operation are the two important features to be considered for an event detection algorithm. Shaw and Jenna proposed a simple and effective event detection and classification algorithm using wide area frequency measurement system [70]. Discrete Wavelet Transform (DWT) is used to remove noise from PMU data and Kalman filtering is used to estimate the ROCOF as well as phase angle difference for frequency measurements. Event detection and classification are carried out using estimated ROCOF and denoised frequency data.

Ma *et al.* presented a software tool, Grid Stability Awareness System, to monitor and analyse power system stability in real time using synchrophasor data [71]. The software suite provides monitoring tools for oscillation, voltage stability, transient instability, angle difference, and event detection. For event detection and analysis, the Matrix Pencil method, Prony method, and Hankel Total Least Square method are used. The monitoring tools are integrated into a framework to make them adaptable to system upgrades and user needs, and to give the operator enhanced situational awareness.

Kavasseri *et al.* demonstrated that the traces left by power system disturbances in a WAMS can be found in the energy function components [72]. By using a particle filter to estimate the internal states of a generator and combining these data with the voltage phasors obtained from PMU data, an energy function can be constructed whose specific components can be monitored to detect events.

Yao *et al.* developed a Mobile Distribution PMU, which consists of an Arduino data acquisition board for sampling of phasors, and an Android-based mobile unit for data processing [73]. After detection of an event based on ROCOF, fast load control is achieved using remotely-operated energy management circuit breakers, which provides frequency response.

Due to the complexity associated with using data from a large-scale power system for event detection, Ma *et al.* proposed a three-step-based graph partitioning algorithm for grouping of buses and then used a hierarchical event detection method based on spectral theory of multidimensional matrix with voltage magnitude as a basic variable [74].

Wiot proposed an adaptive transient monitoring algorithm using a least mean square estimation of filter coefficients [75]. The proposed solution overcomes the problems associated with least mean square Fourier filters when the incoming signal diverges from nominal value or has subharmonic components.

The rotational speed of electrical machine changes when an event occurs. The magnitude of change depends on the severity of event, which cannot be detected in case of a weak event. Chowdhury used the second difference of energy of rotational speed, which experiences a sudden change upon the occurrence of an event [76]. The authors also proposed a new index called the Sharpness Index, which is calculated for each generator and used to locate the event.

Sant *et al.* documented a method used by Texas Synchrophasor Network, which applies a Prony algorithm to PMU data to estimate amplitude, frequency, damping ratio, and phase angle [77]. The screening method employs seven orders of Linear Prediction Model, a window size of 10 seconds, and 1 second sliding step to detect events.

Zhao and Hu proposed a system control theory based numerical simulation approach for hybrid power systems [78]. A linear algorithm is used as a feedback controller whose input is system guard functions and output is step size. Based on this output step size, an appropriate step size is calculated for numerical simulation, which can effectively detect and locate events.

Nadkarni and Soman proposed a multivariate trend-filtering approach for extrapolation of measurement data obtained from PMUs [79]. The proposed method is used for line loading, and frequency event detection based on ROCOF trend.

A wavelet transform based feature extraction approach was proposed by Xu and Kezunovic for event detection and classification [80]. A best-basis algorithm is used to automatically select the most suitable and relevant wavelets for event analysis. Feature vectors are then composed by choosing significant coefficients.

A lab-scale synchorphasor model consisting of a synchronized clock and a PMU within a distribution feeder relay was presented by Sharieff *et al.* [81]. The PMU data were archived using openPDC and an algorithm was developed that used three methods: Min-Max method, Pencil Matrix method, and Fast Fourier Transform method for analysis of a moving window for possible events.

Currently, the performance of many PMU-based event detection algorithms is affected by the window size of data. To efficiently detect the start-time of an event and reduce false alarm rates, Cui *et al.* presented a dynamic programming-based swinging door trending event detection technique in [82] based on data compression using swinging door trending. The proposed method involves dividing data in intervals and using dynamic programming for solving the constituted optimization problems. Slope direction and predefined event rules are then used as a basis to merge adjacent intervals. Events are detected using a threshold. An event classification technique was also proposed considering the sudden frequency and voltage changes.

Singh and Fozdar proposed an approach based on DWT to detect and locate four types of events in real time for generator trip, load rejection, capacitor outage, and 3-phase short circuits [83]. Voltage and frequency signals obtained from WAMS are decomposed by applying a DWT. Change in energy during a disturbance is calculated using wavelet coefficients. A new index based on the energy of wavelet coefficients was proposed in this work for real-time detection of events.

Many of the signal processing algorithms used for PMU-based event detection use a moving Discrete Fourier Transform (DFT) or customized linear band pass filters whose performance is dependent on the selection of user-defined threshold. Callafon and Wells used signal processing with recursive estimation, which can automatically adjust the threshold for each PMU [84]. Later, a step-based realization algorithm quantifies the event based on its dynamic parameters. The algorithm was implemented in each PMU, providing a distributed solution and avoiding communication overhead.

Mei *et al.* proposed a Haar wavelet-based approach with a band pass filter using frequency measurements for dynamic event detection, which can be implemented in a PMU due to its simplicity [85]. With the occurrence of a subsequent event, the estimated post-event damping becomes a poor approximation of the envelope. The estimate of damping is also used to mark the end of event.

Not much attention has been given in literature to low voltage network data analysis. Major events usually occur in high voltage network, but their effects propagate downwards to the distribution system. System dynamics can be studied using data obtained at low voltage level. Vaz *et al.* presented a low voltage network event detection scheme using multiresolution through DWT to decompose the signals into time and frequency domains [86]. Events are detected and classified based on the extracted energy from wavelet detail coefficients. The parameters for wavelet decomposition, threshold and decision variables are optimized using a particle swarm optimization technique. The algorithm was validated using data from the Brazilian and Chilean grids.

A robust signal analysis-based event detection and characterization technique was presented by Negi *et al.* [87].

The event detection algorithm computes spectral kurtosis on sum of intrinsic mode functions and indicates an event by comparing maximum and root mean square of energy contents with the previous analysis segment. Event characterization is carried out based on statistical features of signals. The method was extended to use Nordic grid PMU data to ascertain physical phenomenon like active and reactive power disturbance.

Many event detection techniques reported in literature do not take into the consideration the presence of DER in the system and require high-resolution devices installed at all or most of the buses, which is not feasible in distribution systems. The work by Dutta *et al.* presented a μ-PMU event localization approach for distribution system considering the presence of DERs and mesh topology [88]. A sparse current injected-based distribution system state estimator was developed to estimate voltage phasors at all bused by utilizing μ-PMU data from generator buses. Changes in the state vector reflect network disturbances, which are further analyzed for event localization. A 13-node distribution system was simulated in the OPAL-RT real-time simulator to validate the system.

Shi *et al.* presented a scalable and computationally efficient event detection algorithm based on graph signal processing [89]. In the offline training mode, spatial and temporal correlation matrices are derived from vector autoregression processes, which are used to construct a graph Laplacian. In the online detection mode, the graph signals are converted to Laplacian spectral domain by applying a graph Fourier transform. Under normal condition, the DC component is dominant in the Laplacian spectral domain. In the case of occurrence of events, the high frequency components become prominent, which are used to detect events.

Konakalla and Callafon presented a signal processing approach for online event detection based on synchrophasor data [90]. A discrete time filter of phasors was estimated to create optimal filtered rate of change signals based on phasor data where no disturbance exists by formulating least square optimization. The resulting signals gave better variance than ROCOF. An event detection algorithm checks the number of times for which consecutive samples of filtered signals exceeded the variance bounds. Real-time μ-PMU data were used in Python running on a Raspberry Pi computer for practical illustration.

Meghwani *et al.* developed a synchrophasor data-based forecasting-aided state estimator (FASE) to detect power swing and faults using voltage and current phasors from a PMU [91]. As opposed to a linear state estimator, FASE can detect corrupt data in measurements and replace it with predicted data for correct identification of an event. FASE is essentially a Kalman filter that includes historical data for state estimation using a quadratic state transition model. The residuals yielded by the filtering are used for event identification.

An event detection technique based on an L-1 trend filter was proposed by Jadhav *et al.* [92]. An estimate of frequency is obtained with an L-1 trend filter using frequency data from a PMU. Then a moving window is used to calculate variance of frequency and compare average of the variance with a threshold for event detection. To detect time of inception of an event, an extended L-1 filter is used to estimate the spike component of frequency and detect inception time using the same process. The proposed method produces better results as compared to FIR and Kalman filters.

A multiple event analysis technique was proposed by Yadav *et al.* for event detection, temporal localization and classification using signal energy transformation of frequency measurements from a PMU [93]. For event detection and temporal localization, a Teager-Kaiser energy operator (TKEO) is applied to PMU frequency data, which gives prominent signal energy changes during an event and minor shifts during oscillations. It uses two samples past data, which give it significant advantage for time localization over other methods. TKEO provides better localization of events as compared to Δf and df/dt. For classification purposes, the existing feature-based methods make multiple event analysis complicated due to different combinations of events. An instance based 1NN time series classification using energy similarity measure is proposed using cross-TKEO to find similarities between time series data with reference to cross energy of query signals. The algorithm renders good performance even with intermittent sources in the network and is therefore suited for event monitoring in the presence of renewables. The method is capable of near real-time classification with a maximum detection delay of 18.6 ms, which was validated on both simulated and actual PMU data.

For reliable operation, most of the signal processing-based techniques discussed above, such as [70], [72], [83], [86], rely on data from multiple buses in the network, which involve communication costs. Moreover, the results depend highly on changes in the window size, since window size shapes the range of coefficient energy. Similarly, the requirement of a user-defined threshold also dictates the performance of many signal processing method [86], [90], [92]. The challenging task of setting a threshold for each PMU in the network due to the dependence of threshold on the quality and nature of PMU data limits the performance of these methods. Furthermore, DFT or filtering methods cannot analyze dynamic behavior of the power network using PMU data and demands a sufficient amount of sampling data.

2) STATISTICS BASED METHODS

PMUs are widely installed in geographically dispersed substations throughout modern power systems. Data are recorded and sent to control centers. With the advancement of synchrophasor technology, PMUs can now record data at a high rate, in the range 30-120 samples per second, which requires dedicated communication channels. Utilities are using dedicated communication networks for WAMS, but with the increased installation of PMU, the bandwidth requirements increase, which necessitates significant investment.

Liu *et al.* presented an event detection algorithm based on a local outlier factor, which employs an unequal-interval reduction method to reduce the size of PMU data on site and reconstruct the data in a control center for processing [94]. PCA is used for a similarity search between any two bus data and a local outlier factor provides means for event detection and localization. The proposed algorithm was tested on different cases from the Western Electricity Coordinating Council, South China Power System, and Guangdong Power System.

The synchrophasor data collected and coalesced by phasor data concentrators pose two problems: inconsistent data and management of massive volume of data. McCamish *et al.* presented a PMU data management and archival system that provides efficient data retrieval, and features an event detection algorithm based on a correlation matrix [95]. The proposed algorithm calculates correlation coefficients of parameters at different substations and detects an event when the coefficients deviate from one during a disturbance.

Chowdhury *et al.* considered the measurements recorded in a power system after a disturbance as a result of a random process, and applied a Gaussian Mixture Model to the frequency measurements obtained from generator buses to make them stationary [96]. In the case of an event, the stationarity is affected, which can be obtained from the change in the number of Gaussian components over a sliding data window.

Song and Kezunovic presented the idea that cascading events can be prevented by taking proper action in steady-state [97]. They proposed the computation of a vulnerability index and a margin index to evaluate system conditions. A network contribution factor, generation distribution factor, selected minimum load shedding, and load distribution factor are used to predict overload and undervoltage risks and take control actions.

Kantra *et al.* proposed statistical analysis to detect high impedance faults [98]. It applies a null-and-alternative hypothesis test to the gaussian distribution of the mean of PMU data samples obtained from utility substations to detect frequency deviation from a nominal value. The proposed approach used both simulated and real PMU data to demonstrate the efficacy.

Arefi and Chowdhury proposed a data-driven approach based on recurrence quantification analysis to calculate characteristic features from voltage, phase angle, and frequency data provided by a PMU [99]. A feature matrix consisting of a large number of feature vectors obtained for each disturbance. This matrix is then subjected to PCA for dimensionality reduction. An unsupervised K-means clustering method is then applied for identification of two types of events, short circuit faults and generator trips.

Ge *et al.* used a statistical processing technique based on PCA to measure data trends and look for abnormal system conditions in PMU data installed at the Illinois Institute of Technology [100]. The slope of the trend computed by PCA is used to identify a sudden change and mark the start of an event. A second order difference is calculated to mark the end of the event. The type of an event is determined by defining event detection rules based on event duration and percentage variation in voltage magnitude.

Gardner and Liu proposed a technique for detection and analysis of events using a high resolution global positioning system-synchronized noisy data drawn from a frequency monitoring network [101]. The proposed method forms error ellipses using frequency measurements and uses a Mahalanobis distance metric to compute an activity vector. This activity vector is monitored for triggering of event detection. The event triggering is not dependent on a fixed threshold. Rather, the statistical characteristics of the data define the thresholds because the Mahalanobis distance keeps changing with the variation in covariance of new data.

The work by Kundu and Pradhan demonstrated real-time event detection in a power system by calculating an impedance-based index from PMU data obtained from different locations within a network [102]. The network was divided into subsystems to reduce communication latency associated with WAMS. A variation in impedance is detected with the inception of a disturbance in the network and the disturbance is then classified as either a fault, a line trip or a load change.

Pandey *et al.* presented an ensemble technique to detect, classify, and localize events [103]. They developed a synchrophasor anomaly detection tool based on statistics and clustering techniques: Linear regression, Chebyshev, and Maximum Likelihood Estimation aided with Prony analysis. Density-based spatial clustering of applications with noise is employed for event detection, decision tree for event classification, and graph theory and statistical computation for event localization. The efficacy of the algorithm was verified using industrial data.

Performance of supervised learning techniques depends on the amount of training data available. Similarly, most of the existing unsupervised learning techniques also require prior knowledge of events. To address this issue, Li *et al.* presented an unsupervised learning technique for event detection based on a change-point-detection algorithm [104]. PCA is used to form clusters and extract features from PMU data. A two-stage filtering processing identifies the type of event from the number of clusters, and event severity is determined from the compactness of clusters.

Gajjar and Soman [105], and Lavand *et al.* [106] based their work on a statistical analysis technique called the Ellipsoid Method, which uses PCA and an error ellipsoid for detection of minor and major events in a power system. The idea is that every power system disturbance gives rise to electromagnetic oscillations in the network. These leave a distinctive pattern, which can be observed in frequency measurements. Events can be detected by comparing the volume of an error ellipsoid in the transformed variables with a threshold. The inception point of a major event can not be identified using this method. To tackle this, Gajjar and Soman used Kalman filtering to estimate df/dt and variance of df/dt over a moving window of one second to pinpoint the start of an event.

Lavand et al. employed a Hodrick-Prescott filter to capture the instance of occurrence of an event by estimating a spike component in addition to the trend component in the time series data caused by a disturbance. The Hodrick-Prescott filter proves to be more effective, since it provides a resolution of one sample due to reduced computational complexity.

To tackle the problem of handling a large amount of data from many PMUs in a system, a PCA-based dimensionality reduction approach was proposed Xie *et al.* [107]. After getting the linear basis from PCA in an offline mode, an online event detection algorithm uses pilot PMU data to predict system conditions for non-pilot PMUs and to detect events based on the prediction error between PCA-projected data and actual data. The algorithm was validated on both synthetic and actual PMU data.

A Frequency Disturbance Recorder (FDR) is a low-cost alternative to a PMU. FDRs record voltage magnitude, frequency, and phase angle at 10 samples per second at distribution voltage levels. Phillips and Overbye studied an approach for distribution event detection using voltage measurements from an FDR [108]. Data are first reconditioned by passing through a median filter to remove noise induced by the distribution level network. Pattern recognition is then used for event detection. The statistical features studied for analysis are the mean and standard deviation, which are observed to be insufficient for pattern recognition of event types.

Apart from event detection, event localization is also of critical importance. If the location of a generator trip, for example, is approximated, then UFLS can be used in that area to avoid overloading of tie lines. A two-phase statistical analysis approach based on the measurement of generator rotor frequency was developed by Rovnyak and Mei [109]. In the first phase, system buses are partitioned into groups and one generator is selected as a representative for each group. In the second phase, online event detection is carried out based on generator rotor frequency variance exceeding a certain threshold. The representative generator with the largest variance is used to locate the event.

Meier *et al.* introduced a disturbance detection approach based on a PMU-site clustering scheme [110]. Data streams from a PMU cluster comprised of four or five electrically-near and electrically-far PMUs are collected, which are compared pairwise to create a correlation vector. Pertinent statistical parameters are quantified using a Rayleigh distribution representation of the correlation vector, which are used for event detection. The statistical parameters are also used to devise a clustering scheme, which can provide an adequate level of monitoring while maintaining low computational costs. The scheme was validated using data from lightning strikes.

Foruzan *et al.* presented a real-time event detection technique called true sliding Detrended Fluctuation Analysis (DFA) [111]. DFA has been used for capturing transients in high resolution data by highlighting certain variations in PMU measurements. This technique uses a sliding window for calculating DFA to produce an "F" value, which is an indicator for the transient occurrence, for each part of the data. The algorithm was run on real PMU data.

Parallel detrended fluctuation analysis was used by Khan *et al.* [112] for event detection in a massive PMU data. The process involves detrending the data by calculating the RMS of the fluctuation in PMU data over a window of one second and comparing the F value with a threshold to detect an event. Parallel DFA uses MapReduce cluster computing, which is a parallel programming model, to apply DFA on a large volume of PMU data. The algorithm was implemented within a Hadoop MapReduce framework.

Limited work is reported in literature for detection of multiple events in power systems. Existing work is well suited for small-scale systems but does not perform well for large-scale systems. Song et al. and Wang et al. presented detection, recognition, and localization algorithms for multiple events. A cluster-based sparse coding algorithm was proposed by Song *et al.* [113] for large scale power systems. The idea, based on the hypothesis that buses react in the form of clusters to different type of disturbances irrespective of the type of fault, was verified by experiments. The paper also verified that within a cluster, the reaction to multiple events can be estimated as a linear combination of constituent reactions to each event. The numbers of clusters are formed based on the correlation of frequency signals from buses. The algorithm is able to solve the challenging task of distinguishing frequency oscillations from line loss. Performance of the algorithm was demonstrated on simulated data from the Northeast Power Coordinating Council. Wang *et al.* [114] presented a nonnegative sparse event unmixing method, which was one of the first multiple events analysis methods. It uses distribution-level frequency data for event unmixing and considers multiple events as a linear combination of constituent events. In the linear mixing, the overcomplete dictionary consists of single event signals called "root event patterns" learned from the training and temporal information. To detect the time of event occurrence, the "root patterns" are extended to a series of time-shifted versions, giving a combination of patterns with same shape but different starting times. The overcomplete dictionary estimates a coefficient vector, which indicates the weight of each single event and is used for event detection. The accuracy of detecting cascading events with their starting time was evaluated using both simulated and actual data. The algorithm by Song et al. was showed to have outperformed the algorithm by Wang et al..

Yang *et al.* used a high-dimensional factor model for multiple event detection [115]. Their method uses raw PMU data and random matrix theory to explore temporal correlation between adjacent samples from the same PMU and spatial correlation between different PMUs installed at different locations. The spatial-temporal information is extracted in the form of factors that represent disturbances or faults, and residuals that represent normal fluctuations.

Rafferty *et al.* developed a multiple event detection and classification method for islanding and generation-load mismatch events [116]. A moving window PCA technique provides adaptable event detection thresholds and tackle the time varying nature of power systems. PCA is applied to frequency data to construct two statistics: T^2 quantifies variations of recorded data, and Q quantifies the difference between observations and lower-dimensional PCA representations. The proposed moving window PCA method learns by taking in new normal data samples in the data window and updates the statistics. An event is detected when the statistics exceeded their confidence limits. The proposed method, however, is unable to disaggregate multiple load-loss or generator-loss events, but can only detect and classify the ultimate event, which is due to the reliance on only frequency measurements.

Existing event detection techniques are not capable of detecting both fast and slow events using the same algorithm or to identify multiple fast events during an ongoing slow event. To overcome this difficulty, Iqbal and Jain proposed a Weibull distribution-based approach to identify an event, its time of inception, location, and severity using only frequency measurements from PMU data [117]. The method calculates a parameter called "variability" to determine event characteristics and uses a dual window concept. The underlying idea for using two independent windows was that a small window is more sensitive to fast events whereas a big window can accurately identify slow events. The method is unsusceptible to communication error and delays of up to 90 ms.

Ardakanian *et al.* based their work on the Inverse Power Flow problem, which infers an admittance matrix from PMU data [118]. Convex relaxation and matrix partitioning approaches handle the low-rank structure of PMU data. The proposed algorithm detects and locates events based on changes in the admittance matrix.

Chen *et al.* proposed a scatter plot-based event detection and classification approach [119]. The idea is to use PCA for dimensionality reduction during training, then project PMU measurement on a subspace derived from the pre-event data and use scatter plots for online detection and classification of events. An event is detected if data projection falls outside the subspace. After detection, the event is classified by searching a database of scatter topologies to match the current topology with an existing one. The proposed algorithm was verified for non-oscillatory and oscillatory events by using PMU data from the simulation of a 23-bus system in PSS/E.

A PCA-based event detection, recognition, and localization technique was proposed by Xu and Overbye [120]. PCA is used to investigate system dynamic behavior and highlight dominating buses post-disturbance. A visualization technique provides effective presentation of the extracted system information. Application of the proposed algorithm was illustrated on simulated PMU data. To reduce the heavy computation burden with an increase in system size, a partitional PCA-based method is used wherein PCA-analysis is applied on regional data in parallel.

To address the challenging problem of event detection in the presence of oscillations, a spatial-temporal data analysis approach was developed by Zhu and Hill [121]. Based on the inherent spatial-temporal correlations between different buses induced by an event, this method characterizes spatial temporal nearest neighbors of time series from multiple buses. The proposed method uses binary decisions for event detection, which require manual threshold tuning for application in different systems. The method is susceptible to the adverse effects of missing PMU data.

A feature extraction and pattern recognition-based approach was developed by Patil *et al.* for event detection and classification [122]. The authors used a k-nearest neighbors supervised learning algorithm and an Euclidean distance to extract features and perform pattern recognition of voltage measurements from PMU data. The proposed method was validated on simulated data from the IEEE 14-bus system.

Similar to signal processing techniques, many of the statistical analysis based methods also rely on data from multiple buses in the network [95], [96], [98], [102], [110], [121] entailing communication cost. The performance of many of these techniques is also dependent on user-defined threshold [105], [106], [109], [112], [116], [121]. To reduce computational complexity, statistical indices such as correlation, variance, mean, maximum, and minimum are calculated over a window. These values do not necessarily remain constant and may undergo variation even during same event, which makes it difficult to define a threshold.

3) MACHINE LEARNING/DEEP LEARNING BASED METHODS

With the evolution of advance computational tools and machine learning techniques, Deep Learning has found its applications in power systems. Convolution Neural Networks (CNN), an advance image recognition tool, was employed by Wang *et al.* for event detection and classification of generation loss, load loss, and ramping events in power systems [123]. The abrupt change in frequency caused by generation-load scheduling response is referred to as a ramping event. ROCOF and relative phase angle (RAS) signals are converted to images and used as inputs to a two-layer CNN model. Frequency is not an ideal indicator of power system disturbances since it cannot differentiate a ramping event from an actual event. Therefore, RAS is used as another indicator in this model. Finally, a classifier fusion is used to detect events based on the ROCOF and RAS results. Comparing results of the proposed model with a conventional ROCOF-based event detection algorithm and a frequency-only CNN model showed improvement in accuracy by over 48%. The model was validated on FDR data from the the U.S. Eastern Interconnection for two types of events: generator trips and load disconnections.

Performance of model-based event detection techniques, which rely on a dynamic model of the system to evaluate consistency between actual system behavior and expected behavior, is limited by the nonlinear and hard-to-specify dynamics of the system. Similarly, high dimensionality and uncertainty of the system also hinder the reliability of these methods. Zhou *et al.* proposed a data-driven method called Hidden Structure Semi-Supervised Machine, which uses labeled, partly labeled, and unlabeled data for event detection in distribution networks using μ-PMU data [124]. The non-convexity introduced by the inclusion of partial information is solved by a newly developed global optimization algorithm called Parametric Dual Optimization Procedure.

Aligholian *et al.* used the concept of generative adversarial networks to develop an unsupervised event detection technique [125]. The concept is to train deep neural networks, LSTM in this case, to learn normal trends and mark any pattern deviation from the normal behavior as an event. The algorithm uses voltage angle, current angle, and power factor from μ-PMUs for each of the three phases to train nine generative adversarial network models. The work also proposed a two-step unsupervised clustering method for event categorization. Events are categorized based on origin in the first step. In the second step, maximum correlation is used as a rolling similarity measure to compare any two events and formulate a clustering model within pre-defined categories based on mixed-integer linear programming. The clustering algorithm can identify new event clusters in an ongoing process. Investigation of events in each cluster is carried out using statistical analysis to unmask their implications and significance for utility operators.

Li *et al.* proposed a feature selection-based approach to identify event patterns and then use hybrid supervised learning where the input data were fed to different machine learning models for learning [126]. To improve the performance of this machine learning model with limited labeled data, a computational efficient method was proposed. The method employs semi-supervised learning to use unlabeled data and add strategic event data with the help of active learning via simulation.

A two-layer CNN approach was proposed by Li and Wang for detection of overlapping successive events [127]. The model is trained on dominant eigenvalues of the state matrix, which are robust to topology changes and pre-event conditions as compared to time-series training. A prediction-subtraction approach reduces the effect of first events and efficiently detect successive events.

A prototype study of dynamic event classification for the New York state power grid was presented by Mukherjee *et al.* [128]. A full-scale transmission model of the Eastern Interconnection was simulated in PSS/E for generation of simulation data. LSTM is used for dynamic event classification using three different scenarios: generation loss, load loss, and transmission line loss.

Zhou *etal.* discussed the degraded performance of existing data-driven approaches that stem from the heterogeneity of μ-PMU data containing various events. They proposed a data-driven approach, called "ensembles of bundle classifiers" [129]. Instead of building a single classifier using a classic machine learning approach, the proposed method constructs an ensemble of bundled classifiers using a variation of SVM, and trains each with a small slot of μ-PMU data containing an event. The bundle classifiers are then combined, and the final event detection decision is made based on the most confident classifier.

Al Karim *et al.* developed a feature selection-based machine learning approach to detect events within a microgrid using generator data for the purpose of self-restoration after a fault [130]. The proposed distributed approach, based on an ensemble of bagged decision trees with an added boosting mechanism, was installed at each generator. In the data preparation stage, simulated generator fault data are used to extract dynamic features and form a database. After training the model, the authors evaluated the method using random datasets.

The 3120-bus Polish system was simulated by Ren *et al.* for four types of faults in different zones [131]. Frequency data obtained from synchronous generators provide input to a CNN model. Three types of data encoding are used: time-series stacking, frequency domain stacking using wavelet decomposition, and polar coordinate system-based Gramian Angular Field (GAF) stacking, to generate images for pattern recognition and extraction by CNN. The CNN model configuration is optimized by performing hyperparameter searching. The model accurately classifies and localizes single bus faults and line faults. Both polar coordinate system-based GAF stacking and wavelet decomposition-based frequency domain stacking give better results than time-domain stacking, with GAF stacking superior among the former two.

A deep neural network-based technique was developed by Shi *et al.* for real-time identification and classification of events using real-world PMU data [132]. A CNN provided as a baseline model for the developed approach. Since CNN exploits feature localities in data, which can be impeded by random PMU data, a graph signal processing-based data sorting algorithm places PMUs with highly correlated measurements near each other to reduce variance between PMUs. These sorted PMU data are provided to the CNN model to convert it into a hidden representation. Higher accuracy is achieved by using information loading-based regularization, which controls information compression and modifies mutual information between input features and the representations.

The work by Kesici *et al.* uses a sliding window-based CNN model for online identification of different stages of a power system: pre-fault, fault inception, fault duration, fault clearance, and post-fault [133]. The method uses time-series PMU data of voltage magnitudes as input to the CNN model without converting it to images to avoid loss of information. The model trains on data generated from the simulation of a three-phase fault. The model was validated for two cases with and without noisy data. In the first case, voltage measurements were taken from all buses, whereas in the second case, voltage data were taken from optimally-located PMU buses.

The problem with these supervised machine learning techniques is that their performance is highly dependent on the amount of labeled training data. Some events might not be reflected in PMU data or may go missing in utility event logs. Similarly, the improper labelling of data might introduce bias in the machine learning model. The accuracy and efficacy of these models is negatively affected by the inadequate and improper selection of training data. The limited installation of PMUs restricting the number of recorded events also contribute to this issue. Finally, these algorithms require sophisticated processing tools in control centers.

4) HYBRID METHODS

A prediction-based event detection approach was presented by Wang *et al.* [134]. A recurrent neural network, LSTM-model predicts system states and the prediction error is tracked in real-time. Under normal operating conditions, the prediction error follows a normal distribution. Upon occurrence of a system disturbance, the prediction error changes its distribution. A cumulative sum (CUSUM)-based quickest change detection scheme is then used to detect the abrupt change in error distribution. To tackle the problem of unknown statistics of prediction error before an event, a generalized likelihood ration test is incorporated to CUSUM (GLRT-CUSUM). This brings computational complexity since GLRT-CUSUM uses all past observations at each step, which makes it impractical for real-time implementation. Finally, a Rao test is applied to simplify the complexity.

Liu *et al.* proposed a real-time event identification technique based on advance machine learning algorithms by considering event time and location [135]. The algorithm uses ROCOF for event time determination and wave arrival time difference-based triangulation for location determination. It uses the fact that disturbances spread through the system as a function of time and space. For efficient identification of an event, two-dimensional orthogonal locality preserving projection (2D-OLPP) is used for feature extraction instead of one dimensional PCA. Based on these features, random undersampling boosted trees are used for event identification, which can alleviate the issue of sample imbalance and has a higher recall rate and accuracy. 2D-OLLP is more efficient and can extract features from 2D as opposed to one-dimensional analysis methods.

A supervisory framework for real-time event analysis based on DWT was discussed by Singh and Fozdar using voltage and frequency measurements from PMU data [136]. DWT decomposes the input signals. Occurrence of event is detected based on the energy of wavelet coefficients. A new index was developed that compares the wavelet energy of the current window with the mean energy of the preceding 10 windows for event detection. After detection of event, the event localization algorithm locates the event by monitoring energy of the wavelet coefficients from the voltage magnitudes. Event classification is carried out by training a multi-class SVM: Dendrogram-based SVM on extracted features from wavelet coefficients.

Dong *et al.* applied Dynamic-inner Canonical Correlation Analysis to time-series PMU data to extract latent dynamic variables [137]. The variables were extracted with a descending predictability, which ensures the extraction of oscillating components that have a high predictability. A DFT was then applied to the latent variables to detect and locate low frequency oscillations.

Since PMU data always contain noise and missing measurements owing to communication problems between PMUs and phasor data concentrators, Han *et al.* proposed a data-driven technique that is robust to significant noise levels in PMU data by combining random matrix theory with Kalman filtering [138]. A dynamic Kalman filter conditions PMU data and reduce measurement noise. Under the framework of random matrix theory, Mean Spectral Radius is used for event indication.

A rather elegant approach was proposed by Okumus and Nuroglu where frequency data from WAMS devices FDR are initially passed through a median filter to remove noise [139]. The filtered samples are then averaged over a second and a simple threshold-based approach is used to detect events when frequency variations exceed a certain threshold. A correlation method identifies the event type.

Sohn *et al.* presented an event detection system using a combination of statistical algorithms, residual modeling, short-term Fourier transform, and linear regression using phase angle difference data collected from PMUs installed in the Texas bulk power system [143]. The statistical methods used are mean, variance and correlation, whereas the residual modeling used a normalized least mean square based-adaptive prediction algorithm. Actual events from the Texas electric grid were used to demonstrate the performance of the proposed system.

Souto *et al.* carried out a comparative analysis of various signal analysis-based and knowledge-based event detection methods using real-world PMU data with and without noise [142]. The signal analysis-based detection methods include Fast Fourier Transform (FFT), Yule-Walker Spectral method, Mix-Max difference, and Difference and approximate derivative, whereas knowledge-based event detection techniques include PCA and SVM. The analysis demonstrates that PCA gives superior results in the absence of noise whereas SVM performs well in the presence of noise.

The amount of PMU-recorded data to be stored for system studies can be reduced by devising methods to trigger the storage of such data with the occurrence of events. Dawidowski *et al.* proposed and carried out performance analysis of three event detection algorithms based on linear auto encoders, deep auto encoders, and FFT [141]. Linear and deep auto encoders are machine learning algorithms that are trained to reconstruct the input signal. In the case of an event, the reconstructed normal signal differs from the actual abnormal signal. In the FFT-based algorithm, the reconstructed signal differentiates from the abnormal signal due to harmonic contents engendered by the disturbance. Testing on both synthetic and actual data proved the FFT-based reconstruction to be superior among the three.

Senaratne *et al.* presented an unsupervised event detection method that uses a spatio-temporal frequency domain analysis of streaming PMU data [140]. A convolutive dictionary

TABLE 6. A summary of the most commonly used event detection techniques reported in literature.

Reference	Event Detection Category	Applied Technique
[70], [80], [83], [85], [86], [136]	Signal Processing	Wavelet Transform
[70], [72], [75], [79], [90]–[92], [138], [139]		Filtering
[81], [89], [140], [141]		Fourier Transform
[94], [100], [104]–[107], [116], [120], [142]	Statistical Analysis	PCA
[95], [99], [103], [110], [113], [115], [121]		Clustering and Correlation
[123], [127], [131]–[133]	Machine Learning/Deep Learning	CNN
[125], [128], [134]		LSTM

model is generated to capture the event signature from different PMUs obtained by using short term Fourier transform during an event. The magnitude of event signatures varies across PMUs depending on the distance from the event location. Using this convolutive dictionary, a composite binary hypothesis testing is formulated for unsupervised event detection employing a generalized likelihood ratio test.

Table 6 presents a summary of the most commonly used techniques in the ongoing research on power system event detection.

C. RQ3: WHAT ARE THE MODERN DISPATCHABLE SOURCES OF PRIMARY FREQUENCY RESPONSE IN POWER SYSTEMS?

PFR, or frequency response, as defined by NERC [144] is the automatic and immediate response of resources and load to arrest and stabilize changes in frequency within seconds by local sensing without any centralized system involved. Frequency response is provided by governor response, load response, and any resource that reacts instantaneously based on local measurements. Secondary frequency response is a slower action to correct the supply-demand unbalance and relieve PFR controllers. Secondary control action might not be able to sufficiently compensate the unbalance in case of severe events, in which case, available power reserve is used to provide additional control action termed as tertiary response. It involves using standby power sources, economic dispatch, and dispatching generators to supply local load and/or affect interchange. Figure 5 shows a frequency response schemed that presents different time scales associated with each response [17]*.

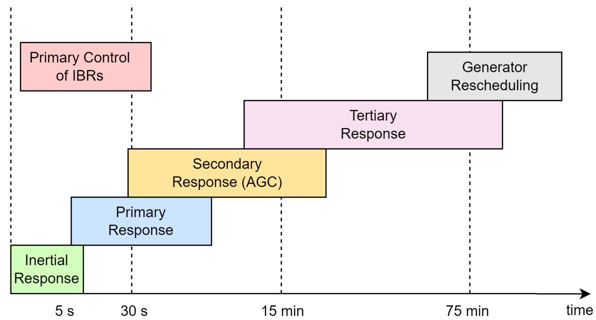

FIGURE 5. Typical timescales of frequency response provided by conventional as well as IBRs [17]*.

1) DISTRIBUTED ENERGY RESOURCES

DER are customer-owned distributed generation, loads, and energy storage systems that are grid-enabled. Various approaches are reported in literature to control DER operation to enable them to participate in inertial and PFR [145]–[147]. Active integration of DERs into distribution systems is the aim of many of these approaches to ensure an economic and secure system operation.

a: SOLAR PV

There is rising interest and concern among utilities and system operators about the ability of RESs to provide PFR. Distributed generation stations, including Photovoltaic (PV), are increasingly becoming subject to the technical requirements imposed by the grid reliability requirements. Among these requirements, frequency response and active power control are critically important. Figure 6 shows the deterioration of the U.S Eastern Interconnection (EI) frequency response to a 4.5 GW generator loss under different levels of PV penetration [148]*. With the growth in PV installed capacity in a small isolated system, the risk of UFLS following an infeed loss increases [149]*. The potential of a centralized storage system is investigated by Cardozo *et al.* to improve frequency response behavior of the system and reduce the risk of UFLS to pave the path for growing PV installation [150]. The study showed promising results in terms of economic dispatch, lower UFLS risk and reduced curtailment, but also manifested some adverse effects including displacement of conventional plants leading to lower inertia.

Many frequency control schemes are described in literature for PVs coupled with internal Energy Storage Systems (ESS). In cases of PV without ESS, the task of frequency control is shifted to the PV generator since in such systems, DC link capacitors are usually characterized by fast charging rates. Limited work is reported in literature on active power control of PV without internal ESS. A detailed PV model for a two-stage grid-connected PV system without internal ESS is introduced by Nanou *et al.* with a suitable control scheme for PFR [151].

To participate in frequency response, a generator must carry some reserve power capacity to release when required by the controls. Since the output of the solar PV is governed by maximum power-point tracking, to enable it to provide PFR,

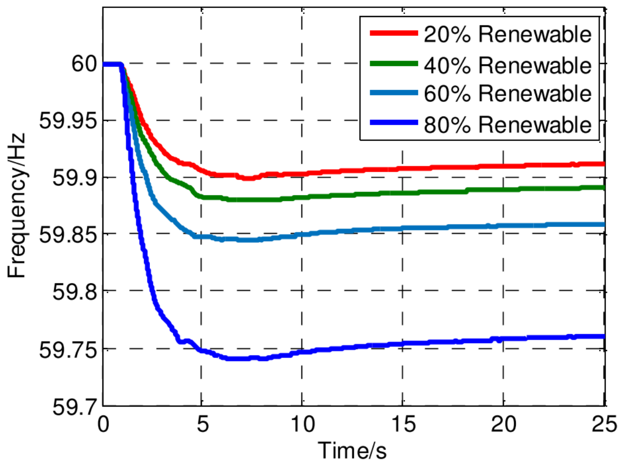

FIGURE 6. EI frequency response change under different PV scenario [148]*.

the PV array may be operated at 10% less than the maximum power point to keep the remaining 10% as reserve [152]. Frequency-watt control, which is analogous to droop control in conventional generators, is a fast frequency control scheme in inverters to control output based on frequency deviation according to a frequency-watt droop curve. PV inverters today are typically operated using maximum power-point tracking and so cannot participate in frequency control without dedicated reserve power headroom. Revision of IEEE 1547 is expected to standardize frequency-watt control [153].

The dynamics of a power system with frequency-watt control-enabled PV inverters were studied by Pattabiraman *et al.* using small-signal stability analysis [153]. Multi-port autonomous reconfigurable solar (MARS) is a new topology for integrated development of PV, ESS, and HVDC links. It is a three phase system that combines PV and ESS via power electronics and can connect to a high voltage AC grid and HVDC. A model-based predictive control scheme for MARS to provide frequency support to grid is proposed by Marthi *et al.* [154]. The proposed control technique is based on a synchronverter-based algorithm. A method known as "communication enabled synthetic inertia" was developed by Concepcion *et al.* for obtaining PFR from PV plants by enabling them to emulate synchronous inertia using communication media to relay global system frequency information to all PV plants [155]. The proposed scheme takes into consideration issues related to communication.

b: ELECTRIC VEHICLES

Recently, there has been an increasingly ambitious goal for deployment of EV technology as a significant element of demand response, driven by the decarbonisation of the transport sector. Inherent storage capabilities and fast power control have enabled EVs to be regarded as a flexible load and a viable source of frequency response. Vehicle-to-Grid capabilities of EVs could enable them to provide ancillary services by injecting power into a distribution network when needed. Studies forecast that annual EV production may exceed 100 million by 2050 [156]*, [157]*.

Numerous studies have been carried out to analyze the impacts of EV penetration on flexibility and frequency response behavior of power systems [158]–[160]. Mu *et al.* used statistical analysis to estimate EV charging load and assess its impact on PFR in the Great Britain power system under two control strategies: energy discharge and load disconnection [159]. Carrión *et al.* proposed a unit commitment problem and investigated the participation of plug-in EV (PEV) in energy, capacity and PFR markets in an isolated power system with high levels of RESs [160]. The proposed model took several factors into consideration such as uncertain demand, intermittent nature of RESs, and N-1 generator contingency. Numerical results showed a reduction in operating cost and cycling of conventional power plants, and indicated economic benefits for PEVs. The contribution of PEVs to PFR is affected by several factors such as battery charger topology and level of PEV deployment. An aggregate model of PEVs was proposed by Izadkhast *et al.*, introducing a participation factor to determine availability for PFR based on stage of charge (SOC), charging mode, and drivetrain power constraints [161].

Literature is available on the use of EVs as virtual power plants [162], [163]. Alhelou and Golshan proposed a four-level hierarchical control method for PEVs to participate in PFR [162]. The idea is to communicate individual EV information such as initial SOC, departure time, and required SOC to an aggregator to calculate the share of each EV in the primary reserve requested by a transmission system operator. EVs were grouped into four categories. Alhelou *et al.* grouped EVs into three categories and proposed a three-level control scheme to determine primary reserve based on EV information such as SOC, arrival time, and departure time [163]. Datta *et al.* presented a method based on controlled charging/discharging of EV in accordance with the droop setting to prioritize stability of a microgrid over battery life [164].

c: BATTERY ENERGY STORAGE SYSTEMS

Increasing interest in Battery Energy Storage Systems (BESS) is driven by the ever growing installation of RESs. Due to the rapid response capability of BESS, frequency response is one of its most widely used applications. However, the inadequate size and location of BESS may have adverse effects on its performance and cost. Ramírez *et al.* proposed an approach for determining size and location of BESS in an isolated grid [165]. Location is determined based on the transmission bus with larger frequency deviation under the most acute generation contingency. A bat optimization algorithm, which is a swarm optimization technique inspired by the echolocation behavior of bats, was used to solve the sizing problem expressed as a constrained optimization problem. Droop control gain and BESS energy are formulated as the two parameters to be optimized. Knap *et al.* presented a method for estimating the size of BESS based on the amount of target energy and power [166]. It requires prior knowledge of system inertia and droop characteristics. After deciding a target value of power unbalance and ROCOF, target inertia constant and power/frequency are calculated to estimate size of BESS.

Many control strategies have been developed for BESS such as model predictive control-based fast frequency control [167], an optimized control model [168], coordinated control strategy with high proportion of wind power [169], and two-layer optimal robust control [170], to mitigate the impact cause by high penetration of RESs.

BESS can not only supply inertial response and PFR but can also render damping support for the oscillations injected in the system by inverter-based generators, which were previously mitigated by static synchronous compensators. Similarly, BESS can also help reduce the cost of electricity owing to its charging/discharging characteristic as it can be charged during low demand periods and discharged during high demand periods [169]. A two-layer feedback control strategy was proposed by Moeini *et al.* for improving frequency response of BESS during disturbance [170]. The first layer comprises a conventional droop slope in addition to an intelligent zero crossing detection unit, with a multi-band power system stabilizer making up the second layer.

Choi *et al.* presented a control scheme for enabling BESS to provide inertia and PFR in the South Korean grid, taking into consideration several factors such as optimizing SOC to prolong the life of BESS, enhancing inertia response during transients, and improving PFR [50]. The efficacy of the proposed scheme to improve frequency response was demonstrated by implementing it in a 376 MW BESS. Figure 7 shows the comparison of frequency response from a 376 MW BESS and a thermal unit with the same amount of reserve power, following a loss of 1.4 GW generation. The replacement of thermal generator with BESS showed an increase of 0.007 Hz/s and 0.028 Hz in ROCOF and frequency nadir, respectively.

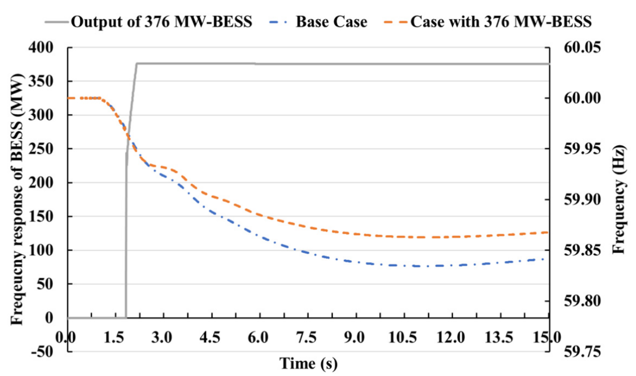

FIGURE 7. Comparison of frequency stability with and without BESS [50].

A simulation analysis of BESS for PFR using a system frequency response model was conducted by Moon *et al.* in the presence of gas, hydro, and steam turbines to reflect the South Korean power system [171]. The study proved superior performance of BESS over conventional generators in terms of response time and dynamic stability, especially within a weak grid.

Figure 8 shows PFR diagram of a BESS equipped power system. P_{g_ref} is secondary frequency regulation amount, K_G and K_{BESS} are coefficients of the unit regulated power of conventional generator and BESS respectively, $G_g(s)$ and $G_b(s)$ are transfer functions of conventional unit and BESS respectively, ΔP_L is the variation in load power, and P_{act}^{RES} and P_{sched}^{RES} are actual output and planned output of RES, respectively. As evident from the figure, integration of additional BESS and RESs will complicate the system, and resultantly increase the required reserve capacity. The economic benefits of conventional unit and operation of BESS will be adversely affected if the reserve capacity is not fully used [172]*.

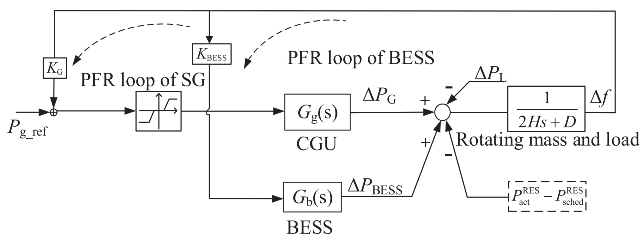

FIGURE 8. PFR scheme of power system with BESS [172]*.

In December 2012, a 1 MW, 250 kWh BESS was installed in Hawaii under the partnership of the Hawaii Natural Energy Institute and the Hawaii Electric Light Company to mitigate frequency variations caused by the high level of RESs in the energy mix of Hawaii. Stein *et al.* presented the results of experiments conducted on the BESS system aimed at investigating trade off between grid service and BESS cycling under different control parameter settings [173]. Certain parameters were shown to produce better grid service with reduced BESS cycling.

Deployment of BESS with proper control strategies has also been investigated by researchers to improve frequency nadir, ROCOF, and steady-state frequency in the presence of PV; results were promising [174]. Hu *et al.* conducted a detailed analysis of BESS performance in terms of SOC, internal resistance, terminal voltage changes, and current while providing PFR and enhance frequency response [175]. Many of the current grid-connected converters, including the standard BESS models developed by the Western Electricity Coordinating Council, are modeled as current sources assuming a constant terminal voltage. Sharma and Sankar proposed a positive sequence BESS model as a voltage source for transient stability studies equipped with independent control of phase voltages [176].

2) DIRECT LOAD CONTROL

With the ever growing needs of RESs, if the demand for ancillary services is only met by the generation side, the efficiency of the system and the potential for large-scale RESs integration will be negatively affected. Therefore, significant attention has recently been given to analyze the benefit of demand response to meet PFR requirements [177], [178]. Secondary control, however, may be difficult to get by Direct Load Control (DLC), which requires communication of an Automatic Generation Control signal to all participating loads. A demand side inertia quantification based on previous event information for the Great Britain power system indicated an average 20% of total system inertia could be provided by DLC [179].

Thermostatically controlled loads (TCLs) such as air-conditioners, refrigerators, and heat pumps have a heating/cooling control device to modulate power for adjusting temperature. The temperature dead-band of TCLs may be adjusted as a function of frequency. TCLs have recently attracted considerable attention for DLC frequency control due to their capability to modulate power consumption.

Several control methods have been developed to enable refrigerators to provide PFR [180], [181]. Borsche *et al.* developed an algorithm for switching of appliances by adjusting duty cycle rather than temperature limits to get a faster response while avoiding synchronization of participating loads [180]. Wu *et al.* developed a dynamically controlled refrigerator model and integrated it in the Great Britain power system to prove the provision of fast FPR without affecting normal operation of refrigerators while maintaining load diversity [181]. The aggregated power consumption of geographically dispersed refrigerators was controlled without real-time communication using local frequency and its rate of change in [182].

The on/off control concept of TCLs cannot be applied to many other kind of loads. For these, the concept of the Grid-Enabled Load (GEL) comes in to play. The combination of a non-critical load that can withstand a wide change in supply voltage/frequency for short periods, a power electronic interface, and communication capabilities can be considered as GEL. The decoupling acquired by the power electronic interface allows for a short term power reserve from such loads by controlling frequency for static loads, or voltage for rotating loads. A study for effective contribution of GELs to fast frequency response in Great Britain was conducted by Chakravorty *et al.* [45]. The study revealed the short-term power reserve from GELs to be greater than the spinning reserve available in the system, which justifies tolerable frequency deviation and ROCOF after loss of a large infeed. An improved optimal load control scheme was presented by Delavari and Kamwa using a systematic gain tuning method to ensure improvement in frequency nadir, steady-state error, and time response of controllable load [40].

Smart meters are widely installed in many power systems across the world and soon are going to have the ability to relay DLC signals, as revealed by recent consultations in the U.K. [183]. The maximum communication delay for UFLS as specified by IEEE standard 1646 is 10 ms [184]*. However, DLC may not prove as a viable solution for PFR unless communication delay can be reduced. Samarakoon *et al.* presented a smart load control scheme based on load grouping using local frequency measurements to avoid communication delay [183]. Samarakoon and Ekanayake investigated a selective load blocking scheme based on local smart meters for supporting PFR to avoid communication overhead and latency associated with centralized control [46]. Segregation of domestic load was carried out based on criticality and blocking was implemented as a function of frequency drop. A demonstration rig comprised of a smart meter and communication-enable smart socket was developed by Vijayananda *et al.* for implementation of a load control scheme to provide PFR [185].

Liu *et al.* investigated the potential of LED lighting to contribute to ancillary services and proposed a decentralized control scheme based on frequency deviation [47]. Although LED lighting do not behave like TCLs, they can provide better flexibility with minimal effect on consumers due to their fast response. Interruptible loads have already been in the spotlight for secondary frequency control. Their potential for PFR is still in area of research. The operation of interruptible loads for PFR would have to be autonomous using local frequency information. Bhana and Overbye analyzed minimum cost of interruptible loads to guarantee acceptable PFR of a system [186].

3) WIND TURBINE GENERATORS

The installation of wind turbine generators and their share in energy portfolios across the world continue to grow. Global wind power installations in 2020 achieved an annual growth rate of 53%. By the end of 2020, the total installed wind capacity in the U.S. was 122 GW [187]*. Increased penetration of wind generation introduces new challenges for operation and control of the system and affects PFC. A recent study found that, as compared to governor action, the increasing level of RESs engendering reduction in inertia is not going to affect frequency response [188]. However, the fast frequency response from controlled inertia of WTs will avoid the UFLS in the system. The study also illustrated that these responses are several times more beneficial than governor action in synchronous-based system.

Fixed-speed wind turbines (WT) do not inherently reduce system inertia due to their electromechanical characteristics. Variable-speed WT (VSWT), however, cause a reduction in the system inertia because their rotating mass is decoupled from the grid. Therefore, recently-designed VSWTs are equipped with inertial and droop controllers to emulate inertia and contribute to PFR. Muljadi *et al.* analyzed the theory, operating principles, and required modification for inertial and PFR in fixed-speed and variable-speed WTs [189].

Many of the existing studies aimed at using WT auxiliary controls to achieve PFR. A limited amount of work has focused on the modelling of wind power frequency response. Dai *et al.* proposed an aggregated multi-machine wind PFR model to demonstrate PFR characteristics with different control parameters and operation states [190]. The dynamic simulation of WTs to analyze impacts on dynamic performance of large power systems is a challenge, which has engaged researchers for the past decade. A VSWT-based dynamic model of a Wind Power Plant (WPP) was developed by Ghosh *et al.* by representing WTGs as input-output based aggregated models to study the linearized dynamics of a large power system for a set of inputs such as wind speed and network frequency [191]. A Balance Truncation-based model order reduction predicts the output of a WPP with changes in the inputs to enable the WF to take an action based on the variation in the inputs.

A fuzzy-logic based controller was proposed by Zhang *et al.* for providing bidirectional real power using various signals such as frequency deviation and ROCOF to improve PFR of WFs with energy storage [192]. More power extraction and less wear and tear may necessitate a large deadband. However, it may affect the capability of WT to provide inertia when required. A theoretical analysis was carried out by Zhang *et al.* to find the safe limits of a deadband to get adequate frequency response and to propose a switching mode for WTGs using the idea of "region of safety" [193].

Many recent works have focused on enhancing the stability and robustness of Doubly-fed Induction Generator (DFIG), which are extensively used in WPPs. A rotor-side controller was employed by Chau *et al.* to develop a control scheme for improving PFR and low frequency oscillation damping of DFIGs [194]. The ability of VSWTs equipped with conventional linear controllers for PFR is limited and cannot deliver maximum power. To enable VSWTs to contribute to PFR by injecting maximum power without undergoing accelerated wear and tear, a nonlinear bang-bang controller for DFIGs was proposed by Toulabi *et al.* [195]. Under normal conditions, the DFIG is controlled by the main controller. Under a disturbance, the proposed controller activates to ensure maximum release of kinetic energy from the WT blades.

Due to increased penetration of RESs in hybrid remote power systems that use diesel generators, large frequency disturbances may be caused by load variations that keep diesel generators under stress during generation balancing. A droop-based primary frequency controller for DFIGs in remote power systems was proposed by Tan *et al.* with a supplementary control loop to enhance PFR [196]. The developed scheme is also capable of reserving power to enhance PFR.

A comparative study for the analysis of permanent magnet synchronous generators and DFIG-based WTs from the perspective of VI control was carried out by Pradhan *et al.* [51]. Two control schemes, dynamic equation-based and adaptive fuzzy-based, were proposed to dynamically modulate the gains of inertia controls to improve PFR of WPPs. The addition of a new control loop for WPP controllers enables them to contribute to PFR using DFIGs, which was investigated by Feltes *et al.* [197]. The proliferation of DFIGs may not necessarily have an adverse effect on frequency response but may possibly result in an improved system behavior as compared to synchronous generators. Nikolakakos *et al.* investigated the impact of DFIGs equipped with energy storage on frequency response [198].

The principle of power system primary reserve is that N-1 faults do not engender the operation of low-frequency load shedding relays [199]. A simulation analysis of dynamic frequency response behavior of a power system with different levels of wind penetration and the required amount of primary reserve to be rendered by WPPs was conducted by Zhao *et al.* [199]. A simulation analysis of a coordinated control approach for inertia, and combined inertia-PFR support between WPPs and conventional generators on frequency characteristics of a power system was investigated by Ataee *et al.* [200]. Krpan and Kuzle developed a linearized model of VSWT to provide inertia and PFR for small disturbance under only one wind speed [201]. The model was integrated into existing system frequency response models to investigate frequency response behavior.

Centralized control approaches for improvement of PFR from WPPs entail complex algorithms. A synchrophasor data-based distributed droop control was presented by Mahish and Pradhan to enhance PFR [202]. Synchrophasor data are used to calculate generation-load mismatch, which is then used in combination with WPP capacity and power reserve to calculate the ratio of power reserve. The power share of WTs are then calculated by taking the ratio of power reserve and wind speed into account. Finally, the allocated power share is generated after calculating changes in droop based on frequency deviations.

Gevorgian *et al.* carried out a simulation-based investigation of system-level frequency response under different penetration levels of wind generation (as high as 80%) for the U.S. Western Interconnection [203]. The study showed that frequency nadir improved with increasing penetration level of WTs equipped with inertia and PFR control. Under large frequency oscillations, WPPs can be a reliable source of frequency response. The overall system performance was significantly improved by the ability of WPPs to provide electronic PFR and intertia.

Figure 9 shows a block diagram that depicts the conceptual framework for possible frequency control loops in variable speed WTs. The P_i, v, ω_T, ACE, ΔP_{ic}, ΔP_{pc}, and ΔP_{sc} are available power, wind speed, WT blade speed, area control error, inertial control action, primary control action, and secondary control action signals, respectively. Parameter α determines the amount of reserve power for frequency regulation. Although variable speed WT experiences inherent delays in synthetic inertial response as compared to synchronous generator, studies have proved its better frequency stabilization capability than synchronous machines in case of a major generation loss. Primary droop control could also help minimize frequency deviations after disturbances, with fast release of reserve power. Figure 9 also shows the secondary response capability of WT, which is required to activate upon request of the system operator. Bevrani et al. have extensively discussed the control mechanism including the role of each control block [204]*.

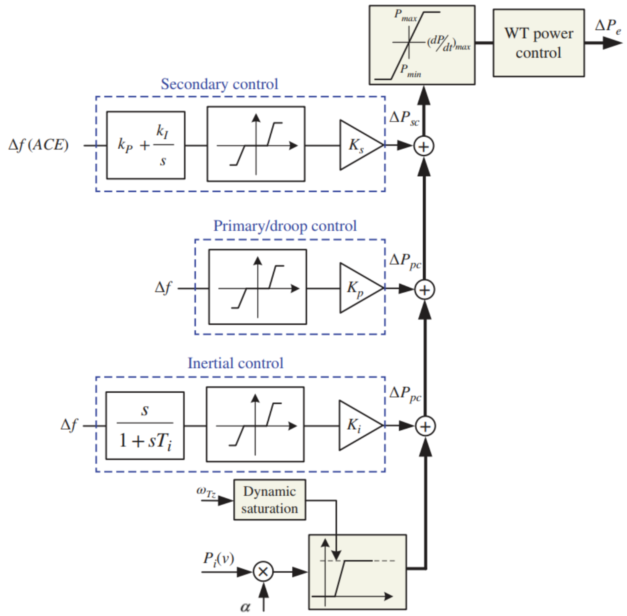

FIGURE 9. **Inertial, primary, and secondary frequency regulation loops in variable speed WT [204]*.**

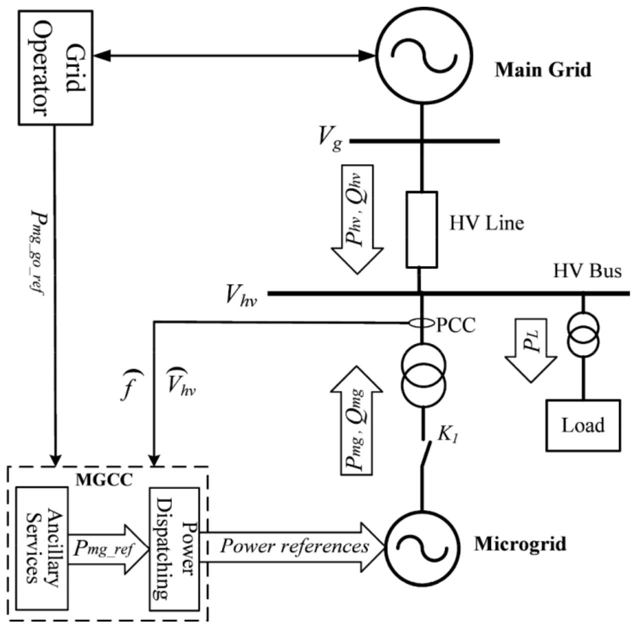

FIGURE 10. **General arrangement of a grid-connected microgrid system [19]*.**

4) MICROGRIDS

A Microgrid is a small network of different types of DERs and interconnected loads that have the ability to operate in either grid-connected or island modes. MGs may also be able to participate in frequency and voltage regulation services on support of a main grid [205]*. In grid-connected mode, MGs support the frequency of the main grid by providing surplus generation, when needed, in addition to serving the load. Different centralized and decentralized control strategies have been developed that control DERs within MGs. Centralized solutions entail high cost for communication systems [206], [207]*. Different decentralized methods have been proposed that do not involve communication cost [208], [209]*, however, they have only considered grid-connected mode or the nature of inverter's primary source has not been considered [210]*. Distributed control of MG is becoming more common as this method combines the benefits of both centralized and decentralized control [211]*.

The capability of MGs to participate in frequency support of a main grid is demonstrated by Li *et al.* [212]*. Pilo *et al.* proposed a centralized control approach for primary frequency control via a microgrid central controller (MGCC) [213]*. This controller communicates with generators and responsive loads to maximize revenues from energy market participants. Simulations showed that MGs that only aim at maximizing individual revenues may be unsafe for the grid [214]*. Ferraro *et al.* proposed an approach to reduce the impacts of MGs on a power grid by allowing switching between a revenue-maximization mode and a frequency regulation mode [215]*. Alfred presented a decentralized approach in which each inverter and controllable load has predefined droop settings to enable automatic response to frequency [216]*.

An advanced interface control system for grid-connected MGs is shown in Figure 10 [19]*. The MG is connected to a high voltage (HV) bus via a transformer. The power transfer between the MG and the grid is affected by the changes in load connected at the HV bus, which could result in considerable variations in frequency and voltage at the HV bus. Grid operators consider grid-connected MGs as a potential source of power reserve, which is enabled by using an appropriate control scheme for MGCC [215]*. The ancillary services act as coordinator between the MG and the main grid to ensure provision of regulation power to meet grid requirements.

V. CONCLUSION

In this survey paper, an overview of the contemporary frequency monitoring and control methods is provided. It presents an up-to-date review of frequency control challenges and achievements in modern power systems. The change in frequency dynamics introduced by large-scale integration of IBRs are highlighted. The reshaping of frequency control paradigm realized by the participation of RESs, virtual inertia, and demand response technologies is also discussed.

Frequency is an essential aspect of system reliability. Any frequency instability, if not arrested in a timely manner, may lead to catastrophic events in power systems. modern power systems characterized by complex topologies engendered with large-scale renewable and distributed generation require advance situational awareness techniques. With the development of synchrophasor technology, many existing frequency event detection techniques leverage the high sampling rate of PMUs to enable system operators to have real-time knowledge of power system networks. WAMS is one of the capable systems to enhance grid reliability. Recently, renewable generation resources, particularly PV and wind, have been the focus of technical regulations for grid reliability. Ongoing research on frequency control has emphasized on the importance of BESS, DLC, and EV technologies to meet the demand for ancillary services in modern power systems.

Based on the impact of IBRs, review of numerous classical and modern event detection methods, and current concerns related to frequency control, research priorities and suggestions for future work can be summarized as:

- With the increasing deployment of WAMS due to their high temporal resolution, advanced data processing algorithms and communication tools need to be used considering the high volume of measurement data.
- The growth in smart grid technologies necessitates focus on the analysis of future frequency regulation markets and cyber-security issues.
- There is no global absolute definition for a frequency event, rather it depends on the critical stability limits. Different system operators might be interested in arresting events with different severity. The detection methods reviewed for this study are not configurable. Research should be focused on configurable event detection techniques to identify events that match the definition described by system operators in the context of their balancing authority.
- New stability models are needed for low inertia systems, which account for the RESs, energy storage, and demand response in the electric grid.
- Effective schemes must be deployed that provide coordination between conventional generators and IBRs in current power systems. The coordination schemes must leverage the energy storage for primary and secondary frequency reponse.
- IBRs and demand response technologies offer a faster frequency regulation support than conventional generators. Therefore, virtual inertia and load-side resources are attractive solutions for frequency control, especially with the recent development in communication and computation technology.
- To prevent unwarranted and excessive demand disconnections in low inertia conditions, current UFLS schemes must be upgraded to ensure quick response and adequate load shedding.

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