A Review of Data-Driven Prognostic for IGBT Remaining Useful Life

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Abstract: Power converters with insulated gate bipolar transistor(IGBT) are widely used in diverse industrial applications such as traction systems. As the IGBT is one of the most fragile components in power electronics converter, remaining useful life(RUL) prognostic of IGBT is important to guarantee system reliability. This paper presents a review of data-driven prognostic for IGBT RUL. In this paper, common data-driven prognostic methods are summarized. Features of data-driven prognostic approaches of IGBT are discussed, and main approaches are compared to each other. Four common problems of these schemes are presented and discussed. In addition, some other desirable studies to improve IGBT RUL estimation are proposed.

Keywords: Prognostic, remaining useful life, data-driven, IGBT.

1 Introduction

Insulated gate bipolar transistors(IGBTs) are power semiconductor switches widely used in medium- and high-power motor drives and power supplies. According to a recent industry-wide survey[1], 31% of responders stated that power semiconductor devices were the most fragile components in power electronic converters. The survey indicated that around 42% of switches utilized in power electronics systems were IGBTs. Fig.1 is a fault distribution chart of converters on CRH3 trains running on Wuhan-Guangzhou high-speed railway in 2009~2013[2]. As shown in Fig.1, IGBTs are the most fragile components, which account for about 64% of all faults. Consequently, IGBTs used in railway applications are considered to be leading edge critical device whose failure rate increases the overall probability of malfunction in railway traction chains[3].

Motivated by such reports of IGBT failures, the technology of condition monitoring(CM) and prognostic is actively applied to detect incipient faults and to take corrective actions before a catastrophic failure occurs. CM is used to assess the current health condition, while prognostic is used to predict the health condition in the future. With only CM techniques, it is still unknown that how much remaining useful life(RUL) is left before a failure occurs.

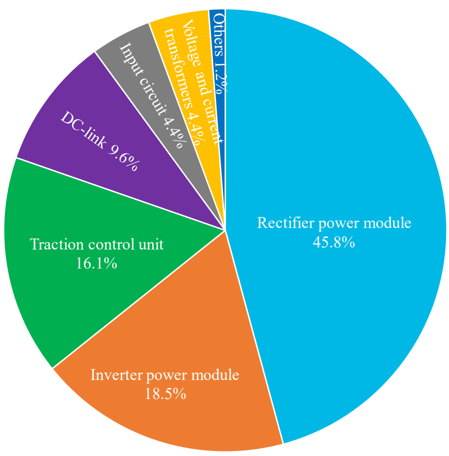

Fig.1 Fault distribution of converters on CRH3 trains[2]

The main prognostic approaches for IGBTs can be classified into two categories: 1) the model-based approach; 2) the data-driven approach. The model-based approach is useful when failure models that emulate the actual failure mechanism are available. On the other hand, the data-driven approach does not require specific knowledge of a product. Instead, information about health condition is extracted from historical data on the performance of a product. Thus, the data-driven approach can be useful when failure models are not available or too complex to formulate.

Kabir et al.[4] presented a review of data–driven prognostics in power electronics. Some literature was listed without the comments on relative merits. Moreover, CM wasn't distinguished from prognostic. Oh et al. [5] presented a review about physics-of-failure, CM, and prognostics of IGBT, but data-driven prognostics weren't widely described.

The aim of this paper is to present a review of existing approaches for IGBT RUL data-driven prognostics. The structure is as follows: the second section describes the failure mode and mechanism of IGBT modules. Next, the third section summarizes commonly used data-driven prognostic approaches. Then, existing data-driven prognostic methods of IGBT are introduced. The fifth section offers the summary of main approaches and four common problems are presented. As well, some other desirable studies to improve IGBT RUL estimation are proposed. Finally, the conclusions are given in the sixth section.

2 Failure modes of IGBT modules

The failure modes of IGBT modules can be divided into two kinds: chip-related failure and package-related

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failure[5-7].

The chip-related failure is generally considered to be caused by overstress(such as transient over-voltage, over-current, electrical-over-stress) and wear out mechanisms during operation[6]. The failure mechanisms of chip-related failure mainly include[6]:

(1) Electrical overstress(EOS).

(2) Electrostatic discharge(ESD).

(3) Latch-up and triggering of parasitic.

(4) Charge effects-ionic contamination or hot carrier injection.

(5) Electromigration, contact, and stress-induced migration.

(6) Thermal activation.

(7) External radiation-mobile ions and particles.

(8) Other mechanisms for MOS-gated devices.

Since overstress is a short transient process, RUL prediction does not apply to such failures. However, as for the chip-related failure caused by wearing out, RUL prediction can be performed.

Package-related failures are most common in power electronic systems. At present, there are two main kinds of package structures:wire-bond structure and press-pack structure[8]. Since wire-bond modules are most widely used[9], this paper only discusses the failure mechanism of wire-bond modules without discussing that of press-pack modules. The structure of wire-bond modules is as shown in Fig.2 [7].

The package-related failure is primarily a wearing out failure due to thermomechanical fatigue stress. In Fig.2, the IGBT module is multilayer structure with various materials, the coefficient of thermal expansion (CTE) which differs. During operation, IGBT modules are subjected to thermal cycling for a long time. Due to the mismatch of CTE, the internal structure of the device is expanded to different degrees under thermomechanical stress, thus causing wearing out of IGBT modules. The failure mechanisms of package-related failure mainly include[10]:

- Bond wire fatigue, including bond wire lift off and bond wire heel cracking.
- Aluminum reconstruction.
- Brittle cracking and fatigue crack propagation.
- Corrosion of the interconnections.
- Solder fatigue and solder voids.
- Gate oxide degradation.

In addition, the most common failure is bond wire fatigue and solder fatigue.

Since the package-related failure is mainly a wearing out failure, which is a gradual process, it is necessary to predict RUL of IGBT modules.

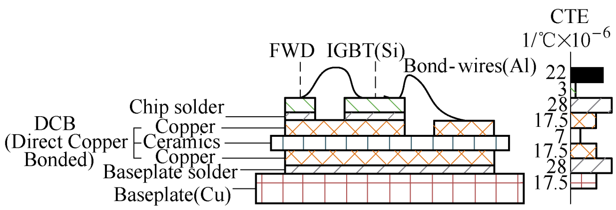

Fig.2 Structure of wire bond modules[7]

3 Common data-driven prognostics

The commonly used data-driven approaches of prognostics are summarized in Fig.3, which mainly includes conventional numerical techniques and machine learning methods[11-12]. Some of the conventional numerical techniques used for data-driven prognostics include Kalman filters[13], particle filters[14], regression[15], statistical methods[16], etc. Machine learning algorithms include neural networks[17], decision trees[18], and support vector machines[19], etc. These methods can be broadly classified into supervised, semi-supervised, and unsupervised learning techniques. Another popular technique used for prognostics is fuzzy logic[20]. When applied to prognostics, fuzzy logic is typically applied in conjunction with a machine learning method, and is used to deal with some of the uncertainty that all prognostics estimates face.

Although lots of data-driven methods are being employed for prognostics in a wide range of different applications, only a few of them have been employed so far for the prognostics of IGBTs. Degradation in electronics is more difficult to detect and inspect than in most mechanical systems and structures due to the small scale (micro- to nano-scale) but complex architecture of most electronic products[21].

4 Data-driven prognostics of IGBT

At present, most of the data-driven prognostics of IGBTs are based on the process shown in Fig.4[22]. Firstly, accelerated ageing experiments are carried out to accelerate ageing and failure of IGBTs. Then, prognostic algorithm will be developed based on the data collected in the experiments. Suitable precursors will play an important role, which will influence the accuracy to a large extent.

The aging failure of IGBT modules is a slow process. As the operation time increases, the modules' performance will decrease due to cumulative damage

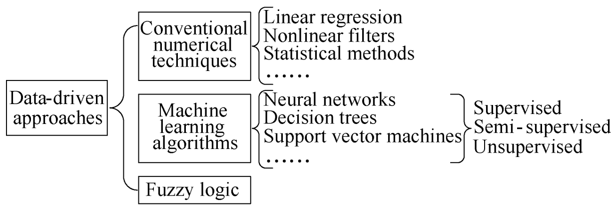

Fig.3 Common data-driven approaches of prognostic

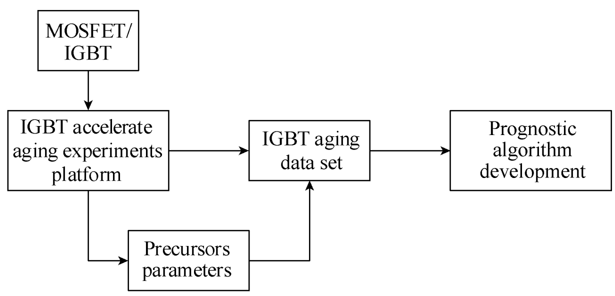

Fig.4 Process of IGBT prognostic algorithm development[22]

caused, thus leading to the change of parameters and signals. That's to say, the precursor can reflect the aging level of IGBT modules. Consequently, the selection of precursors is very important to predict the RUL of IGBT modules.

The commonly used precursors are $V_{CE(on)}$, I_C, V_{GE}, $V_{GE(th)}$, T_{on}, T_{off}, and T_j[23]. It can be seen that $V_{CE(on)}$ is the most suitable precursor for prognostic considering online measurement, genericity, calibration, accuracy, linearity, and sensitivity in Fig.5.

A research group from Cranfield University focuses on RUL prognostic with Monte-Carlo simulation and some literature has been published in [3,22,24]. In these literature, collector emitter voltage(V_{CE}) is used as a precursor parameter. The RUL prediction process of these literature is shown as Fig.6[22]. The stochastic degradation models are developed based on probabilistic distributions. Gamma, Exponential, Poisson and combining distribution models have been studied. According to the literature, the Poisson model has less errors in comparison to the Gamma model. The combined model provides better prediction performance compared to the single statistical distribution model. With failure model based on time delay neural network (TDNN), prediction results can be improved. The RUL result of TDNN failure model using normalization techniques is shown as Fig.7. Errors of the approach with TDNN is less than 4% compared to more than 20% of just stochastic model based approach.

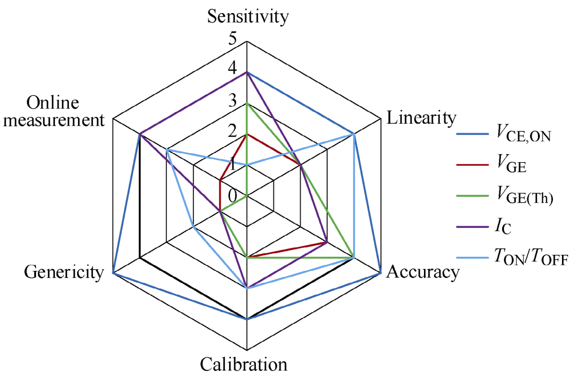

Fig.5 Performance comparisons of precursors for IGBT[23]

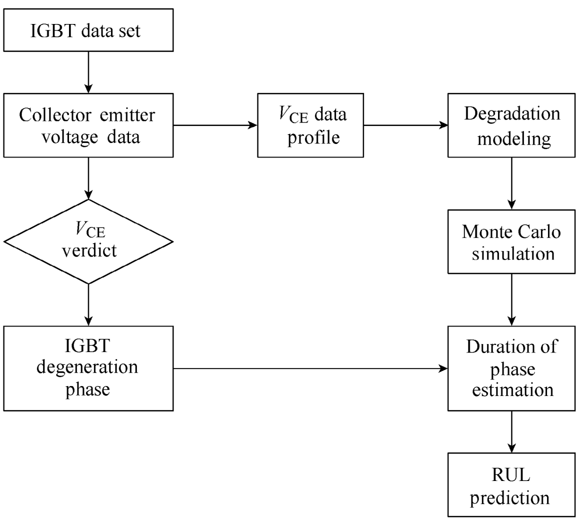

Fig.6 RUL prediction process[22]

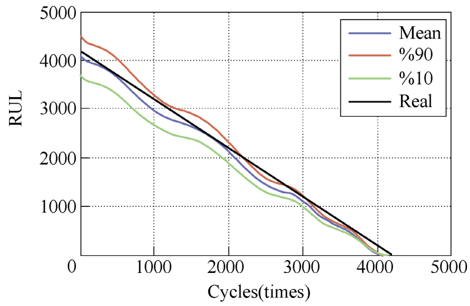

Fig.7 RUL of TDNN failure model using normalization techniques[3]

A particle filtering(PF) based method provides the probability distribution of RULs, which recursively estimates and updates the probability distribution of life model parameters as additional measurements. Saha et al. [25] described a preliminary example with collector emitter current(I_{CE}) as a precursor. Patil et al. [26] proposed a prognostic approach based on Mahalanobis distance(MD) and PF methods. In their study, once an anomalous behaviour was detected by the MD method, an algorithm based on PF was triggered to predict the RUL with an error of approximately 20%. Sequential importance resampling(SIR) PF method was utilized, and V_{CE} was used as a precursor parameter in the study. Haque et al. [23] employed auxiliary particle filtering (APF) when IGBT entered the degradation region identified by a simple slope-based method. The algorithm is shown as Fig.8 and the trajectory of $V_{CE,ON}$ using PF is shown as Fig.9. The APF increased

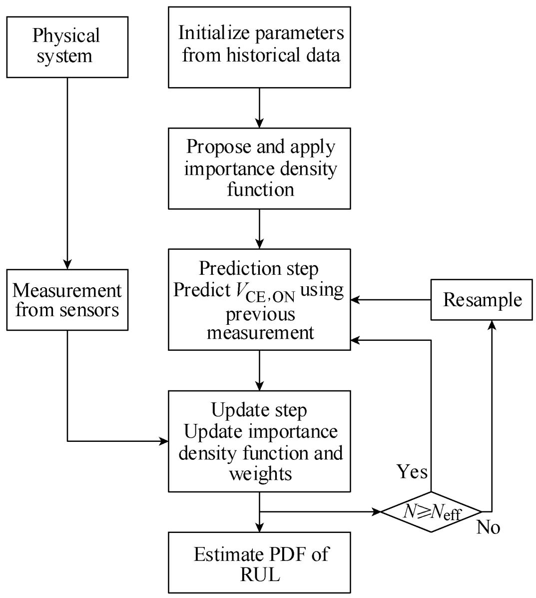

Fig.8 APF-based RUL estimation algorithm[23]

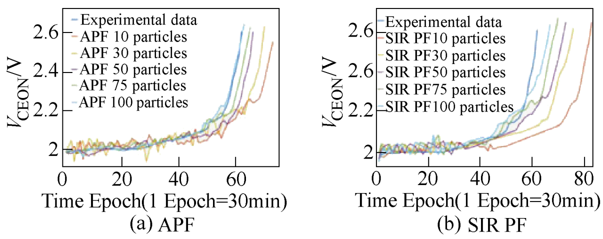

Fig.9 Trajectory of $V_{CE,ON}$ using APF and SIR PF with different number of particles[23]

diversity in samples to reduce estimation variance and a smaller error 17.8% was found.

Ahsa et al. [27] adopted two machine learning methods, neural network (NN) and adaptive neuro fuzzy inference system (ANFIS). Relatively accurate prediction can be made based on information beyond half-life. The errors calculated using NN and ANFIS are 19.04% and 30.91%, respectively. V_{CE} is used as a precursor parameter in the study. Samie et al. [28] presented a prognostic technology based on ANFIS system. They selected $V_{CE\text{-}SAT}$ as precursor parameter and considered temperature as working condition parameter under the condition of a fixed maximum $I_{C\text{-}SAT}$. The error of the best results was 8.1%. Algassi et al. [29] also developed a prognostic technology based on ANFIS in fusion with failure dynamics using V_{CE}, ΔV_{CE}, T_j, ΔT_j as precursors. The process of RUL estimation is shown as Fig.10 and Fig.11 and the prognostic result Fig.12. The error of 1.76% is got.

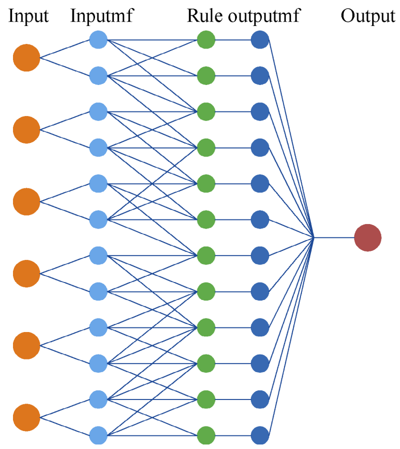

Fig.10 Structure of ANFIS[27]

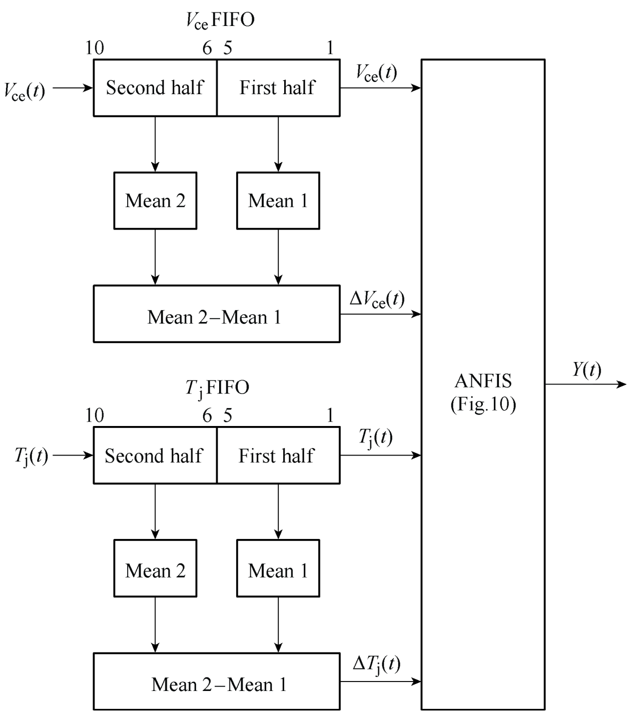

Fig.11 The process of RUL estimation based on fuzzy logic[29]

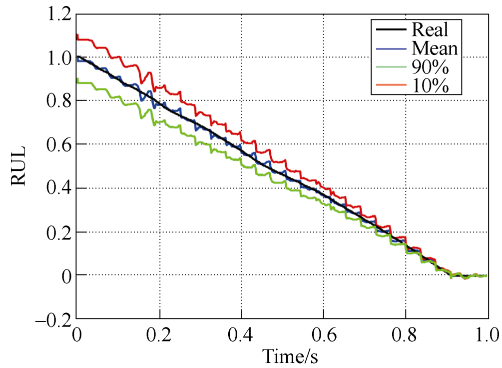

Fig.12 RUL simulation using ANFIS model[29]

Algassi et al. [30] developed a prognostics model based on fuzzy knowledge. The process of RUL estimation based on fuzzy logic is shown as Fig.13[31]. V_{CE} and ΔV_{CE} are used in the fuzzy system as precursor parameters. The experimental data shows that V_{CE} is the best degradation indicator and ΔV_{CE} indicates the dynamic of degradation process[30] . The result is shown as Fig.14 with an error value of 0.51%. However, the relationship between variables and the information of the experts are required to construct fuzzy rules and membership function. Besides, linguistics variables are used, and the boundary demarcation of them greatly affects the accuracy of prognostics.

Algassi et al. [32] proposed a state based prognostic model for predicting RUL. The study employed transition probabilities models to predict RUL, but overall the system did not provide high accuracy of RUL prediction.

5 Summary and discussion

Table 1 is the summary of main approaches. In fact, the accuracy ratio comparison of various methods

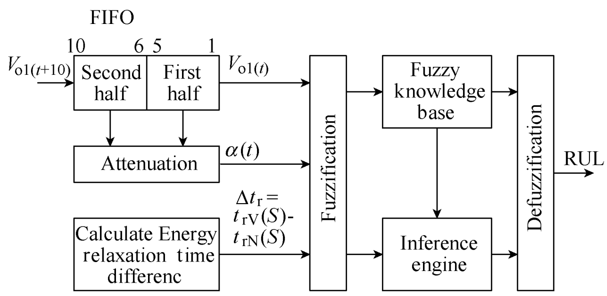

Fig.13 The process of RUL estimation based on fuzzy

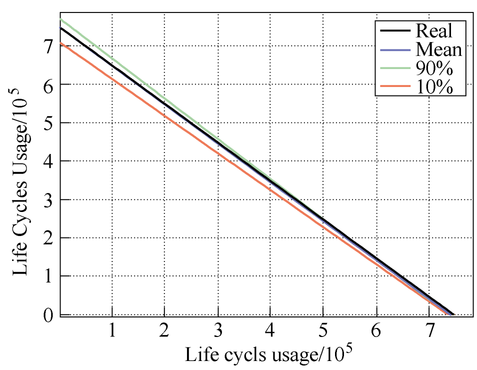

Fig.14 RUL simulation in defuzzified model[30]

Table 1 Summary of main data-driven prognostics approaches of IGBT

Approaches			Precursors	Errors(%)	Advantages	Disadvantages
Conventional numerical techniques	Monte-Carlo simulation	Poisson	V_{CE}	＞20	Computationally efficient, real-time, and embeddable	Low accuracy
		Gamma		＞33		
		Fusion with TDNN		＜4	High accuracy	--
	Nonlinear filters	SIRPF		21	--	Relatively low accuracy
		APF		17.8		
Machine learning	NN			19.04	--	Relatively low accuracy and large data based
	ANFIS			30.91		
			$V_{CE\text{-}SAT}$	8.1	--	
			V_{CE}, T_j	1.76	High accuracy	The structure is difficult to determine, the algorithm is complex, the calculation efficiency is low, and the convergence speed is slow
Fuzzy logic	Fuzzy logic		V_{CE}	0.51	High accuracy	The relationship between variables and the information of the experts are required

from the literature is not significant without unified error calculation method, and it is necessary to consider the period in which the prediction starts (the closer to the failure, the more accurate the prediction is). The evaluation of various methods should consider feasibility, amount of data, amount of calculation, and so on. There are many inherent problems in artificial neural networks, including the difficulty in determining the network structure, the complexity of the algorithm, the low computational efficiency, and the slow convergence rate, which is not conducive to engineering applications. As for fuzzy logic, it requires expert information to construct fuzzy rules, which is not conducive to engineering applications.

In addition to the comments in Table 1, there are four common aspects that need to be improved in the above approaches:

(1) A single precursor V_{CE} is employed in most literature. There are multiple failure mechanisms in the aging process of IGBT. A V_{CE} based technique may fail to detect the degradation as the competing mechanisms cancel the effects of each other. One method of resolving this issue is to do prognostics associated with multi-precursors.

(2) Aging precursors are always impacted by junction temperature(T_j). A more accurate prediction needs to eliminate the effect of temperature. One method of resolving this issue would be to determine a temperature dependent correction parameter to account for changes in temperature.

(3) Precursor measurements of selected samples are used in building failure models or system training step, which are used to predict the RUL of other samples. Individual differences should be considered.

(4) The failure threshold is an assumption, 20% change in the V_{CE} as an example, which will vary as individual differences, multiple failure mechanisms, etc.

The above literature didn't involve the theoretical basis of the selection of data-driven algorithms. Such study is needed to match IGBT aging characteristics and data-driven algorithms. It is not a good approach to use a large amount of algorithms and choose according to the results. Furthermore, reasonable enough prognostic metrics are also missing. In recent literature, accuracy is the only criterion. Prognostic metrics that take into account the prediction horizon length, sensitivity to damage state estimation, modality of confidence distribution, preference distribution around actual time of failure, and stability/robustness of the prediction would be desirable.

A practical method of indicators measurement, noise filtering, and on-line measurement of T_j warrant special attention, as they are the fundamentals of data-driven IGBTs CM and RUL prognostic for accuracy and practicality.

6 Conclusion

Literature and main approaches of data-driven IGBTs RUL prognostic are reviewed in this paper. Features, advantages and disadvantages are commented on. The main approaches are compared to each other. Monte-Carlo simulation with TDNN has the highest accuracy, but PF is more practical. Four common problems are presented and some solutions are proposed. In addition, some desirable studies are proposed.

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