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Assessment of real-time fusion prognosis techniques for power module health management

Transformation of the Top & Tail Work Package 2.2.1 Deliverable E

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1. General Background

1.1 Power Electronic modules Reliability

Power electronics industry requirements have increased significantly in the recent years towards higher integration and functionality. That led to higher power density and dissipation and less heat manipulating capabilities due to smaller sizes and higher power ratings which makes the issue of reliability of power modules a major concern for manufacturers and customers.

A Power Electronic Module is a group of power electronic semiconductor devices (MOSFET, IGBT, Diodes) that are assembled on a substrate and are connected with each other and with the outside world by wire-bonds. Power modules are normally used in utility power systems, power conversion, traction and drive circuits of resistive and inductive loads in industrial applications. Thus, they operate in harsh environments and are subject to rough temperatures, currents, humidity, vibration and other stresses which require high reliability standards to minimize maintenance, cost and down time and to increase lifetime, maintainability and safety.

A power module is constituted of different materials e.g. copper, silicon, ceramic and aluminium that are assembled into a layered structure as shown in figure 1. Those materials have different coefficient of thermal expansion (CTE) and they are subject to thermal cycling due to power dissipated into heat by semiconductor devices under operation. And because of that mismatch in CTEs mechanical stresses generate in the contact interfaces between layers. Along time, cracks start to initiate and propagate between layers leading to mechanical and electrical failures.

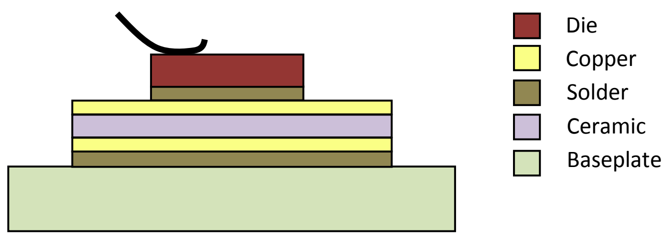

Figure 1. Layered structure of Power Module

Solder layers and wire-bonds are the most vulnerable sites to fail. Cracks initiate at the corners of a solder layer and propagate towards the centre. Similar mechanism happens between a wire-bond and the silicon device which results in an open circuit when wire-bond lifts off. Those failures could induce other failure mechanisms such as latch-up and thermal runaway.

A survey conducted by Shaoyong et al. [1] showed power semiconductor devices to be the most fragile component in power systems and IGBTs devices were found to be the most common for power applications. In that survey, participants were from aerospace, automotive, utility power and many other sectors and the majority of them have considered reliability to be a very important issue.

1.2 Classical reliability methods

Reliability assessment has historically been done based on statistical data of a run-to-failure experiments where a large sample of a product is run under predefined conditions. These data is then used to fit a failure rate reliability model which is used to calculate reliability measures as MTTF and MTBF. Those statistical reliability models are extensively used although they were proven to be inaccurate. Different organisations have published handbooks for reliability models e.g. British Telecom HRD4 and HRD5, CNET, Siemens SN29500 and Mil-Hdbk-217 based on different reliability standards. Those models are updated frequently to cope with the new manufacturing technologies, requirements and designs which change regularly in order to increase reliability of electronic products. Therefore, those handbooks should be under a regular updating process as is mentioned in the introduction of Mil-Hdbk-217 [2].

Those models are based on run-to-failure data collected from field or from experiments which makes it difficult for the new designs to be tested for their reliability during design stage and to check the effect of design parameters on product reliability.

Failure rate reliability models were proven to be inaccurate by many researches [3, 4, 5]. A fact that Mil-Hdbk-217 is used by 80% of manufacturers and that it has not been updated since 1995 raises a big argument about the accuracy of those models and their ability to cope with recent designs manufacturing technologies [6]. In addition, the fact that those models are based on run-to-failure data makes it difficult for new designs to be tested for reliability during design stage and to check the effect of design parameters on product reliability.

Therefore, researches are initiated to look for accurate alternative methods for reliability assessment that could overcome those issues and consider design parameters, environmental and loading profiles, and in-situ measurements to assess reliability during design and field operation. Consequently, reducing maintenance cycles or even eliminates periodic maintenance procedures and relying completely on preventive and predictive maintenance actions depending on evidence of the need [7].

1.3 Prognostics and Health Management (PHM):

The emergence of Prognostics and Health Management (PHM) systems comes as an attempt to overcome issues of failure rate models and monitors the product during normal operation. It reduces maintenance procedures by giving indications of system health state and estimating remaining useful life and consequently reduces costs of system out of service due to maintenance procedures. Moreover, it prevents destructive failures of system components which could cause serious disruptions in system operation.

Prognostics can be defined by the estimation of remaining useful life (RUL) of a system in order to help the decision process of maintenance and logistic support. While, health management in the other hand looks into the effects of parameters affecting system lifetime and controls those parameters in order to extend system lifetime during design phase and during normal operation.

2. Literature Review

2.1 Causes of Power Modules failure

During the lifetime of a power module it is subject to different stresses during manufacturing, storage, transportation and field operation. Those stresses can be categorised into cyclic and overstress. Cyclic stresses are those which are repeated within a time period and have a mean value and amplitude. They could be thermal, chemical, mechanical or electrical stresses. Thermal cyclic stresses are the most influential on power modules due to the mismatch of CTEs of materials constituting the module which results into cyclic shear strains in the contacting interfaces of different materials leading to cracking and voiding.

Thermal overstress is another cause of failure where the device goes under a constant high temperature that causes voids to be induced in the solder layers. Electrical stressing happens when high voltages are applied to the device which results in high electrical field. Power cycles cause the semiconductor to degrade as well and its electrical characteristics to change.

2.2 Failure mechanisms

Time-Dependent Dielectric Breakdown & Hot Carriers

TDDB is a wear-out mechanism that takes place in the oxide layer SiO2 at the gate of a transistor where charges get trapped during operation under high temperature. The accumulation of these charges leads to form a conductive path inside the oxide layer and ends in a short circuit.

Hot Carriers is an overstress mechanism that is generated under high electric fields and high temperature. Similar to TDDB is causes charges to trap into the oxide layer and form a conductive path leading to short circuit.

Threshold voltage, transconductance and gate leakage current are potential indicators of those mechanisms [6, 9, 10, 11].

Latch-up

This mechanism is activated at high temperature and high electrical currents where control over a transistor gate is lost and the device cannot be switched off until current is cut from the power source. This mechanism can lead to thermal runaway which ends up with a device burn-out.

Solder Layer Degradation

As a result of the thermal cycling and due to the mismatch of CTEs of power module materials mechanical strains and stresses induce in the interconnect interfaces and cracks start to initiate between different layers. This process is called fatigue and it affects all interconnects of different materials. Among different layers of power module the solder layer between die and substrate, the solder layer between substrate and baseplate and the interface between die and wire-bond are reported to be the dominant sites of fatigue.

Solder layers have thermal and electrical functions. They are part of the thermal path that dissipates heat generated by power dissipation. Consequently, degradation of these layers by the development of voids and cracks changes characteristics of the thermal path and device temperature will increase [12]. Thermal resistance and capacitance are affected by this degradation and the transient thermal response and steady-state of junction temperature will be affected as a result [13, 14, 15].

In terms of electrical effects of solder layer degradation, it can change collector-emitter resistance [10]. This can be explained by a reduction in the cross sectional area of the conductive solder layer which is inversely proportional to the conductor resistance. An indirect effect results due to temperature increase which changes electrical performance [16, 14].

Solder joint fatigue can initiate and accelerate other failure mechanisms since temperature is the main driving factor for many of them as in the case of latch-up, TDDB and wire bond lift-off [12, 18].

Bond wire lift-off

Another result of thermal cycling and fatigue mechanism is the degradation of the interface between wire-bond and die. Wires are used to connect emitter and gate to conductive traces in the module. Cracks develop between wire and silicon die due to CTE mismatch which end up in a lift-off and an open circuit. It is reported in literature that emitter connections on the die is the dominant wire-bonds that fail before others in the module [14, 15, 19].

The process of reconstruction in emitter metallization reduces electrical conductivity which in turn increases collector-emitter resistance R_{ON} and $V_{CE(ON)}$ [15, 20, 19, 21]. It is reported that lift-off changes parasitic inductance and capacitance of the module which leaves an effect on the transient response of electrical variables [22, 23]. It was found that there is an interaction between wire-bond degradation and solder joint degradation where the later accelerates the failure of wire-bonds [16].

2.3 Failure Modes, Mechanisms and Effect Analysis (FMMEA)

FMEA (Failure Mode and Effect analysis) and FMECA (Failure Mode, Effects and Criticality Analysis) are procedures that organise investigation of physical processes causing failure, their causes, and failure states and effects. They were adopted officially by many firms [24, 25]. Emergence of the need to diagnosis and prognosis to improve system reliability in the field of operation has led to enhance those two procedures since they are not concerned with identifying operational stresses and failure models [26]. Those drawbacks led to develop Failure Modes, Mechanisms and Effect Analysis (FMMEA).

FMMEA comes as an improvement over FMEA/FMECA to cope with the needs of life consumption monitoring and prognostics based on physical models of degradation to determine failure causes and models. The procedure is depicted in figure 2. It starts by identifying the failure mode which is the status that device fails into. It studies potential causes that have led to this failure and its relationship to environmental stresses and loading profiles. Determine mechanism taking place and physical model representing that mechanism. Determine priority of the mechanism based on occurrence frequency and failure severity. The last step is to document the information gathered throughout this procedure.

2.4 Accelerated Aging of IGBT Power Modules

Accelerated aging tests are intended to induce failures in power modules in a shorter period of time for purpose of reliability testing. Power modules can be aged by thermal or power cycling tests. In thermal cycling power module is put inside a chamber that cycles the ambient temperature around a mean value Tm by amplitude ΔT. Power cycling in the other hand put the module in more realistic test environment where electrical current is passed through it that heats the device up to a maximum temperature. The current is then bypassed and the device is cooled down to a minimum temperature and cycle repeats.

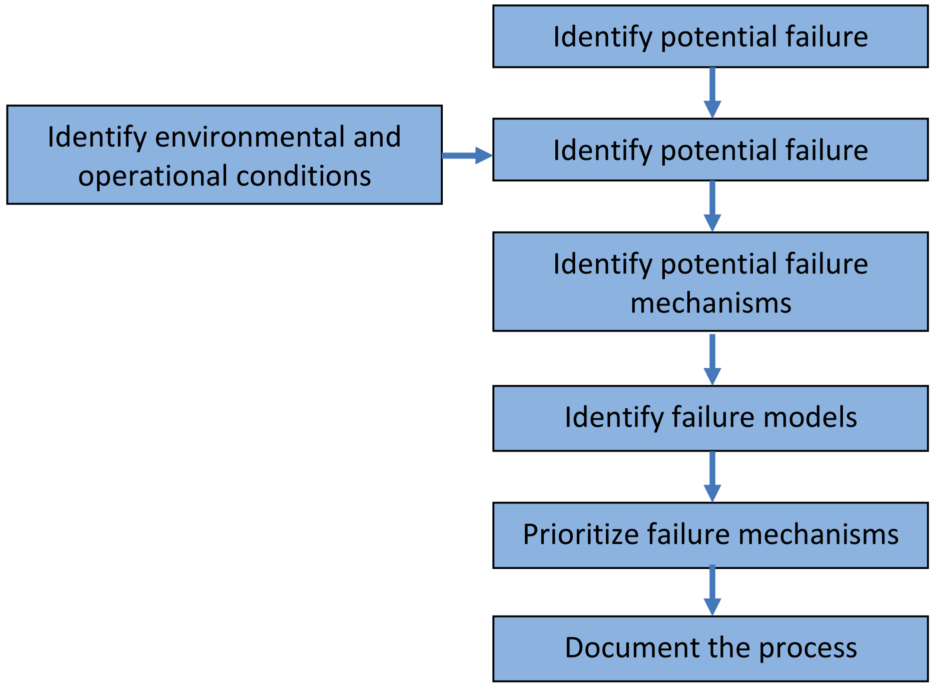

Figure 2. FMMEA procedure [27]

The difference between thermal and power cycling test was described by Engelmaier [28] who has argued that effects of thermal cycling differ from power cycling since all layers go under similar thermal transients that make temperature differences between layers less significant than it is the case with power cycling. Thermal gradients result in power cycling tests while it does not in thermal cycling. Therefore, reliability results produced by thermal cycling tests will be different from those of power cycling tests.

Power cycling of power modules can be done under DC or PWM switching conditions. PWM is supposed to be more realistic than DC switching since it is the normal operating mode for most power application. No standards are available for power cycling tests so that a comparison between the two aging regimes is desirable.

In DC power cycling the gate of transistor is biased by a constant voltage causing current to pass through the device. The main power loss in this test is conduction losses caused by the resistance of the device. Therefore, increasing power dissipated in the device under DC conditions requires increasing the current. The period of current pulse has an effect on the failure mechanism initiated in the module [16]. Anti-parallel diodes of a power module are not stressed in this aging test.

The PWM aging test is done by applying a pulse train with a predetermined frequency and a modulation signal to the gate. The amplitude is chosen so that it is sufficient to bias the gate. Switching losses are the main factor of device heating in this test and it is a function of switching frequency. The higher the switching frequency the more power is dissipated in the device. Measurements of electrical variables are more difficult and challenging under these conditions.

A comparison between the results of aging tests conducted by many researchers under DC [16, 14, 20, 29, 30] and PWM [15, 19, 31, 32] regimes show that the most influential factor on the generated failure mechanism is temperature profile regardless of the excitation signal used, while chip level degradation (TDDB and Hot carriers) in more likely under DC conditions.

Minimum and maximum junction temperature $T_{min,}$ T_{max}, mean junction temperature T_m, temperature swing ΔT, turn-on and turn-off periods and collector current are all parameters that could affect generated failure mechanisms during power cycling tests. Sankaran et al [19] found that ΔT has higher influence on device lifetime than T_m. Similar results are stated by LESIT project [20] which showed that wire-bond lift-offs occur before solder joint fatigue.

So it can be concluded that wire-bond lift-off mechanism are more dominant for large ΔT and small periods, while solder joint fatigue is more dominant for smaller ΔT with longer periods since creep mechanism could accelerate degradation of solder layer. Moreover, interaction between these two mechanisms is more significant at lower stress levels.

2.5 Potential failure indicators

Failure indicators are variables that reflect degradation process in a power module. They can be directly measured variables or they can be extracted from measurement data. Failure indicators are normally affected by factors other than failures such as temperature and loading profiles during normal operation of a power module which masks effect of failure mechanisms. That requires techniques to discriminate different effects and extract effects of temperature, loading and degradation.

Efficiency of PHM systems relies essentially on failure indicators [33]. Therefore, rules were proposed to choose failure indicators for PHM applications in order to be suitable for prognostication. Indicators that are non-monotonic are difficult to extrapolate since their behaviour is unpredictable. Variance of an indicator can affect accuracy of prediction and therefore a small variance is desirable. Some signals can change behaviour according to underlying processes such as changing from monotonic to non-monotonic after an event happens while others could give a late indication of failure. So that choosing the right indicators are an essential step in PHM for power modules.

On-state Voltage $V_{CE(ON)}$

On-state voltage $V_{CE(ON)}$ is the voltage measured across collector and emitter connections while device is in conduction mode. This voltage is a function of temperature, loading and gate voltage. For IGBT devices temperature dependency changes with structure where Punch-Trought (PT) structure has a variable temperature coefficient while Non-Punch-Trough (NPT) structure has a positive coefficient [34, 35] .

On-state voltage was considered an effective failure indicator for online monitoring purposes [10, 31, 36, 37, 38]. It is believed that $V_{CE(ON)}$ is an indicator of wire-bond and solder layer degradation since it is temperature sensitive. It is affected by the electrical resistance which result from the sum of resistances of solder layer, wire-bonds, PN junction, and contact interfaces [21, 29]. As cracks and voids develop in the solder layer it reduces the cross sectional area current is passing through, and as wire-bonds lift off the current passes through fewer number of wires and the active chip area is reduced. Degradation of emitter metallization reduces electric conductivity and increases ohmic resistance [21]. All that leads to an increase in $V_{CE(ON)}$ as failures develop in the power module.

The time between observing a change in the measured voltage and complete failure of a power module was considered in literature. Smet [31] observed an indication of $V_{CE(ON)}$ change at about 14% of the remaining life of the power module while Xiong et al [36] observed the change before 20% of time to failure. Scheuermann [16] observed the change at 30% for low stress conditions. Diversity in tests results are justified by the use of power modules from different brands and different test conditions.

Measurement of $V_{CE(ON)}$ during normal operation of power module is a challenging task due to high voltages and high switching frequency. That requires high common-mode rejection ratio, high bandwidth, high resolution and proper isolation of measurement circuit from the digital system to reduce noise and to prevent hazards of electrical shocks.

Different measurement circuits were proposed to measure V_{CE} during normal operation. Desaturation circuit built in gate drives which is used for protection against short-circuit failures was used by Anderson [10] and Peng [39] to measure $V_{CE(ON)}$. Other solution is presented in [32, 37] where clipping circuit is used as input stage for a differential amplifier to allow accurate measurement of $V_{CE(ON)}$. Due [38] proposed a measurement circuit utilizing a relay to isolate the ADC from power circuit.

Thermal Resistance:

Thermal resistance is the ability of a material to resist heat flow between two points of different temperatures. In a power module different layers of materials are layered on top of each other as shown in Figure 1 to form a heat conduction path where the sum of all thermal resistances of layers are expressed by junction to case resistance $R_{\theta jc}$.

Junction-to-case thermal resistance was considered by many researchers as a failure indicator for solder joint fatigue [14, 16, 15, 32, 40] since it reflects change in thermal conduction path due to cracks and voids. It was reported that wire-bond lift-offs affects $R_{\theta jc}$ since active area of the chip is reduced with lift-offs and that causes the same amount of current to pass through smaller area which increases power dissipation and junction temperature [41].

Challenges in estimating $R_{\theta jc}$ reside in estimating junction temperature T_J which is normally an inaccessible variable. Similar to V_{CE}, real-time measurement of T_J or $R_{\theta jc}$ will be affected by loading profiles and other operational conditions.

Sankaran et al [42] proposed a method to estimate $R_{\theta jc}$ utilizing junction temperature T_J, case temperature T_C, substrate temperature T_S and current using thermocouples and power dissipation look-up tables.

Dawei et al [43] estimated the change in $R_{\theta jc}$ to monitor degradation of solder layer where a thermal model calculates power dissipation from measurements of case temperature, ambient temperature and collector current. Power loss model is made of a look-up table of power dissipated in the module under healthy and degradation conditions of solder layer. A fault severity analysis then calculates the difference between estimated power loss and an initial healthy baseline to extract the change in thermal resistance which determines the state of solder layer.

Thermal Impedance

Thermal impedance is representative of the thermal conduction path which constitutes of resistive and capacitive components. It is used to estimate transient response of the junction temperature. Therefore it contains more information about the thermal path and its constitutive layers. Christiaens et al [44] and Katsis [45] showed the relationship between thermal impedance and temperature of different layers of power modules. They reported that slop of the thermal transient which is a measure of thermal impedance can be used to monitor the condition of solder layers. Katsis [45] related the change in thermal impedance with the percentage of voided area of a MOSFET device.

On-resistance

On-resistance R_{ON} was reported to be a potential failure indicator. It is the ratio of $V_{CE(ON)}$ to I_C during steady state phase of operation. Morroni [46] proposed an online monitoring system using an FPGA to monitor the health of a power converter by observing R_{ON} of a TO-220 power MOSFET. A model of power losses in the converter is used to extract the value of R_{ON} by a curve fitting algorithm utilising voltage and current measurements.

Celaya [47] used R_{ON} as failure indictor of die-attach degradation in an in-situ monitoring of TO-220 power MOSFET. Measurement of current and voltage were recorded to calculate R_{ON}. Dependence on temperature was learnt from experimental data to isolate operating and health conditions.

Button [48] suggested that the increment in R_{ON} would increase conduction losses in a DC-DC converter which would in turn decrease efficiency. That would force that controller to increase duty-cycle to cope with efficiency drop. Consequently, monitoring current vs. duty-cycle trend reveals the undergoing degradation in switching devices.

Threshold Voltage

Degradation of gate oxide due to TDDB and Hot Carriers can be detected by monitoring threshold voltage [49, 50]. It is sensitive to device temperature and it has a negative temperature coefficient [49, 34, 51]. Degradation of oxide layer is not a dominant failure in IGBT devices while it is not the case with SiC devices which suffer from large shifts in threshold voltage because of the degradation of oxide layer under high temperature and high voltage stressing [52] which makes threshold voltage a potential candidate as a failure indicator for SiC devices.

Ringing characteristics

Transient response parameters such as turn-on and turn-off delay times (t_{don}, t_{doff}), rise and fall times (t_r, t_f), and current tail are affected by device degradation, temperature, loading, and gate drive control [53, 34]. Aging of a power module can affect those parameters where t_{doff}, t_f and current tail were observed to change during lifetime of power modules [15].

Those parameters were considered as failure for PHM systems. Turn-off time of voltage waveform was used by Brown et al [12] in an online monitoring system for IGBTs in power inverters to monitor latch-up failure. The overshoot of V_{CE} was observed by Sonnenfeld [54] to be indicative of thermal degradation of an IGBT TO-220 package. Current tail is suggested to be a precursor of latch-up and thermal runaway of IGBTs [55].

Kexin et al [23] and Zhou [22] studied effects of wire-bond lift-offs on parasitic inductance and capacitance of a power module. Gate-emitter voltage waveform, V_{CE} overshoot and rise time and di/dt were all reported to be sensitive to wire-bond lift-offs. Ginart et al [56] proposed an online monitoring system for power converters by extracting switching waveforms from phase currents. Ringing characteristic such as damping factor, natural frequency and frequency contents were identified as potential failure indicators. Signal processing techniques are used to extract those features from measured waveforms for diagnostics purposes.

2.6 PHM Approaches

2.6.1 Data-based Methods

Data-based methods rely on identifying measurable variables that reflect degradation of the system being monitored. Measurement data are analysed and processed to extract signature of degradation using feature extraction algorithms. Extracted features are then used to diagnose failure and to fit models that are used to predict end-of-life using data trending methods as shown in figure 3. Their application could be limited by the availability of measurement data and degradation information contained in that data.

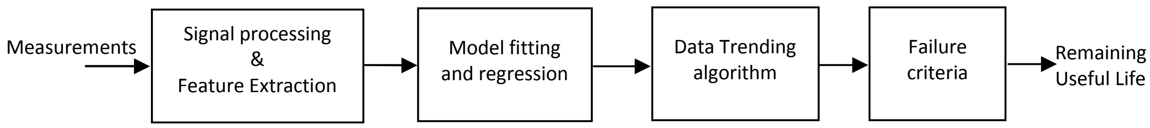

Figure 3. Data-Driven Prognostic

The advantage of data-driven methods relies on their ability to reflect the real conditions of the system during its operation and the ability to diagnose root cause of failure in some cases. Therefore, some projects were initiated to explore applicability of those methods on electronic systems. CBM+ project [7] investigates those methods in order to guarantee reliability of systems under their normal operation conditions.

The drawbacks are represented by the need for training data for model learning under different health conditions of the system which could be difficult to obtain especially when degradation process and failure mechanisms could not be initiated separately during experiment. In addition, data may give late indications of underlying failures which might limit the leading time of detection and prognostication. Data could be masked by different factors such as environment and loading which might make separation between failures a challenging task.

Many attempts were done to learn behaviour of degradation data during real-time operation of systems. Goebel et al [57] used the Gaussian process regression (GP) for battery PHM. His method failed to learn the nonlinear behaviour of the failure indicator extracted from data due to limited size of available data. He noticed that predictions become more accurate as the failure indicator becomes closer to its limit. The same method was applied by Celaya [58] for power MOSFET prognostics using R_{ON} as a failure indicator.

Celaya et al [59] applied Extended Kalman Filter (EKF) for Power MOSFET prognostics. The degradation model was obtained experimentally based on observation of R_{ON} which is described by an exponential model as a function of time. A state-space model is then derived and used for EKF algorithm. The same approach was used in [60] for prognostication of electrolytic capacitor using capacitance data which was found to reflect capacitor electrolyte degradation.

Particle Filter (PF) was applied for IGBT prognostics by Patil [61] where $V_{CE(ON)}$ degradation data was used to fit an experimental model which used then to derive a state-space representation. Saha [55] proposed a particle filter to prognosticate IGBTs using an exponential decay model for the fitting parameters of current tail. An exponential model was fit to the current tail and model parameters where then used as a health indicator. The behaviour of those parameters was found to be exponential which is used to build the state-space model. PF was also used for Power MOSFET prognostics [62] and battery prognostics [63].

Neural Networks were used extensively in the field of diagnostics and prognostics when training data is available. They could learn complex models and correlate many sources of data to a damage measure. NN were not widely applied to electronics PHM because of the limited measurable variables. A major problem with NN from a prognostic point of view is its inability to give a measure for uncertainty. Some solution to this problem was found by proposing Bayesian Artificial Neural Networks.

2.6.2 Physics-of-Failure (PoF) Methods

PoF models started to be considered as a potential candidate for reliability prediction since 1970 [6] because it allows better understanding of the root causes of failures. Failure analysis process carried out on failed components is used to determine the physical process of degradation undergoing in the material. Run-to-Failure experiments are used to monitor the effect of different loading conditions on degradation process and to fit empirical models that represent the physical degradation process. PoF methods are considered to be a design time reliability assessment approach that allows considering effects of design parameters on product lifetime. They incorporate geometrical parameters (thickness, length, area, ….) and material parameters (CTE, Young modulus, …) so that allows considering reliability during design and manufacturing process by examining effects of different materials and different design prototypes.

Those methods are having an increasing attention in recent researches and projects that are conducted by leading organisations such as NASA, French MoD and IeMRC [8, 6, 64]. Research is directed towards developing approaches that allows to integrate PoF into an in-situ implementation utilising real-time loading and environmental stresses.

Implementation of PoF approach requires knowledge of loading profiles such as temperature, humidity, vibration, … , and finding relationships between loading profiles and variables used by PoF models. This problem raises the need to develop reduced order electro-thermal and thermo-mechanical models that could relate measured loading profiles to variables used by PoF models which can be immeasurable such as strains and stress intensity factor.

Electro-thermal model is used to estimate junction temperature of semiconductor devices in a power module. A Thermo-Mechanical model is then used to find mechanical stresses and strains generated at sites of failures. A lifetime model is then used to get an estimate of the number of cycles to failure. That is depicted in figure 4. In the case of arbitrary loading profiles where temperature swings and means are random, loading profile data are analysed using data reduction and cycle counting algorithms to extract loading parameters such as swings, means and rates. A damage accumulation model is then used to estimate accumulated damage as an effect of the applied loading.

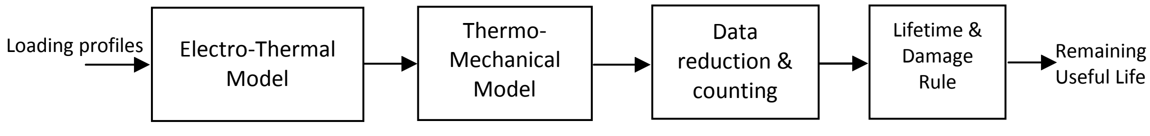

Figure 4. PoF Prognostics

Junction temperature estimation:

Junction temperature of semiconductor devices in is the main contributor in PoF methods. The problem of estimating junction temperature is still an open research problem [41, 65]. It plays a main role in solder layer fatigue and wire-bond lift-off which are the two dominant failure mechanisms in power modules.

Junction temperature can be measured in three ways as stated in literature. It can be measured using thermocouples fixed on the top surface of the chip or using optical sensors such as IR cameras. Thermocouples give local temperature reading and poor dynamical response while the other has the advantage of producing thermal maps of the module but it requires removing dielectric material covering the module. The third method is based on Temperature Sensitive Electrical Parameters (TSEPs) which uses measurements of voltages and currents that are functions of temperature to estimate junction temperature.

TSEPs were reviewed by Avenas et al [65] and compared in terms of sensitivity, linearity, feasibility for online measurements and other factors. He found that the saturation current to be the most temperature sensitive parameter while on-state voltage is the worst parameter in terms of sensitivity. Switching parameters are another TSEP candidate for temperature estimation. All TSEPs are masked by other parameters as well such as loading and dc bus voltage.

Many attempts were made to estimate junction temperature during normal operation of a power device. One of the basic attempts that was implemented on a microcontroller is proposed by Franke et al [66] which is based on an experimentally models for power losses and thermal impedance. Then using measurements of voltages, currents and temperatures junction temperature was estimated as $T_j = f(P_d, Z_{th})$. Kim [67] used measurement of on-state voltage to estimate steady-state junction temperature based on a linearized experimental model of $V_{CEsat} = f(T_j, I_C, V_{GE})$.

Musallam [68] proposed an electro-thermal model for an IGBT power module that gives temperature estimation based on measurements of collector current, duty cycle and the estimated junction temperature as feedback. Power losses were calculated using look-up table. This model is advantageous in the point that it gives an instantaneous junction temperature estimate which allows to be used for PoF approaches, but it is not an adaptive method which would lead to erroneous estimations as the power module ages and thermal conduction path parameters change.

This problem was tackled with an observer –based estimator proposed by Ginart [69] for junction temperature in SiC devices. A state-space model was derived for the thermal path and a reduced-order observer was built to get junction temperature T_J based on measurements of case temperature T_C. The error between measured and estimated case temperature T_C is used to compensate for the degradation in the thermal path. This is advantageous for solder layer monitoring and for accurate prognostication.

A Fourier-series based thermal model of a power module was developed by Du et al [70] which produces maps of thermal gradients in the module. This method proves to have higher efficiency for computation than FEM and FDM models so it seems to be promising in terms of fast computation required for real-time implementation.

A potential method for junction temperature estimation in real-time applications of power modules is mentioned by Barlini [71]. It is based on the fact that di/dt is a temperature sensitive parameter and accordingly defines the transconductance as a temperature sensitive parameter by the ratio of di/dt to dv_{ge}/dt.

Thermo-mechanical modelling:

A thermo-mechanical model is a relationship between temperature loading profile parameters (ΔT, Tm, dT/dt, f_{cyclic}, t_{Dwell}) and mechanical strain ε induced in contacting interface between two different materials due to different CTEs. Many attempts were made to build experimental thermo-mechanical models for solder joint and wire-bonds. Held [20] proposed a thermo-mechanical model for wire-bonds utilising temperature swing ΔT and the difference between CTEs. Ciappa [72] developed a thermo-mechanical model that considers creep behaviour in solder joint under cyclic loading. Engelmaier [28] proposed a model for the solder joint fatigue under cyclic loading considering geometrical high h and length L of the solder layer. A model for plastic and creep deformations in solder joint of power modules was developed by Sundarajan et al [73]. Finite element simulation was used by Yin et al [74] to derive a thermo-mechanical model by fitting a second-order polynomial to simulation results. The model uses swing ΔT and mean T_m of thermal loading profile as inputs to the model.

Lifetime models:

Lifetime model is a relationship between loading parameters and number of cycles to failure N_f or time to failure t_f. Lifetime models were proposed for different stages of failure mechanisms. Fatigue process for example can be divided into two stages, crack initiation and crack propagation. So that lifetime given by crack initiation model refers to number of cycles required to initiate cracks in the material while a crack propagation model is used to give lifetime according to crack propagation rate.

Coffin-Manson law is the most common lifetime model. It represents crack initiation stage in fatigue process. It gives the number of cycles to failure according to determined strain amplitude, while Paris law models the stage of crack propagation [76].

Other forms of lifetime models were proposed by researchers depending on specific application. For power modules reliability purposes, lifetime models for solder joint and wire-bonds fatigue were developed according to run-to-failure data. Manufacturers propose their own models according to their reliability requirements. For example, Dynex semiconductors presented an experimental temperature based lifetime model for wire-bonds in power modules based on junction-to-case temperature [75].

Held [20] conducted a power cycling test on IGBT power modules and found that lifetime of wire-bonds depends on temperature swing ΔT and mean temperature T_m which led to developing a model from Coffin-Manson law and extend it by an Arrhenius term to model effect of mean temperature. This model was extended by Bayerer [77] to include effects of power-on time, chip thickness, wire diameter and wire current.

Accumulated damage rules:

In the case of arbitrary loading profiles where loading parameters change with time cumulative damage rule is used to calculate accumulated damage in the material. Cumulative damage laws were reviewed by Fatemi [78]. The most common damage law is the linear damage rule which was principally introduced by Palmgren and was formulated later in a mathematical form by Miner as the sum of ratios of number of cycles of an applied loading to the number of cycles to failure resulting from a lifetime model.

Other damage accumulation rule was found from Stress-Strain hysteresis loop. The area of the loop was found to be related to damage induced in the material due to cyclic loading. The mechanical energy dissipated due to plastic deformation of the material is calculated from loop area and by assuming a limit to deformation energy lifetime can be calculated [79].

Length of crack is considered to be a measure of material damage after cracks are initiated in the material. This was used by Sasaki [80] to estimate the life of a wire-bond in IGBT power modules where FEA simulation was used to build a thermo-mechanical model to estimate stress intensity factor.

Data reduction & Counting algorithms:

Loading profile for in-situ applications are recorded over long periods of time which poses a problem for data storage and processing of large data chunks. That could be a challenge for real-time systems which have limited processing and storage resources. Here comes the need for data reduction algorithms that extract loading parameters form loading profiles and store them in a compact and condense data formats. Hayes and OOR methods are two examples of data reduction methods which transform large time-based data into peaks and valleys to reduce data size and remove data points which are of an insignificant effect for lifetime estimation purposes [81]. Rainflow counting algorithm is an example of loading parameters extraction algorithms that extract parameters such as mean, swing, and rates and stores it in a binned data formats to achieve further data reduction and save system resources. Vichare [82] stated that a reduction of up to 85% reduction in data storage size could be achieved.

A good example of a well-established implementation of PoF method that was considered for in-situ application for electronics is Life Consumption Monitoring (LCM) developed by CALCE group [83]. It uses online measurements of environmental loading that affects a considered failure mechanism. Recorded data is processed using data reduction and counting algorithms to make it appropriate for storage and for PoF model. The lifetime given by the failure model is converted into a damage that is accumulated using a damage accumulation rule.

Fan [81] applied LCM to monitor the state of solder joints in a PCB by recording board temperature. A similar approach is used by Musallam [84] where online junction temperature estimation is used to estimate junction temperature in a power module. A temperature based Coffin-Mason lifetime model is used with the linear damage rule to get a damage signal for wire-bonds and solder layer. A real-time implementation of rainflow counting algorithm is developed to extract loading parameters.

2.6.3 Fusion Methods

As concluded previously both data-based and PoF methods suffer from disadvantages. Limited accessibility and sensitivity of measurement data to failures is a main obstacle for data-driven methods while it reflects the real health conditions of a power module under operation. PoF methods on the other hand use information of design and materials and utilize loading profiles to give estimates of lifetime but it cannot represent the real conditions of the power module.

Competence of failure mechanisms at different sites is dependent on loading profiles, geometry, material and other manufacturing parameters [41, 92]. So that, interaction of different failure mechanisms and their dominance changes according to different factors. And considering the worst case as a criterion of failure ignores all other information that could be useful for prognosis. That could result in conservative predictions which are inaccurate and cost inefficient.

In order to overcome those disadvantages and utilize all sources of information such as in-situ measurements, loading profiles, material and geometrical information recent research routes in the field of PHM were directed towards fusion techniques [93] that benefit from advantages of both methods to get more robust and accurate assessment of system health and lifetime. In addition, uncertainty reduction is a major objective of fusion techniques. Fusion methods are not about averaging different values but they should provide measures for accuracy and reliability of fused values [94]. A general fusion PHM is described in figure 5.

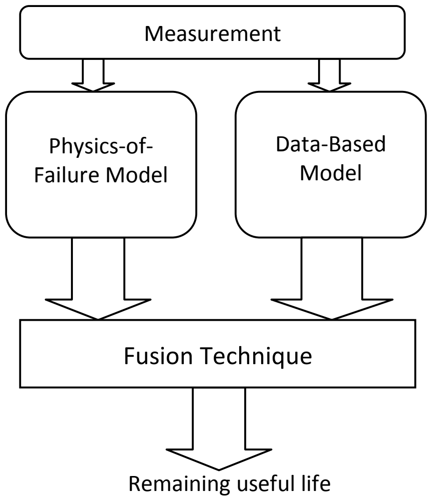

Figure 5. Fusion-based PHM

Knowledge fusion could be done at different levels in a PHM framework. This can be classified on three levels, sensor level where raw data is collected from a set of sensors. Features level where fusion is done on features extracted from data. Knowledge level where information gathered from irrelevant sources such as models, experiments and signal processing outputs are fused together. Level of fusion depends on application, data, models and available sources of information. In cases where sensor data is not easily accessible and measurement data is limited low-level fusion is less probable to be considered. In cases when information come from irrelevant sources higher-level of fusion is more convenient.

Inputs to fusion process should be homogeneous when information comes from different irrelevant sources in different formats such as different types of sensors or outputs of different signal processing stages. That requires transforming data and information into identical formats before fusion.

Output of fusion process may not necessarily be better than its input. That is fusion could produce information that is worse than it was before fusion since bad information (uninformative data) could deteriorate good information (informative data) when combined together. That raises the need for comparable measures to assess the performance of fusion techniques in terms of accuracy, robustness, data size and uncertainty. Saxena et al [95] proposed a set of prognostic performance metrics for purposes of constructing a common ground to compare different techniques in term of error margins, leading time, accuracy and convergence.

Techniques from different disciplines can be considered as fusion techniques. Some have a probabilistic nature while others do not. Bayesian probability and Dempster-Shafer are two examples of probabilistic fusion techniques that take information in the form of PDFs and produce PDFs at the output. While techniques as neural networks and weighted average take individual values and produce a fused single value. The former set of techniques have the advantage to deal with uncertainty measures as a built-in feature while for non-probabilistic methods additional steps should be proposed to tackle uncertainty fusion.

Roemer [96] has reviewed some fusion techniques suitable for PHM applications. Bayesian Inference, Dempster-Shafer, Fuzzy inference and Neural Networks are all potential methods for information fusion. The choice of what method to be used is application dependant. It depends on information amount and format, required output format, real-time resources and computational efficiency. There is an orientation towards probabilistic methods in the field of PHM [95] since it have the ability to handle uncertainty measures especially in fields where data is limited and inaccessible.

Orchard [97] investigated crack propagation failure under cyclic vibration loading by collecting vibration data from a metallic plate using strain gages. Features were extracted from the data and a state-space tracking and prediction method based on Paris' Law was used to estimate crack length in the material. The fusion of PoF model and measurement data was formulated during state-space model construction where vibration data is used to update system states and track crack state.

Goebel [94, 98] proposed a fusion method based on Dempster-Shafer theory for bearing prognostic. A physical and an experimental models were used to give two estimates of crack size. Models performance at different locations of damage space is used to produce a quality measures that are assigned for the models in a form of PDFs. The resulting crack size estimates are weighted by their respective quality measures and results are aggregated using kernel regression based method.

Other attempts to employ Bayesian techniques for knowledge fusion in PHM systems include Bayesian Model Averaging (BMA) for crack propagation in materials [99, 85] and Bayesian Networks which were applied for solder layer degradation [17].

2.7 Management of Uncertainty

One of the key factors in prognostics is the uncertainty of predictions. Any prediction of a variable has a range of probable values in future which are represented by a confidence interval or a PDF. It describes how confidant we are about a predicted value. This uncertainty changes as new information is available. The more data is collected as system propagate towards failure the more certain (or less uncertain) the prediction is and the narrower its PDF is as it is explained in figure 6 and figure 7.

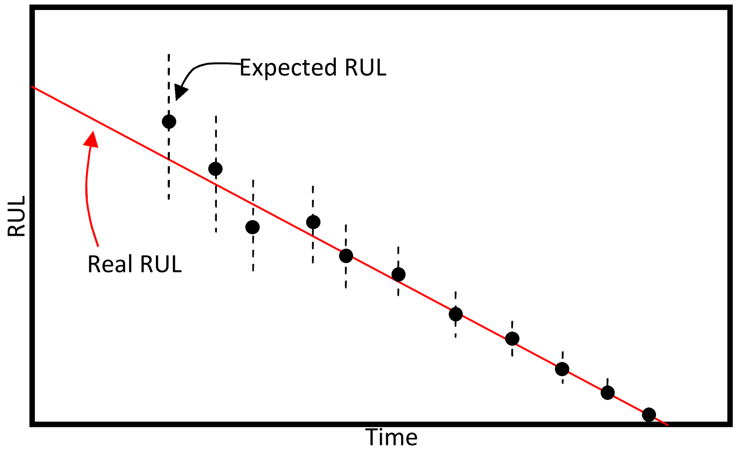

Figure 6. Real and predicted RUL vs time

Uncertainty management tries to find sources of uncertainty in the prognostic process and estimate that uncertainty and find ways to reduce it as more knowledge is available [85]. Uncertainty management was considered by FIDES [8] and IEEE Std 1413-1998 [86] to be an essential factor for reliability prediction.

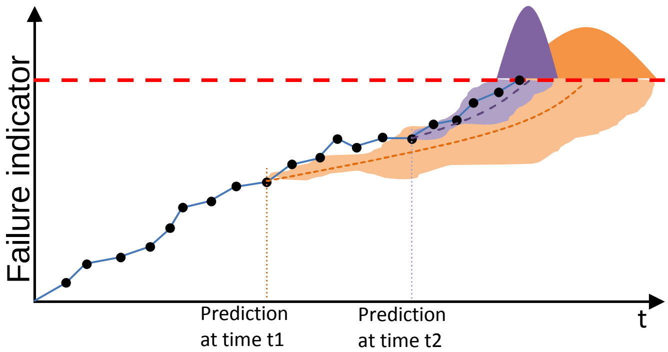

Figure 7. Predictions at two different points.

Uncertainty evolves from different sources such as models, model parameters, future loading profiles, failure thresholds and measurement errors. Uncertainty sources could be reducible or irreducible according to the nature of that source. For example, uncertainty in model parameters such geometrical parameters could be reduced by improving manufacturing process, measurement uncertainty can be reduced by using more accurate sensors. While uncertainty from future loading could be considered irreducible since future loading is unpredictable.

Uncertainty estimation methods can be parametric or non-parametric. If a previous knowledge about the statistical properties of the data is available then a parametric method could be used where parameters of an assumed PDF could be learnt from the data. On the other hand if no prior information about the data is available then a non-parametric method such as histograms or kernel density functions is used.

In cases where data is difficult to obtain resampling methods such as Bootstrap and Monte-Carlo methods are used to generate sets of data by resampling from the original data set and replace some data points with the generated ones. Consequently, producing a population of data sets that can used to estimate different uncertainty sources such as model parameters [87, 88].

Bayesian methods have gained increasing interest in the applications of PHM. Many techniques that are based on Bayesian rules for regression and prediction were proposed to tackle the problem of uncertainty. Relevant Vector Machine (RVM) is a method that captures uncertainty in model regression process [89]. Bayesian Model Averaging (BMA) deals with model uncertainty as in the case where more than one possible model could fit the data or when more than one failure modes are competing according to loading profiles [85].

Applications of uncertainty management techniques in PHM for electronics were demonstrated by many researchers. Histograms were used by Guangfan [90] to estimate PDFs of loading profiles. Vichare [82] used histograms and kernel density estimation to find distributions of loading parameters for in-situ measurements of temperature profile acting on a PCB. Gu [91] demonstrated uncertainty analysis procedure in a PoF method for a PCB subjected to vibration loading where sensitivity analysis was done to determine most critical parameters affecting the damage then Monte-Carlo simulation is used to find distribution of the damage indicator.

3. Summary

It can be concluded from the literature review that application of data-based methods in the field of power module prognostics is restricted by data collection problems due to inaccessibility to the required data and mask effects of operating conditions which distort failure signatures and effects. The matter that raises a need for proposing ways to extract failure signatures from collected data and estimating inaccessible variables which are essential for reliability and prognostic.

Physics based models have constant variables that degrade in reality due to aging effects and shift from their normal values which degrades model performance as system ages. This poses the need for an adaptive technique that can compensate for model parameters shift by updating them using data collected in real-time and find a residual signal or a relationship between model parameters and measurements that can be used in the update process.

Junction temperature is an essential variable for power module reliability assessment and prognostic since it is the main contributor in the two dominant failure mechanisms in power modules which are solder layer fatigue and wire-bond lift-off. This variable is inaccessible and might require invasive methods to measure surface and case temperatures to be used in the estimation process which poses some practical and reliability concerns when implemented in commercial power modules. Therefore, a non-invasive method that can estimate junction temperature from electrical variables and that could compensate for the degradation in the thermal path is desirable to monitor degradation of the solder layer and assess its damage level.

Detecting wire-bond lift-offs and estimating the damage in the contact interfaces through measurements can reduce the chance of any destructive failure in power systems and generate an alarm in advance of a complete component failure.

An online implementable solution that can be integrated into a commercial gate drive to monitor health state of power modules can highly reduce maintenance cost and increase reliability of a power system by monitoring damage in real-time and preventing failures by early detection.

4. Appendix 1: References

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5. Appendix 2: Thesis Outline

Chapter 1: **Introduction**

A general overview of the techniques used in this work, fundamental mathematics and description of work methodology.

Chapter 2: **Literature Review**

An overview of the work done in the field of PHM systems for power modules, Data-based, PoF-based, and Fusion-based Methods.

Chapter 3: **Mathematical problem formulation**

Describe mathematical formulation of electro-thermal model, state tracking or adaptive filtering method, power dissipation model and other experimental models.

Chapter 4: **Experimental determination of model parameters**

Experimental procedures used to estimate parameters of electro-thermal model, look-up tables, and experimental relationships.

Chapter 5: **Real-time implementation platform**

Construction and description of the real-time FPGA system, programming, auxiliary measurement circuits and its application to a power system.

Chapter 6: **Results and Conclusions**

Presentation of real-time system outputs and performance of electro-thermal model and validation of the model with other ways of measurements.