International Journal of Power Electronics and Drive Systems (IJPEDS)
Vol. 12, No. 1, Mar 2021, pp. 558~566
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v12.i1.pp558-566

Investigation of reliability assessement in power electronics circuits using machine learning

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Article Info

Article history:

Received Aug 28, 2020
Revised Jan 12, 2021
Accepted Feb 2, 2021

Keywords:

Condition monitoring
Life cycle
Machine learning
Power electronics
Prognosis
Remaining useful life

ABSTRACT

Recent advances in power electronics (PE) and machine learning (ML) have prompted the technologists to adapt these new technologies to improve the reliability of PE systems. During the process, a lot of investigations on the performance and reliability of PE systems is carried out. The intention of this paper is to present a comprehensive study of advances in the field of reliability of PE systems using machine learning. Recent publications in this regard are analysed and findings are tabulated. In addition to this, literatures published in the prediction of remaining useful life (RUL) of power electronic components is discussed with emphasis on its limitations.

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1. INTRODUCTION

Invention of thyristor in the year 1957 has created a new era in the field of power electronics. Since then, power electronics has found its way in the wide range of applications right from power generation to end-user consumption of electricity. Thorough research and improvements in the semiconductor technologies, converter circuit technology especially in controlled rectifiers [1], [2] has improved performance of the power electronics systems with respect to efficiency and switching speeds. Power electronics components are mainly used in power conversion systems due to their switching capability and efficiency. However, these components tend to get exposed to current surges, high temperatures and continuous switching operations leading to the possibility of power electronics components failing to operate in the expected manner.

Owing to the safety requirements, the automotive (EV) and aerospace industries have brought in the stringent norms in the field of reliability of power electronics systems. Yantao et al [3] mentions that power semiconductor as well as electrolytic capacitors are most susceptible to failures. Failure of any of these, may be one or more components could be a catastrophe provided appropriate fault handling mechanisms are not in place. As per the study conducted [4] on PV modules, power inverters accounted for 37% of unscheduled maintenance incidents by component and contributed for 59% of unscheduled maintenance expenditures.

2. NOTION OF RELIABILITY IN POWER ELECTRONICS

In power electronics circuits (PEC), faults can be either intrinsic (chip related-mostly occur due to high current or voltage) or extrinsic (package related-mostly occur due to thermo–mechanical stress). Reliability in PEC was introduced as early as 1950s [5]. As mentioned in [6], reliability is the probability of any part or the entire system that continues to work without any interruption over a period of time. Reliability may be defined as (1)

$$R(t) = e^{-t/MTBF} \tag{1}$$

where MTBF = Mean time between failures.

The reliability function R(t) versus time [0, t] is plotted in Figure 1 the shape of which resembles bathtub which is the life-cycle of a component. The graph has three distinct phases, namely, burn-in, useful life and the wear-out periods [7, 8]. Every component which comes out of asssembly line is rolled out after the execution of extensive testing processes to handle the infant-mortality rate. However, defects do creep in during the design as well as production phases leading to increase in the failure rate during the first phase.

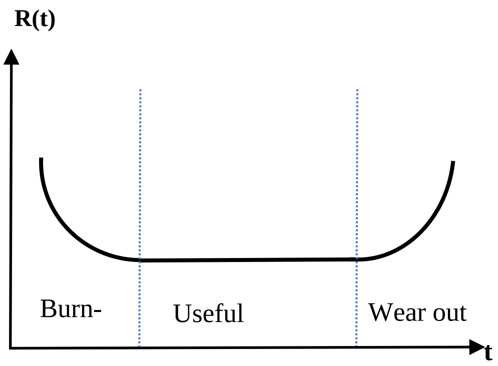

Figure 1. Failure rate curve as a function of time

Once the component successfully completes the first phase, the rate of failure remains flat for a portion of time which indicates the stabilization in the health of the component. Post useful life phase, failure rate increases exponentially. However, by this time the component might have completed its intended purpose.

A lot of research has been already carried out by researchers to make the power electronics systems reliable, ensure high availability with long lifetime and requiring very less maintenance cost. Various fault-tolerant design and control strategies, pattern recognition algorithms have been proposed for making PE systems reliable [9]-[13]. Industries are focussing on Design for Reliability [14] rather than depending on usual way of testing for reliability. Along with these, recent advances in Machine Learnings (ML) have shown great potential in making power electronics systems more reliable [15]-[18]. Condition monitoring (CM) [19] is a process of observing operating characteristics of an electrical system to detect any anomaly in its characteristics. For CM, it is imperative to have decision making algorithms, that decide based on these current measurements and historical data.

In Figure 2, the difference between diagnosis and prognosis is depicted. Assessing the present health of a component and predicting the future health is termed as Prognosis [20] whereas Diagnosis is the process of identifying the nature of failure by external examination. For a successful CM system, accurate prognosis plays important role.

The assessment can be carried out using sensor data obtained by monitoring

a. component’s usage rate and period, ambient temperature and humidity, vibration and shock collectively termed as component’s life cycle environment
b. divergence of operating parameters from their usual values characterized as performance degradation
c. material disintegrating, oxidization, increase in electrical resistance or threshold voltage.

The data so obtained can then be analysed using prognostic algorithms, predominantly, machine learning based on which conclusions can be drawn, the details of which will be discussed in the subsequent sections of this paper. Outcome of the algorithm can then be used for maintenance forecasting, fault detection and advanced warning of failures.

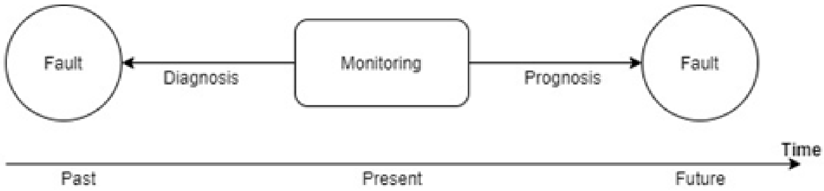

Figure 2. Difference between diagnosis and prognosis

Figure 3 gives a glimpse of number of publications in the field of Power Systems reliability using ML approach for the last ten years. It can be observed that ML approach in reliability has garnered much more interest since 2017. It is a clear indication that scientific and research community has found the prospect and potential in ML's ability in the field of power systems reliability. There have been several surveys published for reliability of electrical systems [21]-[27]. However, this paper gives a broad overview of prognostic or proactive methods limiting the scope to the use of ML for reliability in power electronics systems.

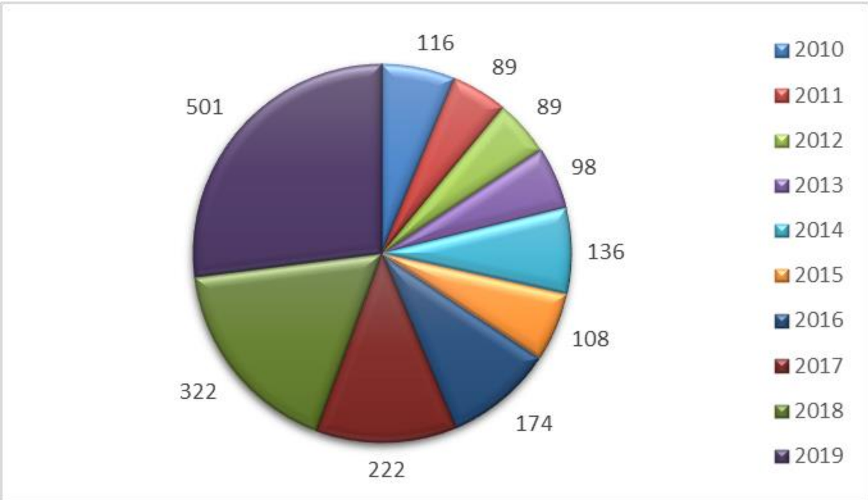

Figure 3. Chart represents number of publications in the field of power systems reliability using ML approach. Source: ieeexplore.ieee.org

3. PROGNOSIS BY MACHINE LEARNING

PE system's maintenance plays key role in the safety of personnel and equipment. If the system should provide business continuity of service with high efficiency, the total cost of ownership naturally increases. Maintenance activities can be broadly classified into three types Reactive, Preventive and Predictive which are summarized in Table 1 [28], [29]. From the table, it can be inferred that, predictive maintenance has clear advantage over other types of maintenance approaches. Feldman et al. [30] study on a display system of Boeing 737 plane revealed that, a ROI of 3.5:1 acheieved when the predictive maintenance was employed instead of reactive maintenance. Also, in power conveters short circuit and degradation faults do not trigger any fault protection mechanism which is an ideal scenario for predictive maintenance.

Total Productive Maintenance (TPM) [31] endorsed as Japanese approach to effective maintenance management developed by Deming to enhance overall equipment effectiveness (OEE) which tend to use predictive maintenance approaches. The OEE can be defined as

$$\text{OEE} = \text{Availability} \times \text{Performance Rate} \times \text{Quality Rate} \quad (2)$$

where

$$\text{A} = \frac{(\text{RA} - \text{D})}{\text{RA}} \times 100$$

where A: Availability, RA: Required Availability, D: Downtime

$$\mathrm{PR} = \frac{\mathrm{DCT} \times Output}{\mathrm{OT}} \times 100$$

where PR: Performance Rate, DCT: Design Cycle Time, OT: Operating Time

$$\mathrm{QR} = \frac{\mathrm{PI} - \mathrm{QD}}{\mathrm{PI}} \times 100$$

where QR: Quality Rate, PI: Production Input, QD: Quality Defect, PI: Production Input

Table 1. Reactive, preventive and predictive maintenance types

Maintenance Types	Description	Applications
Reactive Maintenance (RM)	Corrective based, usually referred to as repair that restores the required function of a faulty item; Advantages, Low cost, Disadvantages: a. Cost associated with replacing the failed part could be more owing to the maintenance of spare parts inventory b. Possible secondary equipment damage due to the cascading effect	a. Small parts and equipment b. Non-critical equipment c. Equipment unlikely to fail d. Redundant systems
Preventive Maintenance (PM)	Diagnostics based, avoids any possible failure by regular inspection conducted during a scheduled shutdown/still working to minimize its impact on business operations Advantages: a. Bathtub curve can be used to predict failure rate of the equipment b. Flexibility allows for the adjustment of maintenance periodicity Disadvantages: a. Since wear-out period is based on theory rather than actual data, PM becomes an expensive strategy b. Labor intensive	a. Most frequently used equipments b. Consumables c. Kind of equipments having a history of failures d. Manufacturer recommendations
Predictive Maintenance (PdM)	It is about equipment condition monitoring using advanced sensor and instrumentation technologies, and its repetitive analysis using predictive algorithms Advantages: a. Though PM requires high investment, it is worth the money since it provides extended life to the equipment. b. Provides a preemptive approach for safeguarding the equipment. c. Reduces the downtime of the equipment. Disadvantages: a. Increased investment in diagnostic equipment	a. Equipment with random failure patterns b. Critical equipment c. Kind of equipments that are less likely to wear and tear

In particular, PM has given rise to a collection of methodologies, namely, probabilistic approach and a fully data driven approach that relies upon ML [32]. In a nutshell, ML comprises of a variety of statistical, probabilistic and optimization techniques that learns from the set of data and becomes intelligent enough to make judgements without human intervention. ML algorithms with emphasis on non-linear models like support vector machines (SVM), decision trees, logistic regression and artificial neural networks as predictive modelling tools have greater predictive performance and are quite popular among researchers [33], [34]. Table 2 aptly summarizes the recent publications on ML algorithms used in prognosis of PE circuits. It is observed that a combination of ML algorithms is used to boost the efficiency of the approach. For example, SVM is computationally heavy, hence requires more training time. By introducing least square to the cost function, the computational complexity is reduced.

Table 2. Literature review on ML approach for reliability in PE system's

Sl. No	References	Machine Learning Techniques	Component/System	Pros and Cons (As claimed by the respective authors)
1	Aravid Sai Sarathi Vasan, et al [35]-[37]	Least Square SVM(LS-SVM)	Bandpass and Low Pass filters	• Used to evaluate RUP • Early fault detection and isolation • Decreases complexity
2	Xi -Shan Zhang et.al,[38]	Support Vector Machines	Complex electronic system Biquad filter	• Long term operation of the system • Reliability analysis using Kaplan-Meier (KM) and Kernel density Estimation (KDE)
3	LanHai and LiuHong- da, et. al, [39]	SVM and Principal Component Analysis (PCA)	Three -Phase rectifier circuits	• Improves generalization ability • Capable of locating faults precisely
4	Jianchen Wang, et al [40]	Chaos theory and Particle Swarm Optimization (CPSO)-SVM	Elliptical filter circuit	• Improves efficiency • Execution time is less
5	Shaowei Chen, et al, [41]	Genetic Algorithm (GA) - SVM	Quad high pass filter circuit	• Prevents dependence of large training samples • Better success rate of diagnosibilty
6	Qingfeng Ma, et al [42]	Decision Tree (DT) and BSVM	Sallen-key bandpass filter Active band-stop filter circuit	• Execution time is less • Testing accuracy is high
8	Tang Jingyuan, et al [43]	SVM and Adaboost	Two-stage four op-amp biquad low-pass filter	• Classification accuracy is high
10	WEI HE, et al, [44] Mehrdad Biglarbegian, et al [45]	Naïve Bayes Classifier	Opamp biquad filter circuit. Gallium Nitride (GaN) transistors.	• Effective fault diagnosing • High latency • Enhances system reliability
11	Piotr Bilski [46]	Random Forest (RF)	5th order lowpass filter.	• Used to detect parametric faults • High accuracy
13	Seongmin Heo, [47] Mehrdad Biglarbegian [48]	ANN Recurrent Neural Network (RNN)	Neural network classifiers - Tennessee Eastman (TE) Gallium Nitride (GaN) power converters	• Increased fault detection accuracy • Better fault detection and classification
15	Q. Sun, et al, [49]	Crow Search Algorithm - LSSVM	Capacitor -open loop Boost converter	• High computational efficiency • Good estimation accuracy
16	W. Chen, et al [50]	PCA (Unsupervised algorithm)	SiC -MOSFET	• Used for offline as well as online fault detection
17	B. Gou,et al [51]	IGBT 3-phase PWM inverter	Random Vector Functional L ink (RVFL) network	• Fault prediction accuracy of 98.83% • Applied to non -linear systems

4. REMAINING USEFUL LIFE (RUL)

For an efficient prognosis, estimation of RUL plays a critical role. RUL can be defined as number of productive hours left in a component at a point of time while it is operating. It can be also termed as useful time left till next maintenance. Based on how the available information is used, the prognostic methodologies are classified into model or physics-driven, data or machine learning-driven and hybrid approaches [52]-[54]. In data driven methodology, degradation characteristics are computed based on the chronological sensor data to train the system model that may be used to compute RUL of the component. Widely applied algorithms include Gaussian process [55], [56], SVM, Least Square SVM (LSSVM) [57], neural networks [58], [59], gamma processes [60] and Hidden Markov Models (HMMs) [61]. Physics based approach demands substantial prior understanding about physical systems which is rare to find in practice. The mathematical models are built on first principle or comprehension of component's failure mechanism. Eyring model [62], Weibull distribution [63], particle filter [64], Bayesian inference-based methods [65] are some of the commonly used algorithms in physical modeling approach. Hybrid models are the combination of both the Data driven approach and Physical modeling based approach. In case of non-linear systems, hybrid models can scale from component level to system level [66]. Based on the failure modes, a component can have various deterioration curves which might result in varied RUL [67].

The following section discusses the work carried out on PdM for reliability assessment of PE systems. Vasan, et al [35] used LSSVM algorithm to address the concerns of the circuit failure by predicting and isolating faults. They also estimated the RUP ((Remaining Useful Performance) by using Bayesian Monte Carlo approach for the filter circuits. Thus, aiding the prevention of system failures [36], [37]. Xi-Shan Zhang, et al [38] proposed fault prognostic technique to realize health management of the complex electronic equipment using SVM algorithm. Reliability analysis is done using Kaplan-Meier (KM) and Kernel density Estimation (KDE) technique. Combining SVM algorithm and Principal Component Analysis (PCA) it is possible to locate the position of the power system faults. It will also help in identifying the type of the fault and reduce the interruption of the system [39]. Jianchen Wang, et al [40] proposed Chaos theory and Particle Swarm Optimization (CPSO)-SVM to enhance the system performance by reducing the execution time. Reliability analysis can also be done using genetic algorithm (GA). GA can also be used to increase the success rate in fault diagnosis [41]. Using decision tree algorithm, execution time can be minimized, thereby improvinig the efficiency of the system [42]. Combining SVM and Adaboost algorithm yields better reliability and high classification accuracy [43]. A probabilistic classifier, Naïve Bayes (NB) algorithm provides accurate results and consumes less training time [44], [45]. The approach is used to detect parametric faults in the fifth order lowpass filter, RF is the favorable classification approach with high efficiency even on the quite small data sets [46]. Neural network classifier and Gallium Nitride (GaN) converters are used in reliability analysis for better fault classification and detection. GaN-based devices have incredible performance and exhibit better material properties when compared to those devices made up of silicon. Using GaN device would be highly useful for power engineers in enhancing the reliability of the system [47], [48]. Crow Search Algorithm-LSSVM is novel approach which yields high computational efficiency for boost converters [49]. An unsupervised algorithm is used for fault prognosis where online as well as offline faults can be detected [50]. Fast Fourier Transforms (FFT) is used by IGBT 3-phase PWM inverter to extract the fault frequency spectrum of three-phase currents.

5. RESULTS AND DISCUSSION

More than 150 papers were reviewed and 67 of them are mentioned in the reference to explain the significance of machine learning in the reliability domain. ML's use in PEC reliability comes with both challenges and opportunities. Prognosis requires live condition monitoring which may be a challenge in itself due to accessibility and environment conditions. ML algorithms are not scable in a way that a particular algorithm is trained and tested for lower rated device may not be suitable for higher rated device. Majority of the reviewed papers have published their results based on the laboratory conditions or using simulation software. However real-world scenarios may vary.

6. CONCLUSION

With the complexities involved in PE Systems, their safety, maintenance and reliability are the major concerns. This paper focuses on providing a review of reliability assessment for PE systems using ML techniques. The advantages, disadvantages and applications of various types of maintenance schemes are discussed in detail. A paradigm shifts towards use of ML has been observed in the approach of handling reliability concerns in PEC. Several ML algorithms have proven their efficacy in the area of reliability and in the better fault prediction models. Prediction of faults take cautionary measures to avoid significant and insubstantial losses in the system. Combining ML algorithm yields better results in achieving highly reliable PE systems. Finding RUL itself is a challenging task. However, it provides an insight into the health of the system. This literature review has been developed to investigate various methods in assessing the reliability of PE systems using ML approach for the benefit of power engineers and researchers.

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