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# Reliability Assessment of IGBT Through Modelling and Experimental Testing

MOMINUL AHSAN<sup>1</sup>, SIEW TEAY HON<sup>1</sup>, CANRAS BATUNLU<sup>2</sup>,  
AND ALHUSSEIN ALBARBAR<sup>1</sup>

<sup>1</sup>Smart Infrastructure and Industry Research Group, Department of Engineering, Manchester Metropolitan University, John Dalton Building, Manchester M1 5GD, U.K.

<sup>2</sup>Department of Electrical and Electronics Engineering, Middle East Technical University Northern Cyprus Campus, 99738 Mersin, Turkey

Corresponding author: Mominul Ahsan (m.ahsan@mmu.ac.uk)

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**ABSTRACT** Lifetime of power electronic devices, in particular those used for wind turbines, is short due to the generation of thermal stresses in their switching device e.g., IGBT particularly in the case of high switching frequency. This causes premature failure of the device leading to an unreliable performance in operation. Hence, appropriate thermal assessment and implementation of associated mitigation procedure are required to put in place in order to improve the reliability of the switching device. This paper presents two case studies to demonstrate the reliability assessment of IGBT. First, a new driving strategy for operating IGBT based power inverter module is proposed to mitigate wire-bond thermal stresses. The thermal stress is characterised using finite element modelling and validated by inverter operated under different wind speeds. High-speed thermal imaging camera and dSPACE system are used for real time measurements. Reliability of switching devices is determined based on thermoelectric (electrical and/or mechanical) stresses during operations and lifetime estimation. Second, machine learning based data-driven prognostic models are developed for predicting degradation behaviour of IGBT and determining remaining useful life using degradation raw data collected from accelerated aging tests under thermal overstress condition. The durations of various phases with increasing collector-emitter voltage are determined over the device lifetime. A data set of phase durations from several IGBTs is trained to develop Neural Network (NN) and Adaptive Neuro Fuzzy Inference System (ANFIS) models, which is used to predict remaining useful life (RUL) of IGBT. Results obtained from the presented case studies would pave the path for improving the reliability of IGBTs.

**INDEX TERMS** Reliability, power electronics, IGBT, finite element analysis, accelerated aging test, data-driven prognostics, machine learning.

## I. INTRODUCTION

Insulated Gate Bipolar Transistor (IGBT) is an electronic device that has high efficiency and fast switching capability and play a vital role in electronic systems. It is easily useable in high voltage and high current applications. IGBTs are used in wind turbines, automotive, railway, household appliances etc. [1].

IGBTs fail more frequently compared to other electronic devices due to thermo-mechanical stresses generated from cyclic temperature changes [1]–[3]. Die attach degradation and wire lift are the leading failure modes for IGBTs due to the high temperature, high electric field and overvoltage, short circuit, loss of gate control and increased leakage current which leads time dependent

dielectric breakdown [4], [4]–[8]. Temperature cycling is one of the important factors in operation to generate stress within the bonded layer of materials having different coefficient of thermal expansions (CTEs) [9]. Thermal fatigue usually occurring in bonding wire or solder joints can cause degradations leading to premature failures [10]. Increment of on-state voltage during power cycling causes power losses that rises the temperature of the entire chip, which speeds up the bond wire lift-off by the generated stress through thermal expansion mismatch between the wire bond and the chip [11], [5]. Fig. 1 shows a magnified view of bond wire lift off with heel crack in an IGBT. Other types of failures at the level of an electronic package are die crack and fracture, severing of interconnections, delamination at bi-material interfaces etc. [5], [12]–[14].

It is possible to take essential failure anticipatory activities and to plan active maintenance schedule by predicting failure

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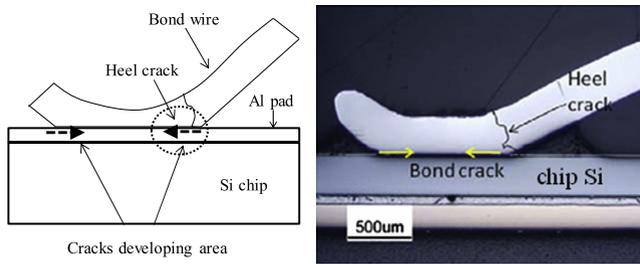


FIGURE 1. Bond wire lift-off and Heel crack mechanism [12].

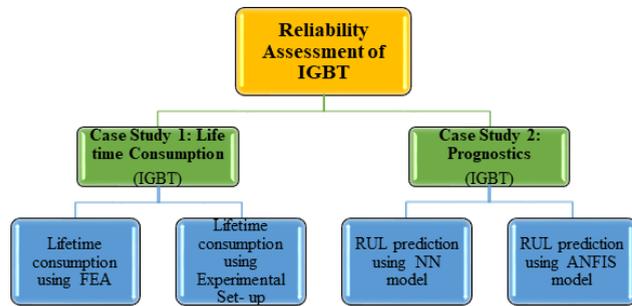


FIGURE 2. The organisation of the paper.

behaviour of electronic products during operation. Therefore, it would be a concrete pathway to explore reliability issues particularly on semiconductor devices in power electronics. It is also significant to use an efficient reliability evaluation method (e.g., prognostics approach) that assesses and predicts the reliability through estimation of end-of-life period of a product during real application [15], [16].

Prognostics is a technique to forecast future health condition of an electronic product. Therefore, preventive steps can be taken before the failure occurs during operation to avoid the risk of sudden failure [17]. Prognostics is related to reliability assessment through measuring Remaining Useful Life (RUL).

The significance of this paper lies in employing two distinct methods to assess reliability of IGBT and the application of the methods are demonstrated with two separate case studies (Fig. 2). The paper starts with a first case study on reliability prediction through lifetime consumption of IGBT using Electro-thermal modelling and Finite Element Analysis (FEA), which is presented in Section II. In this section, experimental validation and critical assessment of the lifetime consumption are demonstrated. In second case study, a data driven prognostics approach for predicting reliability of IGBT is demonstrated in Section III. Machine learning (ML) techniques are involved for predicting remaining useful life (RUL) of IGBT using accelerated aging data. Results are demonstrated comparing with the performance of different ML techniques.

## II. CASE STUDY 1: PHYSICS BASED PROGNOSTICS OF IGBT

Inverters plays an important role to convert DC outputs (e.g., voltage) into an AC output at the targeted frequencies

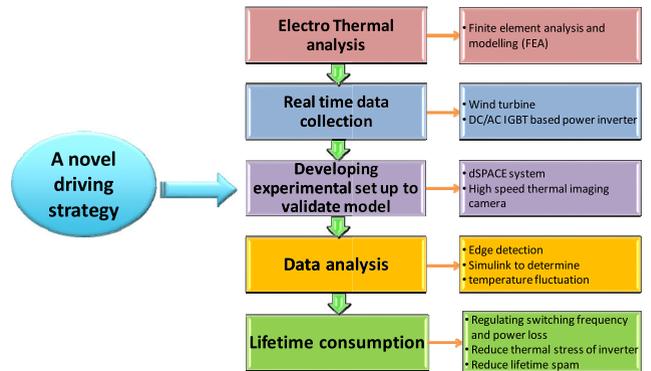


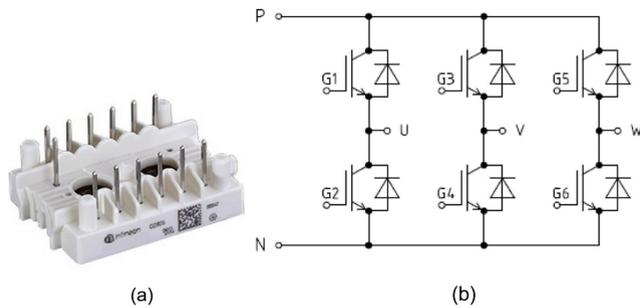
FIGURE 3. Reliability predictions methodology employed for IGBT based inverter.

and amplitudes. This can be controlled by a semiconductor switching devices. For example, IGBT with several switching patterns including square, sinusoidal pulse width modulation (SPWM) or space vector modulation (SVM) procedures can help to drive the devices. The waveforms of practical inverters are found non-sinusoidal that contained certain harmonics in some cases. In reality, the output voltage waveforms of inverters should be sinusoidal. The power loss characteristics of the devices are dependent on various switching methods applied for a particular case [16]. The switching frequency of an inverter influences the power loss, which has huge impact on generating heat in the inverter and eventually influences generating high temperature profiles during operation.

For semiconductor-based inverter, temperature fluctuations are one of the major concerns for reliability problem rather than the average temperature. Constant temperature fluctuations can be maintained if the switching frequency is lowered by 50% but this causes an increment of temperature by 25% [16]. On the other hand, temperature fluctuations can also be kept constant by increasing the switching frequency with the expense of an increase in mean temperature. Existing literature [18]–[20] have not reported about mitigating stresses on IGBT based inverters for adjusting the switching frequency. Therefore, a controlling strategy to adjust the switching frequency is needed. In this study, a driving strategy was applied through electro thermal analysis by finite element modelling that was not found in existing research. In order to reduce the power losses in conventional SPWM, an adaptable frequency-based method is proposed in [21]. The methodology of reliability assessment of IGBT based inverter is presented in Fig. 3.

### A. FINITE ELEMENT (FE) MODELLING

Physics based modelling performs degradation assessment, system reliability modelling and life estimation to maximise lifetime and optimise maintenance policy of critical components. For example, Finite element modelling and simulation can generate failure data, which can be used for prognostics purpose. Physics-based models with high accuracy may be computationally expensive to run. However, prediction results are intuitive based on modelled case-effect relationships in physics-based approach [17]. Effective prognostics



**FIGURE 4.** (a) Picture of an Inverter module and (b) electrical circuit configuration of the module.

methodologies using FEA applied to mechanical systems and structures are widely available than prognostics for electronic devices and systems.

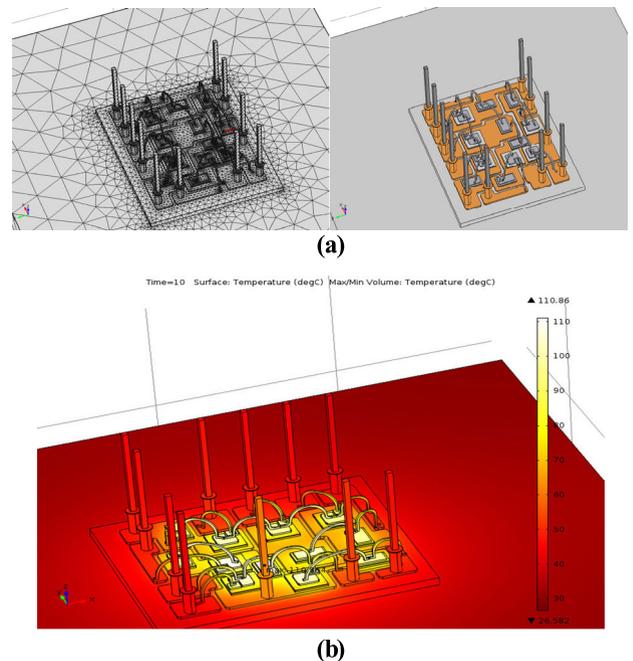
Finite element modelling is compact and result-oriented and hence widely popular among engineering community [19]. It has the capability to apply different types of boundary and loading conditions. However, high computational time with large computer memory and expert engineering judgement required for interpreting the results are the main limitations of this method. In this case study, FEA technique is considered due to its electro thermal modelling methodology that can regulate switching frequency and power loss of IGBT based inverter.

The lifetime span has significantly reduced through thermal stress reduction of the inverter. Thermal damage assessment and lifetime estimation through Finite Element Modelling (FEM) can be employed to ensure the safety and reliability of power electronics devices such as IGBT. The proposed method is applied on generator-based wind turbine system test rig. A double bridge AC/DC rectifier has been used in converting the generated AC in to DC. The target is to investigate reliability of bond wires, which are placed on IGBT and diode chips. Fig. 4 represents the inverter module and its corresponding electrical circuit diagram.

COMSOL package has been used to build finite element modelling of the inverter. Further details of the inverter specification, physical properties of each layer of materials and FE model can be found in [16], [21]. Fig. 5(a) shows inverter module geometry which has been modelled with 111,743 tetrahedral elements. To achieve better efficiency, different mesh size of heat sink with each layers of the module has been applied. Natural convection was employed on the model with a heat transfer co-efficient of  $5 \text{ W/m}^2 \text{ K}$  by setting ambient and heat sink temperatures at  $20 \text{ }^\circ\text{C}$ . During the simulation, each chip was heated by a constant  $10 \text{ W}$  heat source. The heating process for a diode chip is presented in Fig. 5(b).

### B. ELECTRO THERMAL MODELLING METHOD

Inverter module was used to apply electro thermal modelling methodology, which can be found in [16]. Self and coupling effect of chips are considered in the modelling. Then power loss model was developed with the use of IGBT, easy-going



**FIGURE 5.** (a) FE model of the inverter and (b) heating operation of diode top surface.

diode current and voltage for every device. In addition, feedback loop monitored the temperatures for each layer over discrete thermal layer model. Then  $5 \text{ V}$  was adjusted as input DC voltage where the switching frequency was set as  $50 \text{ kHz}$ . Further instantaneous temperature was predicted by dSPACE model and thermal imaging captures were taken in 20 seconds of intervals. Further details of dSPACE model is presented in reference [21]. Fig. 6 compares experimental and FE model results.

Finite element method is essential in order to monitor the device temperature in the dSPACE, as it counts heat interaction of the all layers underneath each chip located in the inverter module. The thermal impedance circuit, designed in Simulink, then embedded in dSPACE, is based on the parameters obtained from FE model.

The SPWM controlled frequency-based switching method was used to decrease the power losses. This method has been studied by other researchers but the algorithm proposed here tracks total harmonic distortion (THD) and meets the required level by using a filter designed for worst case scenario where the possible lowest switching frequency is  $2 \text{ kHz}$ .

The switching frequency regulation algorithm is activated as soon as the power loss block outputs different value than the previous data due to a possible wind speed change. The algorithm control block provides the pre-calculated switching frequency values for the inverter by using look up tables. This method is more efficient compared to online calculation based switching frequency decision algorithms for lifetime decreasing purpose. The switching frequency is decreased as the power loss and temperature increase. By using lookup tables, in case of a huge wind speed decrease, the switching frequency is increased by the algorithm accordingly so that

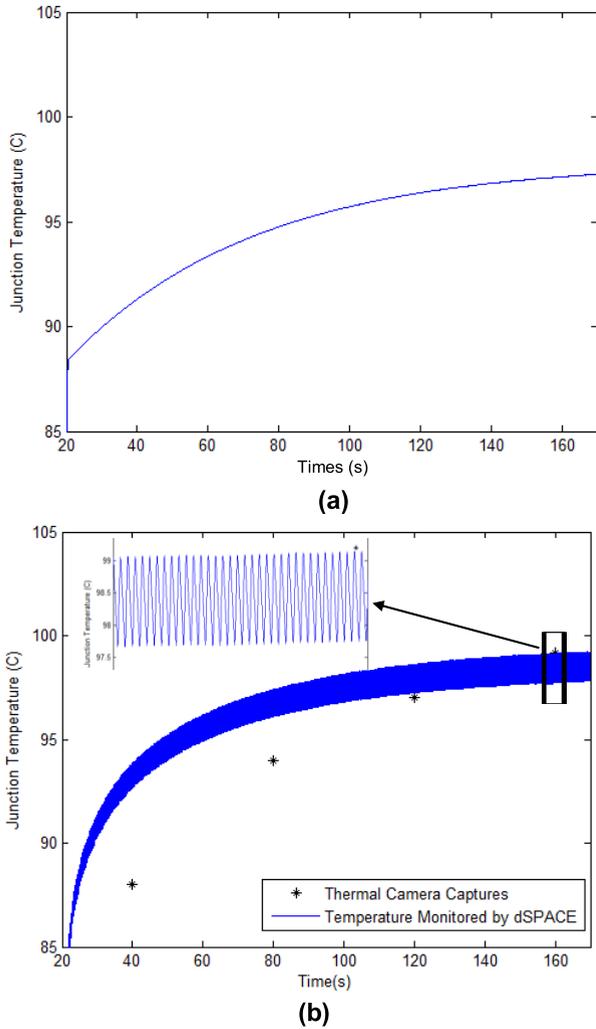


FIGURE 6. Temperatures observed by (a) FE results in model and (b) dSPACE and thermal imaging.

a large temperature cycle is avoided and at the same time THD is also kept at the required level. There are examples of variable switching frequency schemes for reducing switching losses by using other approaches which are also experimentally verified [22].

The switching frequency is adjusted by the ratio of modulation and carrier frequencies ( $f_m$  &  $f_c$ ) in multiple of three. The reason of this selection is to keep each three-phase voltages in symmetric. In SPWM, three sinusoidal references were used ( $V_a$ ,  $V_b$ ,  $V_c$ ) and compared with a triangular carrier wave ( $V_T$ ) to produce the gating signals as shown in Fig. 7. Six gating signals for the inverter module were provided by DS5101DAC platform. The DS5101PWM6 block in dSPACE was used to generate SPWM based gate signals.

Switching frequency was varied due to generate adaptable temperature profile using fixed input voltage. Then various SPWM switching frequency (10 kHz, 50 kHz, 100 kHz and 20 kHz) were employed to the inverter in 20 seconds intermissions. The monitored temperatures by dSPACE and thermal camera with corresponding thermal images can be

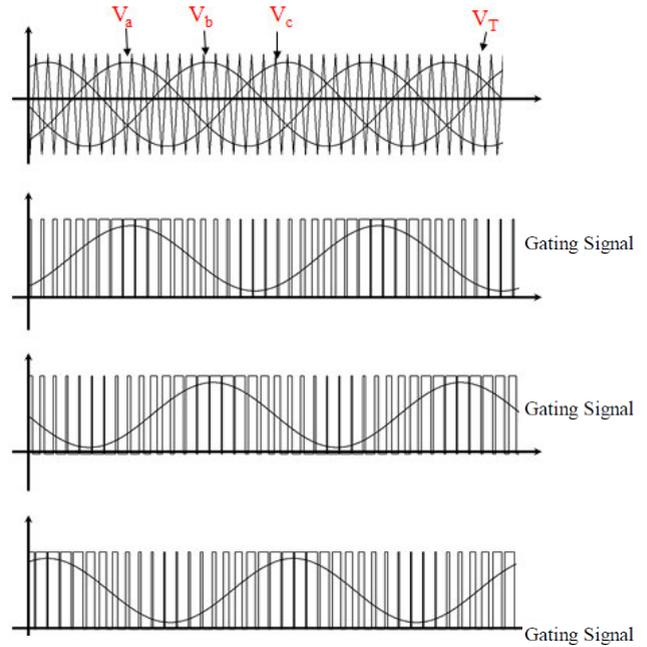


FIGURE 7. Gating Signal Generation with SPWM.

seen in Fig. 8. A conventional, second order LC filter was implemented to reduce harmonic distortions caused by fundamental square waved output voltage of the inverter. It can be seen from Fig. 8(a), that in none of the switching frequencies applied, the total harmonic distortion is more than 10%.

C. EXPERIMENTAL SETUP

The results have been validated using an experimental set-up (Fig. 9), which was built using 1.1 kW permanent magnet generator, AC-DC rectifiers, DC-AC inverter module and other units.

Speed range profile shown in Fig. 10 was used to operate wind turbine generator. While the speed of wind is increased, the switching frequency is adjusted based on power losses. Temperature profiles and temperature variations both are revealed in Fig. 11. Frequency was fixed under 50 kHz with fixed switching frequency. According to the figure it is observed that when the wind speed increases then the inverter’s temperature increases accordingly. The highest temperature has been determined as 85 °C at the speed portion of 10 with fixed frequency operation whereas the temperature was estimated as 80.5 °C with adjustable frequency operation (Fig. 12). Increasing the wind speed increased the thermal profile behaviour. High power losses are happened when the wind turbine generator produces high energy. Therefore, higher temperature profiles are generated with the high wind speeds. Thus, the temperature fluctuations caused increasing thermal stress and fatigue at higher wind speeds.

The gate signals were delivered by dSPACE. The collector current and voltages were captured by the DS2004 A/D platform of dSPACE and processed into power loss and thermal model blocks in the electro thermal model implemented in dSPACE also discussed in [5]. To calculate inverter

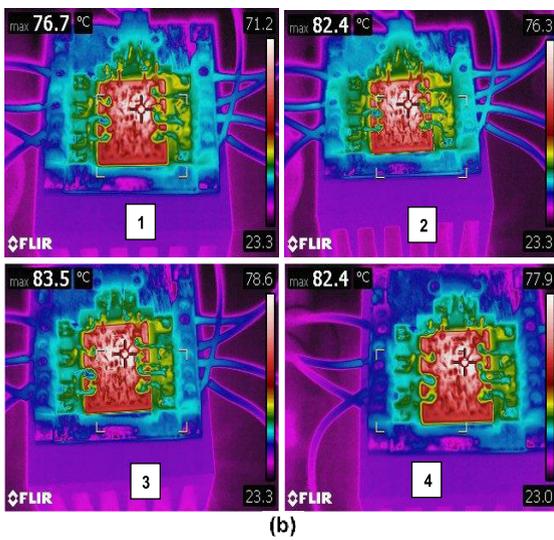
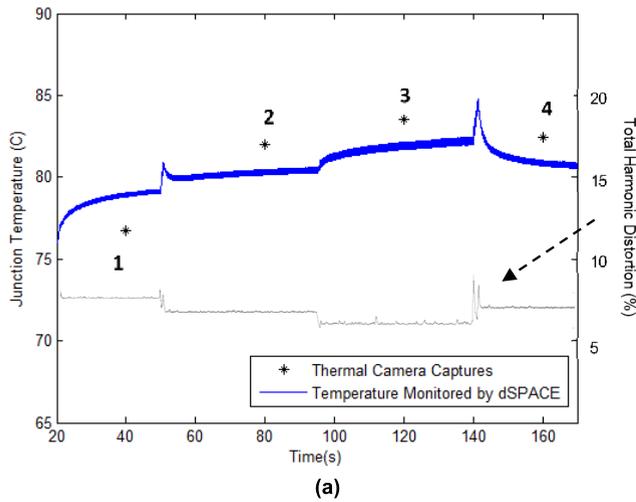


FIGURE 8. a) Temperature detected by dSPACE and thermal imaging, b) Thermal camera image captures.

temperature with the variable speed profile, power losses are processed through look up tables. The thermal model considers self and coupling effect among each chip and it was implemented by thermal network based on the FE model results. IGBT and freewheeling diode current and voltage are directly embedded in power loss models for each device. Then the outputs of power loss model blocks are used as inputs into thermal model block in dSPACE. For verification purpose, thermocouples are placed on the device, to measure temperature variations.

#### D. THERMAL STRESS IN INVERTER

The power losses for fixed and regulated switching frequency operations had been recorded. Then the information was used as inputs for finite element analysis to estimate von Mises stress developed on chip wire bonds as shown in Fig. 13. The maximum von Mises stress appeared at the interface between wire bond layers and silicon solder causes lift as explained in [12], [5]. The proposed variable frequency method reduced the wire bond stress from 54.5 MPa to 45.5 MPa

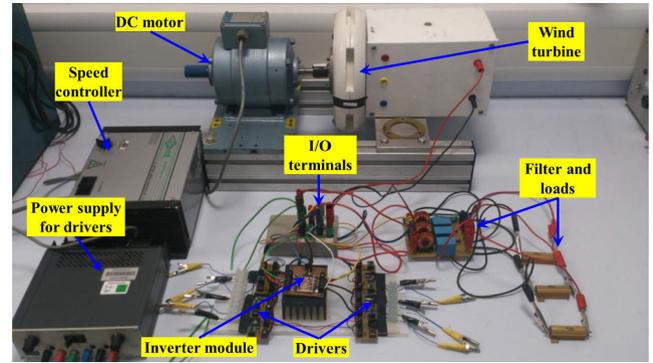


FIGURE 9. Experimental set-up development.

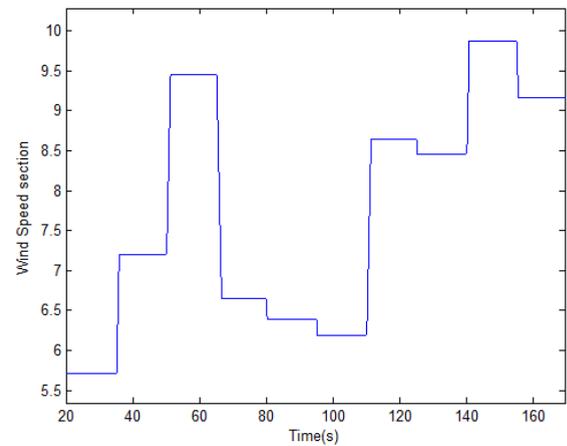


FIGURE 10. Varying Wind speed profile.

when compared to the fixed frequency method leading to around 16% stress reduction. The method was also capable to reduce stress across upper layer of the chip, silicon layer edges and copper. Furthermore, due to highly fluctuated characteristics thermal stress with fixed method was widely distributed compared to localised distribution in the case of variable frequency method.

#### E. RELIABILITY ESTIMATION OF INVERTER

Thermal cycles and life consumption (TLC) of wire bond was calculated using the methodology discussed in [5]. The anticipated number of cycles to failure is calculated using Eq. (1):

$$N_f = 4 \times 10^{17} \cdot \Delta T^{-6.48} \quad (1)$$

Rainflow counting algorithm [23] was employed to calculate the effects of mean temperature ( $T_m$ ), temperature difference ( $\Delta T$ ) and total temperature cycles ( $N$ ). A 3-D graph was plotted to represent the data in Fig. 14. It was observed that high numbers of cycles at mean temperature between 80 °C to 84 °C with fixed frequency strategy were reduced when variable frequency strategy was applied.  $\Delta T$  at 3 °C and 5 °C (Fig. 14(a)) represent mean temperatures of 84 °C and 81 °C respectively which are highlighted by red circles. The significant reduction in number of cycles proves the efficiency of the anticipated method.

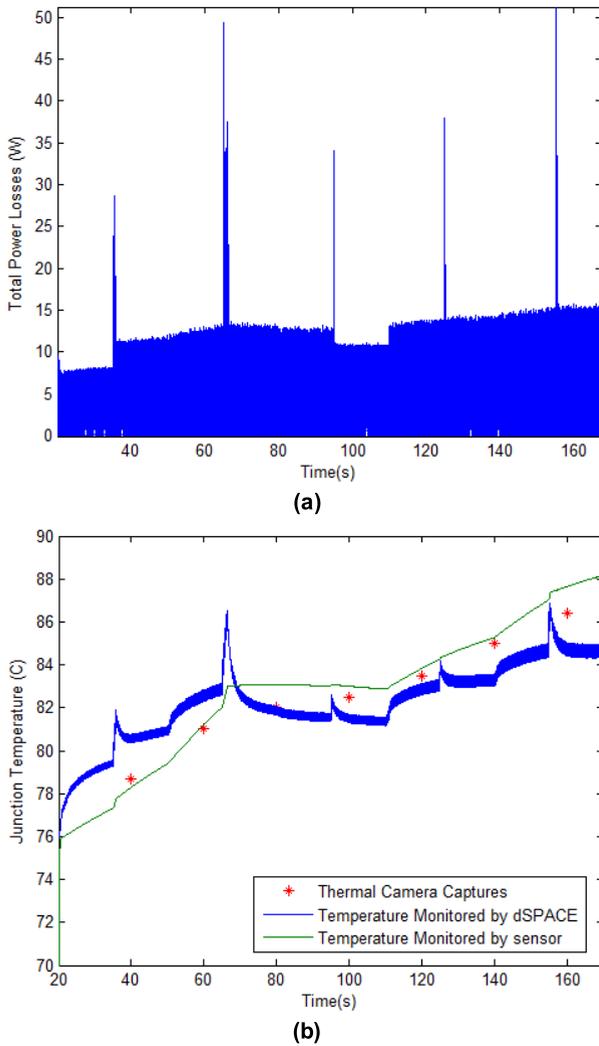


FIGURE 11. (a) Inverter power losses (b) temperature with fixed frequency.

Large stress generated in the inverter due to the high fluctuation in temperatures increased the chances of sudden failure that leads to shorter lifetime. Linear damage accumulation method described in [24] was used to calculate total lifetime consumption of the inverter in Fig. 15. TLC of inverter’s wire bond has been decreased to  $1.45 \times 10^{-5}\%$  compared to the conventional fixed frequency operation ( $1.88 \times 10^{-5}\%$ ). The proposed method has successfully attained approximately 21% less TLC under the same loading and environmental conditions indicated by red circles.

A new driving strategy of operation has been applied for mitigating stresses on IGBT in this case study. Finite element modelling has been employed to characterise electro thermal stress and validate through determination of lifetime consumption of the inverter module.

**III. CASE STUDY 2: DATA DRIVEN PROGNOSTICS OF IGBT**

Data driven prognostics model is developed using degradation data representing physical behaviour of a device in real life operation. Data driven approach requires large data sets

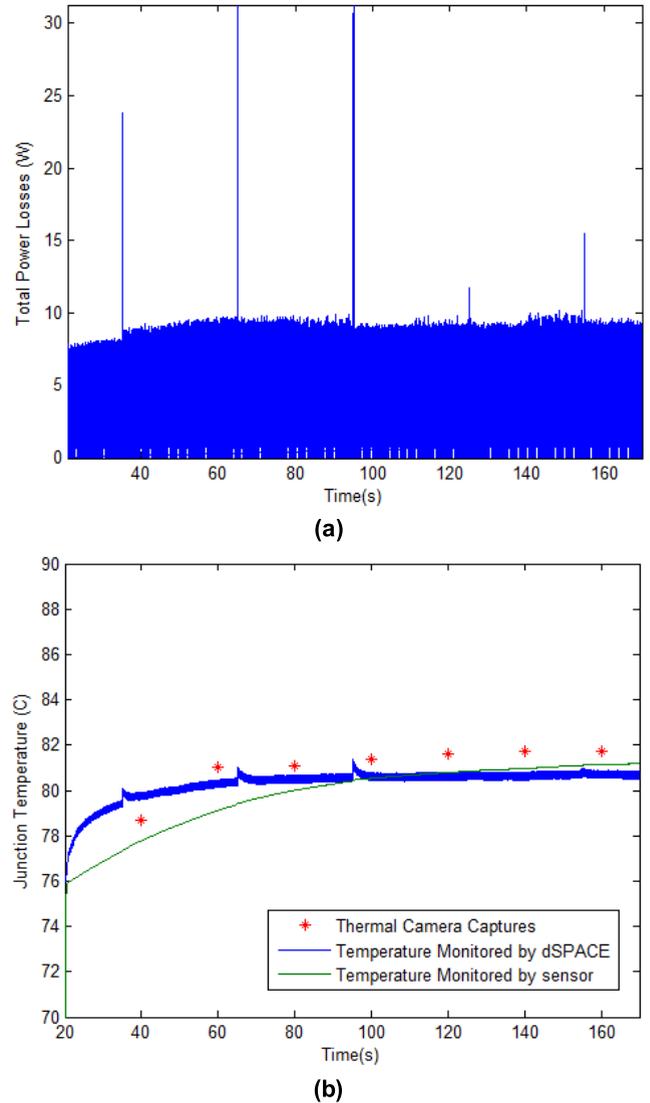
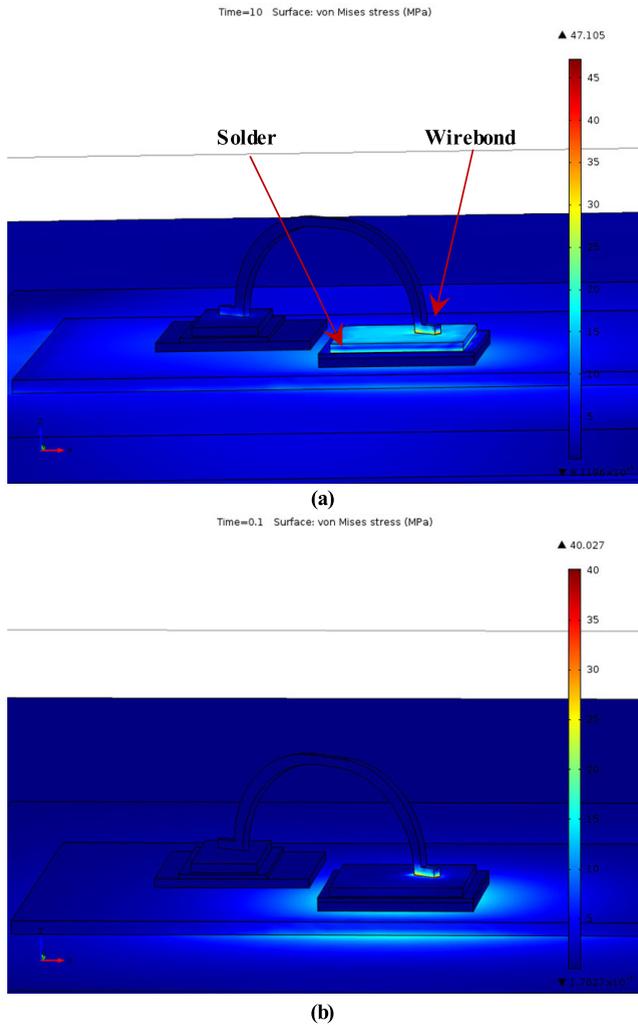


FIGURE 12. (a) Inverter power losses (b) temperature with adjustable frequency.

representing physical behaviours and physical cause-effect relationships are not utilized in this approach. However, data driven approach is currently used for predicting reliability of power electronics [17], [25]. For this case study, the use of data driven approach provides predictions for remaining useful life using degradation data from accelerated failure test. Existing studies [26]–[30] have not investigated particularly estimating Remaining Useful Life (RUL) of IGBT from degradation data using NN and ANFIS.

Recently, substantial research are being conducted particularly on IGBT with the use of data driven prognostics [31]. It is difficult to realise degradation of electronic components due to complexities in developing degradation models. Advance research in predicting RUL of IGBT can mitigate many remaining challenges for prognostics of IGBT. Currently, numerous data-driven prognostic approaches such as Neural network (NN), particle filters (PF), kalman filters (KF), support vector machine (SVM) and diverse statistical



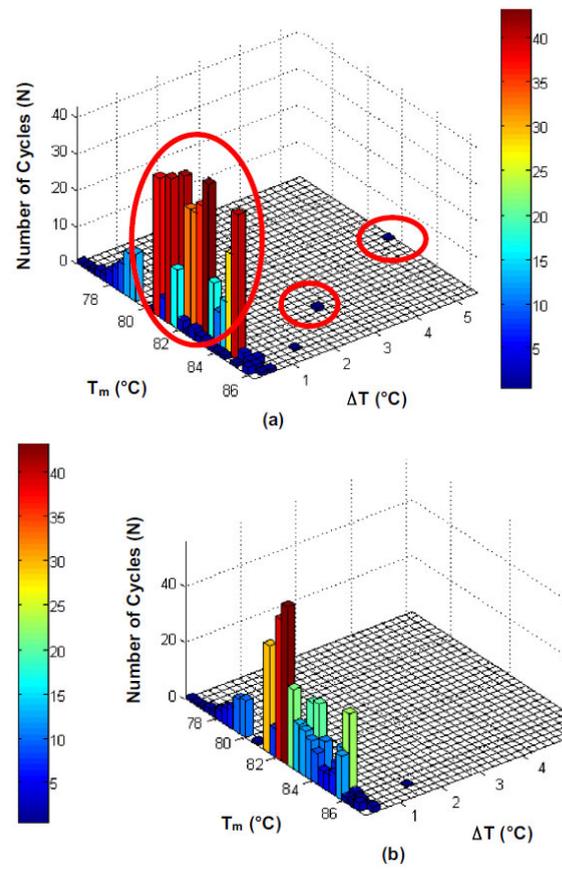
**FIGURE 13.** Surface von Mises stress for (a) fixed and (b) regulated switching frequency operations.

methods are being applied for prognostics of IGBTs [26]–[28], [32]–[35].

**A. PROGNOSTICS CONCEPT**

Failure prognostics deliver predictions for the foreseeable failure time by predicting the future health state and degradation of a certain component or system, and its expected Remaining Useful Life (RUL). The schematic of prognostics with the estimation of RUL is presented in Fig. 16. After detecting degradation point ( $t_d$ ) from a baseline degradation data, RUL can be calculated between the current time ( $t_c$ ) and the time at which the degradation data values (for both estimated,  $t_{fe}$  and actual  $t_{fa}$  cases) cross the defined failure threshold [36].

In general, the IGBT devices take longer approximately have thousand hours lifetime prospect. Therefore, it is necessary to reduce lifetime of the IGBT to understand degradation [37]. IGBT accelerated aging system has a great role to investigate prognostics by using its robust experiments by investigating precursor parameters of the device. IGBT aging test developed by NASA AMES laboratory has been used in this case study [25].



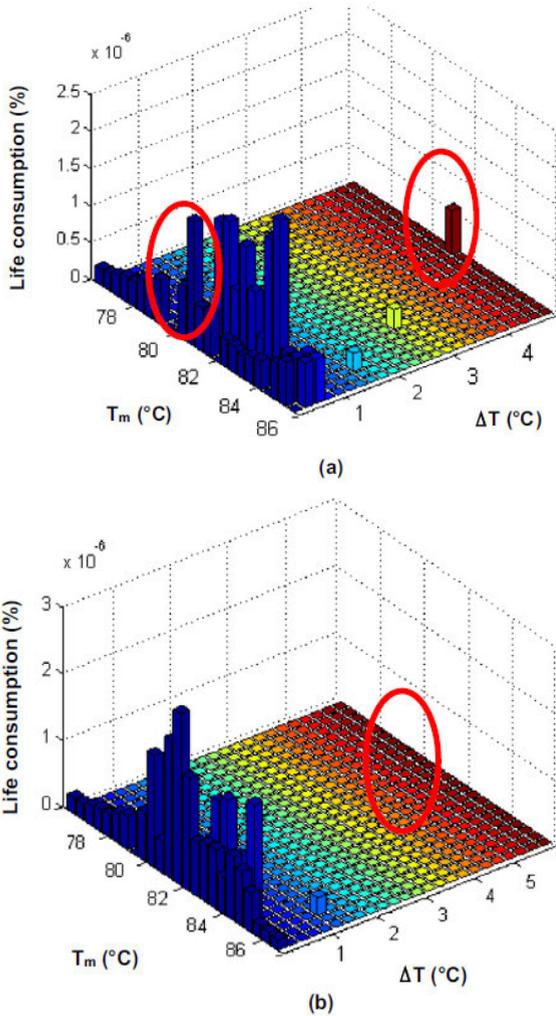
**FIGURE 14.** Thermal cycling data for (a) fixed and (b) regulated switching frequency operations.

Seven IGBT devices are selected to use their degradation data sets. Distinctive degradation patterns are obtained by plotting the data sets. Then degradation phase durations are estimated to calculate the actual RUL of the IGBT devices. The degradation data sets of the first six devices are employed to build NN model and for predicting RUL of the last device. Subsequently, ANFIS model is built with the same data sets and use the model to predict RUL for the last device. Both models are developed using MATLAB. At the end, RUL prediction was conducted and validated the models with calculating percentage of relative errors. The stepwise RUL prediction for IGBT is shown in Fig. 17.

**B. EXPERIMENTAL SET-UP FOR IGBT DEGRADATION**

In normal operation, the expected lifetime of a power electronic device is thousands of hours. Therefore, it is not quite technically feasible to assess reliability of a product under normal operating condition. Accelerated aging experiment allows assessment of reliability within a much shorter time by accelerating the failure of an electronic product [19].

A simulation was conducted using accelerated aging experiment on IGBT in [38]. Quick degradation of IGBT was performed using thermal cycling and electrical overstress for occurring failure of IGBT in their experiment. To conduct the accelerated aging process various influential parameters were



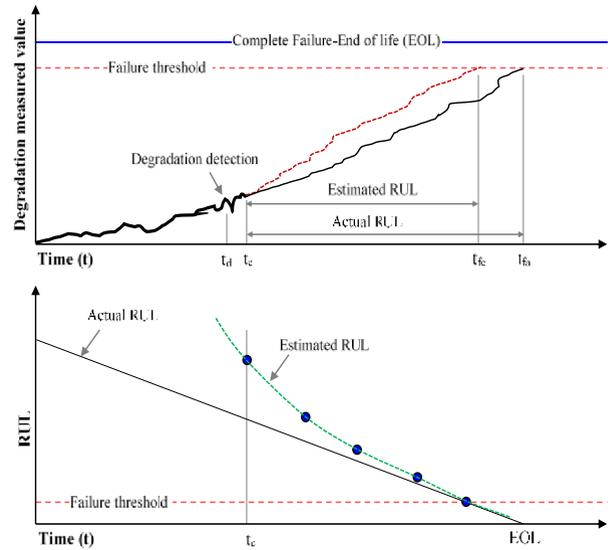
**FIGURE 15.** Total lifetime consumption of inverter's wire bond under different switching operations (a) fixed frequency and (b) regulated frequency.

considered including collector-emitter voltage, collector-emitter current, gate-emitter voltage and gate-emitter current. Whereas temperature was used as the key parameters for their aging process. Electrical overstress causes thermal damage of IGBT by excessive voltage or current when they exceed the specification limits of the device. Therefore, ageing test can perform accelerated degradation of an electronic product and produce valuable data for reliability assessment through data driven prognostics although the initial development time and cost of the experimental set-up is very high.

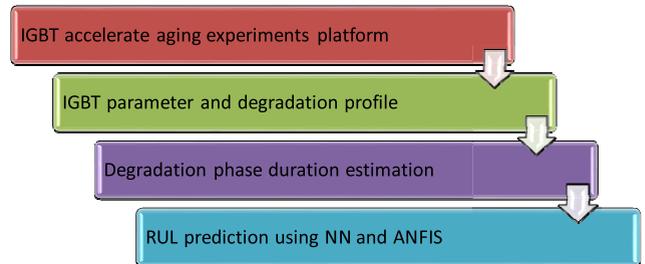
NASA has developed an IGBT accelerated aging experimental platform to conduct degradation procedure of IGBT (Fig. 18).

Then degradation data are to be used for prognostics drives. The objective of aging platform was to perform degradation process and generate aging data to advance a prognostics approach for predicting the RUL of IGBT [25].

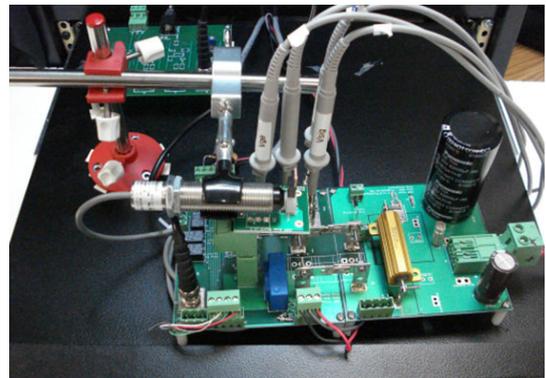
IGBT accelerated ageing experiments in NASA aimed also at the identification of their degradation characteristics. Such data can be utilised in different ways and used



**FIGURE 16.** Schematic illustration of prognostics concepts and estimation of RUL (adapted from [12]).



**FIGURE 17.** Stepwise procedure of RUL prediction for IGBT.



**FIGURE 18.** IGBT accelerated aging test hardware [28].

to improve fault diagnostics, prognostics, and to evaluate RUL. Thermal cycling and electrical over-stress, hot carrier injection and time-dependant dielectric breakdown stimulus are usually used in their accelerated aging experiments. For the rapid degradation and failure of IGBT, thermal cycling and electrical overstress were applied during accelerated aging experiment. There are various environmental parameters including collector-emitter voltage, collector-emitter current, gate-emitter voltage and gate-emitter current were used while temperature was influential parameter to fail the devices at accelerated aging test [39], [25]. All the data sets

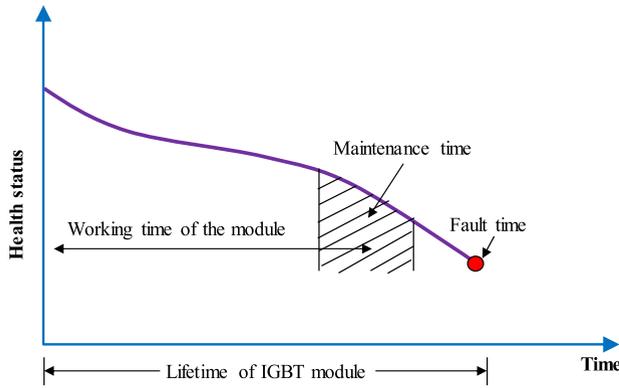


FIGURE 19. Health status of IGBT module during accelerated ageing (adapted from [43]).

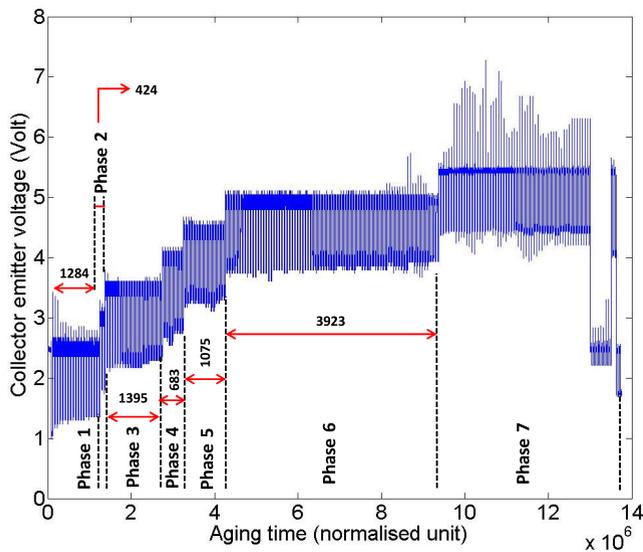


FIGURE 20. Collector-emitter voltage profiles with aging time for IGBT #5.

generated from accelerated aging are collected to use those in further data processing in consequent analysis. The degradation data sets are collected from accelerated aging system to develop and compare numerous data driven algorithms for IGBT prognostics and to assess RUL.

Once bond wire of IGBT module are lift off then usually the current passes rapidly through other wires. IGBT module fails due to the excessive current flowing through unless it is interrupted. Thus, a catastrophic damage is caused to the power converter. The changes of IGBT health status during accelerated aging experiment is showed in Fig 19. It is observed that the health status of the module is decreasing with increasing running time. Once the health level reaches to low level then the module fails. Schedule maintenance can be taken place before breakdown when fatigue of bond wires in IGBT is detected.

### C. DEGRADATION DATA AND PROCESSING

As previously stated, particularly thermal overstress aging condition was applied to carry out the aging tests on

TABLE 1. Duration of load phases with their failure time for seven IGBT devices.

	IGBT No.	P1 (t <sub>1</sub> )	P2 (t <sub>2</sub> )	P3 (t <sub>3</sub> )	P4 (t <sub>4</sub> )	P5 (t <sub>5</sub> )	P6 (t <sub>6</sub> )	P7 (t <sub>7</sub> )	Total IGBT life
Training data	1	875	502	645	1,221	1,602	1,454	5,551	11,850
	2	1,112	1,296	1,663	657	1,107	1,725	1,800	9,360
	3	1,448	0	1,132	903	712	1,312	4,507	10,014
	4	1,225	0	1,160	874	6,50	1,373	2,582	7,864
	5	1,284	424	1,395	683	1,075	3,923	3,284	12,068
	6	942	0	1,337	985	1,625	1,012	8,601	14,502
Val. data	7	1,125	0	872	0	1,237	1,204	1,938	6,376

seven IGBT devices. Every device was tested and observed seven separate phases after applying collector-emitter voltage ( $V_{CE}$ ). The precursor parameter (collector-emitter voltage) is controlled by the power supply for increasing and decreasing voltage as appropriate in the aging process. In this experiment, the  $V_{CE}$  was increased with 0.5V at the one load phase in the profile. Then the next phase was started with 2.5V at load phase 1 and run until reach to the maximum voltage at 5.45V. The failure of IGBT occurred while the time length of every phase (P1-P7) in full load profile was applied to an IGBT and varies from one device to another device up to all devices. It is observed that all the tested devices are failed at load phase 7. Fig. 20 shows an example of an IGBT degradation according to the measured  $V_{CE}$  signal. The data for the  $V_{CE}$  signal clearly indicates the different phases of degradation and until the failure occurrence in the last degradation phase.

From the load profile data, individual phase duration was measured for each IGBT. A summary of the durations of each load phase ( $t_i$ ; interval between two points) for the tested IGBTs is presented in Table 1. The duration of load phase 7 ( $t_7$ ) is considered as RUL for each IGBT devices as the failure occurring throughout the last phase). Total life of each IGBT tested is calculated by adding the duration of all the seven phases ( $t_1-t_7$ ). Seven IGBTs were tested under run-to-failure degradation test during the aging experiment. However, the load profile (i.e., the duration of the individual degradation phases) is not the same for these devices. First six IGBT devices in Table 1 with their phase durations are used as training data sets to build ML models. The data for device number seven are used to validate the models. If the cumulative values for the first six phases of an IGBT (e.g., 8784 for IGBT #5) are subtracted from a total IGBT life (e.g., 12,068 for IGBT #5), the remaining time to failure (e.g., 3,284 for IGBT #5) can be calculated and this in fact is the duration of Phase 7. Therefore, the duration of Phase 7 can be considered as a known output value. However, as the number of data are very small to be inputted as training data, a matrix is created for each IGBT by converting one set of data for six phases into six sets of data.

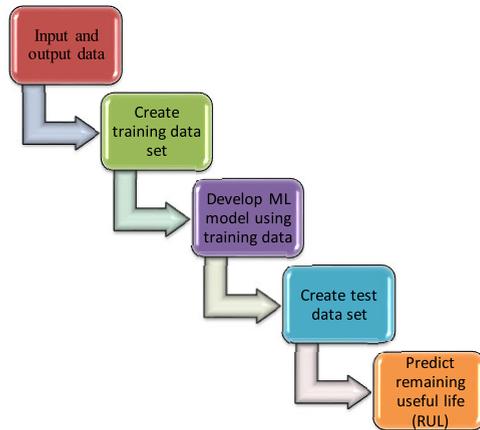


FIGURE 21. RUL prediction steps with Machine Learning.

D. PROGNOSTICS MODEL FOR RUL PREDICTION

1) COMPUTATIONAL STEPS FOR PROGNOSTICS MODEL DEVELOPMENT

To avoid overlapping of data for building ML models, individual various data sets are required to create. In general, ML techniques require training and testing data to create and validate model in appropriate condition. In this case, phase duration of degradation data sets for six IGBTs are taken to train and build the model. The data sets of IGBT number seven has been considered as validation set. The phase durations of six IGBT devices are considered as input data and the corresponding actual RULs are designated as output data. The output data is generated by calculating phase duration of the actual RULs. Then the RULs prediction is performed once the training and testing are completed. Fig. 21 illustrates the ML training and validation steps for building NN and ANFIS models using IGBT failure data obtained from aging tests and performing RUL prediction of the device.

2) RUL PREDICTION OF IGBT

This study has investigated and provided a demonstration of a computational approach to the assessment of the RUL of IGBT modules. The degradation data collected from accelerated aging tests was employed in the models. The main aim is to detect and test the performance of selected ML algorithms that is used to make predictions for the failure time of IGBTs. There is also an opportunity to use the approach to optimise and shorten the duration of applied accelerated reliability tests by adopting prognosis models in-line and use their predictions for the expected RUL to inform on expected test outcome and decisions on earlier test termination.

NN and ANFIS models are flexible to build models with noisy datasets having the capability to capture patterns in data compared to other ML techniques. To assess the model performance, for both the NN and ANFIS models, the data from the IGBT device is used (IGBT #7 in Table 1). Let us first recall that the degradation test is defined with the duration of 7 different degradation phases which are variable

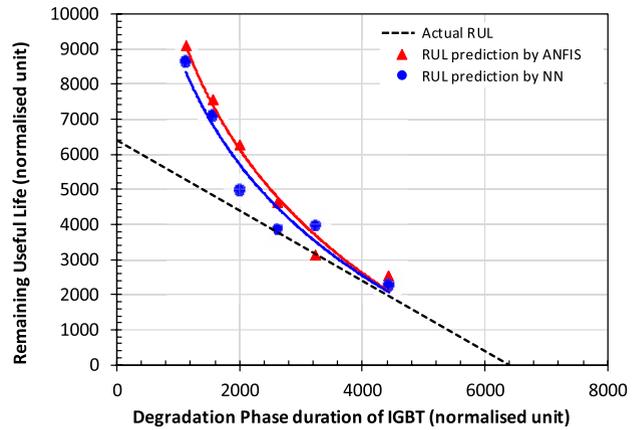


FIGURE 22. Comparison of RUL prediction performances between NN and ANFIS with real RUL.

(they can differ from test to test); at each phase, the collector emitter voltage is increased at constant value while the actual durations of the phases are changed from test by test. First, the model is used under the assumption that only the history of the test, up to the current point when a prediction is made, is known, and the duration of the following degradation stages is not decided. As anticipated, the predicted values for the RUL of the IGBT #7 completed at earlier times of the test are not very precise and express some notable deviation from the actual RUL. These results are detailed in Fig. 22. This can be explained with the lack of information, at the point of making the prediction, what the duration of the degradation phases that are yet to follow will be. However, predicted RUL values gradually improve and converge to the genuine values of different tests phases. That is happened due to receive more durations of each phase are available in the models.

This result makes also clear that despite the very limited amount of data that has been used in the model development, the model is actually very accurate if the complete test profile is defined from the start. At the start of testing the IGBT #7, the durations of each of the first six degradation phases is decided, i.e. the test profile is predefined. The degradation profile for the IGBT device #7 can be expressed as  $(t, V_{CE}) = (t_1, t_2, \dots, t_6, V_1, V_2, \dots, V_6) = (1125, 0, 872, 0, 1237, 1204, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0)$  where  $t_i$  is duration of degradation phase #i and  $V_i$  is the controlled collector-emitter voltage level during degradation phase #i,  $i = 1, 2, \dots, 6$ . Assuming this load profile, the NN model can be used at time zero of the test to provide prediction for the RUL. In a similar manner, the predicted RULs by ANFIS is compared while the real RULs values are attained during accelerated aging experiment. Predictions achieved at the beginning phases are not good as expected due to the unavailable time duration in upcoming load phases. The reason of such outcome released as the load profile of IGBTs for future phases are not perceptible yet. Therefore, large deviations of prediction accuracies found by NN at the beginning of two stages. While the models receive further historical load profiles, the predictions achieved by ANFIS start with better accuracy.

Significant errors are observed at the beginning stages while prediction performances achieved by NN and ANFIS. However, the performances for both models are observed nearer (3.11%, 26.85% and 19.04%) to real RULs at three phases from the end.

The prediction errors obtained by NN and ANFIS are 19.04% and 30.91% respectively. Whereas the relative accuracies are calculated as 80.96% (NN) and 69.09% (ANFIS) correspondingly. In general, larger data sets are important to train and build ML models to obtain good prediction. In the case, the prediction achieved by NN shows prominent result compared to the ANFIS. Thus, NN technique would be suitable to use in accelerated tests RUL prediction under the accelerated loads defined with the test programme.

This study investigated and provided a demonstration of a computational approach to the assessment of the RUL of IGBT modules. The ML techniques used degradation data to build model with data gathered from accelerated damage tests. The target is to detect and test the performance of selected ML algorithms that can be used to make predictions for the failure time of IGBTs. While similar approach can be applied to prognostics of IGBTs under in-service conditions and loads, there is also an opportunity to use this approach to optimise and shorten the duration of applied accelerated reliability tests by adopting prognosis models in-line and use their predictions for the expected RUL to inform on expected test outcome and decisions on earlier test termination.

Neural network (NN) and ANFIS models have been developed and employed in data driven prognostics to assess the competency of the models. The RUL predictions performances for both models were measured distinctly using the IGBT test devices. It is observed that the predicted RULs at preliminary degradation periods have not been achieved correctly for appearing undefined load profile in the context of the yet-to-be-completed degradation phases of the overall test, i.e. the test conditions were tentative. As the model completed larger portion of the applied load profile. Therefore, the accuracy was improved steadily through observing actual RULs and predicted RULs achieved by the ML models. In the case when the load profile is fully predefined, the prognostics models can be used with that information early on in the test and the accuracy of the predictions will be higher even at the early stages of the test.

NN provided better prediction accuracy compared to ANFIS for the observed test data and test conditions. According to the test outcome and intensive investigation on tests data and ML models, it is perceived that NN-based technique would be applicable incorporating with prognostics perspectives for predicting RUL of IGBTs. Larger data sets with various tests profiles are requisite to achieve further understandings and in-depth knowledge of the NN techniques to the similar investigation.

This case study provides new knowledge on assessing reliability by calculating RUL of IGBT from the models developed by ML techniques such as NN and ANFIS with IGBT degradation data.

#### IV. CONCLUSION

Huge efforts have been dedicated to ensure more reliable power electronic devices, greater power generation and lower maintenance costs. The presented FEA, electro-thermal modelling and prognostics-based techniques give better insight for assessing the reliability of IGBTs and more accurate failure prediction in power electronic products.

The proposed driving strategy of IGBT based inverter with controlled frequency technique can reduce the thermal stress developed at the interface of the wire-bonds of the IGBT by 16.51% when compared to the stress generated under the fixed frequency operation mode. The proposed methods can be employed in industry for improving the operational life of IGBT with less breakdown indicating an economic gain and reliable operation.

In addition, a new prognostics approach with the use of NN and ANFIS have been employed for predicting reliability of IGBT using accelerated aging degradation data. ML based analysis techniques demonstrated that they have the ability to predict remaining useful life (RUL). NN-based technique presented better prediction accuracy in predicting RUL compared to ANFIS technique and hereafter refereed to be more applicable in estimating RUL of IGBTs. Power electronics manufacturers will be benefited with the proposed data-driven prognostic approach for easy and quick assessment of their product's reliability.

In order to develop more reliable power electronic devices, more innovative operating strategies, better materials and more effective stress control should be developed. Reliability assessment through finite element modelling, experimental validation and data driven prognostics approach improve understanding of the above mentioned solutions.

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**MOMINUL AHSAN** received the bachelor's degree from the Department of Computer Science and Engineering, State University of Bangladesh, Dhaka, Bangladesh, in 2008, the M.Eng. degree by research from the Faculty of Engineering and Computing, Dublin City University, Dublin, Ireland, in 2014, and the Ph.D. degree from the School of Computing and Mathematical Sciences, University of Greenwich, London, U.K., in 2019. He is currently a Postdoctoral Researcher with the Department of Engineering, Manchester Metropolitan University. His research interests include prognostics, data analytics, machine learning, reliability, power electronics, and wireless communication. He is currently a member of the Institution of Engineering and Technology (IET), an Associate Member of the Bangladesh Computer Society (BCS), as well as a recipient of the Ph.D. Scholarship at the University of Greenwich, in 2014, and the Excellent Poster Award in the International Spring Seminar on Electronics Technology, in 2017.



**SIEW TEAY HON** received the first-class B.Sc. and Ph.D. degrees in control engineering and intelligent wireless rotating machinery condition monitoring systems from Manchester Met University, in 2013 and 2015, respectively. He is currently a Postdoctoral Researcher at the Department of Engineering, Manchester Met University. He has participated in over three projects that delivered cost-effective solutions for industry. His main research activities include developing hardware and software platforms, and algorithms for data analysis and cybersecurity purposes.



energy systems. His work specifically focuses on grid integration of power conversion systems, reliability enhancement of power electronic converters, and thermal performance of semiconductor devices used in renewable energy systems.

**CANRAS BATUNLU** received the B.Sc. degree from Eastern Mediterranean University, and the M.Sc. and Ph.D. degrees in electrical and renewable systems engineering from Leeds and Manchester Met University, in 2016, respectively. He joined the Middle East Technical University North Cyprus Campus as an Assistant Professor, in 2016. His current research interests include power electronics, electrical drives, control systems, material science, heat transfer, and reliability of renewable



His current research activities include Industry 4.0 applications, renewable power systems, smart sensing, as well as intelligent control and monitoring algorithms used for electromechanical power plants.

**ALHUSSEIN ALBARBAR** is currently a Reader with the Department of Engineering, Manchester Met University. He has well over 27 years of industrial working experience and as an Academic Active Researcher. He led and participated in over \$7M of major projects and supervised over 21 research degrees, including 15 doctoral studies. He has published three books, five book chapters, and over 100 technical papers in refereed journals and international conference proceedings.

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