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Review article

A state-of-the-art review on wind power converter fault diagnosis

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A B S T R A C T

The rapid expansion of installed wind energy capacity and the continuous development of wind turbine technology has drawn attention to operation and maintenance issues. In order to keep wind power a competitive energy source, the development of high-reliability and low-maintenance wind turbine systems is imminent, the rise of fault diagnosis provides a guarantee for their satisfactory operation and maintenance. A large number of statistical studies have pointed out that converter fault is the main cause of wind turbine system failure shutdown. Up to now, wind power converters' fault diagnosis has obtained fruitful results, and those are constantly reported in power system literature. This paper presents a state-of-the-art review on wind power converters' fault diagnosis for both short-circuit faults and open-circuit faults of power switch, including model-based, signal-based and data-driven methods. It provides a wide range, involving component fault modes, the robustness and reliability issues, algorithm investigation of fault diagnosis, quantitative analysis and qualitative analysis metrics for assessing the advantages of the developed techniques, and challenges in fault diagnosis design. Main purposes of this paper are: (1) Investigating the current research status of fault diagnosis on wind power converters to update the relevant research literature; (2) Discussing the robustness and reliability issues that must be considered in real engineering and safety critical systems; (3) Providing effective performance indices involves both quantitative and qualitative analysis, so that readers can understand the novelty of the proposed method.

Contents

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1. Introduction

1.1. Background

Growing energy demand and increasingly severe environmental pollution have promoted the need to develop sustainable solutions, and renewable energy has been identified as a suitable alternative to traditional fossil fuel energy generation (Qadir et al., 2021). Fig. 1 shows the worldwide renewable energy share of global electricity production in 2018 (REN21, 2019). Wind energy has become a superior energy resource due to greenhouse gas emissions, short construction period, and flexible investment construction scale. It can be seen from Fig. 1 that worldwide wind power accounts for 5.5% of global electricity production (specifically highlighting in red) and 21% of global renewable energy generation (calculated by 5.50%/26.20%), second only to hydropower. The superiority of wind energy makes the global cumulative installed wind power capacity increase year by year (Raghavendran et al., 2020; Ren et al., 2021), the worldwide installed cumulative capacity of wind power from 1996 to 2020 is shown in Fig. 2.

Wind turbine systems are usually installed in remote areas, grassland, coastal island, or offshore in very harsh environmental conditions, as shown in Fig. 3. Extreme conditions (e.g., humidity, extreme temperatures, snow, salt spray, lightning) and high loads make wind turbines more prone to failures. Therefore, reliability and maintenance costs have become two crucial issues for large-scale wind turbine systems development. High-reliability wind turbine system design can facilitate its good operation and improve the utilization rate of wind energy, so as to increase the penetration and competitiveness of wind power generation (Liu et al., 2020a; Jia et al., 2021). On the other hand, maintenance cost severely limits the large-scale deployment of wind turbine systems (Raza and Ulansky, 2019), it may reach as high as 15% of the life-cycle cost for an onshore system and 30% for an offshore system (Guo et al., 2020). Consequently, it is urgent to study efficient methods to improve operating reliability and reduce maintenance costs of wind turbine system (Liu et al., 2015c; Zhang et al., 2021).

The components such as blades, generator, control system, power converter, gearbox, and sensors in wind turbine systems are easily damaged, their faults can lead to low-reliability and high-maintenance costs of wind turbine systems (Yang and Chai, 2016). Fig. 4(a) and (b) respectively show the annual fault rate and downtime percentage of wind turbine system main components that have been reported in some literatures (Yang and Chai, 2016; Bakdi et al., 2019; Reder et al., 2016; Stenberg and Holttinen, 2010). Obviously, the wind power converter not only has a high annual fault rate but also has a long downtime, so its fault is quite severe. Fig. 4(c) is a breakdown of non-recurring cost from the United Kingdom government (Johnston et al., 2020), it provides an allocation of the total non-recurring cost to individual elements and can be used to assess costs of different

Abbreviations

FDs	Fault Diagnosis
DFIG	Doubly-Fed Induction Generator
PMSG	Permanent Magnet Synchronous Generator
2L-BTB	2-Level Back-to-Back
3L-NPC BTB	3-Level Neutral-Point-Clamped Back-to-Back
MMC	Modular Multilevel Converter
PCB	Printed Circuit Boards
IGBT	Insulated Gate Bipolar Transistor
SC	Short-Circuit
OC	Open-Circuit
NPC	Neutral-Point-Clamped
MLD	Mixed Logic Dynamic
RMS	Root Mean Square
MSDP	Multistate Data Processing
SSFA	Subsection Fluctuation Analysis
FFT	Fast Fourier Transform
DFT	Discrete Fourier Transform
STFT	Short Time Fourier Transform
WT	Wavelet Transform
WPD	Wavelet Packet Decomposition
DWT	Discrete Wavelet Transform
FA	Feature Analysis
JD	Judgment
TFA	Trend Feature Analysis
EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
VMD	Variational Mode Decomposition
IMFs	Intrinsic Mode Functions
NE	Norm Entropy
PCA	Principal Component Analysis
RPCA	Relative Principal Component Analysis
ICA	Independent Component Analysis
ANN	Artificial Neural Network
BPNN	Back Propagation Neural Network
SOM	Self-Organizing Mapping
SVM	Support Vector Machine
LSSVM	Least Square Support Vector Machine
HMM	Hidden Markov Model
RVM	Relevance Vector Machine
mRVM	Multiclass Relevance Vector Machine
BN	Bayes Networks
FLS	Fuzzy Logic System
EPSO	Evolutionary Particle Swarm Optimization
DCQGA	Double Chain Quantum Genetic Algorithm
CSO	Cuckoo Search Optimization
SAE	Stacked Auto-Encoder
GAP	Global Average Pooling
CNN	Convolutional Neural Network
CSA	Crow Search Algorithm
LSTM	Long Short-Term Memory
DBN	Deep Belief Networks
MKSTM	Mixed Kernel Support Tensor Machine

components of offshore wind farm. It can be seen from Fig. 4(c), the turbine accounts for 33% of the total non-recurring cost and the converter in its second level breakdown accounts for 8% of the total non-recurring cost (specifically highlighting in red), so the replacement cost of wind power converter is expensive. When a power converter fails, it may cause damage to generator and other important components, resulting in abnormal operation of the wind power system, and seriously threatening power grid (Smet et al., 2011). Consequently, whether the power converter can operate stably is essential to obtain a wind turbine system with high-reliability and low-maintenance costs.

As the occurrence of wind power converter faults is stochastic and independent, fault diagnosis (FDs) is regarded as an applicable means to detect and isolate faults rapidly. The development of wind power converters FDs has high engineering values, which are described as below:

(1) FDs is capable of providing a dependable theoretical basis for the optimal design of converter topology and configuration. The converters structures are optimized to maintain the performance of wind turbine systems at the desired level despite the existence of faults. For instance, FDs-based converter fault-tolerant control can enhance the endurance under fault status for wind turbine systems (Elsanabary et al., 2021; Shahbazi et al., 2018).

(2) FDs can provide operators with valuable guidance to adopt effective regulate solutions rapidly in the early-stage of converter faults to prevent greater disasters, thereby reducing the unnecessary shutdown of wind turbine systems, and minimizing economic losses caused by converter faults (Mahdhi et al., 2020).

(3) FDs is able to rapidly detect and identify converters faults, and the obtained fault information can be used to optimize the maintenance process. This is significant for making decisions earlier, lessening risks, and reducing maintenance and management costs more effectively (Haghnazari et al., 2015; Kumar and Elangovan, 2020).

1.2. A survey of relevant reviews made previously

A comprehensive search of relevant reviews made previously on fault diagnosis of wind power converters have been conducted. There are many surveys on the condition monitoring and fault diagnosis of wind turbines (Artigao et al., 2018; Zhang and Lu, 2019; Qiao et al., 2015; Qiao and Member, 2015a), but they focus on the investigation of the whole wind turbine system, very little space is given to wind power converters. Moreover, the investigation on the fault diagnosis of wind power converters is not comprehensive, more attention is paid to fault modes and signals, but less attention to fault diagnosis methods. A comprehensive review on signals and signal processing methods used for condition monitoring and fault diagnosis of wind turbines is presented in survey (Qiao and Member, 2015b).

Many surveys on fault diagnosis methods for converter have been published, and several reviews are compared in Table 1.

Surveys (Gao et al., 2015a,b; Wan et al., 2019) provide overviews on model-based, signal-based, knowledge-based and hybrid fault diagnosis methods, focusing on the introduction of various methods, but the qualitative and quantitative analysis of various methods is insufficient. The survey (Lu and Sharma, 2009) reviews the fault diagnosis methods of insulated gate bipolar transistor (IGBT) of three-phase power inverter with T-type topology or traditional two-level topology, mainly including park's vector method, normalized current method, slope method, spectrum analysis method, wavelet transform, neural network, fuzzy logic, etc. However, the reliability and robustness issues are not pointed out, and they cannot be directly applied to the fault diagnosis of modular multilevel converter (MMC) due to only faulty arms can be detected instead of faulty cells. Fault diagnosis methods of signal processing-based, mechanism-based and artificial intelligence-based for switching devices are evaluated and summarized (Liu et al., 2016; Wang et al., 2019), but

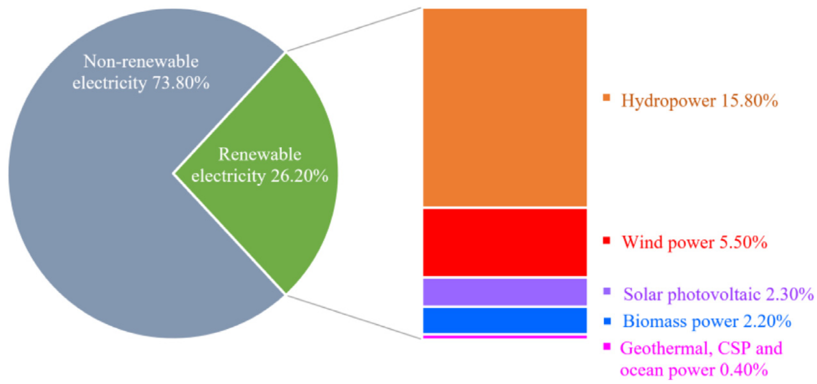


Fig. 1. Worldwide renewable energy share of global electricity production in 2018 (REN21, 2019).

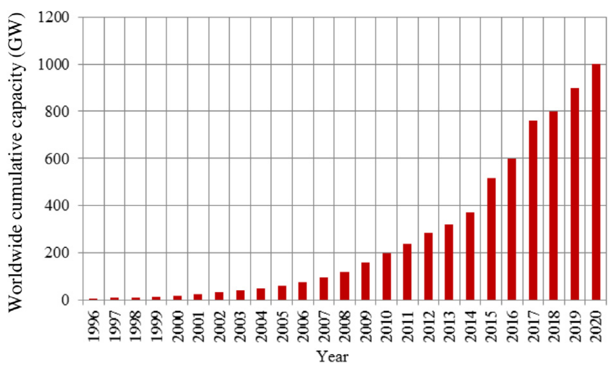


Fig. 2. Worldwide installed cumulative capacity of wind power from 1996 to 2020 (Raghavendran et al., 2020; Ren et al., 2021).

only the applicability to MMC is verified. An overview of fault diagnosis methods for DC–DC converters is proposed (Kumar and Elangovan, 2020).

The above investigated surveys on converter fault diagnosis methods focus on the whole industrial process and system. However, the complexity and uncertainty of wind power systems make the methods in these reviews drawable but not directly transferable to wind power converters. Additionally, the operating conditions and system transients of wind power systems and conventional industrial systems are quite different. The survey (Gao and Liu, 2021) reviews some fault diagnosis methods for wind power converters, including model-based, signal-based and knowledge-based methods, but lacks metrics to evaluate the advantages of the methods. The survey (Yang and Chai, 2016) summarizes several fault diagnosis methods for onshore wind power converters, but it does not talk a lot diagnosis methods, and only a few indicators are used to measure the novelty of the methods.

1.3. Motivations

Numerous fault diagnosis methods for wind power converters have been published in recent decades, they are different in terms of accuracy, rapidity, robustness, model complexity/computational cost, additional hardware requirements, applicable objects, technology application maturity, tuning effort, data required, degree of model dependence, nonlinear signal processing, and multi-fault diagnosis. However, a comprehensive summary is lacking to evaluate the advantages of various methods using so many quantitative analysis and qualitative analysis metrics.

This paper presents a comprehensive review on fault diagnosis of wind power converter, including model-based, signal-based and data-driven methods. It focuses on the following contents: component fault modes, the robustness and reliability issues, fault diagnosis algorithm investigation, quantitative analysis and qualitative analysis metrics, and challenges in fault diagnosis design. The motivations of this paper can be summarized as follows:

(1) Investigating the current research status of fault diagnosis on wind power converters to update the relevant research literature.

(2) Discussing the robustness and reliability issues of wind power converter fault diagnosis models and tools, this point is fundamental when the reliability and robustness features of the proposed solutions have to be verified and validated with respect to real engineering and safety critical systems.

(3) Providing effective performance indices to assess the advantages of the developed techniques, including quantitative analysis and qualitative analysis.

(4) Pointing out several challenges in fault diagnosis design.

The rest organization of this paper is as below: Section 2 details typical faults of a wind power converter and its fault diagnosis framework including effective metrics, and discusses robustness and reliability issues. Section 3 provides a comprehensive and critical review of model-based methods. The performance of signal-based methods is summarized in detail in Section 4. Section 5 presents the advantages and drawbacks of data-driven methods. Section 6 conducts a detailed qualitative and quantitative analysis of the fault diagnosis methods for wind power converters, and points out several technical challenges. Section 7 concludes with several remarks.

2. Typical faults and fault diagnosis framework of a wind power converter

2.1. Typical faults of a wind power converter

Typical topologies of wind power converters include diode rectifier-based converter topology, 2-level back-to-back (2L-BTB) converter topology, 3-level neutral-point-clamped back-to-back converter (3L-NPC BTB) topology and modular multilevel converter (MMC) topology. 2L-BTB converters are applied to doubly-fed induction generator (DFIG) systems and permanent magnet synchronous generator (PMSG) systems with the power of 1–3MW. 3L-NPC BTB converters are applied to PMSG systems with the power of 5–8MW. MMC are used for high-power systems (Yang and Chai, 2016).

Statistical researches show that the main components prone to fault in wind power converters include: power semiconductor

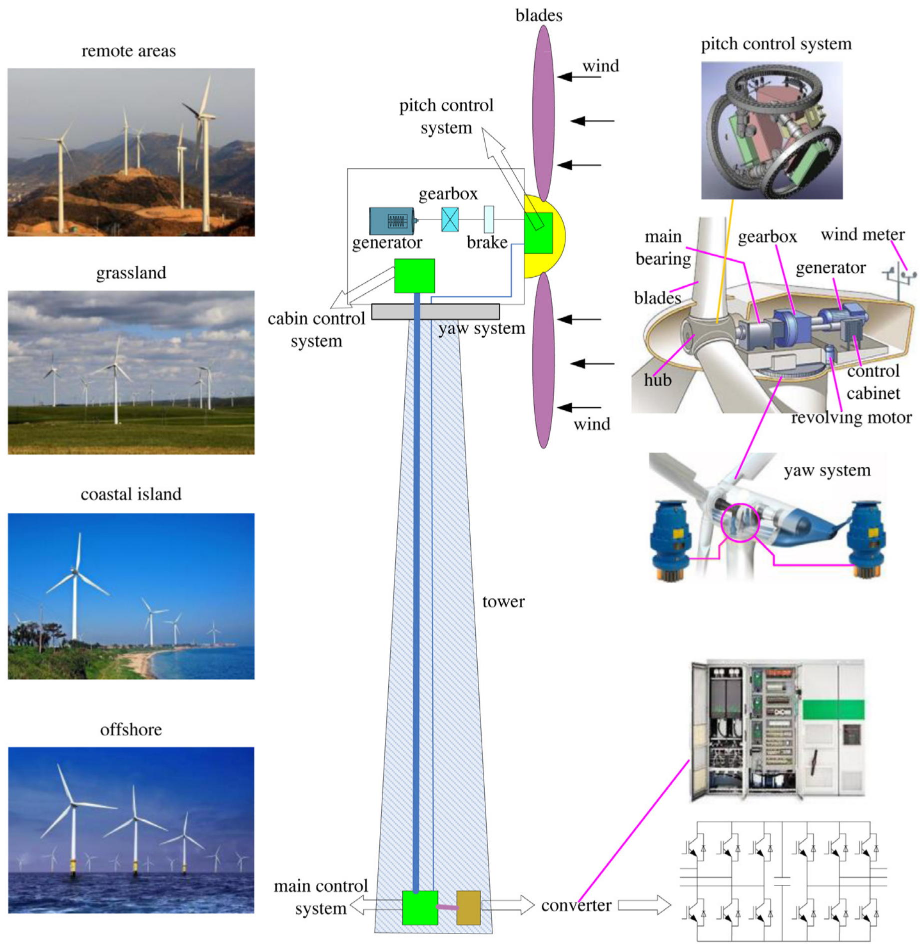


Fig. 3. Wind farm distribution and wind turbine system main components.

devices (e.g., IGBT), printed circuit boards (PCB), and capacitors (Yang and Chai, 2016). As Fig. 5 shows, the fault of power semiconductor devices is one of the main responsible for converter fault. In addition, power semiconductor devices faults are affected by PCB faults, which means that the most common faults in converters can lead to power switch faults (Lu and Sharma, 2008; Lee and Choi, 2014). Typical faults of power semiconductor devices can be divided into Short-Circuit (SC) faults and Open-Circuit (OC) faults (Song and Wang, 2012). Fault mechanisms of power semiconductor devices have been studied in literatures (Shao et al., 2020; Ma et al., 2020; Shao et al., 2021; Lee et al., 2015), as Fig. 6 shows.

The main causes of power semiconductor devices faults in wind power converters are as follows:

(1) The instantaneous current or instantaneous voltage of power converters is too large when the wind turbine is started or suffers from strong gust.

(2) After a long-term operation of wind power converters, heat dissipation performance degradation, and fatigue accumulation of power semiconductors may lead to devices damage.

(3) Dust, corrosive gas, and moisture in wind farms may result in power semiconductor devices abnormal operation or even cause catastrophic faults.

Both SC faults and OC faults of power semiconductor devices would lead to irreversible and irreparable damage for wind power converters (Lu and Sharma, 2009).

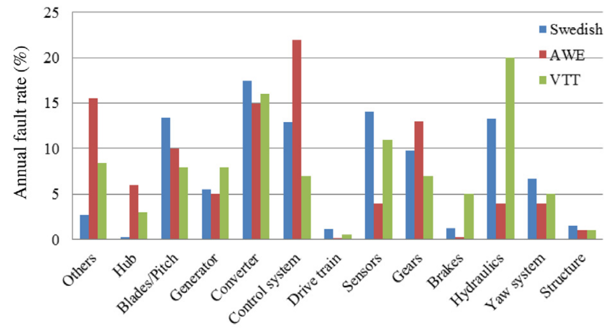
2.1.1. Short-Circuit (SC) faults

SC faults are usually virulent and not easy to deal with, they cause abnormal overcurrent that can result in serious damage to the converter and other components in a short period of time. It is necessary to shut down the driver safely and immediately. Consequently, most of the existing FDs methods for SC faults are based on hardware circuits to minimize the time between the faults occurrence and proper response. Generally, converters are equipped with special SC hardware protection circuit, and SC faults detection has become a standard function of electrical drive (Lu and Sharma, 2009). The use of fast fuses or circuit breakers is SC fault protection schemes, in this case, the SC fault becomes an OC fault (Pei and Kang, 2012).

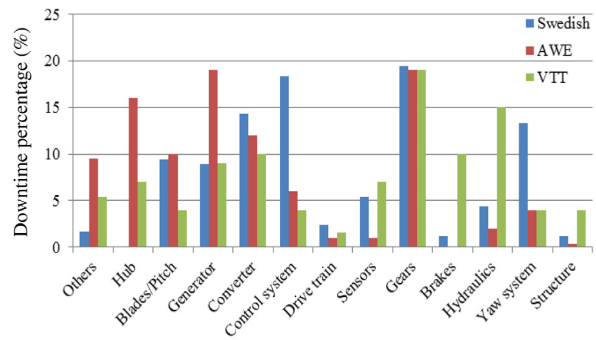
2.1.2. Open-Circuit (OC) faults

Different from the SC fault, the OC fault responds slowly and does not lead to serious damages to the whole system in a short time. Nevertheless, it does degrade the overall converter performance (Lu and Sharma, 2009). When an OC fault occurs, high harmonic distortion appears in currents, and the currents in faulty phase and healthy phase are offset, causing generator torque to oscillate and grid power factor to decrease. On the other hand, the OC fault can result in secondary faults at other components. An OC fault can damage other switches (due to overcurrent stress) and generator (duo to large active and reactive power fluctuations in stator) and may debase the capacitors service life. The fault effect on energy/power loss due to OC faults occurrence has been discussed in detail in Liang et al. (2020).

The OC fault of power semiconductor devices is one of the common faults in converters. It should be noted that the OC fault is potentially undetectable for a long period since it usually does not cause significant changes in currents and voltages. This results



(a) Annual fault rate of components [11-14].



(b) Downtime percentage of components [11-14].

A breakdown of non-recurring cost from the United Kingdom government.

Category	Estimated installed £/MW	Cost %	First Level Breakdown	Estimated installed £/MW	Cost %	Second Level Breakdown	Estimated installed £/MW	Cost %
Turbine	1,320,000	33.0	Nacelle	880,000	22.0	Converter	320,000	8.0
						Gearbox	360,000	9.0
						Other	184,000	4.6
			Rotor	440,000	11.0	Hub	144,000	3.6
						Blade	280,000	7.0
Installation & Commissioning	1,0,40,000	26.0	Foundation	280,000	7.0			
			Cables	360,000	9.0			
			Offshore Substation	28,000	0.7			
			Turbine	360,000	9.0			
Balance of Plant	1,480,000	37.0	Foundation	640,000	16.0			
			Cables	200,000	5.0	Export	164,000	4.1
						Inter Array	56,000	1.4
			Tower	240,000	6.0			
			Onshore Substation	108,000	2.7	Converter	80,000	2.0
						Other	28,000	0.7
			Offshore Substation	280,000	7.0	Converter	200,000	5.0
						Other	56,000	1.4
Development & Consent	160,000	4.0	Environmental Survey	12,000	0.3			
			Met Mast	12,000	0.3			
			Sea Bed Survey	24,000	0.6			
			Dev Services	112,000	2.8			
Total	4,000,000	100		3,976,000	99.4			

(c) Replacement costs for different components [15].

Fig. 4. Annual fault rate, downtime percentage and replacement costs of wind power system main components (Yang and Chai, 2016; Bakdi et al., 2019; Reder et al., 2016; Stenberg and Holttinen, 2010; Johnston et al., 2020). (AWE—European Project AWESOME (Reder et al., 2016); VTT—Valtion Teknillinen Tutkimuskeskus, a technical research centre in Finland (Stenberg and Holttinen, 2010)).

in high maintenance costs and even causes the total system to shut down. Consequently, the FDs of OC faults is necessary for converters.

2.2. The robustness and reliability issues of wind power converter FDs

Wind power converters topology and configuration continue to evolve due to the constant emergence of complex high-power machinery. Besides, wind power converters suffer from numerous stresses and operating condition variations. Therefore, the robustness and reliability issues of wind power converter FDs models and tools should be considered. In particular, this point is fundamental when the reliability and robustness features of the proposed solutions have to be verified and validated with respect to real engineering and safety critical systems.

The robustness issues of wind power converter FDs models and tools should be considered are as follows:

Table 1
Comparison of several reviews made previously on converter fault diagnosis.

Ref.	Journal	Fault type	Reviewed method	Applicable system	Converter type	Reliability and robustness issues	Qualitative analysis	Quantitative analysis
Gao et al. (2015a) (Gao et al., 2015b)	IEEE Transactions On Industrial Electronics	–	Model-based; signal-based; knowledge-based; hybrid/active methods;	Industrial systems	–	–	–	–
Wan et al. (2019)	International Conference on Intelligent Green Building and Smart Grid (IGBSG)	–	Model-based; signal-based; knowledge-based; fusion methods;	Industrial systems	Power electronics	–	–	–
Lu and Sharma (2009)	IEEE Transactions On Industry Applications	OC and SC	Signal-based; data-driven;	Industrial systems	Three-phase power inverters (T-type topology; traditional two-level topology)	–	Resistivity; implementation effort; tuning effort; threshold dependence on detection variable;	Detection time
Wang et al. (2019)	IET Circuits, Devices & Systems	OC and SC	Mechanism-based; signal-based; artificial intelligence-based;	Industrial systems	MMC	–	MMC configuration; submodule structure; sensed parameters; hardware platform; multi faults detection ability;	Submodule number; sensor number; diagnosis time;
Liu et al. (2016)	Electric Power Components and Systems	OC and SC	Model-based; signal-based; data-driven;	Industrial systems	MMC	–	Detected fault types	Number of sensors
Kumar and Elangovan (2020)	IET Power Electronics	OC and SC	Model-based; signal-based; data-driven;	Industrial systems	DC–DC converter	–	Easy implementation and economical; additional hardware; diagnosis speed; cost;	Multiple faults; diagnostic time;
Gao and Liu (2021)	Processes	OC	Model-based; signal-based; knowledge-based;	Wind power converter	–	–	–	–
Yang and Chai (2016)	Renewable and Sustainable Energy Reviews	OC and SC	Model-based; pattern-based;	Industrial converter; wind power converter	Diode rectifier-based converter; 2L-BTB converter; 3L-NPC-BTB converter; MMC;	Load and torque vary	Model complexity; additional hardware; applicable converter types and WT type;	Detection time; the number of faults;
This paper	–	OC and SC	Model-based; signal-based; data-driven;	Wind power converter	Diode rectifier-based converter; 2L-BTB converter; 3L-NPC-BTB converter; MMC;	Robustness issues: wind variations, load changes, the noise and bias in measured signals; Reliability issues: high accuracy, the model–reality mismatch;	Multiple fault diagnosis; additional hardware; model complexity/computational cost; threshold; diagnosis speed; degree of model dependence; amount of data required; tuning effort; applicable system; converter type; applicable objects; technology application maturity; nonlinear signal processing;	Number of faults; diagnosis time; accuracy; precision; recall; F1-score; false detection rate; missed detection rate; robustness;

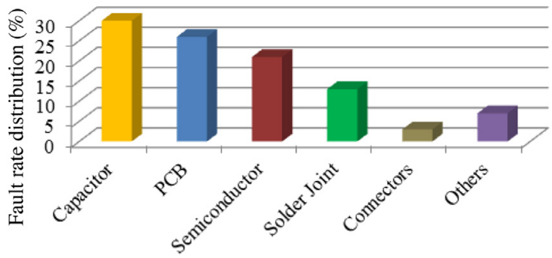


Fig. 5. Fault rate distribution of wind power converters (Yang and Chai, 2016).

(1) Robustness to wind variations

The rapid variation of the wind speed and direction lead to sudden changes of torque in high-dynamic wind turbine systems. The robustness to wind variations of FDs for wind power converters is required.

(2) Robustness to load changes

The load changes may cause false alarms of wind power converter FDs. The fault diagnostic methods for converters need to be highly robustness to system transients resulting from the load changes.

(3) Robustness to the noise and bias in measured signals

Most fault diagnostic methods require sensors to measure currents and voltages. But the signals measured by sensors contain noise and bias, which greatly affect the accuracy of wind power converter FDs. A superior FDs method must consider the robustness to noise and bias in signal.

The reliability issues of wind power converter FDs models and tools should be considered are as follows:

(1) High accuracy

Wind power converters adopt double-closed-loop control in both generator-side converter and grid-side converter, which forces the operating states tracking references. In this case, the changes of current and voltage signals caused by early-stage weak faults will be significantly attenuated, resulting in the weakening of fault characteristics. The reliability of wind power converter FDs requires high accuracy at any time.

(2) The model–reality mismatch

At present, the effectiveness and reliability of most proposed wind power converters FDs are verified in simulation platform and experimental setup. However, the wind turbine systems in actual wind farms are different from the simulation and experimental equipment in terms of configuration and power capacity; besides, the actual power grid voltage shocks and on-site real-time operating conditions are very different from the laboratory environment. The reliability of wind power converter FDs methods requires to solve the model–reality mismatch.

2.3. The FDs framework of a wind power converter

The FDs framework of a wind power converter is shown in Fig. 7. Fault diagnosis methods include three categories: model-based methods, signal-based methods, and data-driven methods (Gao et al., 2015a,b). The model-based method first needs to establish an accurate mathematical or analytical model for a wind power converter system using the physical knowledge about the structures and dynamics of the system, and then obtain fault results by analyzing residual between the estimated value and measured value. The signal-based method first needs to study the behavior of wind power converter system when different components fail, then generates diagnostic variables and thresholds based on the measured signals, and finally identifies the fault state of the converter through symptom analysis. The data-driven method uses numerous historical operation data to obtain system states, it first adopts mathematical technology to the measured signal for data processing and feature extraction, then artificial intelligence algorithm is applied for fault pattern training and recognition.

As Fig. 7 shows, the model-based method makes full use of the system information, so the diagnostic results are reliable. However, this method significantly relies on the precision of system model. The signal-based method is simple and straightforward due to it does not need a precise converter system model, but it requires prior-knowledge of the system. The data-driven method can be easily conducted without precise model of a wind power converter system and prior-knowledge of the system, but it requires a large amount of historical data to train and learn the classifier, so the computation is expensive and time-consuming.

More effective performance indices are exploited in this paper to assess the advantages of the developed techniques for wind power converter FDs besides the robustness and reliability metrics mentioned in Section 2.2. The effective performance metrics for qualitative analysis exploited in this paper are as follows:

(1) Multiple/single fault diagnosis.
(2) Additional hardware requirement.
(3) Model complexity/computational cost.
(4) Threshold: fixed, adaptive.
(5) Diagnosis speed: online, offline.
(6) Degree of model dependence.
(7) Amount of data required.
(8) Tuning effort.
(9) Applicable system: DFIG, PMSG.
(10) Converter type: diode rectifier-based converter, 2L-BTB converter, 3L-NPC-BTB converter, MMC.
(11) Applicable objects: generator-side converter, grid-side converter, back-to-back converter.
(12) Technology application maturity: verified by simulation platform, experimental setup, engineering project.

The effective performance metrics for quantitative analysis exploited in this paper are as follows:

(1) Number of faults.

(2) Diagnosis time: diagnosis time is related to algorithm complexity, a wind power converter fault diagnostic method that quickly detects faults and generates fault alarms is necessary to ensure the rapidity of fault tolerance.

(3) Accuracy: the high accuracy demonstrates the effectiveness of the method.

(4) Precision, recall, F1-score: three metrics from confusion matrix, they are used to assess the multi-classification.

(5) False detection rate: load changes and transients can cause false detection.

(6) Missed detection rate: inappropriate thresholds can lead to missed detection.

(7) Robustness: due for example to uncertainty and disturbance effects in wind turbine systems, such as wind variations (wind speed and direction), generator rotation speed changes, load changes (power grid faults, transient voltage drops, torque, speed), noise and bias in measured signals.

Each category fault diagnosis method of wind power converter has several schemes, as shown in Fig. 8. For a better organization, each category fault diagnosis method will be presented and analyzed in detail in Sections 3, 4, and 5, respectively. The quantitative and qualitative comparison of the performance of various methods will be conducted in Section 6.

3. Model-based method for fault diagnosis of wind power converter

Model-based methods can be further divided into state estimation, parameter estimation, joint state and parameter estimation approaches (Wan et al., 2019; Lu, 2012).

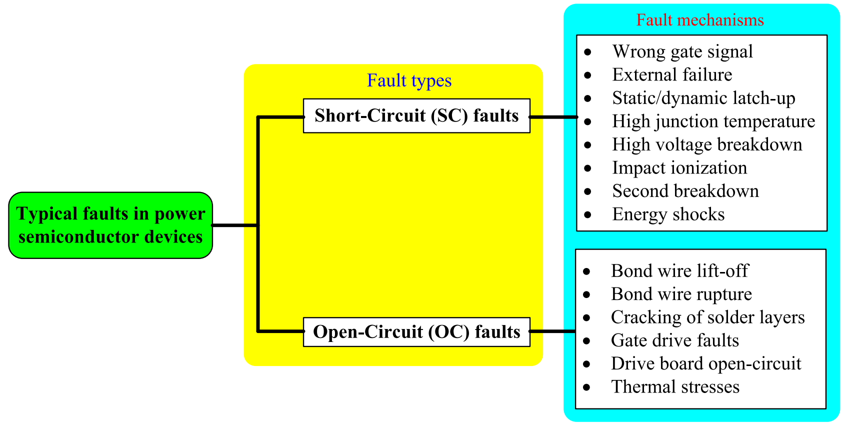


Fig. 6. Fault types and fault mechanisms of power semiconductor devices (Shao et al., 2020; Ma et al., 2020; Shao et al., 2021; Lee et al., 2015).

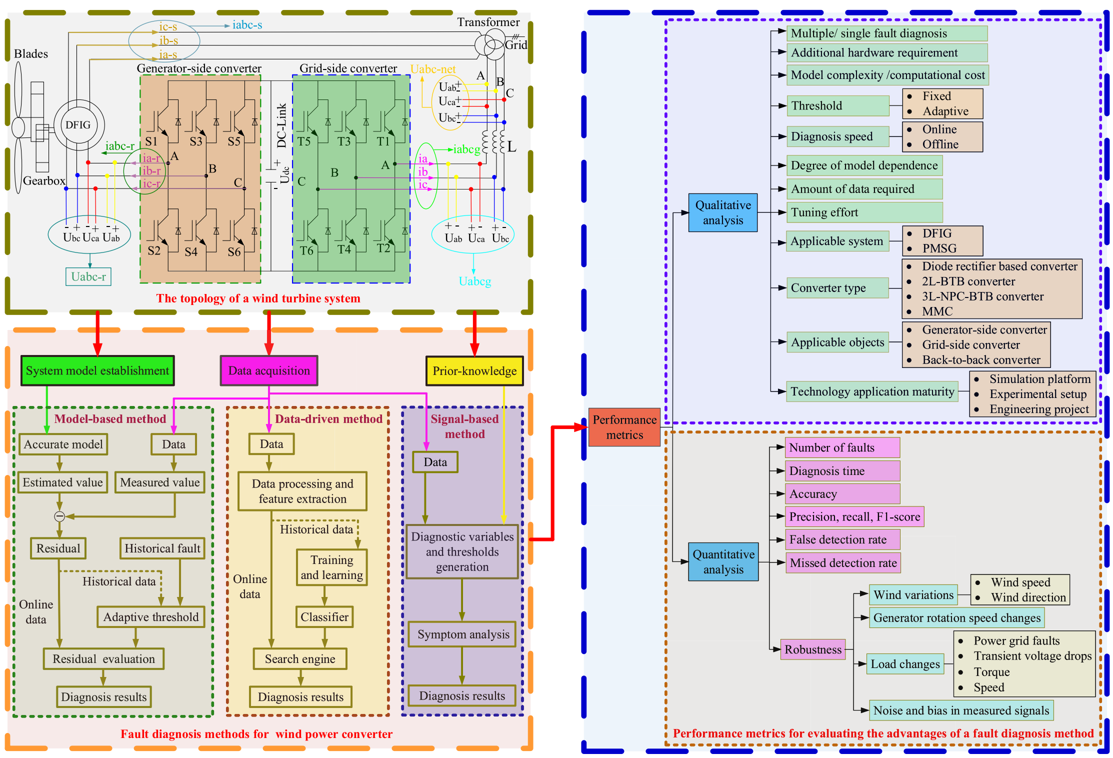


Fig. 7. FDs framework of a wind power converter.

3.1. State estimation approach

3.1.1. Observer-based method

Observers are widely used in model-based methods for converter FDs. The role of the observer is to estimate the system state based on available measurements. The state observer is a dynamic system that outputs residual to diagnostic system. The residual is the difference between estimated outputs and measured outputs. In a healthy state, the residual is null; when a fault occurs, the residual is different from zero.

A nonlinear current observer was adopted to generate residuals to detect and isolate inverter switch faults (Espinoza-Trejo et al., 2013), this method was independent of load and inverter frequency and did not require additional sensors. However, it required at least one fundamental period to isolate the faulty switch; besides, it had a heavy computational burden and needed precise system parameters. Jlassi et al. (2015) employed a Luenberger observer to estimate three-phase generator and grid currents inorder to obtain current residual for the diagnosis of faulty leg, the robustness against false alarms was independently guaranteed for rotor-side converter and grid-side converter under varying operating conditions. Ref. Jlassi et al. (2016) constructed a normalized current factor based on Luenberger observer to detect inverter OC faults, and obtained a lower detection time, but it suffered from model uncertainty.

A mixed logic dynamic (MLD) model was established to estimate current (Ge et al., 2017), and the rapid FDs of inverter was obtained. This method was not affected by the influence of system load and closed-loop control algorithm, thus, it had high robustness and accuracy. But it had no capability for online FDs. Ref. Yong et al. (2020) obtained an online FDs by estimating the phase current with a modified current observer. The current-observer based methods only needs measurements from existing sensors without any additional sensors.

Ref. Shahbazi et al. (2016) proposed a voltage observer based on time and voltage criteria, the wind power converter faults

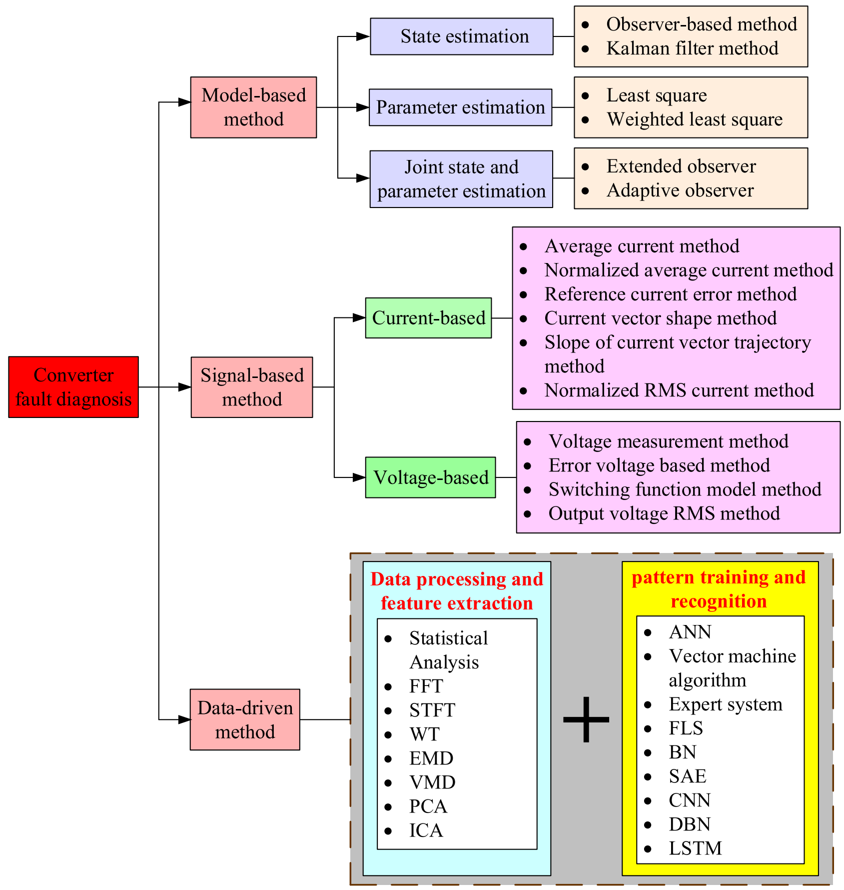


Fig. 8. FDs classification of wind power converter.

were detected by the comparison of observations and measurements of pole voltage. A sub-module voltage-based voltage observer was presented (Zhang et al., 2020a), and rapid fault detect and locate of a MMC were obtained; besides, the method was independent of system parameters. An inverter fault diagnostic method based on voltage residual observer was proposed (Ren et al., 2018), it showed good rapidity without extra circuits, and it had strong robustness to operating conditions.

Some advanced observer techniques for converter FDs have been proposed. A nonlinear proportional-integral observer based FDs scheme was proposed for inverter (Wang et al., 2020; Espinoza-Trejo et al., 2012), it obtained fast fault detection and isolation and was independent of load torque and operating conditions. Shao et al. (2013) proposed a sliding mode observer-based method for OC faults diagnosis in a MMC, and the performance of the observer was improved in Shao et al. (2016). These two methods successfully avoided the effects caused by sampling errors and parameter variation, thus could be easily implemented in the controller, but they heavily depended on the accuracy of the converter switching model and may fail if multiple faults occur in different sub-modules. Mtepele et al. (2019) utilized sliding-mode integral observer to diagnose multilevel converters OC faults. A Lyapunov theory-based sliding mode observer was designed to detect OC faults in MMC sub-module (Song et al., 2020), it can detect both the faulty arm and the fault modes. A high-gain observer was used to detect converter switch faults quickly and reliably (Espinoza Trejo et al., 2019).

3.1.2. Kalman filter method

In Deng et al. (2015), a Kalman filter-based method was proposed to detect the OC fault in a MMC sub-module. The Kalman filter was used to observe the circulating current, and a large residual between the observed circulating current and the actual value was observed in fault cases. However, this method was quite complex and time-consuming. Naseri et al. (2020) used Kalman filters to obtain effective real-time fault diagnosis for OC faults in inverter.

3.2. Parameter estimation approach

Parameter estimation-based fault diagnostic method first estimate the fault-related parameters, and then obtain fault states by analyzing the estimated parameters. The least square method was applied to identify inverter faults (Alavi et al., 2011), this method can isolate the incipient and abrupt faults online. A weighted least square-based three-phase converter fault identification method was proposed (Zhang and Zhang, 2015), the diagnostic results with high accuracy were obtained in both balanced and unbalanced conditions.

3.3. Joint state and parameter estimation approach

This approach can simultaneously estimate the unknown states and parameters online. It can provide FDs function and incorporate with a controller in the fault-tolerant control system (Lu, 2012).

3.3.1. Extended observer

In the extended observer-based method, the unknown parameters are considered as additional states in order to represent system faults, and all extended states, including unknown parameters, are estimated by constructing a state observer. An extended state observer was adopted to track arm current of a MMC (Hu et al., 2016b), this method had advantages of no extra sensors, fewer observation states, and no limitation in the modulation method. Hu et al. (2016a) designed a circulating current equation-based extended state observer, and switch faults were located effectively.

3.3.2. Adaptive observer

The adaptive observer method designs a simple observer directly for the original system assuming that all parameters are known without destroying the system structure, and tries to find suitable adaptive laws to estimate unknown parameters in order to make the observer converge. This method does not need complex observer algorithms and thus can be easily implemented. An adaptive voltage distortion observer was used to improve the diagnostic performance of inverter OC faults (Jung et al., 2013), but its practical implementation was hindered due to the high dependence of parameter estimation. A nonlinear adaptive observer-based FDs for MMC in wind turbine system was proposed to obtain online detection and location for SC faults and OC faults (Liu et al., 2015b), it reduced the false and missed detection.

The model-based method is effective in early-stage weak fault diagnosis. However, the effectiveness significantly depends on the accuracy of system model and parameters.

4. Signal-based method for fault diagnosis of wind power converter

It is important to select an appropriate signal for converter FDs, which can directly affect FDs results. The fault occurrence in the converter can potentially affect the output characteristics, especially the current and voltage distortions. Converter anomalies can be detected by analyzing current or voltage signals.

4.1. Current-based methods

Current-based methods are favored for converter FDs since no extra sensors are needed and they are independent of converter parameters.

4.1.1. Average current method

The amplitude of half-period phase current is zero in corresponding arm when an OC fault occurs in converter one power switch; the amplitude of whole-period phase current is zero when OC faults occur in two switches on one arm simultaneously. Consequently, the average phase current in a period varies after converter switches open. FDs of switch OC faults was obtained by analyzing the average current space vector in one period (Mendes and Cardoso, 1999). However, there existed some issues, such as load dependence, false alarms, and complex tuning. The average of three-phase current was directly used for converter FDs (Rothenhagen and Fuchs, 2005). Average current park's vector method was used to detect faults in three-level neutral-point-clamped (NPC) converter (Abadi et al., 2012), the faults of the upper and lower IGBT pairs in one leg were identified.

Since large instantaneous average current, the direct current average methods have less robustness, and the actual system diagnosis results may be unreliable. The introduction of normalized average current method reduces false alarms to a certain extent, it takes normalized average currents as fault features. Mendes et al. (2014) used modulus and angle of the normalized average current to detect three-level NPC inverter faults, it had strong robustness to transient conditions caused by load and speed changes. Aiming at the problem that the rotor current may be very low around the synchronous speed in doubly-fed induction generator (DFIG) systems, a diagnosis method based on normalized average current was presented (Sae-Kok et al., 2010), it reduced false alarm rate. An improved method considering the low-frequency characteristics of the rotor current was proposed (Duan et al., 2011), but the detection threshold was set by experience.

In order to improve the diagnostic performance, some modified normalized average current methods have been proposed. Ref. Estima and Cardoso (2011) proposed a normalized current average absolute errors-based method, and then proved the independence to operating conditions, but the method was inapplicable when encountering stochastic wind. Ref. Qiu et al. (2016) presented a wind speed-based normalized current trajectory method for the FDs of wind power converter OC faults to overcome the uncertainty of stochastic wind speed. The average absolute value of normalized stator currents was used for the real-time FDs of wind power converter in PMSG system, this method can detect single and multiple OC faults, and it had immunity against false alarm when generator rotation speed changes suddenly (Mahdhi et al., 2020).

The average absolute of normalized three-phase current sum was used for switch FDs (Freire et al., 2014), although calculation cost was low, diagnosis result was affected by the fixed detection threshold. Ref. Zhao and Cheng (2017) proposed a real-time FDs based on absolute normalized current and adaptive threshold for converter OC faults in DFIG-based wind turbine systems, this method can detect multiple OC faults, but it was prone to false alarms when the load changes suddenly. Ref. Zhao and Cheng (2018) used the average of normalized phase current and adaptive threshold to improve the robustness to sudden load changes.

4.1.2. Reference current error method

The defined function residual based on three-phase current signals were used to detect inverter OC faults (Wu and Zhao, 2016). The average of three-phase reference current error was used to calculate diagnostic variables (Estima and Cardoso, 2013), and a fast converter FDs was obtained by comparing with the defined threshold. Although the calculation cost was low, the threshold was challenging to determine, especially when load changed. Ref. Jlassi and Cardoso (2017) proposed a current residual based method, and converter faults were diagnosed by comparing with adaptive threshold.

4.1.3. Slope of current vector trajectory method

Ref. Freire et al. (2010) proposed a method based on phase angle slope of current park's vector to diagnose wind power converter faults, but it only can identify a single OC fault and was not reliable enough for multi-fault identification. A modified slope method was proposed to obtain multiple OC fault diagnosis (Trabelsi et al., 2010), but the detection was slow. The phase angle slope of average current park's vector was used to detect faults (Huang et al., 2015), but it presented a problem of load dependence. The phase derivative absolute of absolute current park's vector was applied as detection variable to diagnose converter multiple OC faults in a PMSG-based wind turbine system (Freire et al., 2013), this method had strong robustness to load and speed transients, but multiple thresholds were required to guarantee algorithm performance.

4.1.4. Current vector shape method

Undesirable current path distorts the output phase currents when converter has an OC fault. In Kwon et al. (2020), OC faults in NPC inverter were diagnosed by analyzing the specific trajectory of current, and rapid detection and location were obtained. Current pattern radius was used to detect OC faults in grid-connected inverter with fast detection and low calculation cost (Choi et al., 2012).

4.1.5. Normalized Root Mean Square (RMS) current method

Ref. Das and Kim (2015) used normalized RMS currents to detect switch OC faults in wind power converters, this method was simple enough to be implemented in the grid-side controller.

In addition, many advanced current-based converter FDs methods have been proposed. Zero current duration was used to detect converter OC faults in the wind turbine system (Lee et al., 2015), but the algorithm parameters had a great relationship with the component performance, system configuration, and operating conditions. An instantaneous amplitude-based fault diagnosis method for back-to-back converters in PMSG wind turbine system was proposed, it had multiple OC faults diagnosis capacity and was robust to speed variations (Xu et al., 2021). In order to obtain high reliability and low cost and volume in harsh environments, the diagnostic variables based on reconstructed three-phase currents were presented for inverter OC faults FDs (Yan et al., 2018). The reconstructed currents had less distortion and less harmonic components.

Current-based methods above adopt signals existing in control system and do not require extra sensors or increase diagnostic costs. However, these methods have load dependence and false alarms issues due to current characteristics. Furthermore, these methods are susceptible to closed-loop control algorithms.

4.2. Voltage-based methods

When a fault occurs in different converter switches, converter voltages present different characteristics. Therefore, it is possible to diagnose converter switch faults by analyzing voltage signals.

4.2.1. Voltage measurement method

In Chen et al. (2019), the switched bridge voltage and corresponding duration were measured to detect inverter OC faults, this method had a short detection time, but required extra circuit, which increased the implementation cost.

4.2.2. Error voltage-based method

Chen et al. (2021) utilized selective calculation method for instant voltage deviation to diagnose three-level rectifiers open-switch faults. Ref. Karimi et al. (2008) used a voltage criterion and time criterion to process the pole voltage error in order to diagnose converter faults. Although fast detection was achieved, it only detected the faulty arm and could not locate the fault switch. The average residual of pole voltages was used for inverter open switch FDs (Choi and Lee, 2012), it attenuated error influence but was not suitable for minimal load level. The measured and estimated pole voltages were directly compared to detect converter faults (Shahbazi et al., 2018), it was suitable for fault-tolerant control system due to its independence from wind conditions, system parameters, and load variations.

4.2.3. Output voltage Root Mean Square (RMS) method

Ref. Tan et al. (2018) proposed a RMS voltage-based FDs method for wind power converter OC faults, this method had the advantage of no threshold, but it only achieved single fault location.

4.2.4. Switching function model method

A fast and low-cost FDs method based on switch function model for inverter was proposed (An et al., 2011), this method measured the collector voltage of lower arm with simple hardware to achieve fault detection and location. However, it required the power supply of system to be greater than the detection circuit, which limited its application.

The DC-Link voltage can also be used for converter FDs (Sen et al., 2016). Ref. Jung et al. (2019) used grid voltage phase angle and DC-link voltage to diagnose faults. The time–frequency analysis of DC-link voltage was used to obtain wind power converter fault states (Ismail et al., 2019).

Voltage-based methods can achieve rapid fault detection and have high robustness to loads and noise. Nevertheless, the measurement of diagnostic voltage may require additional sensors or detection circuits. As a result, the implementation cost and complexity of the system increase.

The signal-based methods are simple and straightforward and have significant real-time performance. Still, they are susceptible to the threshold and have high dependence on the prior-knowledge of the system. Furthermore, the diagnostic results are easily affected by noise and operating conditions.

5. Data-driven method for fault diagnosis of wind power converter

Data-driven method uses mathematical based data mining techniques or statistical methods to diagnose converter faults, its typical procedure includes data processing and feature extraction, pattern training and recognition (Wang et al., 2019). For example, principal component energy-Artificial Neural Network (ANN) (Zhang, 2020), detection parameter-ANN (Ko et al., 2012), histogram-ANN (Sedghi et al., 2011), Correlation Features (mean and covariation)-ANN (Tan et al., 2020), Multistate Data Processing (MSDP)-Subsection Fluctuation Analysis (SSFA)-ANN (Huang et al., 2018b), Fast Fourier Transform (FFT) spectrum analysis (Xia and Ning, 2019), Discrete Fourier Transform (DFT)-Back Propagation Neural Network (BPNN) (Jiang et al., 2012), Wavelet Transform (WT)-Feature Analysis (FA)-Judgment (JD)-BPNN (Zhang et al., 2019), WT-Deep Belief Networks (DBN) (Liu et al., 2017a), Discrete Wavelet Transform (DWT)-ANN (Dhumale and Lokhande, 2016; Parimalasundar and Vanitha, 2015; Rekha et al., 2017), DWT-BPNN (Geng et al., 2020), DWT-Fuzzy Logic System (FLS) (Potamianos et al., 2014), Empirical Mode Decomposition (EMD)-ANN (Khan et al., 2020), EMD-Support Vector Machine (SVM) (Liang et al., 2020; Miao et al., 2017), Variational Mode Decomposition (VMD)-SVM (Yuan et al., 2016), VMD-Trend Feature Analysis (TFA)-DBN (Zhang et al., 2020b), Principal Component Analysis (PCA)-SVM (Wang et al., 2013), PCA-Hidden Markov Model (HMM) (Kouadri et al., 2020), FFT-PCA-multiclass Relevance Vector Machine (mRVM) (Wang et al., 2015), FFT-PCA-Bayes networks (BN) (Cai et al., 2017), FFT-Relative PCA (RPCA)-SVM (Wang et al., 2016), Wavelet Packet Decomposition (WPD)-PCA-ANN (Li et al., 2016), DWT-PCA-RVM-Evolutionary Particle Swarm Optimization (EPSO) (Gomathy and Selvaperumal, 2016), Independent Component Analysis (ICA)-ANN (Hu et al., 2020), DBN-Least Square SVM (LSSVM) (Shi et al., 2019), Sparse Representation (SR)-Deep Convolutional Neural Network (DCNN) (Du et al., 2021). The techniques used in the above-mentioned data-driven methods are described in detail as follows.

5.1. Data processing and feature extraction

Appropriate fault features can improve the accuracy of FDs. As a fact, the fault diagnostic accuracy significantly depends on the signal processing and feature extraction algorithm.

5.1.1. Statistical analysis

These methods are quite mature. The appropriate statistical features of converter time-domain signals in health and fault state such as histogram (Sedghi et al., 2011), mean (Tan et al., 2020), standard deviation (Gao et al., 2019), root mean square (Chen and Bazzi, 2017), skewness (Baghli et al., 2019), and kurtosis (Yuan et al., 2016) are calculated as fault features to represent the fault modes of the converter.

A method using correlation features (mean and covariation) for wind power converter FDs was proposed (Tan et al., 2020), it presented good performance under different wind speeds, and had the advantages of short calculation time and a simple calculation process. The main components were extracted from the distortion and envelope changes of a three-phase current signal as fault features (Huang et al., 2019, 2018a). The principal component energy and the current proportional coefficient were used to construct fault features (Zhang, 2020). The statistical analysis methods are simple and easily implemented but susceptible to noise, loads and operating conditions.

5.1.2. Fast Fourier Transform (FFT)

FFT extends the time-domain signal to frequency-domain in order to analyze signal frequency spectrum. The change of harmonic components in converter signal frequency spectrum is related to converter fault, thus it can be used as a fault feature. FFT was used for spectrum analysis and the spectrum at a specific frequency was utilized to detect inverter OC faults (Xia and Ning, 2019; Khomfoi and Tolbert, 2007b). Discrete Fourier transform (DFT) was applied to the output voltage to select the main harmonic information, and then fault identification was performed by BPNN (Jiang et al., 2012). However, FFT produces error information for the analysis of nonlinear signal due to it is linear assumption; besides, FFT is not suitable for detecting transients or short spikes of signals since it has no time resolution. Consequently, the nonlinearity (due to the existence of nonlinear power semiconductor devices) and non-stationarity (due to the complex operating conditions) of wind power converter signals make FFT unable to guarantee the accuracy of converter FDs.

5.1.3. Short Time Fourier Transform (STFT)

STFT is an extension of FFT to analyze the time-varying frequency response of non-stationary signals, it divides a signal into some small time windows and analyzes these windows using FFT to provide localization in time and capture frequency information. STFT provides a three-dimensional representation of signal frequency response (ie, time, frequency, and amplitude). An STFT-based inverter FDs was proposed (Du and Wang, 2010). STFT-based spectral analysis was applied to detect wind power converter OC faults (Ismail et al., 2019). However, the resolution of STFT is constant because of the use of fixed-width windows, that is, high time-resolution and high frequency-resolution are unable to be obtained at the same time. Thus, the high-computational cost required to achieve a high-resolution is a major drawback of STFT.

5.1.4. Wavelet Transform (WT)

WT decomposes a signal into a group of frequency components and gradually observes the signal from coarse to fine, it can represent the signal characteristics in both time-domain and frequency-domain. A telescopic window can be achieved through appropriate selection of scale factor and translation factor, so WT has multi-resolution characteristics, that is, WT can provide a high frequency-resolution for low-frequency components and a high time-resolution for high-frequency components. WT is outstanding for extracting the time-varying features of non-stationary signals and has been widely used in converter FDs.

WT was used to extract fault features from converter phase voltages to detect MMC sub-module SC faults (Liu et al., 2015a). The energy of each layer was extracted as fault features after WT decomposition and reconstruction of converter original signals (Liu et al., 2017a). Wavelet packet decomposition (WPD) was combined with energy vector to extract fault features of converter voltage signals (Sun et al., 2017). Zhang et al. used feature analysis (FA) and judgment (JD) to amplify the divergence of data obtained by WT (Zhang et al., 2019), it can not only accurately detect the single-switch OC faults of the grid-connected converter in the wind turbine system, but also the double-switch OC faults. Discrete wavelet transform (DWT) was adopted to analyze the converter signal, and the detailed coefficients were extracted as fault features (Dhumale and Lokhande, 2016; Rekha et al., 2017; Potamianos et al., 2014), it had a fast computation. DWT was used to preprocess inverter current to obtain approximate coefficients, and then their energy vectors were calculated as fault features (Wu et al., 2017). WT can also be regarded as a set of bandpass filter to filter signal noise (Liu et al., 2017b), it improved the accuracy of converter FDs but increased the complexity. However, WT is susceptible to the wavelet basis, and it lacks adaptability.

5.1.5. Empirical Mode Decomposition (EMD)

EMD is proposed to effectively analyze the signal with nonlinearity and non-stationarity. Based on local features time scale, EMD decomposes a signal into a group of intrinsic mode functions (IMFs). IMFs need to meet sifting stop criteria and they are simple signals with two properties: the number of zero crossings and extreme points equal or differ at most by one in the entire data set; the maximum and minimum envelopes are locally symmetric about the time axis at any time. IMF is a basis function depending on the original signal rather than predefined, so EMD is an adaptive data-driven technology.

Ref. Khan et al. (2020) used EMD to decompose the voltage signal of wind power converter and took median, RMS, variation, mean, entropy, and standard deviation of IMFs as fault features. An EMD-SVM based fault diagnostic method for three-level NPC inverter was proposed (Miao et al., 2017). Ensemble EMD (EEMD)-Norm entropy (NE) based wind power converter FDs was presented (Liang et al., 2020), the fault features were described by IMF-NE, and the diagnostic results showed high accuracy and outstanding robustness.

5.1.6. Variational Mode Decomposition (VMD)

VMD is an adaptive non-recursive data processing technology, it decomposes a signal into a discrete set of bandwidth-limited sub-signals with sparse characteristics, which known as modes. Each mode generated by VMD can be compressed around a central frequency determined with the decomposition process. By minimizing the sum of mode estimation bandwidths, VMD constructs the mode decomposition into a process of solving the optimal solution of a constrained variational problem.

VMD was combined with skewness and kurtosis to extract the fault features of a wind power converter (Yuan et al., 2016). In Zhang et al. (2020b), VMD was applied to decompose converter three-phase current signals and the trend feature vectors were extracted based on the obtained mode coefficient series, this method not only accurately diagnosed the single and double OC faults, but also had strong robustness to wind speed variation.

5.1.7. Principal Component Analysis (PCA)

PCA can mine the essential low-dimensional features of original data set, so as to appropriately describe the data set major trends. PCA was adopted to extract the features corresponding to various faults, and then fault modes were identified by SVM (Wang et al., 2013), it showed an excellent performance against noise and computational complexity. Ref. Kouadri et al. (2020) used PCA to extract fault features of wind power converter and used Hidden Markov Model (HMM) to classify the fault modes, then OC faults and SC faults were effectively detected.

5.1.8. Independent Component Analysis (ICA)

ICA plays an essential role in actual systems real-time FDs since it allows potential variables not to obey Gaussian distribution. Ref. Hu et al. (2020) proposed an ICA-based FDs for grid-connected NPC inverter, in which ICA was applied to extract fault features, and then ANN was used for fault modes identification. The application of ICA technology reduced the number of ANN input neurons and training time; besides, the lower dimensional input space reduced noise, improved the diagnostic performance.

The performance of various signal processing and feature extraction methods are summarized in Table 2 from the aspects of function, domain, resolution, nonlinear signal processing, complexity/computational cost and signal sampling rate, and then the advantages and drawbacks of each method are presented.

The methods mentioned in Table 2 all can be used to extract features, WT and EMD can also be used to denoising (Liang et al., 2020; Zhang et al., 2019; Liu et al., 2017a; Dhumale and Lokhande, 2016; Parimalasundar and Vanitha, 2015; Rekha et al., 2017; Geng et al., 2020; Potamianos et al., 2014; Liu et al., 2015a; Khan et al., 2020; Miao et al., 2017; Wu et al., 2017; Liu et al., 2017b), PCA and ICA are usually used to reduce the feature dimension (Wang et al., 2013; Kouadri et al., 2020; Wang et al., 2015; Cai et al., 2017; Wang et al., 2016; Li et al., 2016; Gomathy and Selvaperumal, 2016; Hu et al., 2020). Due to wind power converters are composed of multiple power switching devices with nonlinear and time-varying characteristics, signals measured by sensors usually have serious nonlinear properties. An excellent fault diagnosis method should be capable of handling nonlinear signals (Liang et al., 2020; Ismail et al., 2019; Zhang et al., 2019; Liu et al., 2017a; Dhumale and Lokhande, 2016; Parimalasundar and Vanitha, 2015; Rekha et al., 2017; Geng et al., 2020; Potamianos et al., 2014; Liu et al., 2015a; Khan et al., 2020; Miao et al., 2017; Yuan et al., 2016; Zhang et al., 2020b; Du and Wang, 2010; Sun et al., 2017; Wu et al., 2017; Liu et al., 2017b). The adaptive data-driven technique decomposes the signal according to an algorithm rather than a predefined basis function (Liang et al., 2020; Khan et al., 2020; Miao et al., 2017; Yuan et al., 2016; Zhang et al., 2020b).

High-quality feature extraction can effectively improve the accuracy of FDs. The PCA technology is combined with other feature extraction techniques to extract more comprehensive fault features. For example, FFT-PCA (Wang et al., 2015; Cai et al., 2017; Wang et al., 2016), DWT-PCA (Gomathy and Selvaperumal, 2016), WPD-PCA (Li et al., 2016). Firstly, FFT, DWT, WPD were used to extract fault features, and then PCA was applied to obtain lower-dimensional feature samples, which reduced the pressure of classifier training and recognition. ANN was combined with multistate data processing (MSDP)-subsection fluctuation analysis (SSFA) feature extraction method to obtain inverter multiple OC fault FDs (Huang et al., 2018b). Deep Belief Network (DBN) optimized by double chain quantum genetic algorithm (DCQGA) was used for fault feature extraction, and the online diagnosis of single and double switch OC faults were obtained accurately and quickly by LSSVM classifier (Shi et al., 2019), it had high robustness to converter operating conditions. These methods showed that a simple classification algorithm could obtain good diagnostic results as long as the features were extracted appropriately. Besides, the hybrid feature extraction strategy combining signal analysis method and statistical index had obtained good diagnostic performance (Liang et al., 2020; Khan et al., 2020; Yuan et al., 2016).

5.2. Fault classification diagnosis

The converter fault modes can be identified by an artificial intelligence algorithm.

5.2.1. Artificial Neural Network (ANN)

ANN-based FDs can learn and popularize from samples. Since its strong nonlinear approximation and adaptive learning ability, ANN has become a common tool for detecting converter faults (Parimalasundar and Vanitha, 2015; Khomfoi and Tolbert, 2007a). An ANN is trained to identify different fault modes of the converter from the signals containing fault information, which can be original signals (Ko et al., 2012), or features extracted from original signals (Tan et al., 2020; Dhumale and Lokhande, 2016; Rekha et al., 2017; Li et al., 2016).

Ref. Kim and Kim (2020) proposed an ANN-based two-step diagnosis method to identify multiple OC faults in three-phase converters. The three-phase current parameters were input to ANN to diagnose the converter OC faults in high-power wind turbines (Ko et al., 2012). DWT-detail coefficients of current or voltage signals were extracted as fault features to train ANN classifier in order to identify fault modes (Dhumale and Lokhande, 2016; Rekha et al., 2017). WPD-PCA fault features were extracted as ANN input for FDs (Li et al., 2016). Ref. Tan et al. (2020) used ANN to train the correlation features (mean and covariation) among three-phase currents to detect the fault of wind power converter. Ref. You and Zhang (2012) used fault feature and self-organizing mapping (SOM) to diagnose wind power converter faults.

ANN is time-consuming due to it needs numerous data to cover all possible fault modes, which is a great challenge in practice. Besides, it is difficult to prove the reliability and convergence of ANN-based methods since ANN is a heuristic technology. Several issues remain to be further studied: the design of network scale and structure; the balance between rapidity, convergence and real-time of the algorithm; the guarantee of the representativeness and integrity of learning samples.

5.2.2. Vector machine algorithm

Vector machine algorithm is a machine learning technology based on statistical learning theory, it requires less training samples due to high sparse degree and generalization ability. Support vector machine (SVM) was applied to train the features (skewness and kurtosis) to identify wind power converter faults (Yuan et al., 2016). The FFT-RPCA feature was input to SVM classifier, and inverter fault states were obtained accurately (Wang et al., 2016). Ref. Shi et al. (2019) used least square SVM (LSSVM) as a classifier to identify the single and double OC faults, and high robustness to operating conditions was obtained. In Duan et al. (2020), multiclass SVM was used to classify multi-scale entropy features to diagnose wind power converter faults. However, SVM is also a heuristic technique and has similar drawbacks as ANN; besides, the inequality constraints in SVM significantly increase computational complexity. The effectiveness of relevance vector machine (RVM) and multiclass relevance vector machine (mRVM) classifier in converter FDs have been verified in Gomathy and Selvaperumal (2016) and Wang et al. (2015), respectively.

5.2.3. Expert system

Expert system is a rule-based technology, which presents expertise in a set of rules. The expert system-based converter FDs was learned from the converter operational history by human experts, and the mapping between measured values and corresponding fault modes was constructed based on experience (Szczesny et al., 1997). Expert system has the advantages of easy development and transparent reasoning. However, the expert system-based fault diagnostic methods are system-specific with low universality and scalability; besides, apart from the drawbacks of heuristic technique, a major disadvantage of the methods is that their scale increases exponentially with the number of fault modes, increasing the computational cost.

Table 2
Comparison of different signal processing and feature extraction methods.

Methods	Function	Domain	Resolution	Nonlinear signal processing	Complexity/computational cost	Signal sampling rate	Advantages	Drawbacks
Statistical analysis (Sedghi et al., 2011; Tan et al., 2020; Yuan et al., 2016; Gao et al., 2019; Chen and Bazzi, 2017; Baghli et al., 2019; Huang et al., 2019, 2018a)	Feature extraction	Time/ frequency	Rely on input	Possible	Low	Any	Simple/straightforward	Sensitive to noise, operating conditions, and load disturbance
FFT (Xia and Ning, 2019; Jiang et al., 2012; Khomfoi and Tolbert, 2007b)	Feature extraction	Frequency	High	No	Medium	High/medium	Extends time domain signal to frequency domain	Based on linear assumption; has no time resolution
STFT (Ismail et al., 2019; Du and Wang, 2010)	Feature extraction	Time/ frequency	Medium	Yes	High	High/medium	Provides localization in time and captures frequency information	Constant resolution
WT (Zhang et al., 2019; Liu et al., 2017a; Dhumale and Lokhande, 2016; Parimalasundar and Vanitha, 2015; Rekha et al., 2017; Geng et al., 2020; Potamianos et al., 2014; Liu et al., 2015a; Wu et al., 2017; Liu et al., 2017b)	Feature extraction; denoising	Time/ frequency	Medium	Yes	Medium	High/medium	Multi-resolution	Susceptible to the wavelet basis; lacks adaptability
EMD (Liang et al., 2020; Khan et al., 2020; Miao et al., 2017)	Feature extraction; denoising	Time/ frequency	High	Yes	Medium	High/medium	Adaptive signal processing	Mode mixing
VMD (Yuan et al., 2016; Zhang et al., 2020b)	Feature extraction	Time/ frequency	High	Yes	Medium	High/medium	Adaptive signal processing	Boundary effect
PCA (Wang et al., 2013; Kouadri et al., 2020; Wang et al., 2015; Cai et al., 2017; Wang et al., 2016; Li et al., 2016; Gomathy and Selvaperumal, 2016)	Feature extraction; dimension reduction	Time/ frequency	Rely on input	Possible	High	Any	Reduce dimension	Heavy complexity and calculation
ICA (Hu et al., 2020)	Feature extraction; dimension reduction	Time/ frequency	Rely on input	Possible	High	Any	Reduce dimension; real-time	Heavy complexity and calculation

5.2.4. Fuzzy Logic System (FLS)

FLS divides the feature space into fuzzy sets and adopts fuzzy rules for reasoning. In Gmati et al. (2021), predictive current errors were used to generate diagnostic variables, then FLS was used to identify the faulty switches of voltage source inverters. Ref. Yan et al. (2019) combined the normalized average currents with FLS to diagnose power switches faults in inverter. However, diagnostic variables are susceptible to noise, loads and operating conditions. The converter fault leg was successfully detected based on DWT detail coefficient feature and FLS (Potamianos et al., 2014). Ref. Liu et al. (2015a) presented a method based on adaptive neuro-fuzzy inference system for SC faults identification of MMC sub-modules, it had the advantages of high accuracy, good generalization, and time-saving. The FDs and online monitoring for grid-connected inverter OC faults can be obtained using this method (Kamel et al., 2015).

The effective methods for analyzing and designing FLS have not yet been established, generally depending on expert experience and trial-and-error. The selection of fuzzy sets and fuzzy rules are still difficult issues. Besides, the size of FLS increases exponentially with the number of converter fault modes, increasing the calculation burden. Moreover, FLS lacks the self-learning ability that is necessary for a highly demanding real-time FDs.

5.2.5. Bayesian Network (BN)

BN is a probability-based technique, it represents a group of random variables and their conditional dependencies by a directed acyclic graph. BN is suitable for real-time state prediction and has been used in converter FDs since it can solve the uncertainty issue. In Cai et al. (2017), the inverter fault modes were identified by BN, it had high diagnostic accuracy and strong robustness to the uncertainty caused by sensor noise and bias. The accuracy of BN significantly depends on the size of data samples and the availability of prior tests.

5.2.6. Stacked Auto-Encoder (SAE)

SAE is easy to train and efficient to learn. SAE was used to automatically learn rectifier fault features from original signals (Xu et al., 2018). A stacked sparse auto-encoder based fault diagnostic method for inverter was proposed (Yin et al., 2019).

5.2.7. Convolutional Neural Network (CNN)

CNN shows priority in weight sharing and shift-invariance. CNN was used to diagnose converter OC faults in wind turbine system (Xue et al., 2019), it showed significant performance under various operating conditions. A modified CNN model CNN-Global Average Pooling (GAP) was applied for inverter FDs (Gong et al., 2020), it reduced the model parameter quantity of traditional CNN, and high accuracy and rapidity were obtained. In Du et al. (2021), a deep CNN (DCNN)-based fault diagnosis method was proposed, sparse representation (SR) was applied to constructed inverter fault features, DCNN was used to train fault modes, it alleviated overfitting caused by limited training samples.

5.2.8. Long Short-Term Memory (LSTM) network

LSTM can update the information automatically. Ref. Xue et al. (2020) proposed an LSTM network-based method to diagnose wind power converter multiple OC faults, it had strong robustness to wind speed fluctuation and sensor bias and had powerful data processing ability. LSTM was used to combined with short-time wavelet entropy and SVM to diagnose MMC faults (Han et al., 2021), it significantly reduced the number of samples.

5.2.9. Deep Belief Network (DBN)

DBN has a high generalization performance due to establish a joint probability distribution between the observed signal and label. DBN was applied to obtain a fault recognition model of wind power converter by learning fault features (Liu et al., 2017a), this method obtained high diagnostic accuracy and fast convergence. A DBN classifier trained by current VMD-trend feature was used for grid-side converter single and double switch FDs in wind turbine system (Zhang et al., 2020b), it was robust to wind speed variation.

The performance of various fault classification methods is compared in Table 3 including function, complexity/computational cost, and then the advantages and drawbacks of each method are presented.

ANN (Zhang, 2020; Ko et al., 2012; Sedghi et al., 2011; Tan et al., 2020; Huang et al., 2018b; Jiang et al., 2012; Zhang et al., 2019; Dhumale and Lokhande, 2016; Parimalasundar and Vanitha, 2015; Rekha et al., 2017; Geng et al., 2020; Khan et al., 2020; Li et al., 2016; Hu et al., 2020; Khomfoi and Tolbert, 2007a; Kim and Kim, 2020) and deep learning algorithms SAE (Xu et al., 2018; Yin et al., 2019), CNN (Xue et al., 2019; Gong et al., 2020), LSTM (Xue et al., 2020), DBN (Liu et al., 2017a; Zhang et al., 2020b; Sun et al., 2017) all can be used for feature extraction and classification. Deep learning algorithms have better diagnostic results, but are computationally expensive and more time-consuming. It is difficult to prove the reliability and convergence of heuristic technology ANN and SVM (Liang et al., 2020; Miao et al., 2017; Yuan et al., 2016; Wang et al., 2013, 2016; Shi et al., 2019). Rule-based technology expert system (Szczesny et al., 1997) and FLS (Potamianos et al., 2014; Liu et al., 2015a; Gmati et al., 2021; Yan et al., 2019; Kamel et al., 2015) have low universality and scalability, and their scale increases exponentially with the number of fault modes, increasing the computational cost. Probability-based technique BN (Cai et al., 2017) is suitable for real-time state prediction, and can solve the uncertainty issue.

Several optimized algorithms have been developed and applied in order to improve classification performance. Multivariable optimization technologies (e.g., genetic algorithm) can be adopted to seek optimum component combination to train an ANN, and a minimum classification error was obtained (Khomfoi and Tolbert, 2007b). Cuckoo Search Optimization (CSO) and Evolutionary Particle Swarm Optimization (EPSO) were used to optimize FLS and RVM respectively to obtain high FDs accuracy (Gomathy and Selvaperumal, 2016). An optimized DBN using Crow search algorithm (CSA) to select the neurons number in two hidden layers was adopted to identify converter faults (Sun et al., 2017), but the calculation was heavy complexity and expensive.

Some new techniques have been applied in the field of converter FDs. A machine learning method using supervisory control and data acquisition (SCADA) system data was applied to diagnose converter faults (Liu et al., 2020b; Xiao et al., 2021). Kou et al. (2020b) used Concordia transform and random forests to obtain OC fault diagnosis with superior robustness for NPC inverter. Random forests with transient synthetic features was used for three-phase rectifier online OC fault diagnosis (Kou et al., 2020a). Mixed kernel support tensor machine (MKSTM) was applied for OC fault diagnosis (Li et al., 2019). Information fusion technology was used to diagnose inverter faults (Wang et al., 2018).

The data-driven methods can perform intelligent diagnoses without system model and prior knowledge, but the accuracy significantly depends on the sample data and the quality of data training. It should be noted that the more sample data is, the higher accuracy can be obtained, but a longer training time is required. These methods need to be further modified to improve their performance since the drawbacks of expensive computation, long diagnosis time, and complicated real-time implementation.

Several integrated schemes of various fault diagnosis methods have been proposed. Model-based method and signal-based method were mixed to diagnose IGBT OC faults (Maamouri et al., 2019), sliding mode observer was used to estimated currents, then the measured and estimated values of current were applied to define fault indices. Model-based method and data processing method were combined for NPC inverter fault detection and isolation (Sanchez et al., 2019), a sliding-mode proportional integral observers was used.

6. Comparison and discussion on fault diagnosis method for wind power converter

All fault diagnosis methods summarized in this paper have acceptable efficiency and performance. This section conducts a detailed qualitative and quantitative analysis of these methods. Then, several technical challenges and development trends of fault diagnosis methods for wind power converters are pointed out.

6.1. Basic information on different fault diagnosis methods for wind power converters

The basic information of each fault diagnosis method for wind power converters is listed in Table 4, including Reference (Ref.),

Table 3
Comparison of different fault classification methods.

Methods	Function	Complexity/computational cost	Advantages	Drawbacks
ANN (Zhang, 2020; Ko et al., 2012; Sedghi et al., 2011; Tan et al., 2020; Huang et al., 2018b; Jiang et al., 2012; Zhang et al., 2019; Dhumale and Lokhande, 2016; Rekha et al., 2017; Geng et al., 2020; Khan et al., 2020; Li et al., 2016; Hu et al., 2020; Khomfoi and Tolbert, 2007a; Kim and Kim, 2020)	Feature extraction; diagnosis; prognosis	Medium	Simple/straightforward; strong nonlinear approximation and adaptive learning ability	Time-consuming; difficult to prove the reliability and convergence
SVM (Liang et al., 2020; Miao et al., 2017; Yuan et al., 2016; Wang et al., 2013, 2016; Shi et al., 2019)	Feature extraction; diagnosis; prognosis	Medium	Simple/straightforward; high generalization ability	Time-consuming; difficult to prove the reliability and convergence
Expert system (Szczesny et al., 1997)	Diagnosis	Medium	Easy development; transparent reasoning	Low universality and scalability; scale increases exponentially
FLS (Potamianos et al., 2014; Liu et al., 2015a; Gmati et al., 2021; Yan et al., 2019; Kamel et al., 2015)	Diagnosis	Medium	Simple/straightforward	Difficult to select fuzzy sets and fuzzy rules; scale increases exponentially; lacks the self-learning ability
BN (Cai et al., 2017)	Diagnosis; prognosis	High	Can solve the uncertainty issue	Depends on the size of data samples and the availability of prior tests
SAE (Xu et al., 2018; Yin et al., 2019)	Feature extraction; diagnosis; prognosis	High	Easy to train and efficient to learn	Heavy complexity and calculation
CNN (Xue et al., 2019; Gong et al., 2020)	Feature extraction; diagnosis; prognosis	High	Shows priority in weight sharing and shift-invariance	Heavy complexity and calculation
LSTM (Xue et al., 2020)	Feature extraction; diagnosis; prognosis	High	Update information automatically	Heavy complexity and calculation
DBN (Liu et al., 2017a; Zhang et al., 2020b; Sun et al., 2017)	Feature extraction; diagnosis; prognosis	High	High generalization performance	Heavy complexity and calculation

publication year, fault type (OC, SC), category, feature extraction method, fault identification method, used signal, domain, nonlinear signal processing.

The signals used in each fault diagnosis method are also listed in Table 4, which provides a reference for which signal can be selected in the fault diagnosis design. Researchers can select the appropriate signals to design the fault diagnosis method according to their own requirements and actual conditions. Converter fault diagnosis generally uses current or voltage signals.

Current-based methods adopt signals existing in control system, including phase current (Jlassi et al., 2015; Zhao and Cheng, 2017; Zhang et al., 2020b), or circulating current (Shao et al., 2016; Deng et al., 2015). From the comparison of qualitative metrics in Table 5 and quantitative indices in Table 6, it can be seen that, for current-based method, no extra sensors or high diagnostic costs are required, but they have load dependence and sensitive to transients, and are susceptible to closed-loop control algorithms. From Tables 5 and 6, voltage-based methods can achieve rapid fault detection and high robustness to loads and noise, such as pole voltage (Shahbazi et al., 2018, 2016), input or output voltage (Liang et al., 2020; Tan et al., 2018; Wang et al., 2015; Cai et al., 2017; Wang et al., 2016), DC-Link voltage (Ismail et al., 2019). Nevertheless, the measurement of diagnostic voltage may require additional sensors or detection circuits, so the implementation cost and complexity of the system increase.

6.2. Qualitative analysis on different fault diagnosis methods for wind power converter

The qualitative analysis is carried out from the aspects of multiple fault diagnosis, additional hardware requirement, model complexity/computational cost/tuning effort, threshold, diagnosis speed, degree of model dependence, amount of data required, applicable system and converter type, applicable objects, technology application maturity, as shown in Table 5.

(1) Single/multiple fault diagnosis

The fault diagnosis method proposed in Karimi et al. (2008) and Lee et al. (2015) can only detect the faulty leg and cannot locate the faulty switch. The method in Qiu et al. (2016), Freire et al. (2014), Choi et al. (2012) and Shahbazi et al. (2018) can diagnose a single faulty switch and Duan et al. (2011), Mahdhi et al. (2020), Zhao and Cheng (2017), Duan et al. (2020) obtain multiple faults diagnosis.

(2) Additional hardware requirement

Additional current or voltage sensors increase the implementation cost due to the complexity of the system structure (Karimi et al., 2008), and even interfere with the normal operation of the wind power converter. The fault diagnosis method without additional hardware is favored (Xu et al., 2021; Freire et al., 2010, 2013; Choi et al., 2012).

(3) Model complexity/computational cost/tuning effort

Signal-based methods are simple and straightforward due to only the diagnostic variables need to be calculated (Mahdhi et al., 2020; Freire et al., 2014; Zhao and Cheng, 2017). Model-based

Table 4
Basic information on different fault diagnosis methods.

Ref.	Fault type	Category	Feature extraction method	Fault identification method	Used signal	Domain	Nonlinear signal processing
Jlassi et al. (2015)	OC	Model-based	Luenberger observer	Residual analysis, look-up table	Three-phase currents	Time	–
Shahbazi et al. (2016)	OC	Model-based	Voltage observer	Residual analysis	Pole voltages	Time	–
Zhang et al. (2020a)	OC	Model-based	Voltage observer	Fault indicator	Sub-module voltage	Time	–
Shao et al. (2013)	OC	Model-based	Sliding mode observer	Residual analysis	Capacitor voltage, arm currents	Time	–
Shao et al. (2016)	OC	Model-based	Sliding mode observer	Residual analysis	Circulating current	Time	–
Deng et al. (2015)	OC	Model-based	Kalman filter	Residual analysis	Circulating current	Time	–
Liu et al. (2015b)	OC and SC	Model-based	Nonlinear adaptive observer	Limiting checking, residual analysis	Phase currents	Time	–
Qiu et al. (2016)	OC	Signal-based	Wind speed-based normalized current trajectory	Pattern of current's park vectors	Three phase currents	Time	–
Mahdhi et al. (2020)	OC	Signal-based	Normalizing phase currents	Limiting checking, look-up table	Two input power converter currents	Time	–
Xu et al. (2021)	OC	Signal-based	Instantaneous amplitude estimation	Limiting checking	Three-phase currents	Time	–
Karimi et al. (2008)	OC and SC	Signal-based	Error voltage	Limiting checking, look-up table	Pole voltages	Time	–
Duan et al. (2011)	OC	Signal-based	Average current	Limiting checking, look-up table	Three-phase currents	Time	–
Freire et al. (2014)	OC	Signal-based	Average current	Limiting checking	Phase currents	Time	–
Zhao and Cheng (2017)	OC	Signal-based	Absolute normalized current	Limiting checking, look-up table	Three-phase currents	Time	–
Freire et al. (2010)	OC	Signal-based	Slope of current vector trajectory	Limiting checking, look-up table	Three-phase currents	Time	–
Freire et al. (2013)	OC	Signal-based	Slope of current vector trajectory	Limiting checking, look-up table	Phase currents	Time	–
Choi et al. (2012)	OC	Signal-based	current vector shape	–	Phase currents	Time	–
Lee et al. (2015)	OC	Signal-based	Zero current duration	Limiting checking, look-up table	Phase currents	Time	–
Tan et al. (2018)	OC	Signal-based	Output voltage RMS	Look-up table	Output voltages	Time	–
Shahbazi et al. (2018)	OC	Signal-based	Error voltage	Residual analysis	Pole voltages	Time	–
Ismail et al. (2019)	OC	Signal-based	Time–frequency analysis	Time–frequency analysis	DC-link voltage	Time–frequency	Yes
Liang et al. (2020)	OC	Data-driven	EEMD-NE	SVM	Three phase voltages	Time–frequency	Yes
Kouadri et al. (2020)	OC and SC	Data-driven	PCA	HMM	Three-phase currents	Time	–
Cai et al. (2017)	OC	Data-driven	FFT-PCA	BN	Two output line-to-line voltages	Frequency	No
Ko et al. (2012)	OC	Data-driven	Detection parameter	ANN	Three phase current	Time	–
Zhang et al. (2019)	OC	Data-driven	WT	BPNN	Three-phase bridge legs voltage	Time–frequency	Yes
Liu et al. (2017a)	OC	Data-driven	WT	DBN	Three-phase currents	Time–frequency	Yes
Liu et al. (2015a)	SC	Data-driven	WT	Adaptive neuro-fuzzy inference system (ANFIS)	Output phase voltages	Time–frequency	Yes
Zhang et al. (2020b)	OC	Data-driven	VMD-TFA	DBN	Three-phase currents	Time–frequency	Yes
Wang et al. (2015)	OC and SC	Data-driven	FFT - PCA	mRVM	Output voltages	Frequency	No
Wang et al. (2016)	OC	Data-driven	FFT-RPCA	SVM	Output voltages	Frequency	No
Hu et al. (2020)	OC	Data-driven	ICA	ANN	Phase voltages	Time	–
Duan et al. (2020)	OC	Data-driven	LMD-MSE	multiclass SVM	Three-phase currents	Time–frequency	Yes

(*continued on next page*)

methods require accurate physical model of converter to diagnose faults, current observer (Jlassi et al., 2015), sliding mode observer (Shao et al., 2016), Kalman filter (Deng et al., 2015), adaptive observer (Liu et al., 2015b) are all referred to complex modeling and calculation. Data-driven methods require signal processing and classifier training, numerous historical data and complex calculation are used, resulting in a heavy computational burden and high cost (Kouadri et al., 2020; Wang et al., 2015; Cai et al., 2017; Wang et al., 2016). Several optimized algorithms have been developed and applied in order to improve classification

Table 4 (*continued*).

Ref.	Fault type	Category	Feature extraction method	Fault identification method	Used signal	Domain	Nonlinear signal processing
Xue et al. (2019)	OC	Data-driven	Data normalization	CNN	Three phase currents and voltages	Time	–
Xue et al. (2020)	OC	Data-driven	Data normalization	LSTM	Three phase currents voltage	Time	–
Liu et al. (2020b)	For the whole converter rather than a specific fault	Data-driven	Radar charts	CNN, SVM	SCADA system data	Time	–
Kou et al. (2020b)	OC	Data-driven	Concordia transform	Random forests	Three-phase currents	Time	–
Han et al. (2021)	OC and SC	Data-driven	Short-time wavelet entropy	LSTM-SVM	The bridge arm current	Time–frequency	Yes
Gomathy and Selvaperumal (2016)	OC and SC	Data-driven	DWT-PCA	RVM-EPSO; FLS-CSO	Output voltages	Time–frequency	Yes
Khomfoi and Tolbert (2007b)	OC and SC	Data-driven	FFT	NN	Output voltages	Frequency	No
Sun et al. (2017)	OC and SC	Data-driven	WPD	CSA-DBN	Output voltages	Time–frequency	Yes

performance (Gomathy and Selvaperumal, 2016; Khomfoi and Tolbert, 2007b; Sun et al., 2017).

(4) Threshold

Some fault diagnosis methods for wind power converter are based on a fixed threshold, which needs to be adjusted according to the rated power or operating conditions, affecting the reliability of the diagnostic results (Mahdhi et al., 2020; Karimi et al., 2008). Several adaptive threshold-based fault diagnosis methods have been proposed (Jlassi et al., 2015; Zhao and Cheng, 2017), which have strong robustness to system transients. In order to obtain a portable method to be universally applied to different wind power systems and different topologies and configurations, it is advantageous to set as few thresholds and simple tuning as possible.

(5) Diagnosis speed: online, offline

The fault diagnosis method proposed in Mahdhi et al. (2020), Xu et al. (2021) and Karimi et al. (2008) are suitable for online real-time diagnosis.

(6) Degree of model dependence

The model-based method has a high degree of model dependence due to the need for an accurate system model (Shahbazi et al., 2016; Zhang et al., 2020a). The signal-based method uses measured signal and signal patterns' prior knowledge for fault diagnosis, so it has low dependence on system model (Tan et al., 2018; Ismail et al., 2019). The data-driven method only require mathematical analysis of the collected signal to diagnose faults without relying on the model (Xue et al., 2020; Liu et al., 2020b).

(7) Amount of data required

Data-driven methods need a large amount of data to train classifiers, while model-based and signal-based methods have less amount of data required.

(8) Applicable system and converter type

Several works devoted to developing the fault diagnosis method for converters in PMSG-based wind turbine systems (Xu et al., 2021; Liu et al., 2015b), the studies regarding the converters fault diagnosis for DFIG-based wind turbine systems are Zhao and Cheng (2017) and Karimi et al. (2008). Typical configurations of wind power converters mainly include 2L-BTB, 3L-NPC-BTB and MMC. Qiu et al. (2016) and Mahdhi et al. (2020) were used for converter fault diagnosis with 2L-BTB topology, Choi et al. (2012) and Lee et al. (2015) were applied for 3L-NPC-BTB configuration, and Liu et al. (2015b) and Ko et al. (2012) were applied to MMC converter.

(9) Applicable objects

A fault occurs in one side converter may lead to variations in voltage or current of the other side converter. Some methods only have the ability of fault detection and location of single-sided converter, Qiu et al. (2016) for generator-side converter and Choi et al. (2012) for grid-side converter. Xu et al. (2021) can handle the faults of both sided converters at the same time.

(10) Technology application maturity

The fault diagnosis method proposed in Duan et al. (2011), Liu et al. (2017a) and Liu et al. (2015a) are verified by simulation, Mahdhi et al. (2020), Karimi et al. (2008) and Freire et al. (2014) are verified by experimental setup. Some methods give both simulation and experimental verification (Qiu et al., 2016; Xu et al., 2021; Ko et al., 2012; Zhang et al., 2019), the method (Liu et al., 2020b) is verified in engineering project.

6.3. Quantitative analysis on different fault diagnosis methods of wind power converter

The quantitative analysis including the number of faults, diagnosis time, accuracy, precision, recall, F1-score, false detection rate, missed detection rate, robustness is presented in Table 6.

(1) Number of faults

The data-driven method is more suitable for applications with a large number of faults than the model-based and signal-based method (Hu et al., 2020; Xue et al., 2020). Because it can accurately identify faults only by training the classifier model with the collected data, no precise system physical principles and signal patterns' prior knowledge is required (these are detrimental for a large number of fault types). The only downside is that the large number of fault types can make the training of the model extremely time-consuming.

Table 5
Qualitative metrics of different fault diagnosis methods.

Ref.	Single/ multiple fault	Threshold	Additional hardware	Model complexity/ computational cost/ tuning effort	Applicable objects	Technology application maturity	Diagnosis speed	Applicable system/converter type	Amount of data required	Degree of model dependence
Jlassi et al. (2015)	Single and multiple faults	Adaptive	No	Model complexity	Back-to-back converter	Simulation platform and experimental setup	Online	PMSG, 2L-BTB converter	Less	High
Shahbazi et al. (2016)	Single fault	Fixed	No	Model complexity	Back-to-back converter	Simulation platform and experimental setup	Online	DFIG, 2L-BTB converter	Less	High
Zhang et al. (2020a)	Single and multiple faults	–	Yes	Model complexity	–	Experimental setup	Online	MMC	Less	High
Shao et al. (2013)	Single fault	Fixed	No	Model complexity	–	Simulation platform	Online	MMC	Less	High
Shao et al. (2016)	Single fault	Fixed	No	Model complexity	–	Simulation platform and experimental setup	Online	MMC	Less	High
Deng et al. (2015)	Single and multiple faults	Fixed	No	Model complexity	–	Simulation platform and experimental setup	Online	MMC	Less	High
Liu et al. (2015b)	Single fault	Fixed	No	Model complexity	Grid-side converter	Simulation platform	Online	PMSG, MMC	Less	High
Qiu et al. (2016)	Single fault	–	No	Simple/straightforward; low-computational demand	Generator-side converter	Simulation platform and experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Mahdhi et al. (2020)	Single and multiple faults	Fixed	No	Simple/straightforward; low-computational demand	Generator-side converter	Experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Xu et al. (2021)	Single and multiple faults	Fixed	No	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform and experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Karimi et al. (2008)	Fault leg (no ability to localize the faulty switch)	Fixed	Yes	Simple/straightforward; low-computational demand	Back-to-back converter	Experimental setup	Online	DFIG, 2L-BTB converter	Less	Low
Duan et al. (2011)	Single and multiple faults	Fixed	No	Simple/straightforward; low-computational demand	Generator-side converter	Simulation platform	Online	DFIG, 2L-BTB converter	Less	Low
Freire et al. (2014)	Single fault	Fixed	No	Simple/straightforward; low-computational demand	Back-to-back converter	Experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Zhao and Cheng (2017)	Single and multiple faults	Adaptive	No	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform and experimental setup	Online	DFIG, 2L-BTB converter	Less	Low
Freire et al. (2010)	Single fault	Fixed	No	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform	Online	PMSG, 2L-BTB converter	Less	Low
Freire et al. (2013)	Single and multiple faults	Fixed	No	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform and experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Choi et al. (2012)	Single fault	–	No	Simple/straightforward; low-computational demand	Grid-side converter	Simulation platform and experimental setup	Online	3L-NPC-BTB converter	Less	Low
Lee et al. (2015)	Fault leg (no ability to localize the faulty switch)	–	No	Simple/straightforward; low-computational demand	Back-to-back converter	Experimental setup	Online	PMSG, 3L-NPC-BTB converter	Less	Low

(continued on next page)

Table 5 (*continued*).

Ref.	Single/ multiple fault	Threshold	Additional hardware	Model complexity/ computational cost/ tuning effort	Applicable objects	Technology application maturity	Diagnosis speed	Applicable system/converter type	Amount of data required	Degree of model dependence
Tan et al. (2018)	Single fault	Without threshold	No	Simple/straightforward; low-computational demand	Generator-side converter	Simulation platform and experimental setup	Online	PMSG, 2L-BTB converter	Less	Low
Shahbazi et al. (2018)	Single fault	Fixed	Yes	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform and experimental setup	Online	DFIG, 2L-BTB converter	Less	Low
Ismail et al. (2019)	Multiple faults (no ability to localize the faulty switch)	–	No	Simple/straightforward; low-computational demand	Back-to-back converter	Simulation platform	Online	DFIG, 2L-BTB converter	Less	Low
Liang et al. (2020)	Single and multiple faults	–	No	Computationally expensive	Grid-side converter	Simulation platform	Offline	DFIG, 2L-BTB converter	Large	Low
Kouadri et al. (2020)	Single fault	–	No	Computationally expensive	Back-to-back converter	Simulation platform	–	Squirrel-cage induction generator (SCIG), 2L-BTB converter	Large	Low
Cai et al. (2017)	Single and multiple faults	–	No	Computationally expensive	Grid-side converter	Simulation platform and experimental setup	Offline	PMSM, 2L-BTB converter	Large	Low
Ko et al. (2012)	Single and multiple faults	–	No	Computationally expensive	Grid-side converter	Simulation platform and experimental setup	–	PMSG, MMC	Large	Low
Zhang et al. (2019)	Single and multiple faults	–	No	Computationally expensive	Grid-side converter	Simulation platform and experimental setup	Offline	PMSG, 2L-BTB converter	Large	Low
Liu et al. (2017a)	Single and multiple faults	–	No	Computationally expensive	Generator-side converter	Simulation platform	Offline	PMSG, 2L-BTB converter	Large	Low
Liu et al. (2015a)	Single fault	–	No	Computationally expensive	–	Simulation platform	–	MMC	Large	Low
Zhang et al. (2020b)	Single and multiple faults	–	No	Computationally expensive	Grid-side converter	Simulation platform and experimental setup	Offline	PMSG, 2L-BTB converter	Large	Low
Wang et al. (2015)	Single and multiple faults	–	Yes	Computationally expensive	Generator-side converter	Experimental setup	Offline	MMC	Large	Low
Wang et al. (2016)	Single fault	–	Yes	Computationally expensive	Generator-side converter	Simulation platform and experimental setup	Offline	PMSG, MMC	Large	Low
Hu et al. (2020)	Single and multiple faults	–	No	Heavy complexity and calculation	Grid-side converter	Simulation platform	Offline	3L-NPC-BTB converter	Large	Low
Duan et al. (2020)	Single and multiple faults	–	No	Computationally expensive	Back-to-back converter	Simulation platform	–	PMSG, 2L-BTB converter	Large	Low
Xue et al. (2019)	Single fault	–	No	Heavy complexity and calculation	Back-to-back converter	Simulation platform	Online	PMSG, 2L-BTB converter	Large	Low
Xue et al. (2020)	Single and multiple faults	–	No	Heavy complexity and calculation	Back-to-back converter	Simulation platform and experimental setup	Online	DFIG, 2L-BTB converter	Large	Low
Liu et al. (2020b)	–	–	No	Heavy complexity and calculation	–	Engineering project	–	–	Large	Low

(*continued on next page*)

(2) Diagnosis time

Signal-based methods can detect faults in just a few tens of microseconds (Shahbazi et al., 2018; Karimi et al., 2008), while model-based methods take several to tens of milliseconds due to the complex modeling and computation process required (Shao et al., 2013, 2016). The need for signal processing and classifier training on a large amount of historical data makes data-driven methods more time-consuming, typically taking hundreds

Table 5 (*continued*).

Ref.	Single/ multiple fault	Threshold	Additional hardware	Model complexity/ computational cost/ tuning effort	Applicable objects	Technology application maturity	Diagnosis speed	Applicable system/converter type	Amount of data required	Degree of model dependence
Kou et al. (2020b)	Single and multiple faults	–	No	Computationally expensive	–	Simulation platform and experimental setup	Online	3L-NPC-BTB converter	Large	Low
Han et al. (2021)	Single and multiple faults	–	No	Computationally expensive	–	Experimental setup	–	MMC	Large	Low
Gomathy and Selvaperumal (2016)	Single and multiple faults	–	No	Optimization techniques: EPSO, CSO; heavy complexity and calculation	–	Experimental setup	Offline	2L-BTB converter	Large	Low
Khomfoi and Tolbert (2007b)	Single fault	–	Yes	Optimization technology: genetic algorithm; heavy complexity and calculation	–	Simulation platform and experimental setup	Offline	MMC	Large	Low
Sun et al. (2017)	Single fault	–	No	Optimization algorithm: CSA; heavy complexity and calculation	–	Simulation platform and experimental setup	Offline	DC–DC converter	Large	Low

of milliseconds to a few seconds (Wang et al., 2015; Hu et al., 2020).

(3) Effectiveness and reliability

The metrics accuracy/precision/recall/F1-score/false detection rate/missed detection rate are used to evaluate the effectiveness and reliability of a fault diagnosis method. High accuracy/precision /recall/F1-score (Liang et al., 2020; Cai et al., 2017; Xue et al., 2020) and low false detection rate/missed detection rate (Mahdhi et al., 2020; Kouadri et al., 2020) are desirable.

(4) Robustness

The specific parameter variations of operating conditions are summarized to facilitate researchers to quantitatively compare the proposed method with existing methods under the same load changes, transients, wind speed changes, and noise levels. For example, both Liang et al. (2020) and Xue et al. (2019) proposed fault diagnosis methods for converters that are robust to wind speed changes, and the accuracy in Liang et al. (2020) at 20 dB can reach 99.2756%, higher than that of 80% at 45 dB in Xue et al. (2019), so it is obvious that the method in Liang et al. (2020) is more robust to wind speed and noise.

All fault diagnosis methods summarized in this paper have acceptable efficiency and performance. It is difficult to explain which method in Tables 4–6 is more popular due to the complexity and bulk of wind power converter systems. The comparison in Tables 5 and 6 are beneficial for finding the best scheme to handle different faults according to different requirements.

6.4. Challenges on wind power converter FDs

Wind power converters topology and configuration continue to evolve due to the constant emergence of complex high-power machinery. Besides, wind power converters suffer from numerous stresses and operating condition variations. Thus, the wind power converters FDs face severe challenges.

(1) Easy implementation

Wind turbine system is a sophisticated system. Since fault diagnosis is an additional module of wind power converters, minimizing the increase of hardware devices for converter FDs and simplifying the diagnosis algorithm are essential to developing a fault diagnostic method that is easy to implement.

(2) Wind power converter benchmark

At present, most of the proposed methods are tested in simulation platform and experimental setup. Proposing a benchmark for fault diagnosis and fault-tolerant control of wind power converter is of great significance, researchers engaged in fault diagnosis can test a new method against this benchmark and compare it with other previous methods. The benchmark establishes wind power converter model at system level containing a fault setup module, which presents an interface for fault setting, including the faults of sensors, power switches, passive components and actuators. It also provides a verification of the reliability and robustness issues of the fault diagnosis method.

(3) Application in wind farms

The effectiveness and reliability of numerous proposed wind power converters FDs are verified in simulation platform and experimental setup, but the reliability and robustness verification in engineering projects is lacking. The wind turbine systems in actual wind farms are different from the simulation and experimental equipment in terms of configuration and power capacity; besides, the actual power grid voltage shocks, real-time operating condition disturbances and on-site environmental interference are very different from the laboratory environment. Applying the designed converter FDs to wind farms is a major challenge.

6.5. Development trends of fault diagnosis methods for wind power converters

Some development trends of fault diagnosis methods for wind power converters are concluded as follows:

(1) The developments of sensor and database technology have brought convenience to data monitoring and storage, making it possible to obtain massive and sufficient system data. Applying the rapidly developing artificial intelligence techniques to wind power converters FDs to obtain excellent diagnostic performance has become an important trend.

(2) With the increasing complexity of wind power converters, multi-data sources integration based converter FDs has become a new trend. The application of multi-sensor data fusion technology or single-sensor multi-feature extraction information fusion technology can fully mine the fault characteristics of converter, so as to significantly improve fault diagnostic accuracy.

(3) In order to obtain excellent real-time diagnostic performance, the integration of various fault diagnostic technologies is a trend.

Table 6
Quantitative metrics of different fault diagnosis methods.

Ref.	Number of faults	Robustness	Diagnosis time	Effectiveness and reliability: Accuracy/Precision/Recall/F1-score/False detection rate/Missed detection rate
Jlassi et al. (2015)	15 types	1. PMSG stator resistance Rs (Rs = 1.5Rsn, with load torque variation). 2. PMSG stator inductance Ls (Ls = 0.7Lsn, with speed variation). 3. PMSG stator inductance Ls (Ls = 1.5Lsn, with speed variation). 4. Speed variations (600 rpm∼1200 rpm). 5. Load torque variation (no-load ∼64% of the rated value).	Within one fundamental current period	–
Shahbazi et al. (2016)	–	–	Within one fundamental current period	–
Zhang et al. (2020a)	2 types	–	T1 fault: within 300 µs; T2 fault: within 200 µs.	–
Shao et al. (2013)	–	1. Light load condition: 5% load. 2. Parameter uncertainty: l_{cal} = 1.1 l, C_{cal} = 1.2 C, l_{cal} is arm inductance for calculation, and l the actual value; C_{cal} is dc-capacitance for calculation, and C is the actual value. 3. Measurement inaccuracy: add 2% of the systematic error and 10% of the random error to the measure capacitor voltage. 4. Imbalanced capacitor voltage: V_{c1} = 1.25 V_{c4} before fault occurrence.	Within 100 ms	–
Shao et al. (2016)	–	1. Simulation: (1) measurement noise (5% white noise); (2) parameter uncertainty; (3) measurement errors (1% scaling errors in measurement). 2. Experiment: (1) parameter uncertainty (10% error in the inductance; 0.11-Ω parasitic resistance in the arm inductors;); (2) measurement errors (5% scaling error in the measurement); (3) transients (modulation index of the ac voltage changes from 0.6 to 0.95 at 0.07 s and changes back at 0.12 s).	Less than 50 ms	–
Deng et al. (2015)	3 types	1. Simulation: (1) process noise (variance is 4e−5); (2) measurement noise (variance is 5e−4). 2. Experiment: (1) process noise (variance is 5e−5); (2) measurement noise (variance is 3e−3).	Locating fault within 7 fundamental periods	–
Liu et al. (2015b)	3 types	Different operating conditions: 10 MW, 20 MW.	Within 1 fundamental period	–
Qiu et al. (2016)	6 types	1. Constant wind: speed at 5 m/s. 2. Step wind: ranging from 3 to 6 m/s with certain wind speed last for one or two seconds. 3. Turbulent wind: average wind speed of 5 m/s and turbulent scale of 0.1–0.2.	Fast but not defined	–
Mahdhi et al. (2020)	9 types	Generator rotation speed changes.	15 ms	False detection rate: 0%; Missed detection rate 50%
Xu et al. (2021)	21 types	Wind speed variations (10 m/s∼12 m/s).	Within 0.5 fundamental period	–
Karimi et al. (2008)	–	–	Within 10 µs	–
Duan et al. (2011)	21 types	–	55 ms	–
Freire et al. (2014)	–	1. Load transient (from rated load torque to 16% of the rated torque). 2. Time-varying load conditions (with an average load torque of 33% of the rated load, and an oscillating torque component with a frequency of 4 Hz). 3. Unbalanced load conditions (add a 12 Ω resistance to phase a of the grid-side converter).	Within 0.5 fundamental period	–
Zhao and Cheng (2017)	21 types	Wind speed (from 10 m/s to 6 m/s at 6 s).	40 ms	–
Freire et al. (2010)	12 types	Load transients (load torque from 4 Nm to 16 Nm at t = 0.14 s).	Less than a fundamental period	–

(continued on next page)

Table 6 (*continued*).

Ref.	Number of faults	Robustness	Diagnosis time	Effectiveness and reliability: Accuracy/Precision/Recall/F1-score/False detection rate/Missed detection rate
Freire et al. (2013)	15 types	1. Simulation: load torque (from 16% of rated value to rated value at t = 0.12 s, and reduced to 16% of rated value at t = 0.14 s, then increased to 50% of rated value at t = 0.2 s.) 2. Experiment: (1) load torque (from rated value to 16% of rated value at t = 0.17 s.); (2) speed transient (from 600 rpm ∼900 rpm at t = 0.14 s.)	Within 0.5 fundamental period	–
Choi et al. (2012)	4 types	–	Within two fundamental periods	–
Lee et al. (2015)	–	–	Fast but not defined	–
Tan et al. (2018)	7 types	Wind speed (10.5 m/s, 7 m/s).	Less than 1/4 of the period	–
Shahbazi et al. (2018)	–	Independence from wind condition, rotor frequency.	30 μs	–
Ismail et al. (2019)	–	–	9 ms	–
Liang et al. (2020)	22 types	1. Wind speed variation: from 10 m/s to 15 m/s with an interval of 0.0625 m/s. 2. Sensor noise: 5 dB, 10 dB, 15 dB, and 20 dB. 3. Training/testing ratio: 3:2, 10:1, 15:1, 25:1, 35:1, 45:1.	–	Accuracy: 99.2756% (20 dB); 97.8598% (15 dB); 90.0758% (10 dB); 71.8040% (5 dB).
Kouadri et al. (2020)	7 types	Noise	–	Accuracy: 93.61%; Precision: 95.22%; Recall: 95.06%; F1-score: 95.13%; False detection rate: 10%
Cai et al. (2017)	22 types	1. Simulation: (1) frequency and modulation index. (1) train data: frequency varies from 30 Hz to 80 Hz with the interval of 2 Hz and the modulation index varies from 0.6 to 0.9 with the interval of 0.001. (2) Test data: when the frequency is 60 Hz and the modulation index varies from 0.6005 to 0.9005 with the interval of 0.01. (2) Robustness to sensor noise: from 0 to 20 dB. (3) Robustness to sensor bias: from −1.6 V to 1.6 V. 2. Experiment: frequency and modulation index. (1) train data: frequency is 60 Hz and the modulation index is 0.8. (2) test data: when the frequencies are 55, 65, and 75 Hz and the modulation indexes are 0.65, 0.75, and 0.85.	–	Accuracy: 98.48% (10 dB).
Ko et al. (2012)	22 types	–	Within 1.5 fundamental periods	–
Zhang et al. (2019)	22 types	–	–	Accuracy: 99.999%
Liu et al. (2017a)	22 types	–	–	Accuracy: 98%
Liu et al. (2015a)	4 types	–	–	Accuracy:100%
Zhang et al. (2020b)	22 types	Wind speed	–	Accuracy: 100% (simulation); 99.99% (experiment)
Wang et al. (2015)	37 types	10% white Gaussian noise.	Average testing time 131 ms	Accuracy: 98.11% (10 dB)
Wang et al. (2016)	9 types	10% white Gaussian noise.	Less than 12.4 ms	Accuracy: 100%
Hu et al. (2020)	Typical faults: 25 types; Atypical faults: 48 types.	1. The inverter input voltage: 450 V, 500 V, 550 V, 600 V. 2. The load power: 10 kW, 20 kW, 30 kW.	4 s	Accuracy: 95.1%
Duan et al. (2020)	22 types	–	0.0129 s	Accuracy: 99.28%

(*continued on next page*)

7. Conclusion

The continuous development of wind power converters' fault diagnosis reduces the downtime of wind turbine systems caused by converter faults, saves maintenance costs, improves the availability and reliability of the systems, and promotes the large-scale penetration of wind power generation.

This paper studies the typical fault modes of wind power converters, including short-circuit faults and open-circuit faults in

Table 6 (*continued*).

Ref.	Number of faults	Robustness	Diagnosis time	Effectiveness and reliability: Accuracy/Precision/Recall/F1-score/False detection rate/Missed detection rate
Xue et al. (2019)	12 types	1. Wind speed fluctuates around the average value of 10 m/s. 2. Noise: 35 dB, 40 dB, 45 dB, 50 dB.	The time delay is short enough (0.001 s)	Precision: Higher than 91.2% (none noise). Recall: Higher than 92.1% (none noise). F1-score: Higher than 92.2% (none noise); higher than 80% (45 dB).
Xue et al. (2020)	79 types	1. Wind speed fluctuation: varies randomly between 8–18 m/s. 2. Sensor bias: ranges from 0 to 2. 3. Noise.	1. Without interference factors: diagnosis time delay of LSTM is short enough (Td: 0.0016 s). 2. With interference factors: (Td: 0.0022 s).	Precision: 1. Without interference factors: 98% (average). 2. With interference factors: 95% (average). Recall: 1. Without interference factors: 97% (average). 2. With interference factors: 94% (average). F1-score: 1. Without interference factors: 0.98 (average). 2. With interference factors: 0.94 (average). 3. Sensor bias 0.5: 70% (average). 4. Gaussian noise 35 dB: 60%. 5. Experimental evaluation: 96%
Liu et al. (2020b)	–	Wind speed: from 3 m/s to 20 m/s.	–	Accuracy: 94.87% (10-s resolution data); 89.03% (10-min data). Precision: 100% (10-s resolution data); 99.1% (10-min data). Recall: 89.75% (10-s resolution data); 78.76% (10-min data). False detection rate: 5.13% (10-s resolution data); 10.97% (10-min data).
Kou et al. (2020b)	More than 15 types	Different loads conditions: 10 Ω load, 20 Ω load.	Simulation: 4.6 ms; Experiment: half a cycle.	Accuracy: 97.27% (simulation); 98.07% (experiment). False detection rate: 1.93%
Han et al. (2021)	10 types	–	–	Accuracy: High than 93.77%
Gomathy and Selvaperumal (2016)	25 types	1. Case 1: Training dataset/Testing dataset (80/20). 2. Case 2: Training dataset/Testing dataset (90/10).	1. Case 1: 1.43 s (CSO-RVM); 3.34 s (EPSO-Fuzzy). 2. Case 2: 2.06 s (CSO-RVM); 4.47 s (EPSO-Fuzzy);	Accuracy: 1. Case 1: 92.07% (CSO-RVM); 91.24% (EPSO-Fuzzy). 2. Case 2: 95.67% (CSO-RVM); 94.86% (EPSO-Fuzzy).
Khomfoi and Tolbert (2007b)	8 types	Different modulation indices: 0.8, 1.0.	–	Accuracy: 85%
Sun et al. (2017)	10 types	1. Input voltage: varies from 26.6 V to 29.4 V. 2. Training dataset/Testing dataset: case 1 (80/20), case 2 (60/40), case 3 (50/50).	32.6 s (in case 1); 27.36 s (in case 2); 25.83 s (in case 3).	Accuracy: 96.36% (in case 1); 95.68% (in case 2); 92.55% (in case 3); 95% (experiment).

power switch. The reliability and robustness issues are discussed. Then it comprehensively reviews the performances of model-based, signal-based and data-driven methods for wind power converter fault diagnosis. Qualitative analysis and quantitative comparison are carried out detailed.

(1) The model-based method can accurately and real-time diagnose multiple faults. However, the complex modeling and calculation make the diagnosis time longer than that of signal-based method. Additionally, it significantly depends on the precision of system model and parameters. Furthermore, proper tuning of observers is required to guarantee the performance of fault diagnosis, this means additional implementation work and computational effort.

(2) The signal-based method is simple and straightforward. It has significant real-time performance and is suitable to be integrated into the wind power converter controller for fault-tolerant control. However, it is susceptible to load changes and system transients and requires prior-knowledge of the system.

(3) The data-driven method can be easily conducted only with the measured signals, so it has excellent portability among different wind power systems. It has superior nonlinear signal processing ability, strong reliability and robustness, and multiple fault diagnosis ability by using advanced algorithms. However, it requires a large amount of historical data for training, so the computation is expensive and time-consuming, and it has poor real-time performance.

The existing fault diagnosis methods for wind power converter diagnose faults based on the significant changes of system state, which is not effective for early faults. Additionally, the balance between high diagnostic performance and implementation effort, and the portability in different wind power systems also need to be considered. These open problems stimulate the exploration of more advanced fault diagnosis methods, such as advanced artificial intelligence technique-based method, multi-data sources integration-based method, and various fault diagnosis technologies hybrid method.

The future work on fault diagnosis for wind power converters can be involved in the wind power converter benchmark and application in wind farms. The contribution of this paper has focused on fault diagnosis methods, little exploration has been given to the fault prognosis and health management of wind power converters, such as fault prediction, fault-tolerant control, condition monitoring, and condition-based maintenance, these also are future issues that could require further investigations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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