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Moradzadeh, Arash ; Mohammadi-Ivatloo, Behnam ; Pourhossein , Kazem ; Anvari-Moghaddam, Amjad

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Data Mining Applications to Fault Diagnosis in Power Electronic Systems: A Systematic Review

Arash Moradzadeh, *Student Member, IEEE*, Behnam Mohammadi-Ivatloo, *Senior Member, IEEE*, Kazem Pourhossein, Amjad Anvari-Moghaddam, *Senior Member, IEEE*

***Abstract*— Early fault detection in power electronic systems (PESs) to maintain reliability is one of the most important issues that has been significantly addressed in recent years. In this paper, after reviewing various literature based on fault detection in PESs, data mining-based techniques including artificial neural network, machine learning, and deep learning algorithms are introduced. Then, the fault detection routine in PESs is expressed by introducing signal measurement sensors and how to extract the feature from it. Finally, based on studies, the performance of various data mining methods in detecting PESs faults is evaluated. The results of evaluations show that the deep learning-based techniques given the ability of feature extraction from measured signals are significantly more effective than other methods and as an ideal tool for future applications in power electronics industry are introduced.**

***Index Terms*—Power electronic systems, reliability, fault detection, fault tolerant, artificial neural network, machine learning, deep learning.**

I. Introduction

NOWADAYS, electrical energy has become an influential factor in the scientific, economic and welfare fields of human daily life. In recent years, the expansion of electrical energy applications and the increase of electrical energy consumers have made distributed generation (DGs) dramatically replace traditional power systems [1], [2]. On the other hand, DGs such as renewable energy sources (RESs) and energy storage systems have been widely used to reduce fossil fuel consumption and solve environmental problems. But the important point is that the production, storage and utilization of electrical energy in the economic and daily life cycle require power electronic systems (PESs) [3]. PESs have a significant role in integrating RESs, energy management, and reliability of power grids, and other related infrastructures and systems [4], [5]. Energy/power conversion using PESs is easy and low cost. Despite all the advantages of PESs, their high vulnerability to natural disasters, frequent switching in harsh environment, and etc. that results in power outages or system shutdown and accordingly increased cost of operating, is one of their biggest disadvantages. Long-term sustainability without power interruption is one of the most important factors in the needs of PESs applications. In most cases, severe environmental conditions such as high temperatures, over voltage and over current, wear-out of electrical components, radiation, vibration and mechanical damages, thermal damages, hardware design or control defects, and electromagnetic stresses are major causes of critical failures in PESs. Some studies have shown that semiconductors of the primary side (low voltage, high current) and resonance elements used in PESs can be the main sources of damage due to various factors. Faults that occur mainly in different parts of the PESs are divided into two categories of structural faults (hard faults) and parametric faults (soft faults) [6]–[8]. Each of the hard and soft faults are divided into various types of anomalies, which are introduced as follow:

A. Hard faults

Hard faults occur due to drastic changes in the value of parameters related to the components or circuit structures in the PESs. These faults are observed in two cases of SC fault and OC fault. Hard faults can have effects such as a sudden increase in current and a sudden voltage drop in PESs. Thus, the occurrence of a hard fault provides the basis for serious and catastrophic damage to the entire system. Hard faults generally do not occur directly in the system and are happen often due to the intensity and persistence of soft faults in the circuit [9], [10].

B. Soft faults

Soft faults mainly refer to the parameters of the circuit components from their tolerance range, but they do not affect the circuit connections. Soft faults are known as parameter drift and cause a gradual decrease in system performance and ultimately cause aging and wearing out [11]. The occurrence of

Arash Moradzadeh is with the Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz 51666, Iran, (email: arash.moradzadeh@tabrizu.ac.ir; arash.moradzadeh@ieee.org).

Behnam Mohammadi-Ivatloo is with the Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz 51666, Iran (e-mail: mohammadi@ieee.org).

Kazem Pourhossein is with the Department of Electrical Engineering, Tabriz Branch, Islamic Azad University, Tabriz, Iran (e-mail: k.pourhossein@iaut.ac.ir).

Amjad Anvari-Moghaddam is with the Department of Energy (AAU Energy), Aalborg University, 9220 Aalborg, Denmark (aam@energy.aau.dk).

soft faults does not completely interrupt the operation of the circuit in PESs, but causes an unacceptable operation of the circuit by creating an unwanted output. Studies and experiments have shown that the soft faults can become a hard fault if they are not detected and fixed in a timely manner [9].

In recent years, various studies have been conducted on the stability and reliability of power electronic converters, and based on more than 200 products from 80 companies, it has been concluded that capacitors and power semiconductor devices include more than 50% of PES failures (As shown in Fig. 1). Occurrence of any faults in these systems will cause serious damages to the entire system.

Maintenance in PESs is an topic that has posed many challenges and includes reliability, stability, condition monitoring, fault detection, and useful life estimation [12]. Several review papers over the past decade have addressed this issue [10], [13]–[15]. Advanced analysis of condition monitoring and fault diagnosis in PESs is reviewed in [13].

However, the study includes very limited methods of faultdiagnosis based on Artificial Neural Network (ANN) algorithms. Authors of [10] examine the condition monitoring techniques of capacitors in power electronic converters, which also emphasize the methods of parameter identification based on ANNs. In addition, a variety of ANN-based techniques called the dynamic Bayesian network and object-oriented Bayesian network have been employed in [16], [17], for industrial applications such as transient and intermittent fault detection in complex electronic systems. In another valuable study [18], the hybrid applications rule-based algorithm and back propagation neural network (BPNN) for fault detection in a diesel engine are introduced. In this study, the signals are processed via wavelet threshold denoising and ensemble empirical mode decomposition. Early fault detection in permanent magnet synchronous motor has been done in [19] by presenting data-based approaches called Bayesian network. In this study, to improve the fault detection process, wavelet threshold denoising and minimum entropy deconvolution techniques are employed to pre-processing and denoising the input signals. In [14], a summary of machine learning methods used to manage the reliability of energy systems has been provided. Another valuable study [15], examines the application of ANN

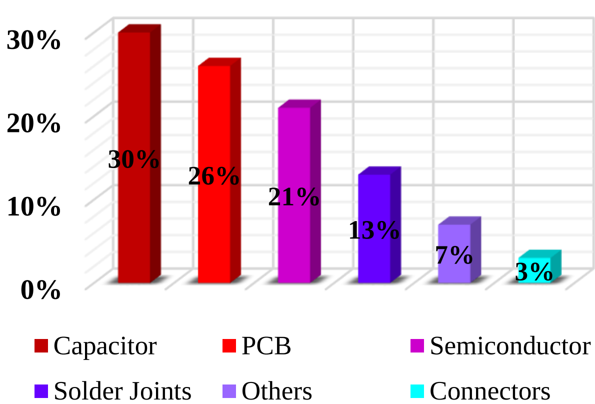

Fig. 1. Percentage of PESs failures [7]

techniques in PESs. This paper is also generally limited to ANN algorithms.

Accurate and early detection of any of the faults in PESs is one of the most important issues that has created many challenges for researchers and craftsmen in the fields of power electronics and industrial electronics. Most of the recent research has identified, analyzed, and diagnosed all types of faults in PESs in different ways. Some of them have succeeded, but some others have failed to detect the fault correctly. Identifying and diagnosis any faults in PESs requires an evaluation of the impact of each fault on the system [4], [20]. So far, in various studies several categories of fault detection methods have been introduced and employed in PESs. Frequency-domain based techniques, Wavelet Transform (WT), ANN algorithms, machine learning-based procedures, and deep learning applications are the most important methods discussed in identifying faults of PESs. Fault detection in PESs began with conventional methods and the use of numerous sensors. These methods were expensive and suffered from problems in timely and accurate fault detection. Meanwhile, with the advent of the Internet of Things, the use of intelligent sensors has led to the exchange of a wide range of data in energy systems technologies and PES applications. After that, traditional and conventional methods did not perform reasonably well in the face of high volumes data. Thus, the increasing volume of data provided a good basis for the application of data mining science and other techniques such as ANN, machine learning, and deep learning. In addition, the challenges and specific features of PESs such as high sensitivity in condition monitoring for aging detection, the need for online monitoring, and high adjustment speed in control, has increased the need for data mining applications in PESs dramatically.

In this paper, the application of data mining techniques such as ANN, machine learning, and deep learning algorithms in detection of PES faults are reviewed in detail. By examining the machine learning and deep learning techniques, the gaps in previous research that mainly focus on ANN techniques are filled. Furthermore, this paper introduces the types of faults in PESs and the necessity of timely fault detection, investigates the impact of each fault on the system, and reviews a variety of fault diagnosis methods. Finally, the fault prognosis models that can be a very important step in the increasing the reliability of PESs will be explored.

The rest of the paper is organized as follows. Section II reviews studies conducted to identify faults in PESs. Section III introduces and categorize the fault diagnosis methods in PESs. Routine of fault diagnosis in PESs is presented in Section IV. Section V introduces the sensors and instruments for signal measurement in PESs. Section VI describes fault-tolerant in PESs. Finally, the concluding remarks are presented in Section VII.

II. Historical and Literature review of Fault Detection in PESs

The main objective of this study was to review and evaluate the performance of each of the methods used to detect faults in PESs. This evaluation includes all studies conducted on fault detection from the beginning to the present and looks at future challenges over time. Thus, the initial studies related to fault detection in PESs in the form of a sub-section called historical review and other recent studies under the title of the literature review are presented in the continuation of this section.

A. Historical review of fault detection in PESs

So far, many solutions have been utilized based on the classification presented in the previous section to detect faults related to PESs. A probabilistic applications of ANNs called radial basis function (RBF) was reported in 2003 in [21], to identify SC fault associated with an inverter driver. In another valuable study [22], using ANN algorithms, single commutation failure, double not successive commutation failure, and double successive commutation failure in a converter used in high-voltage direct current (HVDC) system have been identified. In [23] and [24], the ANN applications are employed to detect OC faults and hard faults (which refer to the analogue part of the circuit) in a delta-sigma converter, respectively. Transistor switch faults in a voltage source inverter have been identified in [25] by a new model of ANN based on the controller of space vector modulation.

As can be seen from the reviewed literature, the ANN applications have been used continuously for several years as fault diagnostic methods in PESs. In 2007, two advanced neural network called self-organizing maps (SOM) and learning vector quantization have been introduced and used to detect the SC and overcurrent faults of transistor utilized in isolated DC-DC converters in multi-phase multilevel motor drives [26]. Later, a hierarchical fuzzy-based diagnostic solution was introduced in [27] to identify the SC and AC faults of switches in a direct current (DC)-motor-based brake-by-wire system. In a PV system, fault in DC transmission line, commutation fault in one of the thyristors of the inverter, and single-phase fault in the AC system in the inverter side have been diagnosed using an improved ANN algorithm called, ADAptive linear neuron [28]. The SC fault associated with converter-fed induction motors is identified in [29] using the Feed Forward Neural Network method and based on the FFT signals of the system.

B. Literature review of Fault detection in PESs

With the advancement of technology and the expansion of the data volume related to various issues of power systems and PESs, the performance of ANNs was reduced to some extent. To improve the detection process and increase the accuracy of detection operations, in 2009, a supervised kernel-based method and support vector machine (SVM) were first proposed as applications of machine learning in power electronics [30]. In the study, the proposed methods were employed to detect OC fault of switch in pulse-width modulation (PWM) voltage fed power converter of brushless DC motor drive. In another valuable work [31], rotor faults corresponding to a converter-fed induction motor and changeable rotors have been categorized using machine learning techniques called radial basis neural network and k-means. The SVM technique has been proposed in [32] to identify thyristors faults in a three-phase full-bridge controlled rectifier.

The proper performance of machine learning techniques in various studies led to the rapid development of the use of these methods in the science and industry related to power electronics. For the first time in 2013, a new machine learning technique called Extreme Learning Machine (ELM) has been proposed to predict the inter-turn SC fault in a three-phase converter-fed induction motor [33]. In the same study, in order to express the effectiveness of the suggested procedure, one of the ANN methods called MLP is also utilized to identify faults, which the results emphasize the superiority of the ELM method. Identification and classification of six types of faults including the SC, pulse loss, AC single-phase grounding, AC two-phase grounding, AC three-phase grounding, and DC grounding in an HVDC converter have been performed via the SVM in [34].

In the process of using different machine learning techniques, a new algorithm called Least-Squares Support-Vector Machine (LSSVM) in 2014 has been introduced and utilized to detect the SC fault in a three-phase squirrel-cage induction motor fed by a sinusoidal PWM converter [35]. In the same work, the effectiveness and high performance of the suggested method has been compared to other ANN and machine learning techniques such as MLP, ELM, SVM, and the Minimal Learning Machine was approved. Various faults in Inverter side of a 12-pulse Line HVDC commutated converter include Single Line to Ground (Rectifier side), Double Line to Ground (Rectifier side), Line-to-Line (Rectifier side), and DC Fault have been identified and categorized by an ANN technique called Levenberg Marquardt backpropagation algorithm in [36].

As stated in the literature, the utilize of data mining techniques in detecting PES faults began with the employing supervised algorithms and over time led to a significant increase in their use. With the expansion of data volume, these methods encountered some problems in the training phase, such as overfitting or data missing. In 2015, in two valuable studies [37], [38], one of the unsupervised methods of data mining called Principle Component Analysis (PCA) has been introduced for the first time to fault detection and improve the problems of supervised methods. In those studies, the PCA technique for detecting the SC switch fault in a cascaded H-bridge multilevel (5-level) inverter has been combined with the FFT and SVM methods to significantly increase the fault detection accuracy. In [39], Discrete Wavelet Transform (DWT) and Fuzzy Inference Logic methods have been selected to detect the various faults include DC SC to ground, OC of insulated gate bipolar transistor (IGBT), SC damage of IGBT, DC link capacitor, and single line to ground fault of a machine terminal is used in a 3-phase inverter. In another study [40], the OC faults of thyristors used in a 3-phase full-bridge rectifier in 21 types have been investigated via the support vector data description and SVM techniques. A multi-layer ANN based on multi-valued neuron with a complex QR-decomposition has been designed and utilized in [41] to identify capacitor faults in a Class-E DC-AC inverter. In [42], four type of converter faults (namely backfire, fire-through, commutation failure, and misfire) used in an HVDC transmission system are identified by a wavelet-based ANN. A hybrid model of Park's vector transform, DWT, and ANN methods have been presented in [43] to identify single and multiple OC switch faults under variable load conditions in a 3-phase voltage source inverters. In another valuable study [44], the OC and SC faults diagnosis in a 3-phase inverter circuit has been performed using optimized machine learning algorithms. In this paper, wavelet and PCA graph methods are selected for statistical processing of measured signals, and fuzzy logic system and relevance vector machine methods are utilized to fault detection and classification. So that, diagnostic methods are optimized using evolutionary particle swarm optimization and cuckoo search optimization algorithms. In [45], an unsupervised data mining technique called weighted Kernel PCA has been introduced and utilized to detect the OC switches faults in the 3-level inverter.

In 2016, another powerful machine learning technique called the decision tree has been proposed for the first time in [46] to detect the OC fault tested in a voltage source inverter of induction motor drives. In [47], an improved ANN algorithm called kernel SOM has been proposed to detect the SC fault in 3-phase converter-fed induction motors. Identification of AC filter's health status based on the opening/closing current of AC filter's breaker in an AC filter in converter station in [48] has been detected via the RBF neural network. In [49], an active semi-supervised fuzzy clustering algorithm with pairwise constraints has been utilized to detect the fault of the OC switches faults in a multiphase multilevel neutral point clamped (NPC) converters in a five-phase machine. In [50], the identification of parametric faults (the parametric degradation trends of resistors and capacitors from accelerated life tests) in a benchmark Sallen–Key filter circuit and a DC-DC converter system is performed via a kernel learning-based procedure. In another valuable study [51], unsupervised techniques called PCA and Kullback-Leibler divergence have been employed to detect incipient bias fault and incipient ramp fault in an inverter used in China Railway High-speed 2.

Over the past years, the use of ANN and machine learning techniques in power electronic applications has shown significant growth potential. However, advances in science and the complexity of power systems and the increasing volume of monitored data from industrial equipment and power systems have increased the need for feature extraction and pattern recognition methods. In 2017, for the first time, deep learning techniques were used to fault detection in PESs [7]. In this paper, the deep belief network as one of the deep learning algorithms has been suggested to identify hard faults such as OC and SC faults but also the soft faults such as the component degradation of power MOSFET, inductor, diode, and capacitor in a DC-DC converter (closed-loop single-ended primary inductance converter). The method proposed in this paper was optimized using the crow search algorithm. In another valuable work in 2017 [52], one of the other deep learning applications called, Sparse Autoencoder has been introduced to detect the OC fault in various modes of a cascaded H-bridge seven-level converter. Hard and soft faults in the super-buck converter circuit have been investigated in [53] using the Kernel Entropy-Based Classification approach and ELM methods. In [54], one of the novel deep learning applications called Long Short-Term Memory (LSTM), a prominence version of the Recurrent Neural Network (RNN) has been suggested for fault detection and scalable reliability in high-frequency Gallium Nitride power dc-dc converter. In 2018, in a valuable study [55], one of the powerful applications of deep learning in feature extraction called Convolutional Neural Network (CNN) has been proposed and utilized for the first time to detect OC fault in modular multilevel converter (MMC). In [56], eight kinds of DC bus capacitor faults and energy storage inductor in dual-buck bidirectional DC-AC converter have been investigated by fuzzy cerebellar model neural network. Six different fault situations in a PWM DC–DC converters using multilayer multivalued neuron neural network have been identified in [57]. In another valuable study [58], various machine learning techniques called k-nearest neighbors (k-NN), Bagging, AdaBoost, MLP, SVM, and Naive Bayes have been employed to identify half broken rotor bar and broken rotor bar in an induction motor. In that study, the performance of each of the methods used is evaluated and compared, and finally Naive Bayes and Bagging methods are selected as the best models. The Deep CNN technique in [59] investigates the SC and OC faults in MMCs. In another study [60], a hybrid machine learning technique called mixed kernel support tensor machine detects the OC fault in a MMC. The IGBT OC fault detection in a traction inverter has been performed using a combination of WT and SVM methods in [61]. In [62], a hybrid solution based on wavelet packet and ELM techniques, which is also optimized using the Firefly algorithm, has been proposed to detect the OC switch fault in a phase shifted full bridge converter. The Sparse Autoencoder based Deep Neural Network method has been selected as one of the hybrid applications of deep learning in [63] to detect the OC fault in a 3-phase full-bridge rectifier. The OC fault associated with a Permanent Magnet Synchronous Generator Wind Energy Converters and Modular Multi-level Converter has been investigated in [64] and [65], respectively, using neural network-based techniques. The OC faults and current sensor faults in grid-tied 3-phase inverters have been identified in [66] by presenting a method that innovatively combines two types of diagnosis variables, line voltage deviations and phase voltage deviations. A hybrid method based on integrating the wavelet packet transform and LSTM has been introduced in [67] to Identify SC and OC faults in a five-level nested neutral-point-pilot topology. In [68], the CNN technique has been used as one of the deep learning applications to identify OC faults in the back-to-back converter in permanent magnet synchronous generator-based wind generation system. In another valuable study [69], the CNN method has been selected as a diagnostic tool to detect inverter faults in the PV system and symmetrical/unsymmetrical faults in the distribution line. In [70], the CNN procedure has been represented as a powerful tool to diagnosis OC switch fault in a hybrid active NPC inverter. The ELM and Random Vector Functional Link network techniques, as machine learning applications, identify and classify OC fault in an IGBT utilized in a 3-phase PWM converter [71]. In a novel study in 2020 [72], detection of multisensor-based traction converter faults has been performed by the LSTM technique in an experimental setup. The proposed LSTM in this study, extracts the long-term patterns and dependencies in time-series effectively, and learns hidden fault features from traction converter multisensor signals adaptively, without needs of expert knowledge or system modeling. In [73], an unsupervised learning approach based on PCA has been suggested for detecting semiconductors and modules faults in Silicon Carbide MOSFETs. Moreover, in order to increase the accuracy and reduce the time horizon of abnormally detection, a PCA-based pre-processing approach is applied to the measured signals from the system.

As reviewed in the above literature, today deep learning applications based on their high capabilities in pattern recognition and feature extraction are mainly utilized in fault detection applications of PESs. Nowadays, researchers are dramatically improving deep learning methods or looking for new ones. In 2021, for the first time in [74], another deep learning technique called Temporal Convolutional Network has been introduced and employed to identify and classify OC faults and six unknown faults in a 3-phase voltage inverter.

A review of fault detection studies in PESs showed that learning-based techniques were mainly used for this purpose. In some other studies, using techniques based on hardware equipment, control, and mathematical calculations, faults in PESs have been identified [75]–[82]. Ref. [75] introduces a compensation control method based on a mixed switching strategy to detect the OC switch faults in a boost DC-DC converter. In another valuable study [76], the fault fast switch fault in a AC-DC Converters of Hybrid Grid Systems has been diagnosed using the threshold point calculation method.

A review of various studies shows that the faults related to the PESs occur mainly in industrial equipment, which increases the need for rapid detection to prevent serious damage to the system and power electronic instruments. Based on literature reviewed, the ANN algorithms have been the most widely used to detect PES faults. Since 2009, machine learning methods have come into play with the improvement of problems related to ANN techniques and their use continues. Deep learning techniques based on their high ability to extract features and high performance speed have been utilized to detect PES faults since 2017 and the use of these methods is expected to increase in the coming years.

A review of the literature in this section shows that the studies performed to detect the PESs faults have mainly focused on the detection of hard faults. It is important to note that hard faults are caused by soft faults, and if diagnostic methods focus on timely detection of soft faults, the hard faults can be prevented.

III. Fault Diagnosis Methods in PESs

The PESs are critical components in the power/energy systems and industrial equipment that ensure the stability and efficiency of these systems. Therefore, the health of PESs must be fully guaranteed and any abnormalities in these systems must be detected and corrected in a timely manner. Choosing the suitable method for fault detection in PESs is very important. The method selected must have the ability to act very quickly and with high detection accuracy. As reviewed in the literature, many methods for fault detection in PESs have been introduced and used so far. The continuation of this section categorizes and introduces all of the model-based and data-based fault detection techniques in PESs and finally evaluates the performance of the methods used, technically. The block diagram in Fig. 2 categorizes the types of learning-based algorithms of data mining techniques.

A. *Model-based techniques*

The model-based fault detection approaches have long been widely used in PESs. The performance of these techniques is based on physical processes and interactions between system components. Thus, fault detection in the system is based on the impact of physical changes in the converter model or any PES's component. The use of model-based techniques requires knowledge of the structure of a system and the characteristics of its components [7], [83]. Model-based techniques are divided into two classes: Qualitative and quantitative procedures. The qualitative-based methods do not require accurate numerical models and this is the reason why they are more resistant to noise and modeling errors. However, these model-based methods are not very accurate and do not have the ability to accurately determine the magnitude of the fault. However, quantitative methods include fault detection and the ability to determine the magnitude of the fault. Therefore, quantitative methods can be utilized for fault prognosis applications as well as estimating the useful lifetime of the PESs [84]. So far, fault detection in PESs has been performed in many studies based on model-based techniques.

In [85], quantitative fault detection has been performed by proposing a diagnostic model-based technique called a hybrid bond graph (HBG). A hybrid circuit model, based on the HBG and global analytical residuals redundancies has been introduced for fault detection in [86]. A model-based fault detection technique is proposed in [84] to detect SC faults in switches as well as incipient and abrupt faults in switches and detectors on a dc-ac half-bridge inverter. In this study, the proposed model is modeled based on the HBG and the residues. In [87], a model-based technique for detecting OC faults in a single-phase DC/AC converter, which includes an H-bridge and a capacitor with parallel resistance and current source on its DC side, has been presented. The technique proposed in this study is based on dynamic regressor extension and mixing, and works

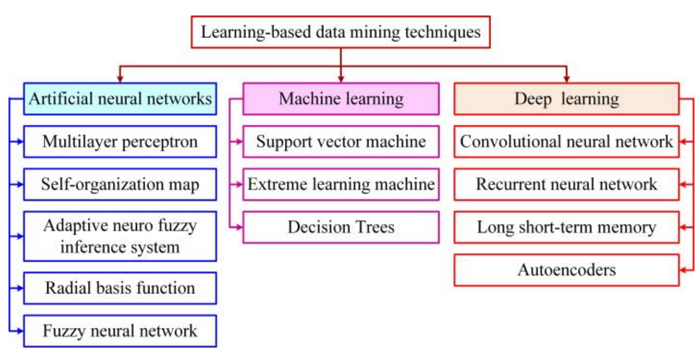

Fig. 2. Classification of types of learning-based algorithms of data mining techniques

based on fault signature estimates. The OC fault detection in a two-level three-phase converter has been done in [88] by providing a hybrid model-based and data-based approach. The performance of the model proposed in this study is based on parameters and observations related to output currents, grid voltages, and DC voltage. A model-based state estimator procedure has been suggested in [89] for OC fault diagnosis in switches of a nanogrid prototype with a 380 V DC distribution bus. This nanogrid consists of four various switching power converters, including a buck converter, an interleaved boost converter, a single-phase rectifier, and a three-phase inverter. In [90], the OC fault detection of single-phase three-level neutral-point clamped converters used in an electric railway has been performed by introducing a model-based fault detection approach. The proposed algorithm detects the faults using the signals existing in the control system. In order to identify the single-phase PWM rectifier open switch faults, a model-based approach based on the mixed logical dynamic model and residual production has been proposed in [91].

A review of the literature shows that model-based fault detection techniques have been widely used in the industrial applications of PESs. However, these techniques suffer from high dependence on the model and physical behavior of the system. Thus, issues such as the types of harmonics and component exhaustion can cause misleading changes in the fault pattern and complicate the fault detection process. In addition, in many cases, it is very difficult to calculate accurate mathematical representations, and the mathematical modeling of the physical model of the system under study is very complex [7]. Therefore, nowadays, in valuable studies [15], [92], the use of data-based techniques that have no dependence on the physical model of the system and do not have any computational complexity has been suggested.

B. *Artificial Neural Network (ANN)*

The ANN has been one of the most prominent areas of research for the past few decades and is growing rapidly nowadays. ANN is also referred to as artificial intelligence which is a system derived from human intelligence and based on training that is utilized to analyze and process various types of data [93], [94]. So far, various algorithms have been introduced for ANN that are used for applications such as regression, classification, and pattern recognition in various scientific and industrial fields. Applications such as maximum power point tracking (MPPT) control for wind power conversion systems [95], optimal and intelligent control in power electronic converters [96]–[99], intelligent controller for light emitting diode (LED) [100], [101], remaining useful life estimation for super-capacitors [102], and the identification of a variety of anomalies are considered to be the capabilities of ANN algorithms in PESs. A valuable review paper [15], fully introduces and reviews the applications of neural networks in PESs. Due to the fact that this paper mainly emphasizes the introduction of techniques used in the identification of PES anomalies, the ANN techniques used in this regard are classified and introduced as follows:

1) *Multilayer Perceptron (MLP)*

The MLP is one of the ANN algorithms with a layer-by-layer feed-forward structure that can mainly model different functions to solve many complex problems. In addition, solving problems such as regression, categorization, and non-linear modeling are other applications of MLP [103]. As shown in Fig. 3, the input layer *(x)*, hidden layer, and output layer *(Y)* forms the structure of this network, respectively. The first layer receives the inputs and transfers them to the next layer for processing. Operational calculations and determination of weight *(W)* and bias *(b)* for data are performed in the hidden layer. The MLP uses a supervised learning procedure named back propagation for training. After completing the calculations in the hidden layer, the output layer can finally provide the desired estimation for *n* input samples as follow [104], [105]:

$$Y = f(b + \sum_{i=1}^{n} w_i x_i) \quad (1)$$

One of the most important issues in achieving the ideal prediction by MLP is determining the number of neurons in the hidden layer. The MLP network training is done in a supervised-based manner with a network called backpropagation [106].

2) *Self-Organization Map (SOM)*

SOM is one of the ANN algorithms with supervised and unsupervised learning capability, which was first proposed in 1982 by Kohunen [107]. The SOM analyzes and processes data based on the mapping of high-dimensional data in a low-dimensional network while preserving the inherent nature of the data. This algorithm is mainly used in prediction, classification, clustering, and data visualization applications [108], [109].

The process of SOM performance, like other ANN-based techniques, is based on two modes of training and mapping. In the first stage of the SOM implementation process, the input dataset is transformed into a low-dimensional dataset (map space) during the training process. Then, low-dimensional data is classified based on the Euclidean distance mapping.

The map space consists of components called neurons or nodes arranged in a two-dimensional rectangle or a hexagonal

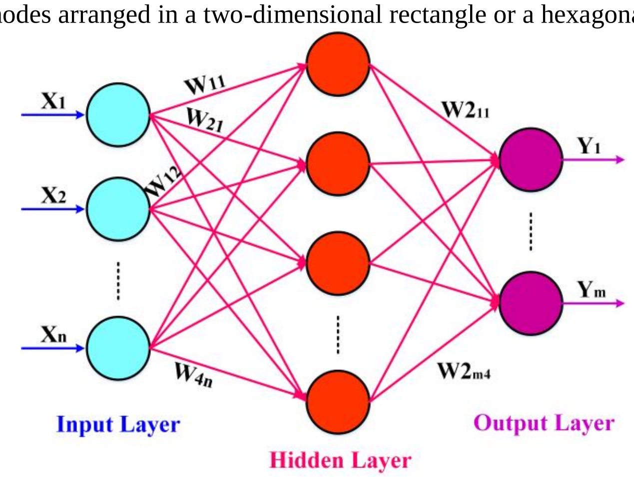

Fig. 3. Block diagram of MLP

grid. The number of nodes and their arrangement are determined in advance and according to the larger objectives of data analysis and exploration. Each node in the map space is associated with a weight vector. The data related to the map space is classified based on the weights of each node and their Euclidean distance on the feature space.

Mapping complex high-dimensional relationships between input and output into a low-dimensional space while maintaining the topological structure of the original data is one of the most important features of SOM. Studies have shown that SOM is one of the best learning algorithms in text clustering research. The simplicity of SOM is one of its salient features compared to other two- or multi-layer neural networks. As Fig. 4 shows, in a simple SOM topology each input neuron is directly connected to the output neuron [110].

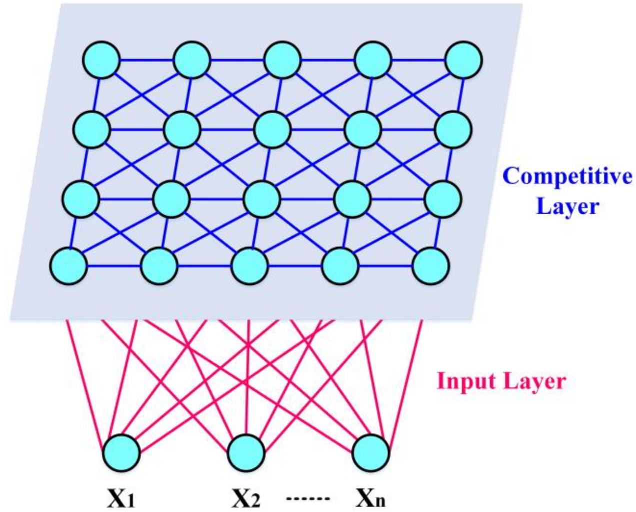

Fig. 4. Block diagram of SOM

3) *Adaptive Neuro Fuzzy Inference System (ANFIS)*

The ANFIS was first introduced in 1993 by Jang as a combination of ANNs and fuzzy inference to solve complex problems and to estimate nonlinear relationships between input and output functions [111]. In this hybrid model, the fuzzy part establishes the relationships between the input and output variables. Meanwhile, fuzzy membership functions become more efficient with the help of neural networks. An ANFIS model uses the Takagi-Sugeno fuzzy inference system to form a feed forward network of five layers. In this structure, the desired output is calculated based on parameters that are adjusted by the learning algorithm to minimize modeling error [112], [113]. In such network, estimation of the parameters of the membership functions is also done by the backpropagation or a mixture of backpropagation and least-square. The ANFIS is a supervised training network used primarily for modeling nonlinear functions, classification, regression, and estimating chaotic time series [114]. The training process of ANFIS network is completed in a two-step approach. The default parameters are trained via the gradient descent and, in the backward pass, by the back-propagation algorithm.

In the ANFIS structure, the input layer, called layer 0, consists of *n* nodes, where *n* is the number of inputs. The next layer is layer 1 and is called fuzzification layer, in which each node denotes a membership value as a Gaussian function with average as presented in (2):

$$\mu Ai(x) = \frac{1}{1 + \left[\frac{x - ci}{ai}\right]^{2bi}} \tag{2}$$

where *ai, bi, and ci* represent the parameters of the function and their values are matched in the learning phase by a back-propagation algorithm. At each step, as the parameters change, the membership function of the linguistic term *Ai* changes.

In layer 2 of the ANFIS structure, the multiplication operation for each node is represented by the strength of the rule. Thus, to find the firing strength of a rule in which the variables x_0 have a linguistic value of *Ai* and *xi* has a linguistic value of *Bi*, the membership values denoted by $\mu Ai(x_0)$ and $\mu Bi(x_1)$ are multiplied in the antecedent part of Rule *i*. The number of rules in layer 2 is represented by *pn* nodes. Thus, *n* and *p* represent the number of input variables and the number of membership functions.

$$wi = \mu Ai(x_0) * \mu Bi(x_1) \tag{3}$$

Layer 3 is called the normalization layer and normalizes the strength of all rules based on the following equation:

$$\bar{W}i = \frac{Wi}{\sum_{j=1}^{R} Wj} \tag{4}$$

where *wi* demonstrates the firing strength of the *i*-th rule. This layer contains p^n nodes.

Layer 4 in the ANFIS structure is a layer consisting of adaptive nodes. Each node in this layer calculates a linear function in which the leading multilayer feed-forward neural network error function is used to adjust the coefficients of the function as follows:

$$\bar{W}ifi = \bar{W}i(p_0x_0 + p_1x_1 + p_2) \tag{5}$$

pi's represent the parameters where *n* denote the number of system inputs and $i = n + 1$. Finally, $\bar{W}$ is the output of layer 3. The back-propagation algorithm is used as the training algorithm in ANFIS and the parameters are updated with a learning step.

Layer 5 is the output layer that the net sum of the output of the nodes in layer 4 expresses its function, and finally, the output is expressed as follows:

$$\sum_i \bar{W}ifi = \frac{\sum_i wi\, fi}{\sum_i wi} \tag{6}$$

where the output of node *i* in layer 4 is expressed as $\bar{w}ifi$. Finally, the overall output of the ANFIS is based on the summation of the consequences of the rule.

In recent years, in addition to fault detection in PESs, the ANFIS has been employed in other applications related to power electronics and industrial electronics, such as control, modeling, estimation, and harmonic elimination [113], [115]–[117].

4) Radial Basis Function (RBF)

The RBF was introduced in 1988 by Broomhead and Lowe as one of the generalized structures of feed forward ANNs [118]. In this type of neural network, biological neurons have a local response. Like other ANN algorithms, the RBF has a structure with an input layer, a hidden layer, and an output layer. In the input layer, the number of nodes is equal to the number of input dimensions. In the second layer, which is the hidden layer, the number of nodes depends on the complexity of the problem. In the third layer or output layer, the number of nodes is equal to the output data dimension [119]. In this structure, the input layer distributes the normalized input variables to the hidden units of the hidden layer. An RBF associated with a center vector with dimensions equal to the number of input variables is implemented by each hidden unit. In the RBF structure, the output layer is connected linearly to the hidden layer. Thus, the simple structure of RBF has made this algorithm faster and more efficient than algorithms such as MLP [120].

The orthogonal least-squares algorithm, clustering and gradient-based algorithm can be named as the most widely used RBF network training algorithms [121]. The overall output of an RBF network for a dataset D containing N patterns of (x_p, y_p) is expressed as y_p, where x_p is the input samples. The output corresponding to the i-th activation function $\emptyset_i$ in the hidden layer is computed as follows:

$$\emptyset_i(\|x - c_i\|) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_j^2}\right) \tag{7}$$

where $\|.\|$ shows the Euclidean norm, σ_j and c_i represents the width and center of the hidden neuron j, respectively. Finally, the output associated with the node k of the RBF output layer is calculated as:

$$y_k = \sum_{j=1}^{n} w_{jk}\emptyset_j(x) \tag{8}$$

The RBF is mainly used for classifying, forecasting, and estimating the relationship between input and output variables. However, the network has been used in recent years for issues such as control, stability, and anomaly detection in power electronics [122]–[124].

5) Fuzzy Neural Network (FNN)

A fuzzy system performs the control and estimating process by mapping the fuzzy sets in input product hypercube to the fuzzy sets in an output hypercube. Fuzzy systems behave like associative memories that associate output fuzzy sets with input fuzzy sets [125]. Using the concept of fuzzy system, a fuzzy neural network (FNN) can be created for forecasting, categorizing, and mapping applications between input and output variables. The FNN has the advantages of fuzzy logic and neural networks. It is able to combine fuzzy reasoning in the management of uncertain information and the ability of ANNs to learn from the process. The training process of FNN network is performed by using back-propagation and gradient algorithms.

In FNNs it is based on the fact that input represents a precondition and output is considered as the result of a rule. An FNN, in addition to all its control and training capabilities, suffers from limitations such as static problems in the scope of application due to the limited advanced network structure and poor performance in large and time-series data processing [126]. However, these systems are mainly used in power electronics applications such as anomaly detection, control [127], [128], and controller design [97].

Literature review provides an overview of the performance of ANN-based techniques in power electronics applications. It is observed that the ANN-based algorithms have been widely used in power electronics industry and science. Given the focus of this paper on fault detection in PESs, Table I categorizes fault detection studies in PESs based on the ANN algorithms.

C. Machine Learning

Recently, machine learning in particular has become a highly active research field as well as an essential technology. Machine learning techniques have been able to suitably solve problems related to various scientific and industrial applications. The continuation of this section introduces the various machine learning techniques that are mainly used in power electronics applications.

1) Support Vector Machine (SVM)

The SVM is one of the supervised machine learning techniques that was first introduced in 1995 [129]. The SVMs were introduced specifically to solve problems related to classification and then generalized as support vector regression for use in linear regression problems. In general, categories related to two or more variable classes, estimation, and pattern recognition are various applications of SVM. Additionally, the SVM can globally evaluate any multivariate function with any level of approximate accuracy [130], [131]. As Fig. 5 shows, the main idea of SVM is to estimate an optimal hyperplane as the decision surface and to maximize the edge of isolation between the two data types. Finding the suitable hyperplane and predicting each sample in the corresponding class can be accomplished by training the SVM model on the training dataset, a process that involves sequentially optimizing an error function [132].

Creating a linear mapping for the $Z = \{X_i, Y_i | i = 1, 2, 3, \ldots, n\}$ dataset by SVM is based on the following relation:

$$\gamma = \omega^T\theta(x) + b \tag{9}$$

where ω and b represents the weight vector and bias. $\theta(x)$ denotes the agent of a nonlinear mapping function. Computation

TABLE I
STUDIES THAT HAVE IDENTIFIED FAULTS BASED ON ANN TECHNIQUES

Method	Ref	Year	Fault type	PES application	Advantages	Limitations
MLP	[22]	2003	Single commutation failure, Double not successive commutation failure, Double successive commutation failure	3-phase cycloconverter drive scheme HVDC converter Multilevel-inverter drive	Capable of implementing on complex nonlinear problems and data. Fast performance after training and save in the test stage. Ideal and accurate performance against small datasets. It's very simple structure makes it easy to design the desired network.	The effectiveness of independent variables from dependent variables is not known in this method. Computations of this method is complex and time consuming Model performance and test results are highly dependent on the quality of the training process In processing high dimension data, it mainly suffers from over-fitting problems Does not have the ability to model time-series data and extract correlations between input and output variables in this data
	[29]	2009	SC	Converter-fed induction motors		
	[31]	2011	Rotor fault	Converter-fed induction motor and changeable rotors		
	[148]	2012	OC switch fault	Three-parallel converters in a wind turbine		
	[149]	2013	OC	Proton exchange membrane fuel cell and DC-DC Converter		
	[33]	2013	Intern-turn SC	Three-phase converter-fed induction motor		
	[35] [150]	2014 2015	SC incipient fault Four different levels of switches fault	Three-phase squirrel-cage induction motor fed by a sinusoidal PWM converter Series hybrid electric vehicles		
	[57]	2018	Boundary conduction mode, discontinuous conduction mode, CCM, deviations in nominal values of capacitor, power inductor, and duty cycle	PWM DC-DC converters and their applications for the buck and boost DC-DC converters		
	[151]	2018	Stator SC	Three-phase induction motors		
	[29]	2019	SC	Converter-fed induction motors		
	[65]	2019	Single-Submodule OC fault	Modular multi-level converter		
BPNN	[21]	2002	OC and SC	3-phase cycloconverter drive scheme Duals converters applied in DC drives	Correction of trajectories in weight and bias space through gradient descent is one of the most important features of this technique. Due to the removal of weight links, it provides a very simple network structure. It has fast and easy programming. No prior knowledge of networks is required. Its training process is independent of the features of the function. Allows efficient calculation the gradient in each layer completely.	Mainly in solving most problems, it has a high dependence on the type of inputs. It is highly sensitive to complex and noisy data. Cannot do time-series data modeling. The processing of large volumes of data by this method suffers from the problem of over-fitting. Not able to extract features from input data.
	[32]	2012	Faults in a single thyristor and the faults happening in two thyristors at the same time	Three-phase full-bridge controlled rectifier		
	[33]	2013	Intern-turn SC	Three-phase converter-fed induction motor		
	[52]	2017	OC switch fault	Cascaded H-bridge seven-level converter		
	[152]	2017	Diode OC	Three-phase full-bridge rectifier		
	[7]	2018	OC, SC, component degradation of power MOSFET, inductor, diode, and capacitor	DC-DC Converter (closed-loop single-ended primary inductance converter)		
	[56]	2018	Eight kinds of faults related to DC bus capacitor and energy storage inductor	Dual-buck bidirectional DC-AC converter		
	[59]	2018	Switch OC and SC	MMC		
	[61]	2018	IGBT OC	Traction inverters		
	[153]	2019	Multiple OC switch fault	A back-to-back converter in doubly-fed induction generator-based wind turbine systems		
SOM	[26]	2007	Driver power supply under voltage, transistor SC, and overcurrent	Isolated DC-DC converters in multi-phase multi-level motor drive	The process of test and evaluating new data after network training is very fast. The SOM has a very simple network structure that avoids the complexity of computing. It can also be used as an unsupervised procedure. It can be used as a tool to dimension reduction of high-dimension data.	The process of training a network to deal with high-dimension data is time-consuming. Despite processing large data, it does not have the ability to model the time-series mode of data. The training process of this network and its performance in the test phase is highly dependent on the quality of the input data.
	[33]	2013	Intern-turn SC	Three-phase converter-fed induction motor		
	[47]	2017	SC	Three-phase converter-fed induction motors		
RBF	[154]	2003	OC	Inverter drive		

	[31]	2011	Rotor fault	Converter-fed induction motor and changeable rotors	It has a fast process of determining the network parameters and training stage. The RBF has a high ability to solve function approximation problems for data and surfaces with regular peaks and valleys. Ideal performance and high resistance against noisy data are the prominent features of this technique. Fast performance after training in the test stage.	The large number of neurons increases the complexity of the network for processing input variables and determining their correlation with output variables. The RBF network training algorithm is incapable of processing and modeling robust and complex nonlinear systems. Like other traditional neural networks, it suffers from time-series data modeling and high-dimension data.
	[60]	2018	Switch OC	MMC		
	[64]	2019	OC	Permanent magnet synchronous generator wind energy converters		
	[64]	2020	OC in both single and double switches	A permanent magnet synchronous generator system for wind turbines		
FNN	[21]	2002	OC and SC	Duals Converters Applied in DC Drives	This technique has a much better and more accurate learning ability and the convergence error in this network is very small. Compared to other ANN techniques, it has a high ability in modeling and mapping nonlinear systems. The structure and training process of this network requires less adjustable support parameters than other ANNs. Better integration of this network with other control design methods is a prominent feature of this method.	The limited structure of this network causes limitations such as static problems in its application areas. High-dimension data processing is not very accurate and it is not possible to discover the correlation between input and output variables in time-series data by this method. In the face of noisy data, especially in the training process, suffers from over-fitting problems.
	[23]	2004	Fault-free circuit	Delta-sigma converter		
	[27]	2007	OC and SC switch faults	A dc-motor-based brake-by-wire system		
	[44]	2016	Transistor OC	Three-phase inverter circuit		
	[155]	2017	Structural and functional faults	Analog to digital converter		
	[49]	2017	Switch OC	Multiphase multilevel NPC converters in five-phase machine		
	[56]	2018	Eight kinds of faults related to DC bus capacitor and energy storage inductor	Dual-buck bidirectional DC-AC converter		

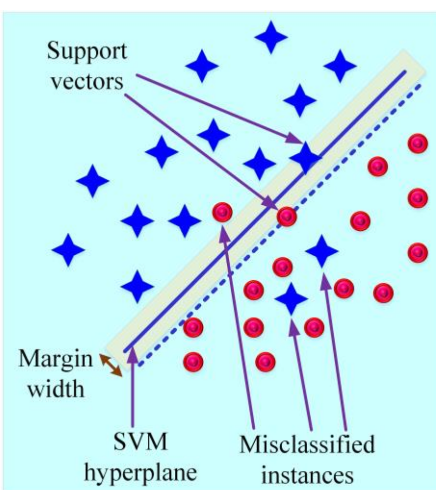

Fig. 5. Main idea of SVM

of support vectors associated with each class are described as:

$$\begin{cases} b + W^T.X_i = +1, & for\ d_i = +1 \\ b + W^T.X_i = -1, & for\ d_i = -1 \end{cases} \tag{10}$$

where d_i shows the related class, i.e., $d_i = +1$ of class A and $d_i = -1$ related to class B.

In the SVM structure, the transfer of inseparable data to a high-dimensional linear space and their classification based on the linear hyperplane is possible using a vector mapping function $\varphi(x)$. Finally, the implementation of the decision function is done as follows:

$$f(x) = sign\left(\sum_{i=1}^{N} a_{0,i}\left(\varphi(x)\varphi(x_i)\right) + b\right) \tag{11}$$

The training process of the SVM network is based on different kernels. Various types of kernels such as linear, nonlinear, and polynomial can be used as SVM training algorithms.

As mentioned in the literature, the SVM has been used extensively in recent years to identify faults related to PESs. However, its use is not limited to this topic and it has been utilized in other applications such as estimating the batteries state of charge, reliability, and control issues [133]–[136].

2) Extreme Learning Machine (ELM)

The ELM was first introduced in 2006 as one of the machine learning applications and learning tool based on a modification of the traditional single hidden layer feed-forward neural network [137]. The ELM technique is mainly used for classification applications, regression-based forecasting in short-term intervals, and estimating the relationship between input and output variables. As Fig. 6 shows, the ELM structure is consisting of the input layer, hidden layer, and output layer [138]. Unlike the ANN algorithms and some machine learning techniques, the ELM has a very fast training process and

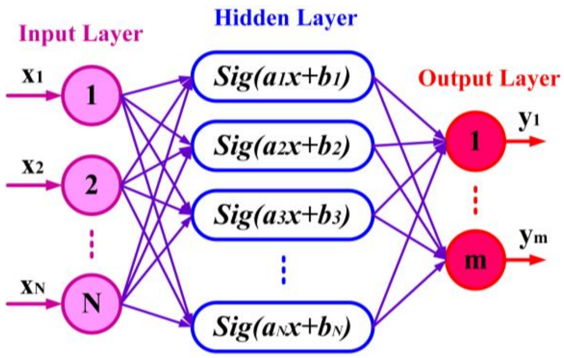

Fig. 6. Schematic diagram of a ELM network

randomly selects hidden thresholds during the training period and analyzes the output weight without iterative calculations.

The ELM as an efficient tool has unique advantages such as higher performance and suitability for kernel functions and nonlinear activation. The best feature of the ELM algorithm is its very high training speed, which is based on the simplicity of its structure [139], [140].

The gradient descent-based back-propagation training algorithm is most widely employed for the training of ELM [141]. In the first step of ELM, the network parameters are assigned randomly. Then, the output matrix related to the hidden layer calculation for the input weight vectors $x_i = [x_{i1}, x_{i2}, \ldots, x_{iN}]^T$ is calculated as follows:

$$\sum_{i=1}^{\tilde{N}} \beta_i f_i(x_i) = \sum_{i=1}^{\tilde{N}} \beta_i f\left(a_i . x_j + b_j\right) = t_j, \qquad j = 1, \ldots, N \tag{12}$$

where b_i denote the hidden layer bias and i is the number of hidden layer neurons, and the hidden neurons are assigned as $\tilde{N}$. The weight vectors which connect the input nodes and i-th hidden layer nodes are shows as $a_i = [a_{i1}, a_{i2}, \ldots, a_{in}]^T$. The output weight vectors that connect output layer neurons with the i-th hidden neuron is demonstrated as $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}]^T$. In the ELM architecture $f\left(a_i . x_j + b_j\right)$ is the activation function and is represented as follow:

$$f\left(a_i . x_j + b_j\right) = \frac{1}{1 + e^{-(a_i . x_j + b_j)}}^{-1}, \quad i = 1, \ldots, L, \quad j = 1, \ldots, N \tag{13}$$

The equation (12) can be written as follows [142]:

$$H\beta = T \tag{14}$$

with

$$H = \begin{bmatrix} f(a_1 . X_1 + b_1) & \cdots & f(a_{\tilde{N}} . X_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ f(a_1 . X_N + b_1) & \cdots & f(a_{\tilde{N}} . X_N + b_{\tilde{N}}) \end{bmatrix}_{N \times N}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{N \times m} \qquad T = \begin{bmatrix} t_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{N \times m}$$

where H is the hidden layer output matrix, β and T show the output weight matrix and the matrix of target output, respectively. Finally, the input weight and bias in the training stage are generated randomly, and the output weight can be calculated by using the Moore-Penrose generalized inverse of H as follow [142], [143]:

$$\beta = H^{\dagger} T \tag{15}$$

This technique has been used since 2013 to detect faults in PESs and has since been used in the power electronics industry for applications such as design, control, condition monitoring, and nonlinearity mitigation for light-emitting diode communications [144]–[147].

3) *Decision Trees (DT)*

The decision tree is a type of inductive learning and is known through a systematic method known as recursive binary partition. This technique can be used in different application ranging from linear regression models, classification, and feature extraction, to pattern recognition [156], [157]. As Fig. 7 shows, the structure of decision trees consists of tree-shaped diagrams [158]. Thus, this tree is formed from components called branches and three types of nodes called root node, internal node and leaf node. In this structure, the dataset is divided into a number of subsets through a series of dichotomous classifications. In the interconnected structure of the decision tree, nodes are the points in the tree where features are processed. Branches are also test results that form the next nodes. Among the nodes, the root node is the highest node, the internal nodes in the middle and the leaf nodes at the end are known as the end nodes. The decision tree training and testing process ends when a node reaches a certain predetermined class purity level and there is only one output type in that node [158], [159]. In some reviewed studies, the decision tree technique has been used to identify PESs anomalies. In some other valuable studies [151], [157], [160], [161], these techniques have been used in various applications of power electronics and industrial electronics. After introducing each of the machine learning techniques and introducing their various applications in power electronics, the classification of fault detection studies in PESs based on the machine learning algorithms is performed in Table II.

D. *Deep Learning*

The complexity and nonlinear behavior of PESs have increased the need for accurate and high-performance methods in fault detection operations. Although the ANN and machine learning

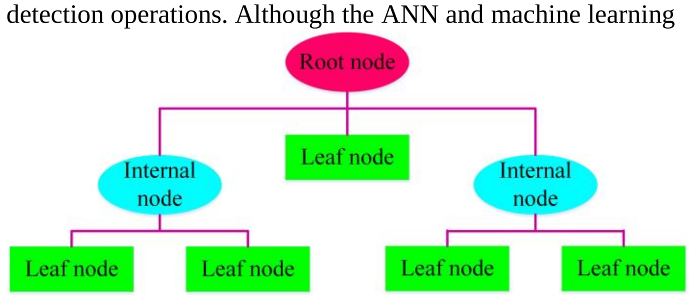

Fig. 7. Schematic diagram of a decision tree

TABLE II
STUDIES THAT HAVE IDENTIFIED FAULTS BASED ON MACHINE LEARNING TECHNIQUES

Method	Ref	Year	Fault type	PES application	Advantages	Limitations
SVM	[30]	2009	OC switch fault	PWM voltage fed power converter of brushless DC motor drive	The high impact of this method on high-dimensional data is a prominent feature. In data where the number of features is more than the number of rows of data, SVM can provide an acceptable application. High ability in classification applications even for multi-class data based on creating a hyper-plain that separates the features of each class well. Generalizability for regression and estimation applications. Compared to ANN techniques, it uses much less memory to process data.	The SVM algorithm is not suitable for large data sets. In the face of noise data that is closely correlated between target classes, it does not perform as well. In cases where the number of features of each data point exceeds the number of training data samples, SVM will perform poorer. Choosing an optimal kernel for SVM is one of the main problems of using this method. Improper performance in the face of time-series data is considered as one of the problems of this method.
	[32]	2012	Faults in a single thyristor and the faults happening in two thyristors at the same time	Three-phase full-bridge controlled rectifier		
	[34]	2013	valve SC, valve pulse loss, single-phase grounding, two-phase grounding, three-phase grounding, DC line grounding	HVDC converter		
	[35]	2014	SC incipient fault	Three-phase squirrel-cage induction motor fed by a sinusoidal PWM converter		
	[37]	2015	Switch OC	Cascaded H-bridge multi-level (5-level) inverter		
	[40]	2015	thyristors OC fault	Three-phase full-bridge rectifier		
	[162]	2016	Switch OC	Three-level NPC inverter		
	[152]	2017	Diode OC	Three-phase full-bridge rectifier		
	[155]	2017	Structural and functional faults	Analog to digital converter		
	[7]	2018	OC, SC, component degradation of power MOSFET, inductor, diode, and capacitor	DC-DC Converter (closed-loop single-ended primary inductance converter)		
	[56]	2018	Eight kinds of faults related to DC bus capacitor and energy storage inductor	Dual-buck bidirectional DC-AC converter		
	[59]	2018	Switch OC and SC	MMC		
	[60]	2018	Switch OC	MMC		
	[61]	2018	IGBT OC	Traction inverters		
	[153]	2019	Multiple OC switch fault	A back-to-back converter in doubly-fed induction generator-based wind turbine systems		
ELM	[33]	2013	Intern-turn SC	Three-phase converter-fed induction motor	The ELM has a very simple structure that minimizes computational complexity and speeds up the training process of this network. The selection of hidden thresholds is done randomly so that the output weight is evaluated without iterative calculations. ELM has high performance and stability in kernel functions and nonlinear activations. It performs very well in the processing of nonlinear systems.	It does not provide acceptable performance in processing data whose number of features is more than the number of rows. Processing large data with this technique does not have good results. Modeling the time-series relationship of input data by ELM is not possible. The training process in the data that the output labels are close to each other has more problems.
	[35]	2014	SC incipient fault	Three-phase squirrel-cage induction motor fed by a sinusoidal PWM converter		
	[163]	2016	Closed-loop	Single-ended primary inductance converter		
	[53]	2018	Soft and hard faults	Super-buck converter circuit		
	[62]	2018	Switch OC	Phase shifted full-bridge converter		
	[71]	2019	Switch OC	Insulated gate bipolar transistor (IGBT) used in three-phase PWM converter		
DT	[31]	2011	Rotor fault	Converter-fed induction motor and changeable rotors	Compared to other techniques, decision trees require less effort for data preparation during pre-processing. In the face of noise data, there is no need for pre-processing. They provide acceptable performance in the training process without the need for data scaling. After completing the training process, the test stage is performed at a very high speed by the saved network.	The smallest changes in the data process cause large changes in the structure of the decision tree and cause network instability. In dealing with large and high-dimension data, they often involve a lot of computational complexity. The decision tree often takes more time to model training. They do not have acceptable generalizability for regression applications and estimation of insufficient continuous values.
	[46]	2017	OC	Voltage source inverter for induction motor drives		
	[151]	2018	Stator SC	Three-phase induction motors		

techniques have been widely used in PESs, increasing the value of monitored data from new smart systems has also reduced the accuracy and performance of these techniques. Today, deep learning techniques are employed as algorithms with high ability to extract features and accurately analyze and model the nonlinear behavior of PESs. Deep learning has various algorithms such as the CNN, RNN, LSTM, and Auto-encoders. In the continuation of this sub-section a complete introduction of such method together with its capabilities in fault detection and other applications of industrial and power electronics are outlined.

1) Convolutional neural network (CNN)

The CNN is one of the most prominent deep learning techniques, known as a powerful tool in feature extraction. This technique has been used in many scientific and industrial fields so far. Classification, feature extraction, and high volume data processing have been the most important applications of this technique [164], [165]. The CNN, by providing a layer-to-layer structure and in-deep training, has been able to cover many of the shortcomings of ANN and machine learning algorithms. Fig. 8 shows the structure of CNN which includes the input layer, convolution layers, pooling layers, fully-connected layers, and finally the classification layer (Soft Max) [166], [167]. Each layer in this structure offers a unique function until the ideal output is predicted. The input layer receives the input data and transmits it to the first convolution layer. Each convolution layer consists of kernels that act as filters on the data and extract their features. Convolution operations associated with each layer are done as follows [166]:

$$y_{ij} = \sigma(\sum_{r=1}^{F}\sum_{c=1}^{F} W_{rc}X_{(r+i\times S)(c+j\times S)} + b)$$
$$0 \le i \le \frac{Hd - Fd}{S}, \qquad 0 \le j \le \frac{W - Fd}{S} \tag{16}$$

where y_{ij} represent the output of each node in the convolutional layer. Hd and Fd represent the length and height dimensions corresponding to the input variables, respectively. S stands for stride length. W_{rc} and b denotes the weight and bias associated with each node. The activation function in this layer is shown as term σ. The activation function in each convolution layer of CNN is performed by the rectified linear unit (ReLU), as a nonlinear activator function, as follows [168]:

$$F(x) = \max(0, x) \tag{17}$$

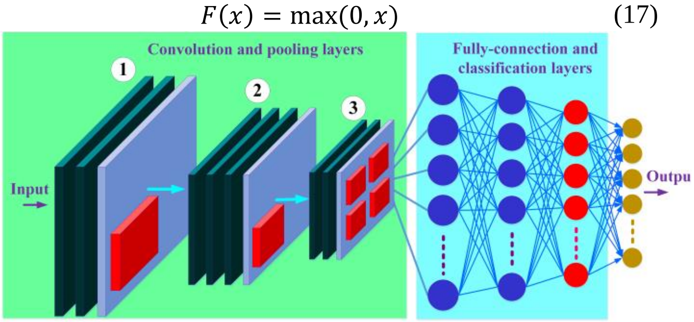

Fig. 8. Layer-to-layer structure diagram of CNN

The extracted features by each filter are collected by the pooling layer in each convolution layer and transferred to the next convolution layer as a feature map. The pooling operation in each layer can be done on two bases, average pooling and Max pooling. The pooling operation is done in each convolution layer as follows [168]:

$$x_j^l = f\left(\beta_j^l pooling\left(x_j^{l-1}\right) + b_j^l\right) \tag{18}$$

where x_j^l is the output of the j-th filter in convolution layer l; $pooling$ () denote the pooling operation and β represent the pooling kernel.

Studies have shown that Max pooling can be more efficient because it contains the highest value of extracted features. This run continues to the last convolution layer until the feature map extracted from the last convolution layer is considered as the input of fully-connected layers. The fully-connected layers are a type of feed forward-based neural networks that is responsible for determining the weight and bias of the nodes in the extracted features. The CNN training process is performed in fully connected layers using an MLP neural network. In the final stage of CNN, a SoftMax layer predicts and classifies the extracted features based on designated labels [169], [170].

In the evaluation of CNN applications, various studies show that this technique has been used not only in fault detection of PESs, but also in estimating electric motor temperatures and SOC estimation of batteries [171], [172].

2) Recurrent neural network (RNN)

The RNNs are a class of deep learning techniques based on artificial neural networks used to process sequential data. Estimating the correlation between input and output variables, processing large volume data, forecasting, and classification are the various applications of RNNs [173], [174]. As shown in Fig. 9, the connections between nodes in an RNN form a guided graph along a time sequence. In addition, the RNNs in the training phase use recurrent units to store past information to use the stored information as input to subsequent layers. This recurrent process enables RNNs to perform excellently in identifying the behavioral pattern of the input data [175]. However, as the training process increases in length and the process becomes longer, training RNNs to obtain long-term data dependence becomes more difficult and requires more memory. As a result, the network encounters problems such as gradient vanishing or rarely, gradient explosion, which makes gradient-based learning methods impractical [175], [176]. To solve this problem and improve the training process for time-series data and high-dimensions, two algorithms, LSTM [177] and gated recurrent unit (GRU) [178] have been introduced.

In recent years, the RNN techniques have been widely used as a powerful tool for a variety of applications such as converter control, harmonic prediction at nonlinear loads, maximum power factor searching, and impedance measurement in PESs and industrial electronics [179]–[181].

The LSTM is one of the most prominent versions of RNNs, which was first proposed in 1997 to improve traditional RNN performance and learn long-term features [177]. The main idea that LSTM pursues is the introduction of an adaptive gateway mechanism that determines the extent to which the memory unit retains the previous state while at the same time, it remembers the features of the current input data. This function is very suitable for processing and predicting events with long intervals and delays in time-series. Furthermore, the classification, forecasting, signal processing, and pattern recognition for high-dimensional data are prominent applications of LSTM [182], [183]. As Fig. 10 shows, each LSTM unit is formed as an input gate, output gate, forget gate, and memory cell as the hidden layer. In addition, the LSTM network replaces neurons in the hidden RNN layer with a memory unit to realize the memory of past information [184].

Gradient descent and back-propagation through time are among the well-known algorithms used to training various types of RNN networks such as LSTM and Bidirectional LSTM. The back-propagation through time is a generalization of back-propagation for feed-forward networks. The mathematical formulation related to the LSTM architecture is as follows:

$$f_t = \sigma(W_{lf} l_t + W_{mf} m_{t-1} + b_f) \tag{19}$$

$$i_t = \sigma(W_{li} l_t + W_{mi} m_{t-1} + b_i) \tag{20}$$

$$o_t = \sigma(W_{lo} l_t + W_{mo} m_{t-1} + b_o) \tag{21}$$

$$a_t = tanh(W_{la} l_t + W_{ma} m_{t-1} + b_a) \tag{22}$$

$$c_t = c_{t-1} \phi f_t + i_t \phi a_t \tag{23}$$

$$m_t = o_t \phi tanh c_t \tag{24}$$

where σ shows the logistic sigmoid function, f_t, i_t, and o_t represent the forget, input, and output gates, respectively. c_t and a_t are the memory cell and hidden vector, respectively. $W_{l*} = \{W_{lf}, W_{li}, W_{la}, W_{lo}\}$ and $W_{m*} = \{W_{mf}, W_{mi}, W_{ma}, W_{mo}\}$ denote the trainable weights associated with respective gates. b_f, b_i, b_o, and b_a represent output biases for each gate. Finally, operator ϕ represent the Hadamard product.

Each of these gates in the LSTM structure offers a unique function to predict the final output in the best possible way. Details on the structure and function of LSTM are introduced

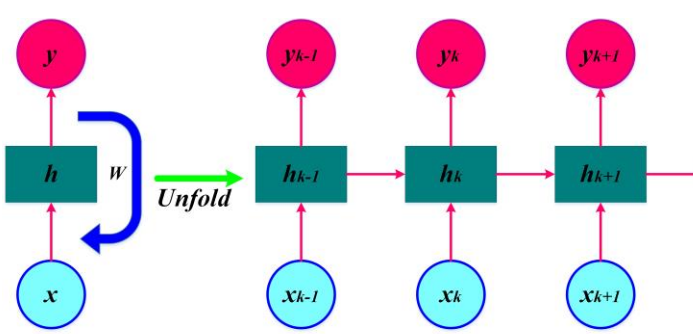

Fig. 9. Structural schematic diagram of RNN

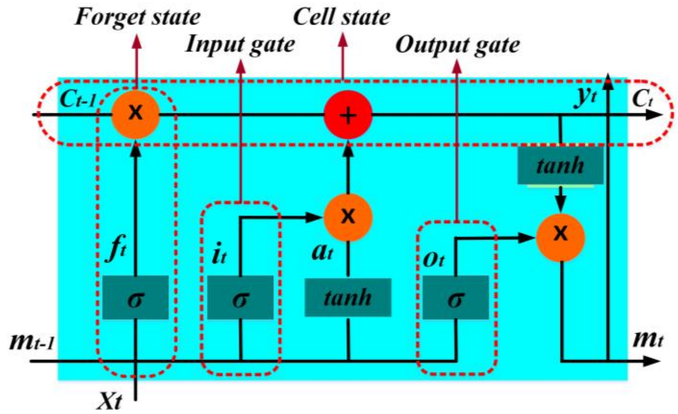

Fig. 10. Block diagram of a LSTM unit

in [185]. As stated in the literature on the ability of the LSTM technique to detect PESs faults, it should be noted that this method is also used in a variety of issues such as pulsed load monitoring and tolerance control related to PESs [67], [186].

3) *Autoencoders (AEs)*

An autoencoder (AE) is one of the deep learning applications that is often applied to reduce the dimension of the data and extract the data features with minimal reconstruction error. As Fig. 11 shows, an AE consists of an encoder and a decoder network, which also consists of an input layer, several hidden layers, and an output layer [187], [188]. The structure and function of AE is such that based on nonlinear layers it can retain the most data-related features and the most important information after dimensionally reduction. In the AE training phase, with proper retrieval of the input data, maximum information about the original input data is stored by hidden cells in the hidden layers [164].

The encoding and decoding operations via AE for the input variable x is performed as follow:

$$f = g(\omega_x * x + b_x) \tag{25}$$

$$y = g(\omega_y * x + b_y) \tag{26}$$

where y is the output features and f denote the network features. ω_x, ω_y, b_x, and b_y represent the input-to-hidden weights, hidden-to-output weights, bias of hidden units, and bias of output units, respectively. $g(.)$ demonstrate the activation function.

Minimizing reconstruction errors is one of the main objectives of AE training. To achieve this, the proximity between x and y must be expressed by computing the loss function *(L)* for *n* input samples as follows:

$$L_{AE} = \frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2 \tag{27}$$

Following this proceeding, the reconstruction error is computed as follows:

$$RE = \sum_{i=1}^{n} (x_i - y_i)^2 \quad (28)$$

AE is trained based on clean x data. The test of the AE is performed using x-noise data obtained by adding noise to clean x-data. Upon completion of this process, the reconstructed output becomes as $\hat{y}$ and L_DAE is defined as follows:

$$L_{DAE} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{y}_i)^2 + \frac{\lambda}{2}(\|W_1^2\|_F^2 + \|W_2^2\|_F^2) \quad (29)$$

AEs are divided into different categories, each of which has been used in various applications in industrial electronics and power electronics [186], [189]. A review of the literature showed that in recent years, deep learning techniques have been very successful in various applications of the power electronics industry. So that these techniques were able to compensate for the shortcomings of ANN and machine learning methods and were considered a great success in identifying faults related to PESs. Table III lists the fault detection studies in PES based on deep learning techniques.

It should be noted that the significant points that should be noted are the determination of the number of epochs and the determination of the amount of data to perform the training and test steps related to supervised techniques. In learning-based data mining techniques, part of the data is considered for training and another part for test or validation the network. The determination of each of these values is the responsibility of the user and it is commonly shown in various studies that 70% to 80% of the data is selected for the training process and the rest for the test or validating the network. Determining the number of epochs or iterations related to each network can also be done in different ways. Thus, in many techniques, this process is based on the trial and error method and, in others, it is based on optimization algorithms. The most ideal number for epoch is achieved when the results of training and test processes are accompanied by the least amount of error values.

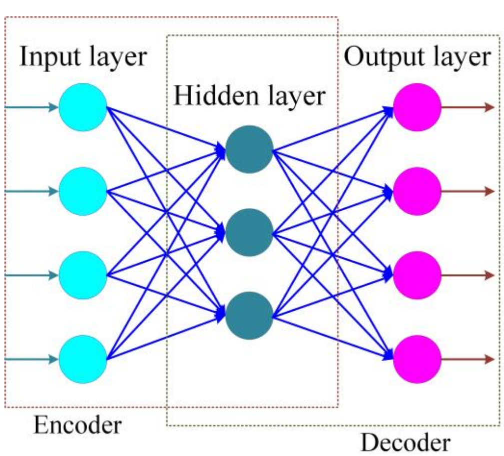

Fig. 11. The structure diagram of a Autoencoder

E. Unsupervised Techniques

PES converters have the nonlinear behavior, and in the face of some anomalies, the behavior of these systems changes significantly. Any fault or anomaly that occurs on the PES converters induces effects on the system behavior, the extraction of these effects from the characteristic curves of the system starts the process of anomaly detection [38]. As noted in the literature, intelligent learning-based techniques have been used in most studies as a variety of fault detection tools. However, in most cases, these techniques have suffered from some problems in the face of complex systems and high dimension data that contain noise with abnormal behavior in the signals received from the system.

Many studies have shown that different faults have different effects on voltage and current signals from electronic power converters, and using these signals as input to diagnostic methods requires a preprocessing operation. In signal preprocessing, the correlation between the variables is removed, the variables are reduced, and the most significant though components are extracted by weighing the various variables to somehow see the effects of the fault on the signal more clearly [73]. Unsupervised data mining applications have been used effectively to solve these problems and perform signal preprocessing to improve the anomaly detection process in PESs. Unsupervised techniques mainly include dimensional reduction techniques, which can be referred to as methods PCA [38], [73], kernel PCA [45], Kullback-Leibler [51], Isometric feature mapping [190], and feature learning [191]. In addition to fault detection in industrial electronic equipment and PESs, these techniques have been also used in other applications [165].

IV. Routine of Fault Diagnosis in PESs

The fault detection process in PESs is based on a step-by-step procedure. In the first stage, the signals related to the healthy and damaged state of the system are measured. In the second stage, the measured signals can be normalized, filtered or pre-processed according to certain criteria in order to reduce the data dimension, and to use important parts of the signals. In the third stage, the selected diagnostic technique is designed and finally, the available signals are used as input to the desired procedure. Every PES has characteristics curves that show the performance of the system at a given time point. Each anomaly that occurs in PES has a special effect on the voltage and current signals, which most diagnostic methods used to identify faults by considering voltage and current signals as indicators. These signals are measured by sensors in the system and provided to the users. Sometimes signal measurement sensors in PESs can also be damaged while posing new problems to the system performance. Fault detection techniques must be exact and intelligent enough to detect the effects of system harmonics, sensor abnormalities, and hard and soft faults. Fault detection using voltage and current signals can also be done in the frequency domain. Thus, the signals measured in real-time are transmitted to the frequency domain using the fast Fourier transfer (FFT) to be used as input for diagnostic methods. Each

TABLE III
STUDIES THAT HAVE IDENTIFIED FAULTS BASED ON DEEP LEARNING TECHNIQUES

Method	Ref	Year	Fault type	PES application	Advantages	Limitations
CNN	[55]	2018	OC	MMC	Use local spatial coherence at the input (often images), which allows the CNN network to weigh less due to the sharing of some parameters. Benefiting from a layer-by-layer structure makes them less computationally complex. Excellent performance in feature extraction and pattern recognition from input data and ideal for image processing applications. Contains a weight division in layers that increases the speed of training stage.	In the face of noise data, various pre-processing steps must be used so that the accuracy of the results is not reduced. This method does not have sufficient capability in spatially invariant to input data. Using CNN requires a lot of training data. So that it does not have acceptable performance in the processing of low data. Time-series mode modeling of input data is also not possible using this method.
	[59]	2018	Switch OC and SC			
	[68]	2019	Switch OC	Back-to-back converter in permanent magnet synchronous generator-based wind generation system		
	[69]	2019	Switch SC	5-level neutral-point-clamped voltage source inverter connected to PV integrated microgrid system		
	[70]	2020	Switch OC	Hybrid active NPC inverter		
	[74]	2021	Power tube double-open faults and power tube triple-open faults	Three-phase voltage inverter platform		
RNN	[54]	2018	degradation fatigue modeling	High-frequency Gallium Nitride (GaN) power dc-dc converter	The RNN network remembers all the events reviewed in the training process. Performs data time-series modeling to an acceptable degree. It can easily provide a strong hybrid model with other conventional techniques based on ANN or deep learning. High-dimensional data processing is also a prominent feature of these networks.	Suffers dramatically from the problems of gradient vanishing and exploding. RNN networks have a very difficult training process. No processing of long sequences data when using tanh or relu activation functions. The training process is very time-consuming and does not provide acceptable performance in processing noisy data.
	[7]	2018	OC, SC, component degradation of power MOSFET, inductor, diode, and capacitor	DC-DC Converter (closed-loop single-ended primary inductance converter)		
LSTM	[54]	2018	Degradation fatigue modeling	High-frequency Gallium Nitride power dc-dc converter	Completely solves and eliminates problems related to gradient vanishing and exploding in RNNs. Provide acceptable performance in large and sequential data. Modeling the time-series mode of the data and extracting the correlation between the input and output variables in this type of data.	In time-series data when features are sequential, modeling input features is difficult and somewhat impossible. The selection of parameters related to the network structure is of great importance and the network output is highly dependent on the specified parameters. The training process is time-consuming.
	[67]	2019	Switch SC and OC	Five-level nested neutral-point-pilot (NPP) topology		
	[153]	2019	Multiple OC switch fault	A back-to-back converter in doubly-fed induction generator-based wind turbine systems		
Autoencoder	[52]	2017	Switch OC	Cascaded H-bridge seven-level converter	They can be used as the supervised and unsupervised for a variety of data-based applications. Autoencoders have an acceptable ability to remove noise from data and is ideal for real-world data. For forecasting applications, they can easily provide a hybrid model with other deep learning techniques. Autoencoders provides acceptable performance for processing time-series data even when they contain noise.	The choice of ideal model parameters is tedious and has a significant impact on network output. In unsupervised approaches and dimension reduction applications, some important data information can be removed. They have a high sensitivity in the training process and the output of the test phase is very effective from the training phase. Autoencoders have a high structural complexity and it is difficult to add or remove a layer.
	[63]	2018	Switch OC	Three-phase full-bridge rectifier		

of the introduced methods, based on a specific strategy, detect faults based on the measured voltage and current signals. The simplest possible case is related to ANN techniques. These techniques do not have the ability to extract features and process time-series data and only detect faults based on the determination of weight and bias on the input signals. The machine learning techniques have the ability to recognize complex patterns and modeling non-linear data, but have difficulty processing signals with high volumes and dimensions. Finally, deep learning techniques with the ability of feature extraction in a layer-by-layer structure, especially for high dimension and time-series data, have been successful in timely and accurate detection of PESs faults. Fig. 12 shows the fault detection routines in PESs based on the applications of ANN, machine learning, and deep learning techniques.

V. Sensors and Instruments Needed for Signals Measurement

Fault detection in PESs is based on voltage and current curves. Voltage and current measurement in PESs requires instruments and sensors that are used based on their unique accuracy and bandwidth. Sensors are devices that can sense or identify and react to certain types of electrical or optical signals. There are different types of sensors related to measuring voltage and current, which are classified based on their performance and method of measurement, which the continuation of this section introduces each of them.

A. Current sensors

Current sensors are typically classified into three categories: shunts (resistance), current transformers, and Hall effect sensors. Each of these sensor classes has a different performance in terms of accuracy and bandwidth, depending on their maximum measurable frequency. However, some special sensors, such as shunts, have significant direct current measurement capabilities. While current transformers are not very capable of performing such measurements. Current measurement using shunts has several major advantages such as high accuracy, low cost (but can be more expensive for high accuracy measures), robustness, and high bandwidth.

However, this technique suffers from the lack of galvanic insulation between the power circuit and the control or monitoring circuit where the extracted signal is processed.

B. Voltage sensors

A voltage sensor is used to monitor and calculate the supply of voltage to a device. Voltage sensors have the ability to detect AC voltage or DC voltage level. The inputs of these sensors is voltage and can provide state of switches, analog current level, analog voltage signal, a current signal or an audible signal, and frequency as output. The output provided varies by type of sensor. Thus, in some of them the output can be sine or pulse trains and in others it can be presented as amplitude modulation, pulse width modulation, and frequency modulation output. Measurements in voltage sensors are based on voltage divider. Voltage sensors are classified into two types include capacitive type voltage sensors and resistive type voltage sensors.

Small size and light weight, high safety for personnel's, very high degree of accuracy, non-saturable, very wide dynamic range, ability to combining the voltage and current measurements into a single physical device with small dimensions, and eco-friendly are the important advantages of voltage sensors over the conventional measuring methods. In addition to fault detection, voltage sensors have some other important applications such as power failure detection, temperature control, load sensing, power demand control, and safety switching.

C. Feature extraction from measured signals

Measured signals from the system are utilized as input to the fault detection method because they contain the system performance and the effects of the fault on the system circuit. Techniques used in a variety of ways analyze input signals to achieve abnormal effects of faults. However, the range of the measured signal must be within the standard range. Considering low sampling rate or sampling in low range for signal measurement loses significant information about system behavior, while considering more range and high sampling rate also causes obvious information to loss between incomprehensible information. After measuring the signal, choosing the appropriate method for analysis is considered the most important step in fault detection in PESs. Each method identifies and estimates the effects of different types of faults on the measured signal based on its ability. Among these, feature extraction from measured signals can be the best approach to analyze the types of fault effects and achieve the diagnostic goal. Simply put, in the feature extraction approach,

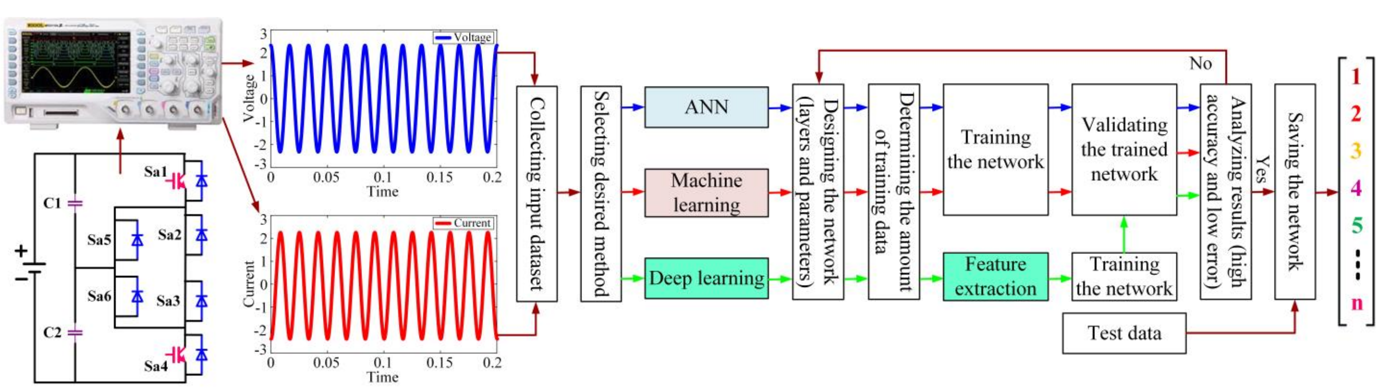

Fig. 12. Fault detection routines in PESs based on the applications of ANN, machine learning, and deep learning techniques

unnecessary values and parameters are excluded from the sampled signal, and the effects and pattern of anomalies occurring in the system are made available as obvious and valuable information for evaluation. This approach can dramatically speed up the fault detection process in PESs and increase detection accuracy. In general, the power electronic equipment used in the system carries the noise or harmonics in the measured signal, which most fault detection methods fail to distinguish these harmonics from the effects of faults. Using intelligent techniques that have the ability to extract features can easily solve this problem and can distinguish between harmonic behavior and fault effects. Accordingly, the use of feature extraction and pattern recognition techniques is significantly recommended for fault detection applications in PESs that always have natural system harmonics and noises. Among the introduced methods, ANN algorithms determine the relationship between input variables (signals measured from the system) and output (type, location, or intensity of faults) by determining the weight and bias in the hidden layers. These techniques require a long-time and high processor memory in the face of high dimension signals and suffer from other problems such as overfitting. Machine learning techniques have improved ANN problems in terms of speed and memory, but these techniques also require proper datasets and in most cases involve overfitting problems. In the meantime, deep learning techniques have been able to solve problems related to previous solutions with a layer-by-layer structure that provides a deep learning of input data. These techniques significantly benefit from the feature extraction block in their structure and based on the extraction of prominent features from the measured signals, they detect faults. Fig. 13 shows the feature extraction procedures of signals measured. It can be seen that the fault behavior pattern in voltage or current signals is extracted and used by removing large volumes of the signal.

The penetration of deep learning techniques in power electronics applications has been able to solve major problems in this industry and on the other hand these techniques can be employed as a powerful tool in fault prognosis and online monitoring of PES.

VI. Fault-Tolerant in PESs

Fault-tolerant is a prominent feature of each system so that the system can continue to operate and work in the event of failure of some of its components. Stability and uncertainty in PESs is one of the most important issues that has posed many challenges in recent years. Accordingly, fault-tolerant is one of the most important factors in PESs that must be addressed. A fault-resistant design enables the system to continue to operate at the desired level, possibly at a reduced level, if part of the system fails[192], [193]. In organizing a fault-tolerant system, the first step is to diagnose and, more importantly, to prognose the fault [194]. Timely fault detection and accurate protection can prevent the fault from progressing and its harmful consequences. The next step is the fault-tolerant function, which consists of fault separation and reconfiguration. The second step is always based on the design of the hardware plugin and the control of the relevant fault-tolerant [192]. To date, many solutions to fault-tolerant operations in PESs have been proposed and utilized in various studies. The presentation of fault tolerance methods relies mainly on the type of hardware redundancy and according to this, classified into three main categories as follows: 1) switch-level, 2) leg-level, 3) module-level. Table IV classifies the fault tolerance methods in PESs based on these three categories.

The use of fault tolerance methods in PESs makes the system able to continue to operate for a limited time after the fault occurs. However, the performance of the system and its efficiency decreases compared to the normal state, but the effect of the fault that occurred in the system is not clearly seen. Accordingly, fault tolerance methods make many conventional techniques in the early stages unable to detect faults and the system continues to behave in a damaged state. It should be noted that under these conditions, deep learning algorithms that have the ability to extract features from the system and are able to detect the smallest noise related to the system, can detect occurred faults in the early stages.

VII. Conclusion

Power electronic systems (PESs) are considered to be vital components in power/energy systems, and the stability of the power/energy systems mainly depends on the health of PESs.

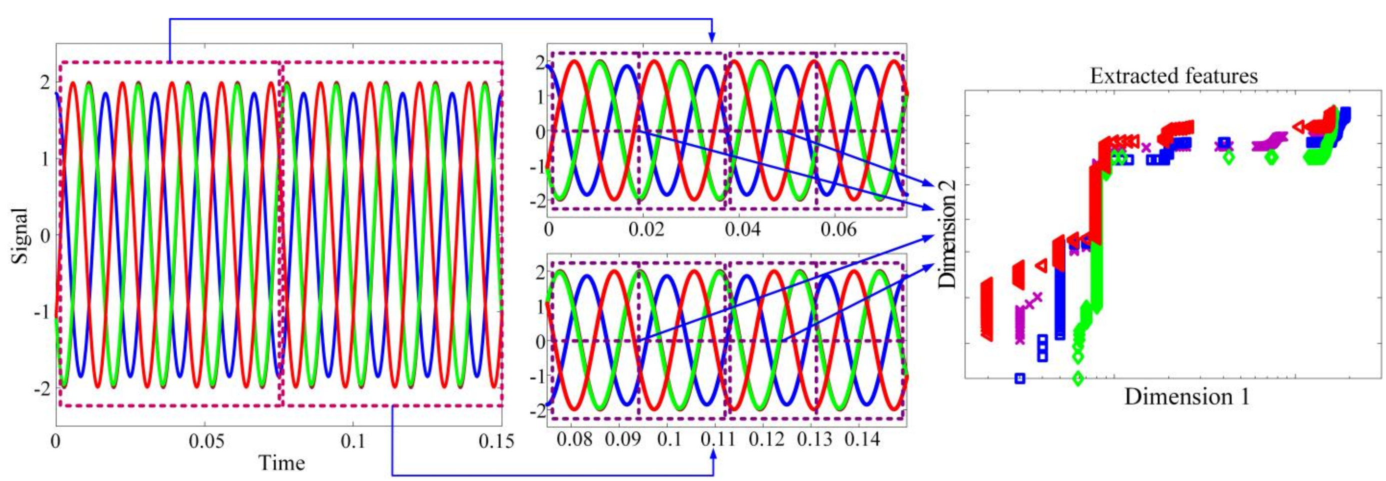

Fig. 13. Feature extraction routine of measured signals

TABLE IV
CLASSIFICATION OF STUDIES PERFORMED IN ORDER TO FAULT-TOLERANT IN PESS BASED ON THE METHOD USED

Level type	Method	Ref.	PES application
Switch-level	Inherently redundant switching states	[195]	Three-level active NPC inverters
		[196]	T-Type Three-Level Inverter
		[197]	High-power active NPC three-level inverter
		[198]	Single-phase MMC-based inverter
		[199]	Interleaved DC–DC boost converters for homes and offices
	DC-bus midpoint connection	[200]	Five-phase permanent-magnet machine drives
		[201]	Six-phase permanent magnet synchronous motor
		[202]	A single field-programmable gate array chip
	Redundant parallel or series switches installation	[203]	Matrix converter
		[204]	Two-level voltage source converter with IGBTs directly in series, Modular multi-level converter
Leg-level	Adding redundant legs in series or parallel connection to main legs	[205]	Open-end winding permanent magnet synchronous motor system based on winding reconnection
		[206]	Single dc-link dual inverters
		[207]	Three-level topology based on the NPC converter
		[208]	Three-phase permanent magnet synchronous motor
		[209]	modified topologies of NPC converter based on adding a fourth leg, which is based on the flying capacitor converter structure
Module-level	Neutral-shift	[210]	Cascaded H-bridge inverter
		[211]	MMC
		[212]	Cascaded H-bridge multilevel inverters based on level-shifted pulse width modulation
	DC-bus voltage reconfiguration	[213]	Modular medium-voltage drives
		[214]	Symmetrical and asymmetrical cascaded multilevel converters
		[215]	Static synchronous compensator based on cascaded H-bridge multilevel converter
	Redundant modules installation	[216]	Modular multilevel HVDC converter
		[217]	Multilevel modular capacitor-clamped DC–DC converter
		[218]	MMC

A variety of factors cause anomalies in PESs that could threaten the system security and reliability. Such issues call for an urgent need of early fault detection in PES. In this paper, different types of faults related to PESs and various diagnostic methods were evaluated. Several literature has been reviewed since the beginning of the fault detection process in PESs. After introducing the types of faults related to PESs, a basic classification of fault detection methods based on data mining techniques and signal measurement sensors in PESs was presented and each method was introduced with a detailed description. The fault detection procedure was described by evaluating the performance of various model-based and data-based methods such as artificial neural network (ANN), machine learning, and deep learning algorithms in the various studies. In a general evaluation, it was observed that model-based techniques, due to the structural complexity and dependence on the physical model of the system, which causes significant problems in the fault detection process, are used in a limited number of cases. Among the extensive data-based techniques, deep-learning techniques due to their high capabilities in modeling the time-series state of real-time data, eliminating data-related noises which is caused by the working conditions of PES equipment, and the ideal performance in detecting the slightest correlation between the effects of the fault and detecting it, even among large volumes of data, has surpassed other data-based methods and is now commonly recommended to fault diagnosis in PESs. Given that feature extraction is considered as the key to the success of deep learning techniques in diagnostic applications, a brief description of the feature extraction process from the measured signals was presented. Finally, in a general evaluation, deep learning techniques were introduced and proposed as one of the applications of data mining for use in other areas of power electronics industry.

It should be noted that the development of power systems has led to the introduction of modern systems based on the Internet of Things and the online use of most PESs and related equipment in power systems and industrial applications. This process causes PES devices, in addition to physical faults related to the system, to be attacked by cyber-attackers, which can lead to a variety of irreparable risks. Accordingly, for future studies and to maintain the security and stability of power and energy systems, develop methods that have the ability to prognosis faults or any failure in the system and can distinguish the effects of cyber-attacks from faults. In addition, it is recommended to use deep learning-based autoencoder approaches that can reconstruct false signals from cyber-attacks in online applications and send a clean communication signal to the user or equipment.

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Arash Moradzadeh (S'19) was born in Tabriz, Iran, in 1991. He received the B.S. degree in electrical power engineering and the M.S. degree in power electronics and electrical machines from Islamic Azad University of Tabriz, Tabriz, Iran, respectively in 2016 and 2019. He is currently working toward the Ph.D. degree in power electrical engineering with the University of Tabriz, Tabriz, Iran.

His current research interests include power and energy systems, cyber-physical systems, energy management, intelligent energy systems, transient in power systems, diagnostics and condition monitoring of power transformers, frequency response analysis, and application of data mining methods to design, optimize and analysis of energy systems.

Behnam Mohammadi-Ivatloo (S'09–M'12–SM'17) received the B.Sc. degree in electrical engineering from University of Tabriz, Tabriz, Iran, in 2006, and the M.Sc. and Ph.D. degrees both in electrical engineering from Sharif University of Technology, Tehran, Iran, in 2008, all with honors. He is currently a Professor with Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran. His main area of research is economics, operation, and planning of intelligent energy systems in a competitive market environment. He was editor of several books published by Springer and Elsevier. He as an Associate Editor of the IEEE TRANSACTIONS ON POWER SYSTEMS and IEEE ACCESS journals.

Kazem Pourhossein received the B.Sc. degree in electrical engineering from K. N. Toosi University of technology, Tehran, Iran, in 2002, the M.Sc. degree in electric power engineering from Zanjan University, Zanjan, Iran, in 2006, and the Ph.D. degree from Science & Research branch of Azad University in 2012, Tehran, Iran. He was with R&D department of IranTransfo from 2004 to 2006 working on transient phenomena in power transformers. He is currently an assistant professor in Tabriz branch of Azad University. His research interests include power transformer diagnosis, condition monitoring of power apparatus, high voltage, transients in power systems, renewable and sustainable energy systems and pattern recognition of energy systems.

Amjad Anvari-Moghaddam (S'10–M'14–SM'17) received the Ph.D. degree (Hons.) from University of Tehran in 2015 in Power Systems Engineering. From 2015 until 2019 he was a Postdoctoral Research Fellow at Aalborg University. Currently, he is an Associate Professor and Leader of Intelligent Energy Systems and Flexible Markets (iGRIDS) Research Group at the Department of Energy (AAU Energy), Aalborg University where he is also acting as the Vice-Leader of Power Electronic Control, Reliability and System Optimization (PESYS) and the coordinator of Integrated Energy Systems Laboratory (IES-Lab). His research interests include planning, control and operation management of microgrids, renewable/hybrid power systems and integrated energy systems with appropriate market mechanisms. He has (co)authored more than 250 technical articles, five books and nine book chapters in the field. Dr. Anvari-Moghaddam serves as the Associate Editor of the IEEE TRANSACTIONS ON POWER SYSTEMS, IEEE ACCESS, IEEE SYSTEMS JOURNAL, IEEE OPEN ACCESS JOURNAL OF POWER AND ENERGY, and IEEE POWER ENGINEERING LETTERS. He is the Vice-Chair of IEEE-PES Danish Chapter and serves as a Technical Committee Member of several IEEE PES/IES/PELS and CIGRE working groups. He was the recipient of 2020 DUO – India Fellowship Award, DANIDA Research Fellowship grant from the Ministry of Foreign Affairs of Denmark in 2018, IEEE-CS Outstanding Leadership Award 2018 (Halifax, Nova Scotia, Canada), and the 2017 IEEE-CS Outstanding Service Award (Exeter-UK).