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REVIEW

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Overview of recent progress in condition monitoring for insulated gate bipolar transistor modules: Detection, estimation, and prediction

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Abstract

The insulated gate bipolar transistor (IGBT) is one of the most fragile components in power electronics converters. In order to improve the reliability of IGBTs, various measurements are taken according to the condition monitoring (CM) technique. Traditional CM techniques include the measurement and estimation of the device operation conditions. Recently, emerging techniques have been developed, not only for the detection and estimation but also for the prognostics of IGBTs with the condition data. In this paper, a review is performed on the recent progress in the CM techniques for IGBTs. First, some emerging electrical and thermal measurements are reviewed. Based on the sensed data, the health indicator estimation techniques are summarised. Moreover, for the emerging prognostics and health management applications, some remaining using lifetime (RUL) prediction methods are reviewed. Finally, the research gaps and directions are discussed for the CM in IGBT applications.

1 | INTRODUCTION

Power electronic converters are widely used in renewable power generation, high voltage direct current (HVDC) transmission systems, high speed railways, electrical vehicles etc. In these applications, the reliability of the power electronics converter is one of the key research issues of the system [1]. The reliable operation of the power electronics converters will ensure the security of a system and lower the maintenance cost of the system operation during its whole lifetime.

Insulated gate bipolar transistors (IGBTs) with the advantages of large power capability, low saturation voltage, and high switching frequency are widely adopted in high-voltage and high-power electronics converters [2]. However, the IGBT is one of the most fragile components in the system. Some industrial survey reports show that 39% of the system failure of power electronic converters can be attributed to the failure and damage of the IGBT devices, and the failure of the IGBT and its driver accounts for more than 50% of the system failure [3, 4].

Condition monitoring (CM) is an effective tool to improve the reliability of IGBTs. It can be defined as the real-time measurement of the condition of a component [5, 6]. The basic part of the CM is the sensors, which are used to detect the voltage or current related to the IGBT. The voltage sensors can be general operation amplifiers; however, in order to get a comparable voltage result, some standard testing current source (CS) should be provided [7]. Current sensors are also widely used practically, such as the Hall sensors. Recently, more magnetic sensors have been developed, which may achieve higher performance [8–13]. Some emerging research studies are also being carried out on the integrated sensors at the device gate driver (GD). This technique would be promising since the implementation would be simple [14, 15].

Based on the measured signals, more state indicators of IGBT can be derived for the IGBT health management. Various health state indicators are adopted for the IGBT diagnostics and prognostics, including but not limited to the junction temperature, thermal impedance, on-state resistance

etc. An estimation process is adopted to generate the indicators from the measured signals. A simple example can be the look-up table when deducing the junction temperature from the voltage or current measurements, and the sensed voltage or current is also known as the temperature sensitivity electrical parameter (TSEP) [7, 16–24].

Other IGBT states, such as power loss, thermal impedance, can be derived by physical models as well. Existing models are developed in the literature [25–27]. But apparently, these off-line models will suffer from challenges of accuracy or sensitivity if the working condition is varying. In practice, additional feedback control or model parameter extraction is usually adopted using the online sensed signals. When proposing such physical models, it is found that the states of IGBT are deeply coupled. For instance, the junction temperature model and power loss model parameters would vary when the working temperature or degradation level is changed. The coupling effects would be complex, and it would be hard to get analytical results. Some artificial intelligent (AI)-assisted optimisation and model feature extraction methods are proposed [28, 29].

Moreover, the estimation can be model-free and directly deduced from data. It is possible to take the IGBT module as a black box and extract the relationship between its input and output by data-driven methods [30, 31].

The remaining useful lifetime (RUL) is another critical health state of IGBT. The prediction method is the key technique in the RUL analysis. Although some lifetime models are proposed for RUL prediction [32–38], the data-driven methods are obviously advanced in dealing with this kind of problem with huge historic data [39–44]. In recent years, the data-driven methods in condition estimation and prediction have developed very fast, thanks to the progress of AI and high performance programing chips [45–51]. According to the sensed data, the unexplored or uncertain states are generated by the neural network or other deep learning tools.

Due to the requirement of high reliable power electronics in modern power grids and electrical vehicles, CM techniques are used in much broader aspects for the IGBT health management. The monitored signals are not only limited to the electrical ones but also include power loss, temperature, RUL etc. In this paper, the CM techniques for IGBT are summarised into three catalogues, and the recent developed techniques can be clearly classified. From the review, the bottleneck of the IGBT CM is shown and the future directions are identified. The main contribution of this paper lies in two aspects. Firstly, this paper summarises and compares the existing CM methods from the convenience and cost aspects, which has not been studied before. It is helpful for practically choosing and designing the detection circuit. Although there are couple of review papers on condition monitoring published already, they are mainly focusing on the bench marking of accuracy, sensitivity, and effectiveness of these methods. However, it is unclear which of these methods is more practical useable, especially considering the cost and convenience. Secondly, since the IGBT CM is still challenging because some states are hard to measure directly, possible research directions are proposed based on the state of the art. Particularly, some practical issues and possible technical solutions are proposed for the HVDC applications from the authors' experience.

2 | DETECTION METHODS

To acquire the health state of the component in equipment, sensing is an essential process. Sensing can be classified into temperature, voltage and current sensing methods. However, for online real-time measurement, temperature sensing is hard to achieve due to the IGBT package. At present, the voltage and current sensing circuits are usually adopted. However, accuracy, sensitivity and easy implementation are still challenging problems.

2.1 | Voltage detection

The collector–emitter on-state voltage (V_{ce}) is a key parameter to represent the degradation of the IGBT module. The online V_{ce} measurement technique can be used to predict the wear-out status of IGBT modules during a normal converter period. This method requires IGBT circuit connection. The V_{ce} measurement circuit in [7] uses a similar technique as the desaturation protection. The V_{ce} measurement circuit is shown in Figure 1. Assuming that the two diodes are identical ($V_{D1} = V_{D2}$), V_{ce} can be measured by subtracting the voltage drop on diode D2 from V_b.

However, the voltage measurement circuit highly depends on the architecture of the power converters in terms of topology and control. To solve the problem, authors in [8] propose a converter-level method for measuring the on-state voltages of all power semi-conductors in a single-phase inverter by using only a simple circuit. The proposed circuit has better accessibility because of converter-level implementation, and the isolation stage can be simplified with it.

2.2 | Current detection

The principle of the current detection methods is to use Ohm's law to convert the sensing voltage into current. This needs a sampling resistor that is inserted into the power loop of the device. According to the connection type of the resistor, these kinds of methods can be further classified into extra resistor type and integrated resistor type. However, these may cause additional power loss and cost. Therefore, the sensors based on the Hall effect or magnetoresistive effect are attracting much attention. The main advantage of these methods is that they can be non-invasive.

Hall element is a mature sensing technique and is currently one of the most widely used magnetic sensors in the industry. A Hall sensor is capable of measuring DC, AC and complex waveform currents with galvanic isolation. A closed-loop Hall sensor can improve measurement accuracy (linearity and
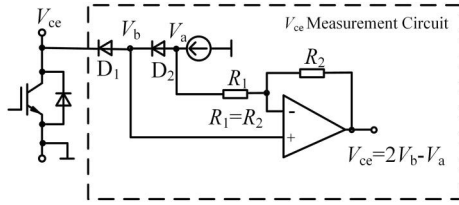
FIGURE 1 V_{ce} measurement circuit [7]

gain drift) and bandwidth, and its current output is especially useful for applications in a noisy environment [9].

Rogowski coil is a classic magnetic current detecting method. It detects current using Faraday's law of electromagnetic induction. Authors in [10] propose an output-current measurement method of a pulse width modulation (PWM) inverter using a tiny printed circuit board (PCB) sensor that is based on the Rogowski coil and can be integrated into an IGBT module as shown in Figure 2, reproducing the output current including its polarity using a single PCB sensor at the low-side switch per leg. Authors in [11] also designed a square Rogowski coil, which can be used in chip current measurement in press-pack IGBTs. Compared with the traditional square Rogowski coil with equidistant inter-turn arrangement, it has higher position accuracy and anti-interference ability. Compared with other methods, the cost of Rogowski coils is relatively higher.

Other ways to measure current include magnetoresistive sensors. Magnetoresistance refers to a type of element whose resistance value changes with the surrounding magnetic field. The reason for this phenomenon is that the electron spins and generates a magnetic field. The external magnetic field can adjust the direction of the electron spin in the device, and different electron spin directions will affect the resistance of the electron movement. Due to its small size and increasing sensitivity, magnetoresistance is also regarded as a very promising current sensor technology.

Magnetoresistance can be divided into anisotropic magnetoresistance (AMR), giant magnetoresistance (GMR), and tunnel magnetoresistance (TMR). Anisotropic magnetoresistance has only one layer of magnetic resistance material. When the magnetisation direction in the ferromagnetic film changes from parallel to the current direction to perpendicular to the current direction, the resistance value generally changes by 2%–4% [12].

A lower resistance change rate means a lower signal-to-noise ratio, which is also the main disadvantage of AMR. Giant magnetoresistance is proposed to increase the resistance change rate of AMR. Giant magnetoresistance is composed of two layers of ferromagnets wrapped with a layer of non-magnetic metal, and the resistance change is caused by electron spin scattering [13]. The resistance change rate of GMR is approximately 12%–20%. Tunnel magnetoresistance further improves the resistance change rate on the basis of GMR [14]. The schematic diagram of the structure of the TMR element is shown in Figure 3, which is a sandwich structure. The upper and lower layers are made of ferromagnetic materials.
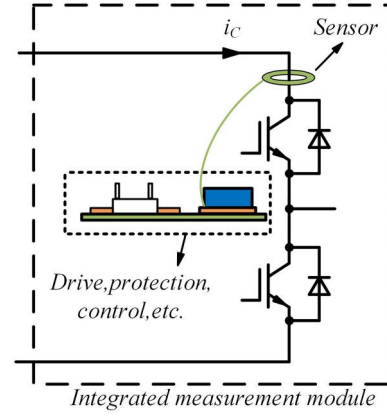

FIGURE 2 Integrated Rogowski coil in an insulated gate bipolar transistor module [10]

In order to eliminate the electromagnetic interference caused by high-frequency switching, authors in [12] used a differential structure composed of two TMR chips to measure the current of the IGBT power terminal. The measurement result has a better fit compared with the Rogowski coil. Using the TMR devices, a fast current sensing can be achieved, and the IGBT protection can act in 1.23 µs, which is much faster than traditional methods.

2.3 | Smart gate driver with integrated sensor

Integrating the sensor into the GD is a simple, cost-effective way to detect the IGBT state. In [14], a smart GD circuit, which can monitor ageing-related parameters such as the threshold voltage (V_{th}), and on-state saturation voltage drop ($V_{ce,on}$) is designed. The circuit is specifically designed to be easily embedded. Apart from the GD components, the circuit has a CS to provide a small test current; two diodes are included to protect the GD circuit from the applied high voltage between the C-E terminals during off-state and to provide isolation between the CS and GD. The circuit can operate in the V_{th} measurement, the $V_{ce,on}$ measurement, and the normal operation modes. The measurement procedure takes less than 100 µs, which is feasible for most practical applications.

A smart IGBT GD integrated circuit (IC) is presented in [15] with an integrated collector current sensor and an on-chip digital processor. The proposed current sensing method utilises the low-voltage gate signal to indirectly predict the collector current. With the on-chip temperature compensation, an accuracy of ±0.5 A is achieved within the current range of 1–30 A for turn-ON and 1–50 A for turn-OFF from 25 to 75℃. The proposed smart GD IC is fabricated employing a 0.18 µm binary-coded decimal process, and the chip is fitted into a 5 × 5 mm pad frame. Apparently, this technique is complicated but has the advantage of integrated design. Meanwhile, the GD will become much smarter, and other complex driving control can be achieved.
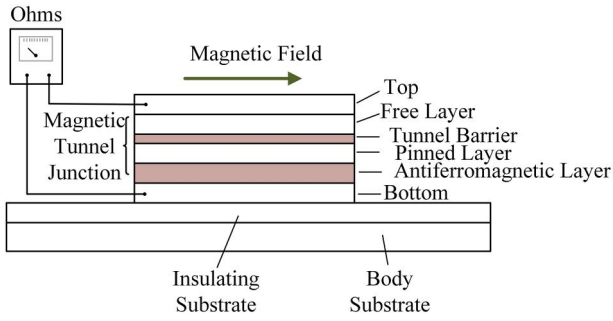
FIGURE 3 Basic structure of tunnel magnetoresistance

The above methods are summarised in Table 1 in terms of convenience and estimated cost from the seller (mouser.cn). The cost is not accurate for particular designs, and it is only listed for the comparison of different techniques.

3 | ESTIMATION METHODS

Some physical or non-physical variables are required in the analysis to represent the IGBT state or health condition. These variables can be the directly sensed voltage or current or estimated variables from the sensed data. For example, the power loss and junction temperature is difficult to measure; however, there are still some ways to estimate them using sensed data. This estimation process can be model-driven and data-driven.

3.1 | Model-driven

The model-driven CM method is suitable for systems with constantly changing IGBT operating conditions. Theoretically, the condition change of IGBT device depends on the internal state of the device and the operating point. The model-driven method can be used to track the change of the operating point of the system. The main idea is building a model between the measured variables of the IGBT and its internal state by an offline testing experiment and then using the real-time online monitoring data as the input of the model, to derive the output of the IGBT state, as shown in Figure 4.

Junction temperature is a key state variable for IGBT reliability evaluation and health management. The junction temperature estimation based on temperature-sensitive electrical parameters is a typical estimation method and has attracted much attention because there is no need to destroy the IGBT module package. In [16], a model-based active junction temperature estimation method is described. The estimation system consists of three parts: device model, loss model and thermal model. Junction temperature T_j, bus voltage V_{dc}, switching frequency f_{sw}, collector current I_c and case temperature T_c are chosen as inputs in the estimation system. The junction temperature will be further iterated into the estimation system to form a closed-loop system for the estimation of the junction temperature.

In [7, 17], an online estimation method of IGBT junction temperature based on V_{ce} measurement is proposed, which designs a high-precision on-state voltage measurement circuit and combines the regression problem solving method to find the relationship model between on-state saturation voltage drop $V_{ce,on}$, junction temperature T_j and collector current I_c, and based on this model, the on-line measurement of junction temperature can be realised. This method can also be popularised in the complex system.

In [18], a new method for the online estimation of IGBT junction temperature according to the gate plateau voltage during the switching process is proposed. It is known through experiments that the width of the Miller platform $T_{difference}$ in the gate emitter voltage V_{ge} curve changes with the temperature, which can be used to measure the junction temperature of the IGBT. On this basis, the relationship between junction temperature T_j, module-rated voltage V_n, rated current I_n and the width of the Miller platform $T_{difference}$ needs to be established. This method does not require any modification to the module, nor does it require the use of any complex thermal model.

In [19], a method of junction temperature estimation based on gate peak current is proposed. Since the internal gate resistance R_{Gint} is temperature-dependent and will change with temperature, it can be used for junction temperature monitoring, but the resistance is often difficult to measure directly. Therefore, the internal resistance R_{Gin} can be measured indirectly to establish the relationship between the gate voltage V_{Gpos} at turn-on, the gate voltage V_{Gneg} before turn-on, the peak voltage V_{peak} of the external resistance, and the internal resistance R_{Gint} and then realise the junction temperature estimation model building of the IGBT.

In [20], an on-line estimation method of IGBT junction temperature based on the turn-on voltage drop is proposed, which takes into account the influence of the temperature change of the measurement circuit and the change of the IGBT load current and makes the corresponding compensation based on the turn-off phase of the IGBT. Experimental analysis shows that there is a linear relationship between the IGBT junction temperature and the on-state voltage drop of the IGBT, which can be used as a basis for junction temperature estimation. Through experimental verification, the estimation error of IGBT junction temperature is derived to be less than 1.88% under various working conditions.

In [21], a new IGBT module junction temperature estimation method is proposed to adapt to various working conditions and improve calculation efficiency. First, based on the superposition theorem, odd–even modal analysis and frequency domain analysis, the effects of power loss, frequency and thermal parameters on thermal coupling are studied. Finally, experiments verify the effectiveness of this method to measure junction temperature. In [22], an IGBT junction temperature extraction method based on the inherent stray inductance is proposed, and it expounds the fact that the temperature-sensitive electrical parameters can be extracted by the induced voltage.

TABLE 1 Detection method of IGBT health status

Approaches		Convenience	Cost comparison
Voltage detection	V_{ce} measurement	Need to connect the measuring circuit to IGBT	~30 RMB
	On-state voltage (OV) measurement	Non-invasive	~60 RMB
Current detection	Hall sensor	Non-invasive	~20 RMB
	Rogowski coil (PCB type)	Non-invasive	~160 RMB
	TMR	Non-invasive	~50 RMB
Smart gate driver with integrated sensor	Smart GD circuit	Need to change gate driver circuit	~30 RMB
	Smart IGBT gate driver IC	Integrate IGBT gate driver IC with a collector current sensing circuit, and each chip needs a special order	~120 RMB

Abbreviations: GD, gate driver; IC, integrated circuit; IGBT, insulated gate bipolar transistor; PCB, printed circuit board; TMR, tunnel magnetoresistance.

FIGURE 4 Steps of insulated gate bipolar transistor condition online estimation

In [23], an IGBT junction temperature extraction method based on the maximum collector current drop rate is proposed, and the inherent linear relationship between the maximum collector current fall rate and the junction temperature is studied. Based on the parasitic inductance L_{eE} between the IGBT module Kelvin and the power emitter terminals, the maximum dI_c/dt can be easily measured; this method has good application prospect. In [24], an IGBT junction temperature estimation method based on the turn-off delay time t_{doff} is proposed, and the inherent parasitic inductance L_{eE} of the IGBT module is used to extract the turn-off delay time t_{doff}. In addition, the dependence between junction temperature and turn-off delay time is studied. By monitoring the induced voltage across L_{eE}, the start and end points of the turn-off delay time can be determined. In [25], a thermal estimation method is proposed for the transient process of IGBT under current steps. An improved thermal resistance is added to the thermal network of the IGBT package. Then, the transient junction temperature rise of the device can be predicted.

In addition to the junction temperature, the thermal state estimation of the IGBT is also very important, mainly related to the estimation of loss E_{loss}, thermal resistance R_{th} and thermal capacitance C_{th} of IGBT. In [26], a novel method of IGBT loss estimation that combines the temperature-dependent IGBT model with the power loss model is proposed, the IGBT-diode electrical transient model is established, and the non-linear characteristics of the IGBT and the reverse recovery characteristics of the diode are considered to simulate the transient switching waveform. Based on the loss model and actual monitored parameters such as junction

temperature, voltage, current etc., a loss model is established to realise IGBT power loss estimation.

In [27], a method for estimating the thermal network parameters of the IGBT modules is proposed, by using the junction temperature cooling curve. It has two advantages: (1) there is no need to know the power loss of the IGBT; (2) there is no need to heat the IGBT to thermal steady state. This method can directly obtain the thermal resistance capacity (RC) parameters of the fourth-order Cauer-type thermal network by establishing the relationship between the RC parameters and the time constant of the junction temperature response curve. The above estimation methods are summarised in Table 2.

Some numerical tools, such as the Kalman filter, are used to estimate the model parameters by model iteration. In [28], the on-state voltage V_{CE}(ON) obtained under high current during the normal operation of the power converter is used as a thermally sensitive electrical parameter to measure the junction temperature. The change of IGBT junction temperature is non-linear. Therefore, the first two terms of the Taylor series are used to approximate the non-linear system linearly, and then the Kalman filter method is used to estimate and realise the adaptive junction temperature T_j estimation. Kalman filter is suitable for the case where the system is linear and the noise is Gaussian, but the system usually does not always meet the above conditions. The particle method has better estimation accuracy when the system is non-linear or the noise is non-Gaussian [29].

In particular, the model-based TSEP method is summarised in terms of cost and complexity, as shown in Table 3. Also, the estimated cost is listed from a commercial seller (mouser.cn) for the comparison of different techniques. It can be seen from Table 3 that both cost and complexity need to be comprehensively evaluated. The TSEP method is beneficial to analyse the thermal characteristics of semi-conductor devices under offline conditions. The measurement of the junction temperature line is closely related to the sensor bandwidth, measurement circuit and other factors, which has a great influence on the measurement accuracy.

TABLE 2 Model-driven estimation method for IGBT

Input	Mathematical model	Output
$T_j, V_{dc}, f_{sw}, i_c, T_c$ [16]	$V_{ce} = f(i_c, T_j)$ $E = f(i_c, V_{dc}, T_j)$ $P_{cond} = f(i_c, V_{ce}, T_j)$ $P_{sw} = f(f_{sw}, E_{on}, E_{off}, T_j)$ $T_j = f(P_{loss}, Z_{thjc}, T_c)$	T_j
$V_{ce(on)}, I_c$ [7, 17, 20]	$V_{ce(on)} = f(T_j, i_c)$	
$T_{difference}, I_n, V_n$ [18, 20]	$T_{difference} = f(T_j, I_n, V_n)$	
$V_{Gpo}, G_{neg}, V_{peak}$ [19]	$R_{Gint} = \dfrac{V_{gpos} - V_{Gneg}}{(V_{peak}/R_{Gext})}$ $\quad - R_{Gext} = f(T_j)$	
t_{doff}, I_L [22, 24]	$T_j = f(t_{doff}, I_L)$	
I_c, V_{eEmax} [23]	$V_{eEmax} = -L_{eE} \cdot \dfrac{dI_c}{dt}\big|_{max}$ $= f(T_j, I_c)$	
V_{ce}, I_c [21]	$T_j(t) = f[V_{ce}(t) \cdot I_c(t)]$	
V_{ce}, I_c [26]	$E_{loss} = f(V_{ce}, i_c)$	E_{loss}
V_{ce} [27]	$T_j(t) = f(V_{cesat})$ $T_{vj}(t) = T_j(t) - T_a$ $\quad = \sum\limits_{n=1}^{4} \alpha_n e^{-t/\tau_n} = f(R_{th}, C_{th})$	R_{th}, C_{th}

Abbreviation: IGBT, insulated gate bipolar transistor.

3.2 | Data-driven

The data-driven method treats the IGBT power module as a black box or half-black box. In order to estimate the IGBT characteristic parameter value, the sensed internal or external signal of the IGBT power module is used as the input or output mapping relationship. Data-driven IGBT module CM directly derives model monitoring data from conventionally collected conditions instead of considering comprehensive system physical model expertise so that it only requires a certain amount of data without having a comprehensive understanding of the system [30, 31]. Intelligent algorithms can be implemented faster and calculations are more efficient than other technologies, so data-driven methods are suitable for complex systems.

In [32], the operating status of the full-bridge rectifier based on the IGBT module is analysed, and the static neural network is used for status monitoring. The operating status of the device is diagnosed according to the deviation between the actual measured value and the theoretical value. In [33], the least squares support vector machine algorithm is used to diagnose the open circuit fault of the power device IGBT. The results show that the model has good accuracy and real-time performance. The intelligent algorithm for IGBT CM can usually be divided into system parameter identification and data mining.

System parameter identification can be model-free. The model-free method does not require prior knowledge of IGBT devices. It is essentially a regression tool $f(\bullet)$ using intelligent algorithms to establish the functional relationship between input and output [34]. In [35], a case temperature identification method using genetic algorithm to optimise back propagation neural network is proposed to monitor the state of IGBT, as shown in Figure 5. This method takes electrical parameters as input and case temperature as output. The predicted case temperature value of the module is compared with the normal value to realise the state evaluation of the device. The model-free method is very sensitive to external noise because there is no system model. A common way to alleviate this problem is to use large amounts of data, but the collection of data is time-consuming and expensive.

In [36], an extreme learning machine optimised by the whale optimisation algorithm is used to evaluate the ageing state of IGBT modules. First, the electrical and thermal characteristics data of different ageing stages is used to divide the ageing state of the IGBT into five stages, and the above data is used to deal with the extreme learning machine training optimised by the whale optimisation algorithm. The ageing model establishment is then realised. Finally, the electrical and thermal characteristics of the IGBT to be tested are input into the ageing model to determine the ageing state of the IGBT.

Data mining is to search the information hidden in a large amount of raw data through algorithms to achieve the task of monitoring the status of IGBTs. In [37], the k-Nearest Neighbour anomaly detection algorithm is applied to the current, voltage and temperature data, and the fault is detected before the IGBT enters the failure region. In [38], a self-organising map-based method for identifying the health status of IGBTs is proposed. This is basically a clustering method, which uses the 'distance' between the input measured values (including collector current I_c, collector-emitter voltage V_{ce} and case temperature T_c) and the normal value to divide the state of IGBT devices into healthy state, partially degraded state, severely degraded state and fault state. Although the strategy is simple, the data mining algorithm helps to determine the health state from the big raw data automatically.

Obtaining IGBT characteristic parameter values based on data-driven methods usually requires offline training of the network model using a certain number of samples and then combining the signals detected at a certain time in the future with the trained model to obtain the current state of the IGBT. As the IGBT is in the process of performance degradation, the degradation trend and evolution law of its characteristic parameters may change over time. Therefore, in order to accurately estimate the IGBT state within the full life cycle range, it is necessary to continuously introduce enough new sample data to retrain the network to update the network model parameters. On the other hand, the presence of noise in the measurement data will affect the accuracy of the evaluation and prediction. Therefore, in order to eliminate the impact of such measurement errors, researchers usually need to obtain as much feature parameter data as possible. However, obtaining a large amount of data becomes a difficult point, which needs to be further discussed.

T A B L E 3 Summary of different TSEPs

TSEP	Cost evaluation	Implementation complexity
On-state voltage (V_{CEon}) (low current)	The measurement circuit needs to use a MOSFET of 70 RMB, an operational amplifier of 50 RMB, and an FPGA control board of 500 RMB (~620 RMB).	The measurement circuits are relatively simple and easy to implement.
On-state voltage (V_{CEon}) (high current)	The measurement circuit needs to use four diodes of 200 RMB, an op amp of 50 RMB, and a digital signal process (DSP) controller of 250 RMB (~500 RMB).	
Peak gate current (I_{Gpeak})	The measurement circuit needs four resistors for 4 RMB, an op amp for 50 RMB, and a DSP controller for 250 RMB (~304 RMB).	
Gate threshold voltage (V_{th})	The measurement circuit needs to use 12 resistors of 12 RMB, 2 diodes of 100 RMB, 5 capacitors of 1 RMB, 3 operational amplifiers of 150 RMB, and a DSP controller of 250 RMB (~517 RMB).	During the measurement, the gate resistance easily causes synchronisation jitter, which can cause significant temperature measurement errors. The measurement circuit is complicated.
Gate turn off miller plateau length ($V_{ge,off}$)		A complicated trigger circuit is required, which will cause additional interference to the system. The measurement circuit is complicated.
Saturation current (I_{sat})	The measurement circuit needs to use a current transformer of 150 RMB and a DSP controller of 250 RMB (~400 RMB).	Temperature correction is difficult.
Short circuit current (I_{sc})		Thermal runaway is likely to occur during the short circuit process, which will reduce the reliability of the power module. Implementation is difficult.
Turn on delay time (t_{don})	The measurement circuit needs to use a time interval measurement chip of 30 RMB, and a FPGA control board of 500 RMB (~530 RMB).	A complex circuit composed of a pulse signal sampler, a pulse input signal shaping circuit, and a time interval measurement circuit is required to accurately extract the time in the switching process, which is difficult to implement.
Turn off delay time (t_{doff})		
Turn off time (t_{off})		
Current change rate (di_c/d_t)	The measurement circuit needs to use a current transformer of 150 RMB and a DSP controller of 250 RMB (~400 RMB).	It is necessary to convert the voltage or current rate of change into a suitable observable signal, which has high requirements on the measurement circuit.
Voltage change rate (dv_{ce}/d_t)	The measurement circuit needs to use four diodes of 200 RMB, an op-amp of 50 RMB, and a DSP controller of 250 RMB (~500 RMB).	

Abbreviations: DSP, digital signal process; MOFSET, metal-oxide-semiconductor field-effect transistor; op-amp, operation amplifier; TSEP, temperature sensitivity electrical parameter.
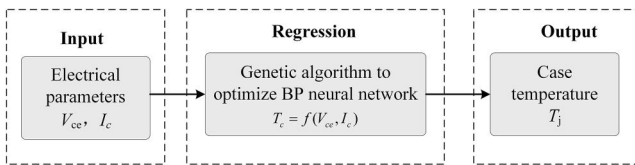
F I G U R E 5 Diagram of state extraction by neural network [35] BP, back propagation

4 | PREDICTION METHODS

As an important aspect of IGBT CM and health management, the remaining using lifetime (RUL) prediction predicts the remaining life of the in-service device based on sensed data [30]. The monitored result is the time left for the IGBT device.

The general prediction process of IGBT RUL is shown in Figure 6. In order to predict the RUL of an IGBT device, the following three problems need to be solved: (1) How to establish the life model of the power device? (2) How to determine the current condition of the in-service device? (3)

How to choose an appropriate prediction method? The content of question 2 is briefly summarised in Section 3.2 above. For question 1, the literature is reviewed as the model-driven method, and once the model is established, the RUL prediction result is easily found. For question 3, the prediction method is critical since the input is only raw data, and related works are reviewed in the following data-driven part.

4.1 | Model-driven

Lifetime model technology can be used for the fatigue ageing prediction of bonding wires and solder layers of IGBT modules. Model-based methods are divided into physical model and analytical model. The analytical model does not consider the specific failure process of the IGBT, only the life model obtained based on statistical principles, such as the Lesit model [39], the Norris–Landzberg model, and the Bayerer model. In [40], the Norris–Landzberg model is improved by using the least squares method to fit the test data, and the lifetime model is given as shown in Equation (1):
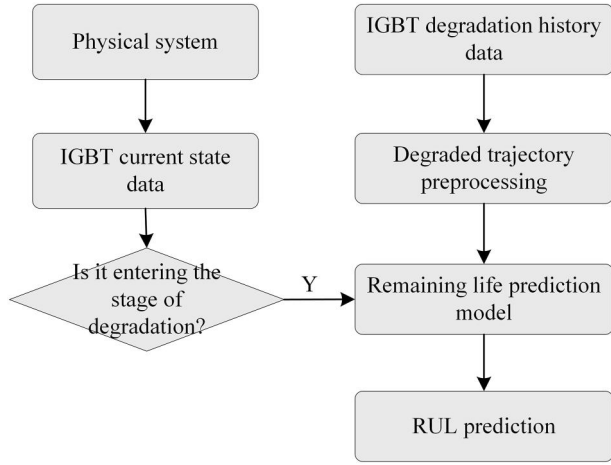
FIGURE 6 Remaining useful lifetime (RUL) prediction process. IGBT, insulated gate bipolar transistor

$$N_f = A\left(\Delta T_j\right)^\alpha \left(\frac{i_{st}}{i}\right)^M \left(\frac{273 + T_{j\max}}{T_{jm}}\right)^N \exp\left(\frac{Q}{RT_{jm}}\right) \quad (1)$$

where R is the air constant, A, α, Q, M, and N are constants, i_{st} is the rated current, $T_{j\max}$ is the rated maximum junction temperature, i is the collector current, and ΔT_j and T_{jm} are the difference and average value of the maximum junction temperature and the minimum junction temperature, respectively.

The physical of failure of the above bonding wires' and solder layers' ageing process is clear. Therefore, the physical model of IGBT is usually used to analyse the physical characteristics of the device and explain the ageing of the device from the physical mechanism.

The physical modelling process is more complicated but has practical significance. The failure factors of power devices are diverse, such as overstress, temperature, material properties etc. The combined effect of these failure factors determines the physical life model of the device.

Physical life models include Coffin–Manson–Basquin model based on plastic deformation, Syed model based on creep, Morrow model based on energy, and Stolkarts model based on fatigue damage and their improved models. In [41], the failure life of the IGBT module is defined according to the deterioration of the collector-emitter on-resistance R_{ce}. In this paper, the self-acceleration effect in the process of bonding wire damage is considered, R_{ce} is fed back to the power loss model, and the degradation delay stage and the degradation stage are proposed to describe the degradation process of the collector-emitter on-resistance $R_{ce,on}$. The degradation model is used to predict the life of the IGBT. In [42], in order to solve the influence of noise heteroscedasticity, a generalised autoregressive conditional heteroscedasticity model is proposed. It shows that with the increase of modelling data scale, the matching degree of predicted RUL and actual ageing data gets higher.

4.2 | Data-driven

The lifetime analysis of both physical model and analytical model is basically based on statistical law. The change of the ageing characteristic parameters of the power device depends on the internal state of the device as well as the operation state. The model is used to track the change of the system operation state and then the condition of the IGBT is analysed.

However, due to differences in manufacturing processes, material properties, and operating conditions, the life of in-service IGBT devices has individual differences based on the overall compliance with the life model law. Therefore, it is not easy to predict the RUL of an in-service device based on the device CM information. The development of sensing technology and computing science provides an effective way for RUL prediction, that is, a data-driven prediction method.

Some recent methods are summarised in Table 4. The data-driven method does not require specific knowledge of the IGBT device. The health condition information is extracted from the historical data of the characteristic parameters of the IGBT. The RUL prediction process with the intelligent algorithm of IGBT is shown in Figure 7. The non-linear regression between the characteristic parameters of the IGBT and the degradation information is processed by an intelligent algorithm [43]. The regression model is used to predict the degradation trend to determine the ageing degree of the device and RUL of the IGBT is estimated.

The key issue in predicting RUL is the ability to quantify uncertainty. Affected by system noise, measurement noise, changes in actual operating conditions and different manufacturing processes, RUL is actually a random variable [43]. Therefore, the quantification ability of the confidence interval is very important to the accuracy of RUL prediction. The particle filter and Gaussian regression process can calculate the probability density function of RUL. In [45], a particle filter method including sequential importance sampling and sequential importance resampling is used for IGBT RUL prediction. The existence of random errors leads to large errors in RUL. In order to reduce the RUL estimation error, the index of the sampled particles is used as an auxiliary variable to increase the particle dimension. This auxiliary particle filtering method can maintain the diversity of samples and reduce the RUL estimation variance. Other applications of particle filtering to predict RUL of IGBT can be found in [44, 46]. Since $V_{CE,on}$ is a time series with random non-stationarity, the variable scale function of the optimal scale Gaussian process (OSGP) regression model enables it to deal with the randomness and non-stationarity of the time series. In [47], the ant lion optimiser model is used to find the scale function and the corresponding scale of the OSGP model, and the OSGP model with the optimal scale function and the optimal scale is applied to the RUL prediction of the IGBT power module. In addition, neural networks [49] and the adaptive-network-based fuzzy inference systems [50] are applied to the RUL estimation of IGBT.

Any abnormality of the IGBT, such as fatigue ageing, will affect its characteristic parameters. These parameters

TABLE 4 Data-driven prognostics approaches for IGBT

Approaches		Errors	Precursors	Features
Statistical methods	Monte-Carlo simulation	-	V_{ce}	Computationally efficient, relatively low accuracy
	Particle filtering [44]	21%	V_{ce} or I_{CE}	Relatively low accuracy
	Auxiliary particle filtering [45]	17.8%	V_{ce}	Reduce particle and increase diversity in samples with low computation time, relatively low accuracy
Artificial intelligence	OSGP model [47]	0.99%	V_{ce}	Higher prediction accuracy and can adapt to less training samples.
	Time delay neural network [48]	3.65%	V_{ce}	Use normal distribution function to fit failure model, high accuracy
	Feedforward neural network [49]	-	V_{ce}	Uses the time-domain features to extract useful information, this method requires initialisation
	ANFIS [50]	1.76%	V_{ce}, T_j	High accuracy, the algorithm is complex

Abbreviations: ANFIS, adaptive-network-based fuzzy inference systems; IGBT, insulated gate bipolar transistor; OSGP, optimal scale Gaussian process.
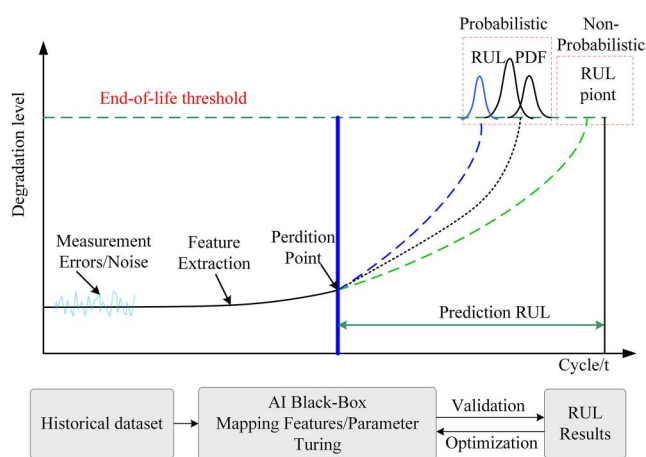
FIGURE 7 Flow chart of prediction Remaining useful lifetime (RUL) with the intelligent algorithm [34]. IGBT, insulated gate bipolar transistor; PDF, probability density function

reflect the ageing state of the IGBT. In RUL prediction of IGBT, there is usually a single potential failure precursor parameter, as shown Table 4. The change of the precursor parameters may be caused by the ageing of the IGBT, or may be caused by the change of the environment and operating conditions. Therefore, the information provided by a single parameter is limited for IGBT RUL prediction. It has become an inevitable trend to use multi-parameter compounding and the use of data-information fusion technology to predict the RUL of power devices. This method has already been applied in the RUL of SiC metal-oxide-semiconductor field-effect transistor and would be potential in an IGBT RUL prediction [51].

In order to make RUL predictions more practical, the following issues need to be considered: (1) The current RUL prediction methods mostly use intelligent algorithms. These algorithms regard IGBTs as black boxes or semi-black boxes without considering their physical characteristics and failure mechanisms, which are not convincing to practitioners in the industry. It is an urgent task to provide interpretable intelligent algorithms and understand the operation

mechanism of intelligent algorithms. (2) Using intelligent algorithms to predict IGBT RUL requires a large amount of data sets for model training. Data collection experiments are usually time-consuming and expensive. Therefore, the establishment of an ageing database of IGBTs is urgently needed, which can help academia and industry develop RUL prediction applications and improve the health assessment system of IGBTs.

5 | DISCUSSION AND FUTURE DIRECTIONS

As shown in the above sections, the results from CM in IGBTs is quite useful to improve the power electronics system reliability, especially under the harsh and varying working environment. From the direct measurement data, the health indicators, which are the IGBT characteristic parameters that reveal the degradation progress, such as the on-state resistance, junction temperature swing etc., can be much more helpful for determining the health stage of the devices.

With the in-depth research of IGBT physical of failures and the powerful data-driven computing tools, the concept of CM is broadening itself and there can be various output conditions. It can be concluded that the measurement will lead to a cost increase at hundred yuan, and even though the on voltage and gate current are relatively simple to implement, it is still not easy considering practical constraints like isolation. Moreover, the accuracy of data-driven methods needs improvement for the practical applications.

Here, based on this review of recent progress, the challenges and future directions are provided from our point of view. In practice, very few CM techniques are adopted in commercial IGBTs, which might be cost sensitive. The challenges would lie in the following aspects:

(1) The physical measurement should be simple and accurate, especially under the complex electromagnetic environment. Since the IGBTs work under high voltage and high current states, how the detection or TSEP estimation

techniques can be easily implemented in the circuit is a challenging aspect.

(2) For high voltage large capacity applications, like the HVDC system, CM is challenging due to the isolation rules. Therefore, some indirect detection methods can be considered, such as the measurement in the valve control system and cooling system. And the measurement sensitivity is also critical since the voltage and current are over kV and kA levels on the IGBTs.

(3) More joint health indicators can be developed to reflect a full picture of the IGBT condition, and the real-time online CM requires a simple and fast prediction algorithm.

Therefore, with the application of IGBTs in power grids, CM will play an important role for system security and maintenance. However, with the help of economic computing chips, more accurate condition information can be derived from the raw data. Some future directions will be as follows:

(1) Smart GDs for IGBT with sensing circuits and computing chips in it;
(2) More accurate health indicators that can be used for IGBT diagnostics and prognostics;
(3) Application of emerging edge AI for condition estimation and prediction.

For the high voltage application in HVDC stations, there are sensed signals from the existing valve control system and cooling system. The valve control senses the DC voltage of the submodule and the arm current at a frequency of several kHz. Thus, there is huge amount of data, which should be useful for the state estimation of the IGBT. It is possible to calculate the power loss or conducting resistance of the IGBTs. Meanwhile, direct temperature detection is possible for the cooling system or even on the package of IGBTs. Several fibre optic sensors can be placed along the cooling water pipe to measure the temperature difference of the water. This is also an effective way to acquire the internal temperature and power loss of the IGBTs. With the above power loss and temperature information, various effective estimation methods can be adopted for such high voltage applications.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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