

TOPICAL REVIEW

An Overview of Lifetime Management of Power Electronic Converters

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ABSTRACT An expected lifetime of converters is of great importance for optimal decision-making in the planning of modern Power Electronic (PE) systems. Hence, the lifetime management of power electronic systems has attracted a lot of attention in academia and industry. This paper is a guideline for managing the lifetime of power converters. Analyzing the different kinds of failures, failure modes and their corresponding mechanisms are investigated in the first section along with the failure data needed as input parameters of the assessment. In the second section, lifetime prediction in two aspects of component-level and system level is discussed and all the possible techniques to achieve them are investigated and compared. All the steps required to predict the lifetime in the component-level including electrothermal modeling, cycle counting, lifetime model, damage accumulation, parameter estimation, and lifetime distribution are described and then system level methods consisting of reliability block diagrams, fault-tree analysis, and Markov chains are examined and compared. The last section contains the roadmap of the lifetime extension including the reliable design and condition monitoring.

INDEX TERMS Reliability, lifetime management, lifetime analysis, lifetime prediction, lifetime extension, empirical model, physics of failure, failure mechanism.

I. INTRODUCTION

Using renewable energy systems is one of the most practical solutions for reducing carbon footprint [1]. This technology is powered by power electronics as the core of its energy conversion process. Power electronic converters, on account of their high efficiency and performance, are finding exponentially widespread utilization in various applications such as adjustable speed drives, interfacing of renewable energy sources with the grid, electric vehicles, dc distribution

systems, smart grid, and microgrid technologies [2], [3], [4], [5], [6].

The growing use of electronic power converters in various industries has made their reliability a top priority [7]. Power converters' reliability is a major concern in industrial applications because of using prone-to-failure components e.g., high-power semiconductor switches and electronic capacitors [8]. If a component or a subsystem of a power electronic system experiences a fault, it may lead to the shutdown of the whole system [9]. These unscheduled interruptions not only jeopardize safety but also increase the cost of system operation [10]. For example, in hybrid electric vehicles, a fault in electric propulsion systems impairs fuel economy and

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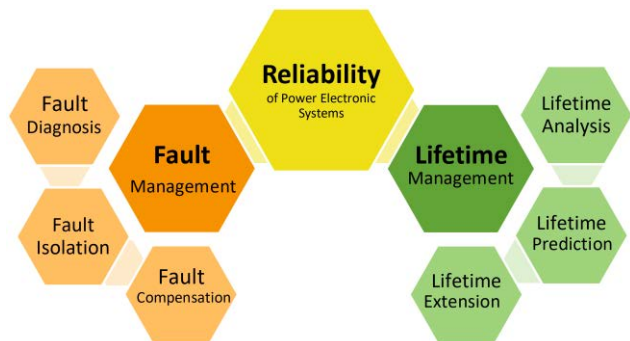


FIGURE 1. Guideline of the reliability of power electronic systems.

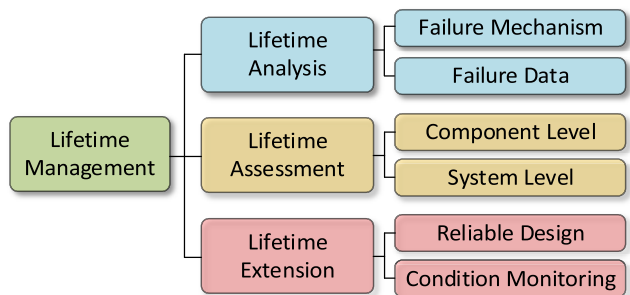


FIGURE 2. Roadmap of lifetime management.

lengthens the cost recovery period. In a photovoltaic system, the cost of failure is equal to the value of the energy that would be generated while the system is down plus the cost of repairing and replacing the faulted parts [11], [12].

Fig. 1. depicts the general guideline for the reliability of the power electronic based systems. As shown in this diagram, power converters’ reliability can be discussed from two aspects including fault management and Lifetime management. These two areas are mostly considered as two distinct subjects in research. Fault management deals with sudden catastrophic faults in the converters including short circuit and open circuit. It is about protecting the systems from faults by using circuit breakers and diagnosing and configuring the faults when they have already happened. Lifetime management is the other aspect of reliability which is mostly about predicting and extending the lifetime of the power converters. It consists of three major subcategories: lifetime analysis, lifetime prediction, and lifetime extension as shown in Fig. 2. This survey focuses only on the lifetime management aspect of reliability.

Reliability analysis, which contains identifying the prone-to-failure components along with the mechanism of the failures, is the fundamental step for lifetime management. The short lifetime of power electronic devices is mostly due to thermal stresses in their switching devices such as IGBTs and MOSFETs, especially in high switching frequencies. It can cause the failure of these components which leads to either a catastrophic failure (i.e., open-circuit and short-circuit) or a wear-out failure which causes unreliable performance in the

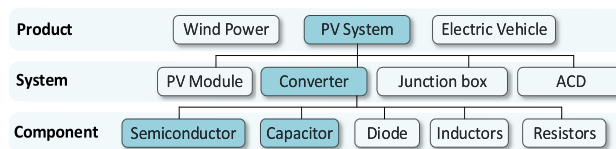


FIGURE 3. Structure tree of a power electronic system, considering PV system as an example.

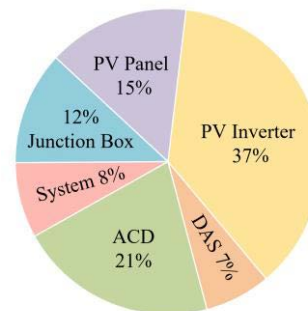


FIGURE 4. Distribution of unscheduled maintenance events of a PV plant [2].

operation of the system. Hence, an appropriate assessment procedure is required to improve the reliability of the converters and particularly their switching devices [13].

Predicting the lifetime of power converters is very important for converter manufacturers and operators [14]. Different from the conventional performance indices for power electronic systems, e.g., power density, efficiency, total harmonics distortion, etc., reliability is a concept that is difficult to measure and quantify. Traditional approaches utilize the data of the reliability handbooks for predicting the probability of random chance failures within the useful lifetime. However, the wear-out failures affect the converters’ long-term performance, and therefore predicting and assessing the lifetime of these kinds of failures is done using either model-based lifetime prediction methods or data-driven methods [15].

The structure tree tool can provide a graphical representation of the system structure and identify the interactions between the several subsystems or components of the PV systems. An example structure tree of a typical PV system is given in Fig. 3 in which the PV system can be divided into several independent systems (e.g., PV module, PV converter, junction box, and ACD), which can then be further classified into different subsystems. Among various power products at the system level in Fig. 3, according to the pie chart shown in Fig. 4, the reliability of PV systems is severely affected by inverters. In fact, inverters are very much subject to failures with about 21 percent of the unscheduled maintenance events of a PV plant [2], [16]. From the system-level to the component-level, among the different components of an inverter, capacitors, power switches and PCBs are the most critical elements in case of failure as demonstrated in Fig. 5 [17].

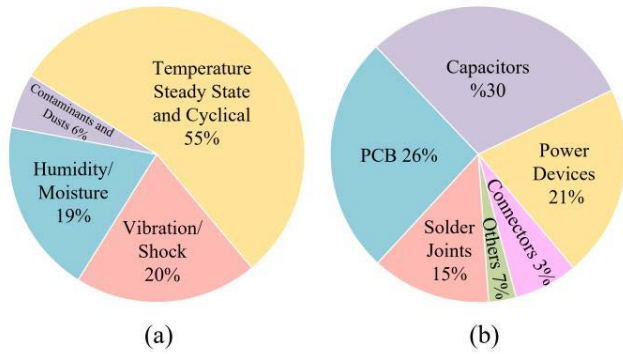


FIGURE 5. Surveys on failures of converters: (a) Distribution of sources of stresses for failures of electronic equipment [2], [16] (b) Failure distribution among major components in a typical converter [2], [19], [20].

In this paper, first, the lifetime analysis including the failure modes and mechanisms of power devices are investigated. Also, various kinds of failure data as the input of the process of assessing reliability are explained. Then, the lifetime prediction methods are examined from two aspects one of which is component-level including handbook-driven, model-driven, and data-driven techniques and the other one is system-level. The third part of the paper deals with increasing the lifetime by using a reliable design process the necessity of which is undeniable for any electronic product. This section also discusses conditioning monitoring which offers benefits for maintenance scheduling and reduced downtime.

II. LIFETIME ANALYSIS

The reliability analysis of a converter is the first step to assessing and expanding its lifetime. It consists of investigating the failure mechanisms of different components of a system along with identifying the failure data of the assessment [18]. The fundamental failure mechanisms of the power electronic components and the way they affect the reliability along with the stressors such as vibration, temperature, cosmic radiation, humidity, and the interactions between them during the operation is necessary to know. An understanding of the input failure variables including environmental stressors, field data, and historical data from the handbooks process of predicting the lifetime is vital to know [21].

A. FAILURE MECHANISM

The purpose of this part of the analysis is to identify the most critical components in a power electronic system, their major failure modes, mechanisms, indicators, and their corresponding stressors causing the failure [22], [23].

Fig. 5. shows the failure rate of critical components of an inverter. As the core part of the drive system, the power semiconductors are very prone to failure due to their frequent on-off switching and the influence of thermal and electrical overstress. Fig 5(a) indicates that temperature is the most dominant stressor of electronic equipment with 55 percent of the distribution. Fig 5(b) represents that power devices

such as IGBTs and MOSFETS account for about 21% of an inverter's failures [24]. It also shows that the capacitors have the highest failure rate in power converters. In the absence of redundancy and reconfiguration in a converter, a failure of these components leads to a system's failure, which is considered catastrophic for mission critical converters [18]. PCB is the second highest failure-prone component of a converter with 26 percent chance of failure. Some PCBs' failures happen because of accumulated damage and fatigue and others can be erratic (random), or sudden due to the shocks.

Typically, there are multiple failure mechanisms associated with a specific component each of which should be evaluated individually. There are various failure mechanisms at the chip, packaging, and component levels. Hence, in a complex system where there are a limited number of models and associated parameters, the Physics of Failure (PoF) may be difficult to apply. Thus it is important to identify and focus on the critical failure mechanisms in specific applications [25].

In the following, the failure mechanisms of two major critical power electronic components are discussed and stressors and failure modes of each failure mechanism are explained in tables 1 and 2.

1) POWER SEMICONDUCTOR SWITCHES

Power semiconductor devices are considered as one of the most reliability-critical components in a power electronic system [26]. Failure modes of power switches are either chip-level or package-level [27]. These structures for a SiC MOSFET are shown in Figs. 6 and 7 respectively. Table 1 summarizes important overstress failure modes and their corresponding failure mechanisms [13].

Most chip-level failure modes are associated with gate oxide and body diode. The body diode failure of power MOSFETs is basically caused by stacking faults. Chip-level failure modes of SiC MOSFETs mostly occur at the gate oxide and body diode. Gate oxide degradation failure is primarily caused by the tunneling current into the gate oxide layer [28]. High electric field stress and high-temperature stress also contribute to gate oxide degradation [23]. The gate leakage current i_{gss} would increase. It leads to the increase of both the threshold voltage shift and drain leakage current. The body diode failure is normally caused by the recombination-induced stacking fault mechanism. The main cause of the body diode degradation is the forward voltage bias stress [29] which leads to an increase in forward voltage and drain leakage current.

Bond wires and solder layers are the main locations for the package-level failures of SiC MOSFETs. Fig. 7 shows the typical package-level structure of a SiC MOSFET which is mainly composed of the chip die, the baseplate, and the bond wire. Solder layers connect the baseplate and the substrate and also the substrate and Si chip. Solder film between the ceramic substrate and the baseplate is the most vulnerable to failures [30]. There are mainly three stresses causing the package-level failures as follows [31]. Thermomechanical

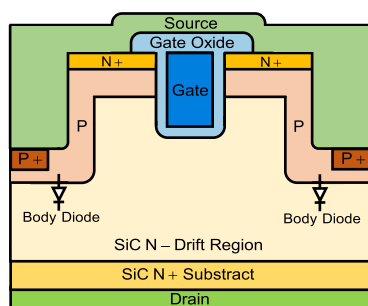


FIGURE 6. SiC MOSFET chip-level structure.

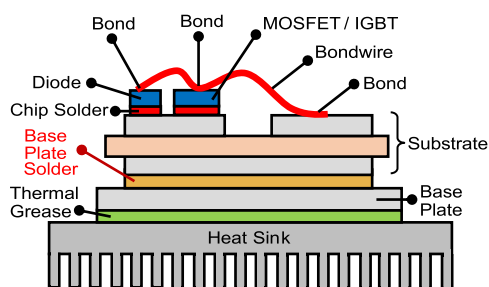


FIGURE 7. SiC MOSFET package-level structure.

stress caused by the CTE mismatch among different materials results in temperature swings leading to solder-fatigue, crack growth, and bond wire failures. However, the highest thermo-mechanical stress that solder joints will be exposed to is occurred during the cooling phase after soldering. [32] The continuous thermomechanical stresses result in the formation of voids and cracks in the solder layers and reduce the effective area accessible for heat loss reduces leading to a rise in the module thermal resistance. This further results in an increase in the device junction temperature which may cause acute localized heating; further possibly leading to catastrophic burnout [33]. Humidity is the second main stress which intensifies the impacts of mechanical stresses, causing a plummet in the metal atom bonding energy. Therefore, the crack growth rate at the tail of the bond wire increases due to atom corrosion. High current density stress is the third stress caused by the relatively small SiC die-size. It leads to acceleration in electromigration-related degradation [34] causing high junction temperature in bond wires which further leads to the increase of on-state drain-source voltage and resistance [35].

Despite identifying several different failure mechanisms, currently, most lifetime prediction models mainly focus on package-related failures.

For IGBTs, failure locations, modes, mechanisms, causes, and indicators are mostly similar to Table 1 with some differences. For IGBTs, failure indicators for gate oxide failure are gate leakage current and Miller Plateau time duration. For solder layer failure, the indicators are voltage change rate, current change rate, junction temperature, and low order harmonic [42], [43].

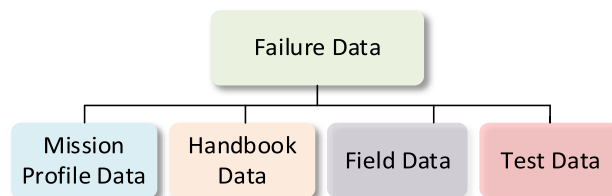


FIGURE 8. Different types of failure data for lifetime prediction process.

2) CAPACITORS

Capacitors play an important role in power electronic circuits as they are used to absorb harmonics, suppress dc-link voltage ripple, provide sufficient energy for transient and abnormal operations, and balance the instantaneous power difference between the front-end and rear-end of converter systems [44], [45]. They are also used as dc-link in applications such as grid-connected inverters, adjustable speed drives, photovoltaic applications, and power factor correction converters. However, capacitors are considered the most reliability-critical components in power electronic converters. Their sensitivity to electrical and thermal stresses results in the disadvantage of a high degradation failure rate [46]. As shown in Fig. 5, about 30% of converter failures are due to the degradation of capacitors [47].

Generally, three types of capacitors used in dc-link applications are electrolytic capacitors, ceramic capacitors, and film capacitors [45] of which failure mechanisms, modes, causes, and indicators are shown in Table. 2.

B. FAILURE DATA

The failure data is the input of the lifetime prediction process. As demonstrated in Fig.8, the failure data can be classified into mission-profile-based data, historical data, and the data derived from accelerated tests as test data [18].

1) MISSION PROFILE

A mission profile is the defined operating conditions of a system which may include internal parameters such as voltage, power, speed, etc., and/or external parameters e.g., temperature, irradiance, humidity, altitude, etc. [47]. In other words, a mission profile quantifies the total amount of stress applied to a system during operation [47]. A mission profile can be defined in different time scales, e.g., a minute mission profile or an annual mission profile. Typical mission profiles for power electronic systems can be the wind speed in wind energy, solar irradiance in photovoltaic applications, speed and torque variations of the electric machine in motor drive applications, output voltage and current operating ranges, customer usage behavior, and also the environmental factors like temperature, humidity, vibration level, etc. [48]. In the case of PV applications, the solar irradiance and ambient temperature are considered as mission profiles [49]. Since producing photovoltaic energy is highly dependent on these two parameters, the mission profile of the PV system can

TABLE 1. Location, modes, mechanisms, causes and indicators of failures in MOSFETs.

Failure location		Failure modes [36]	Failure mechanisms [37]	Failure Causes [38]	Failure Indicator [18, 39]
Chip-Level	Gate oxide	Short-circuit, Increased gate leakage current, Increased gate threshold voltage.	Electrical overstress and ESD, Time-dependent dielectric breakdown.	High electric field, Gate voltage exceeds its breakdown voltage, High temperature	Threshold voltage shift, Drain leakage current, Miller Plateau voltage amplitude.
	Body diode	Increased drain leakage current	recombination-induced stacking.	The forward voltage bias stress	Drain leakage current, Body diode forward voltage.
Package-Level	Bond wires	Increase on-state resistance, Open-circuit.	Bond wire cracking and lift-off, Al Corrosion, bond wire melting.	high temperature, CTE mismatch, Thermo-mechanical stresses	Drain-source on-state voltage, Drain-source on-state resistance, Thermal resistance, Bond wire resistance.
	Solder layers	Open-circuit.	Solder fatigue	high temperature, CTE mismatch, High current density	On-state drain-source voltage, Solder layer resistance.

TABLE 2. Failure location, modes, mechanisms, causes and indicators of capacitors.

Capacitor	Failure modes [36, 39]	Failure mechanism [36, 40, 25]	Failure Causes [30]	Failure Indicator [41]
Electrolytic capacitors	Open-circuit	Self-healing dielectric breakdown	Voltage stress, ambient temperature, ripple current stress,	capacitance, equivalent series resistance (ESR), the dissipation Factor, the insulation resistance, leakage current
		Disconnection of terminals	vibration	
	Short-circuit	Dielectric breakdown of the oxide layer	Voltage stress, ambient temperature, ripple current stress	
	Performance drift	Electrolyte vaporization	ambient temperature, ripple current stress	
Electrochemical reaction including oxide layer degradation and/or anode foil capacitance drop		Voltage stress		
Film capacitors	Open-circuit	Self-healing dielectric breakdown	Voltage stress, ambient temperature	
		Connection instability by heat contraction of a dielectric film	ambient temperature, ripple current stress	
		Reduction in electrode area due to the oxidation of evaporated metal	Humidity	
	Short-circuit	Dielectric film breakdown	Voltage stress	
		Self-healing caused by overcurrent	ambient temperature, ripple current stress	
		Moisture absorption by film	Humidity	
Performance drift	Dielectric loss	Voltage stress, ambient temperature, ripple current stress, humidity		
Ceramic capacitors	Open-circuit	Severe cracking	Ambient temperature, ripple current stress, vibration	
		Dielectric breakdown	Voltage stress, ambient temperature, ripple current stress	
	Short-circuit	Cracking; damage to the capacitor body	vibration	
	Performance drift	Oxide vacancy migration; dielectric puncture; insulation degradation; micro-crack within the ceramic	Voltage stress, ambient temperature, ripple current stress, vibration	

vary widely depending on the geographical locations of installation [50]. In electric vehicles, the torque–speed curve over time determines the operating conditions of the power

electronic converters within the drive system, which finally affects the electrical and thermal stresses of the key power components.

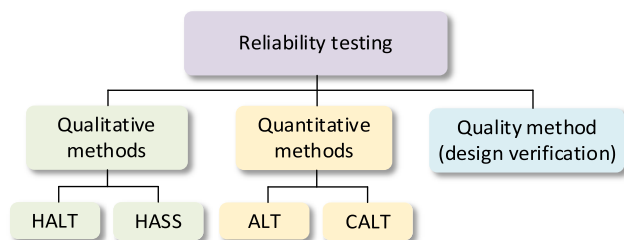


FIGURE 9. Classification of reliability tests.

2) HANDBOOK DATA

In traditional power electronic engineering, the reliability is modeled based on historical data provided by reliability handbooks such as MIL-HDBK-217F. Although the data in most of these handbooks are considered to be outdated and their corresponding prediction approaches suffer from poor accuracy, some of these handbooks like FIDES are still popular in some applications [51]. A summary of commonly used handbooks is provided in Table 3.

3) FIELD DATA

Field Data is a record of the product's performance for its customers provided from call centers, return approvals, exchanges, repairs, and warranty claims, all provide information on field failures. It includes all stresses, expectations, and component variations. The recorded data can be the installation date, the date of failure, usage conditions, failure modes, and failure mechanism.

4) TEST DAT

There are three types of reliability tests as demonstrated in Fig.9. In Accelerated Lifetime Test (ALT), in order to simulate the wear-out failure modes and their corresponding stressors in the laboratory environment, the stresses experienced in the field are applied to accelerate some of the dominant failure modes the component experiences in the field [52]. Calibrated Accelerated Lifetime Test (CALT) is similar to ALT in some aspects but it is applied when the available test time is limited which is described in detail in [53].

Qualitative accelerated lifetime tests including Highly Accelerated Lifetime Tests (HALT) and Highly Accelerated Stress Screening (HASS). These tests are used to find the main weak-points points and are usually employed during more mature stages of the design development, when a functional product-level, system-level, or component-level prototype is already available.

In the HALT approach, the purpose is to make some cases fail under specific test conditions and discover as many failure modes as possible in order to provide failure data for the dominant field failure modes [18].

Qualitative testing approaches tests are applied to determine the robustness of the product design, while quantitative lifetime tests are performed to find the reliability performance of the product [54].

There are also quality (or design verification) testing methods that are employed to ensure that an application-dependent set of specific requirements such as international standards (e.g., IEC 60747, IEC 60384 1401, JESD 22 1411) is met [55]. For instance, power modules are required to undergo a series of tests such as mechanical shock, temperature cycling, power cycling, high-temperature reverse bias, high-humidity reverse bias, and low-temperature storage test to ensure a certain level of quality. Similarly, the capacitors need to pass a series of environmental and exposure qualification tests such as thermal shock, high temperature, damp heat, vibration, charge, and discharge to be considered as a market-ready qualified product [38].

III. LIFETIME PREDICTION

The optimal and reliable converter manufacturing, including cost-effective design, decision-making on investment, operational planning, and maintenance scheduling, requires a deep understanding of the system's reliability. Moreover, analyzing novel converter topologies, switching schemes, redundant operation, control schemes, and evaluating the effect of operating conditions on the long-term performance of converters needs a proper lifetime model of the converter. Hence, the lifetime prediction of power converters is of great importance to be carried out [23]. The lifetime estimation of a system is first made by using the component-level models to estimate the failure rate of each component. Then the provided failure rates are summed to generate the system-level lifetime estimation.

A. COMPONENT LEVEL LIFETIME PREDICTION

The failure rate $\lambda(t)$ is one of the widely used reliability metrics in reliability engineering. It is defined as the frequency at which a component or a system fails [56]. Based on the conventional life cycle bathtub curve, as demonstrated in Fig. 10 there are three regions for the failure rate of electronics devices over time including early failures, constant random failures, and wear-out failures [57], [58].

The first part of the curve is dedicated to early failures. A high number of failures occur during this period due to errors in the design phase or the manufacturing process. However, the failure rate decreases over time due to removing the failed and defective products at the beginning of the stage. By performing burn-in or screening tests, early life failures can be addressed.

The constant phase of the diagram, placed in the middle part of the curve, describes the useful lifetime of a product. This stage contains random failures which are typically caused by random fluctuations and transients of stresses exceeding the strength of the component or mishandling of the product [59].

The third part of the curve consists of the wear-out failures of a product. Similar to the human body, as the product including its components and materials ages, the occurrence of failures increases. As an example, the failure of power switching devices at this stage is usually caused by corrosion,

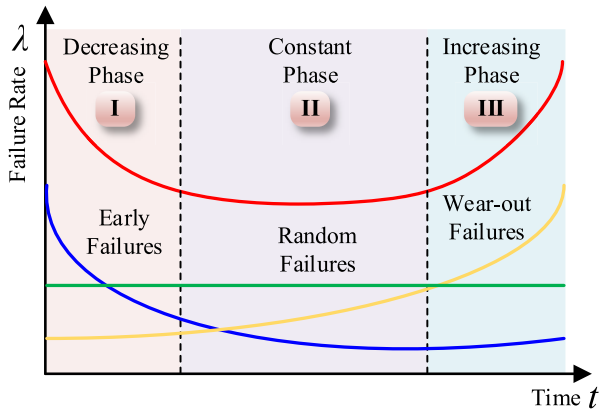


FIGURE 10. Bathtub curve of the failure rate.

oxidation, or fatigue. Increasing the service time makes the wear-out failures dominate the failure probability [60].

A fundamental step for investigating the lifetime prediction of products is understanding the metrics used in reliability engineering [14], [21].

Failure rate as the frequency of failure over time is described as follows: [61].

$$\lambda(t) = \frac{-1}{R(t)} \frac{dR(t)}{dt} \tag{1}$$

The reliability $R(t)$ can be represented as the probability of functionality of a product at a certain time [62]:

$$R(t) = \exp\left(-\int_0^t \lambda(\tau) d\tau\right) \tag{2}$$

Similarly, the unreliability $F(t)$ can be defined as the percentage of a group of products that fail at a certain time t which can be calculated as follows [3]:

$$F(t) = 1 - R(t) \tag{3}$$

Mean Time to Failure (MTTF) represents the expected time to failure for a non-repairable system. A larger MTTF indicates higher reliability and a lower failure rate [61].

$$MTTF = \int_0^{\infty} R(t) dt \tag{4}$$

Classification of lifetime prediction Methods is shown in Fig. 11. In the first step, lifetime prediction methods are divided in aspect of the type of failures: random failures and wear-out failures. There are also hybrid methods that combine the different techniques of the two major categories.

1) RANDOM FAILURES LIFETIME PREDICTION

Handbook-driven prediction methods are based on models developed from statistical curve fitting of historical failure data, which may have been collected in the field or from

manufacturers. These methods tend to present reliability estimation for similar or slightly modified components.

Random failures happen in the constant phase of the bathtub curve of failure rate [63]. Therefore, by considering failure rate is considered constant in (2), the component reliability over time “t” can be expressed as:

$$R(t) = e^{-\lambda t} \tag{5}$$

By replacing (5) in (4), MTTF is equal to the reciprocal of the failure rate:

$$MTTF = \frac{1}{\lambda} \tag{6}$$

Due to ease in dealing with a constant failure rate, the exponential distribution function has proven popular as the traditional basis for reliability modeling. The reliability parameters using exponential distribution are demonstrated in Fig. 12. These parameters are reliability function $R(t)$, Probability Distribution Function (PDF) $f(t)$, which for constant failure rate is λ times more than reliability function, hazard rate $h(t)$ which equals to λ and unreliability function or Cumulative Distribution Function (CDF) $F(t)$ which has been presented in Eq. (3).

The most common handbook used for lifetime estimation is the Military Handbook 217 (MIL-HDBK-217) which was first released in 1991 [64]. This approach suffers from being too general and application independent along with being imprecise as it does not take into consider the root cause of the failures. It is a simple lifetime prediction method that considers only the constant phase of the failure rate curve including random failures and neglects the wear-out stage. Generally, MIL-HDBK-217 failure rate predictions are more pessimistic than other reliability handbook predictions. However, this is variable and depends on the components.

MIL-HDBK-217 standard consists of two approaches for assessing reliability including Parts Count Analysis (PCA) and Parts Stress Analysis (PSA). The PCA technique requires less information such as part quantities, quality level, and application environment. It is most applicable during the early design or proposal phases of a project. This method does not factor in the numerous variables and uses worst-case generic or base failure rates and pi factors. PCA usually results in a more conservative result with a higher failure rate or lower system reliability than PSA. PSA requires more detailed information and is usually employed later in the design phase. PSA approach typically results in a lower failure rate or higher system reliability than PCA. A similarity between PCA and PSA is that both prediction techniques use relatively similar formulas.

PCA utilizes only the estimated values whereas in the PSA method calculated and measured values are used. The general the formula for calculating the failure rate in this method is as follows [65] in which λ_b is the base or generic failure rate and other parameters are introduced in Fig. 13.

$$\lambda_{MOSFET} = \lambda_b \times \pi_T \times \pi_A \times \pi_Q \times \pi_E \tag{7}$$

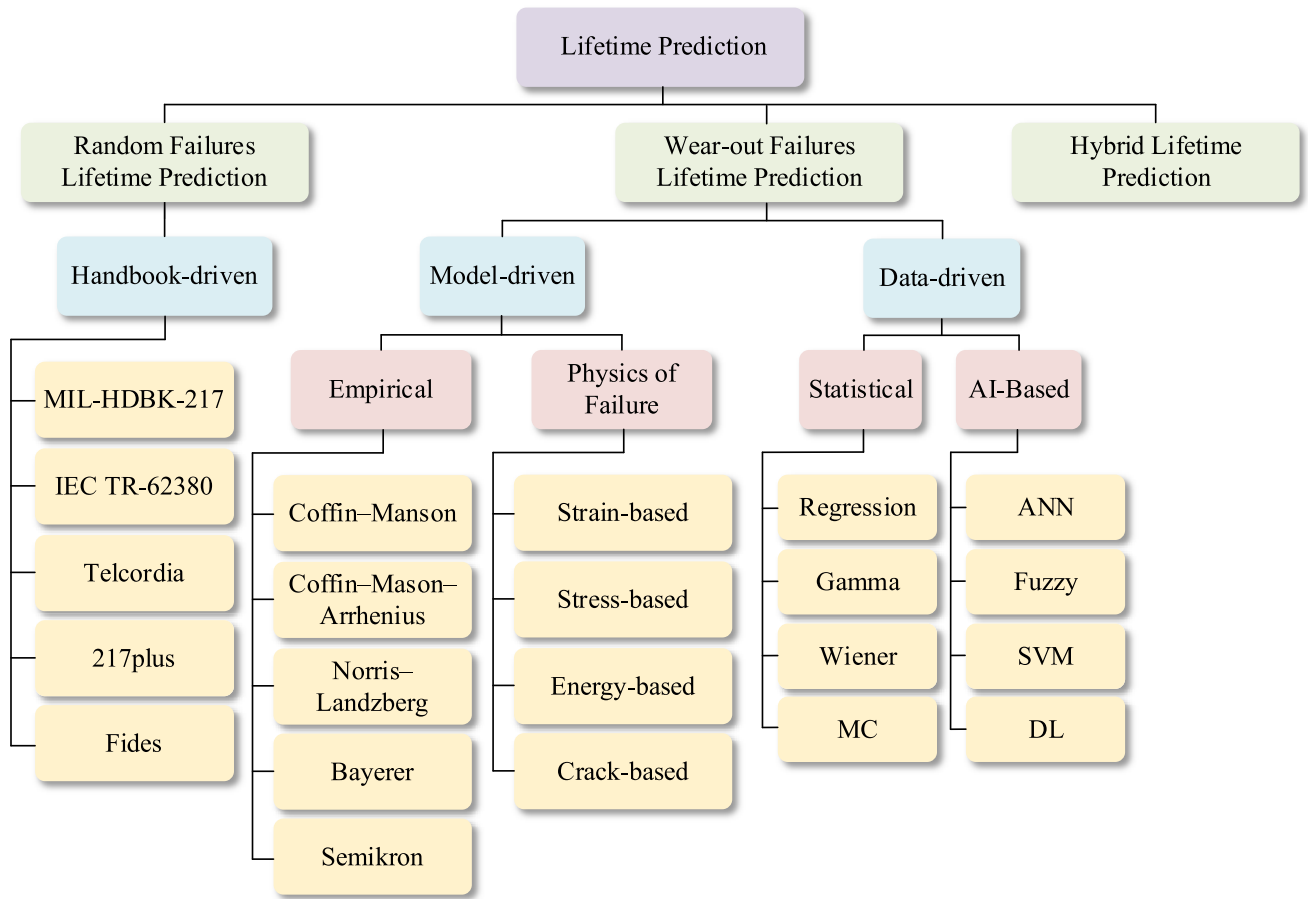


FIGURE 11. Classification of lifetime prediction methods.

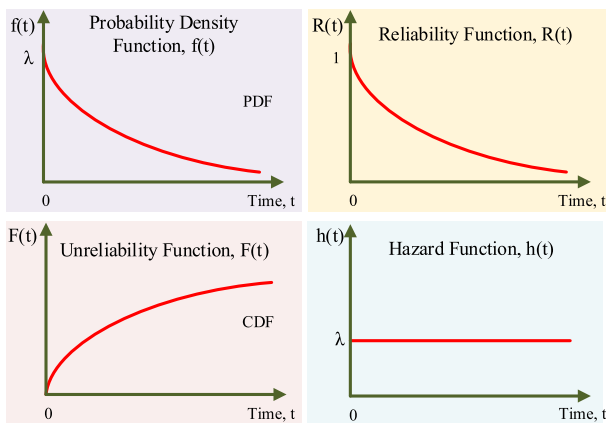


FIGURE 12. Exponential distributions of reliability for random failures.

For capacitor:

$$\lambda_{Capacitor} = \lambda_b \times \pi_T \times \pi_V \times \pi_C \times \pi_Q \times \pi_E \quad (8)$$

The overall converter's failure rate can be calculated as:

$$\lambda = \sum_{i=1}^n N_i \pi_{Qi} \lambda_{bi} \quad (9)$$

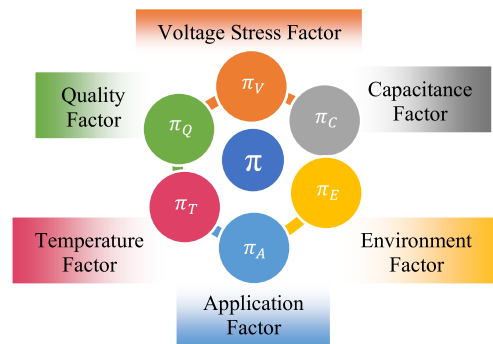


FIGURE 13. Failure parameters diagram.

where, n is the number of parts categories (e.g. MOSFET, capacitor, diodes, etc.), N_i is quantity of i_{th} part, π_{Qi} is the quality factor of i_{th} part, λ_{bi} is the base failure rate of i_{th} part. The π -factors vary for component types and categories.

Later on, International Electrotechnical Commission (IEC) released the IEC TR-62380 handbook, also called RDF 2000, which takes into account the failure mechanisms for calculating the failure rate throughout a mission profile. IEC TR-62380 considers the mission profile for constant failure

rate prediction, but not for the wear-out prediction. Thus, the calculated lifetime may not be precise enough for different operating conditions [58]. As the provided data of this handbook was not updated and the failure mechanisms were not accurately modeled, it has been replaced by IEC 61709, which provides a general guideline for mission profile-based failure rate estimation.

Having faced the problems associated with the military handbook methods, Bellcore telecommunications company decided to design its own reliability prediction standard for its commercial telecommunication products. In 1997, the company's name was changed to Telcordia. Telcordia Issue 3 is a widely used reliability prediction standard, while Telcordia SR-332 Issue 4 represents the latest Telcordia standard. Three methods are used in the Bellcore/Telcordia standard for dealing with failure rates at both the infant mortality stage and the steady-state stage. The first method is similar to the MIL-HDBK-217F standard method which utilizes the generic failure rate along with the device quality factor (π_Q), voltage stress factor (π_V) and temperature stress factor (π_T). In the second scheme, test data are combined with the first method based on specific SR-332 criteria, while in the third scheme, failure rates are estimated by applying a statistical model. Using this method, the predicted failure rate is calculated by taking the weighted average of the generic steady-state failure rate and the field failure rate. Telcordia is a popular reliability assessment approach in the commercial sector. Nonetheless, its use has continued to grow throughout a wide variety of industries.

Quanterion Solutions Incorporated developed the reliability prediction standard 217Plus in 2015, which was released initially as PRISM. A wide range of electromechanical components is taken into account in the failure rate models in 217Plus, which have their roots in MIL-HDBK-217. This standard supports all aspects of a handbook-driven approach including detailed stress calculations, parts count calculations, operating profiles, cycling factors, and process grades. In 217Plus, the Part Count section provides tables describing the device failure rates as a function of the system environment and operation profile. The Part Count section of 217Plus includes a number of tables for device failure rates that are based on the combination of the system's operating profile and environmental factors. It will be possible in this case to obtain the device failure rates by using a table lookup instead of calculating.

$$\lambda = \sum_{i=1}^n N_i \sum_{j=1}^m \pi_{ij} \lambda_{ij} \quad (10)$$

where, n is the number of parts categories, N_i is quantity of i_{th} part, m is the number of failure mechanisms appropriate for the i_{th} part category, π_{ij} is π -factor for the i_{th} part category and j_{th} failure mechanism, λ_{ij} is failure rate for the i_{th} part category and j_{th} failure mechanism [66].

Fides approach takes into account failures that are derived from development or manufacturing errors and overstresses

such as electrical, thermal, and mechanical. The methodology also deals with non-functioning phases such as dormant application and genuine storage [67]. The evaluation method of FIDES does not consider infant mortality and the wear-out periods of the components except for some special cases for some sub-assemblies [67].

$$\lambda = \Pi_{PM} \Pi_{Process} \lambda_{Phy} \quad (11)$$

where Π_{PM} is the quality and technical control over manufacturing of the item, $\Pi_{Process}$ comprises all the steps of item processes from specification to field operation and maintenance, and λ_{Phy} is the quality and technical control over manufacturing is the physical failure rate of the item, which can be calculated in the mission profile phase as:

$$\lambda_{Phy} = \sum_i^{Phases} \left[\frac{t_{annual}}{8760} \right]_i \times (\lambda_i \Pi_i) \times \Pi_{Induced,i} \quad (12)$$

where annual is the phase duration in hours during the year. The factor $\Pi_{induced,i}$ is the induced stress factor, which includes electrical, mechanical, or thermal stresses as:

$$\Pi_{Induced,i} = (\Pi_{Placement} \Pi_{App} \Pi_{Rugg})^{0.511 \times \ln(C_{sensitivity})} \quad (13)$$

where $\Pi_{Placement}$ denotes the effect of the item placement in the system, Π_{App} represents the influence of the usage environment for the application of the product contacting the item, Π_{Rugg} represents the influence of the policy for taking account of overstresses in product development. The calculation is explained in [68] but if it is not evaluated, a default value of 1.7 is suggested with reduction in the accuracy of the final result. and $C_{sensitivity}$ is the sensitivity of the item to over stress.

Wear-Out Failures' Lifetime Prediction: In comparison with random failures lifetime prediction methods, wear-out failures' prediction is typically more complicated with more steps to calculate the reliability. The diagram in Fig. 14, demonstrates the different steps of a typical wear-out failure prediction process. The first step to do so is collecting the failure data including at least one from mission-profile data, test data, and field data. If using the mission-profile data, the next step would be the translation of this data to the thermal profile using electrothermal modeling. After the cycle counting process, a proper lifetime model should be chosen to provide the number of failures per cycle. The deviation of the output parameters after the damage accumulation is estimated to give a precise result. Lifetime distribution results in reliability are demonstrated by either CDF or PDF.

a: ELECTROTHERMAL MODELING

The fundamental step in the mission profile based reliability prediction is translating the converter's mission profile to the corresponding stresses in its prone-to-failure components [72]. Fig. 15 shows the three steps to translate the mission profile in order to achieve the junction temperature change. The first step in extracting the temperature profile from the

TABLE 3. Summary of major handbook standards.

	MIL-HDBK-217 [64]	IEC TR-62380 [69]	Telcordia [70]	217plus [71]	FIDES [68]
Last Update	1995	2016	2006	2015	2009
Operation profile	NO	Yes	NO	Yes	Yes
Thermal cycling	NO	Yes	NO	Yes	Yes
Thermal rise in part	Yes	Yes	NO	Yes	Yes
Solder joints failures	NO	Yes	NO	Yes	Yes
Induced failures	NO	NO	NO	Yes	Yes
Failure rate data base for other parts	limited	limited	NO	Yes	Yes
Infant mortality	NO	Yes	NO	Yes	NO
Dormant failure rate	NO	NO	NO	Yes	Yes
Test data integration	Yes	Yes	NO	Yes	NO
Bayesian analysis	NO	NO	NO	Yes	NO

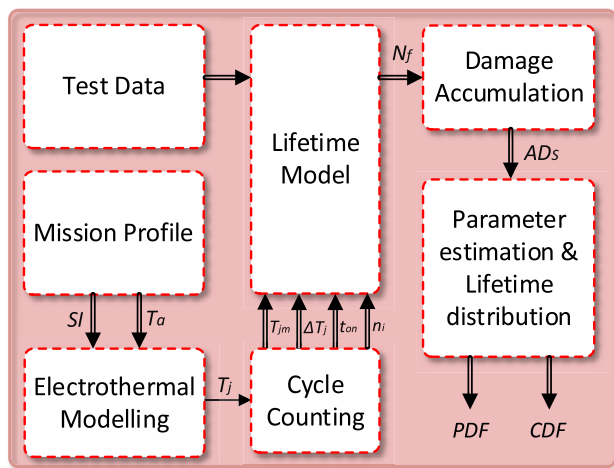


FIGURE 14. General diagram of a typical component-level lifetime prediction process.

mission profile is deriving the electrical parameters from it by using the mechanical system, electrical system, and controller. Extracted electrical parameters are used to calculate the losses in the switches and diodes using the loss model. The thermal model is used to extract the thermal loading or junction temperature from the power losses. The Cauer model or Foster model can be used as the thermal model as shown in Figs. 16(a) and 16(b) respectively [73]. A mix of both Cauer and Foster thermal models is presented in [74], which addresses the shortcomings of the two mentioned models. Using this process, the junction temperature of the power device is obtained.

b: CYCLE COUNTING

The lifetime of a power converter is associated with the magnitude and frequency of the temperature cycles. Each cycle applies different stresses to the module and resulting

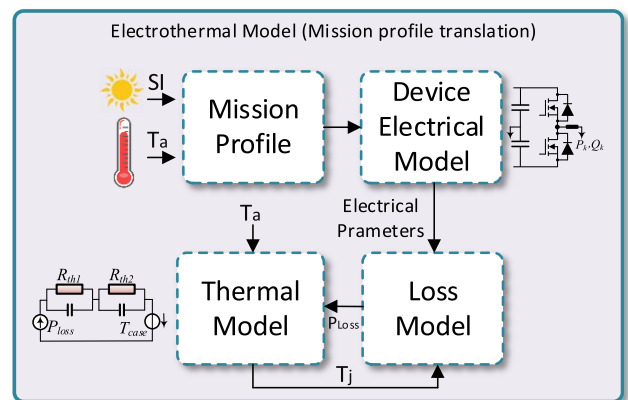


FIGURE 15. General diagram of a typical electrothermal model.

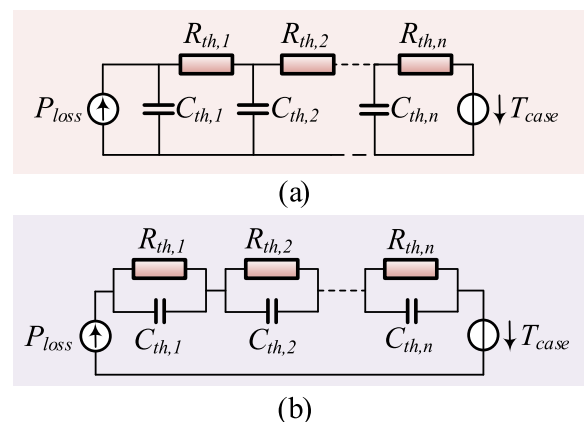


FIGURE 16. Thermal models: (a) Cauer model, (b) Foster model.

in a particular consumed lifetime. By using cycle counting, lengthy irregular load-versus-time histories are summarized by providing the number of times cycles of various sizes [50]. Parameters of cycle counting including input parameter T_j

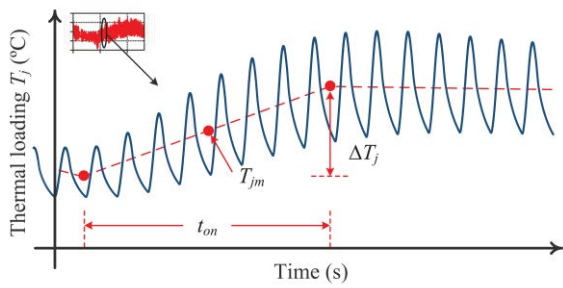


FIGURE 17. Thermal loading parameters.

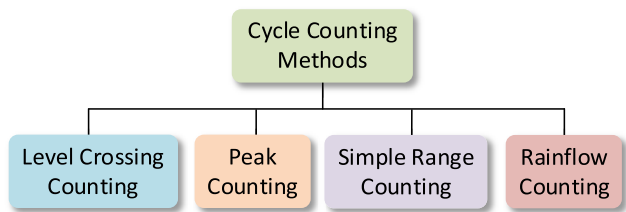


FIGURE 18. Methods of cycle counting.

and output parameters T_{jm} , ΔT_j , t_{on} are demonstrated in Fig. 17. The definition of a cycle varies with the method of cycle counting. Several cycle counting methods have been developed for lifetime prediction three of which are level crossing counting, peak counting, range counting, and the rainflow counting (Fig. 18) [42], [75].

In the level crossing counting technique (Fig. 19(a)), one count is recorded each time the positively sloped portion of the load exceeds a preset level above the reference load, and each time the negative sloped portion of the load exceeds a preset level below the reference load. Reference load crossings are counted on the positively sloped portion of the loading history. There is no difference in counting whether positive or negative slope crossings. The distinction is provided only to reduce the total number of events by a factor of two.

Peak counting (Fig. 19(b)) identifies the maximum or minimum load value. Peaks above the reference load level along with the valleys below the reference load level are counted. A modified version of his method can be obtained by counting all peaks and valleys disregarding the reference load [76].

The range counting method considers the difference between two successive reversals as a range. When a valley is followed by a peak, the range is positive, while when a peak is followed by a valley, the range is negative (Fig. 19(c)).

In the rainflow counting method (Fig. 19(d)), the first step is to rotate the loading history by 90 degrees such that the time axis is vertically downward. By imagining a flow of rain starting at each successive extremum point a loading reversal (half-cycle) is defined by allowing each rainflow to continue to drip down these roofs until it falls opposite a larger maximum or smaller minimum point, meets a previous flow falling from above and falls below the roof. By pairing

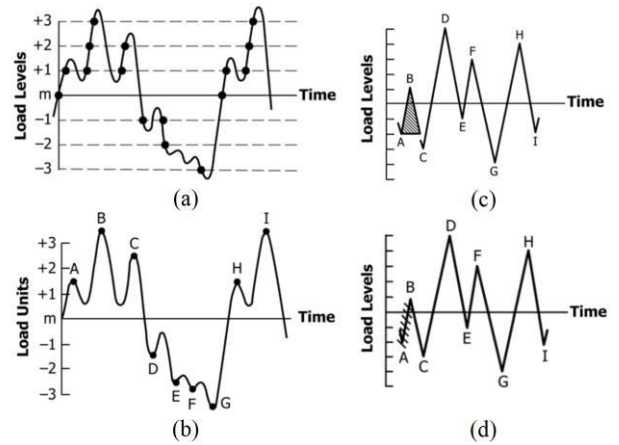


FIGURE 19. Load-time diagrams of different cycle counting methods.

up the same counted reversals, hysteresis loops (cycles) can be identified. In the rainflow counting approach, a large data storage system is required since it only processes the data in chunks which is inconvenient to implement in a real-time application. To address this issue, a real-time rainflow counting technique is proposed in [43] which uses a recursive algorithm.

c: LIFETIME MODEL

Handbook-driven approaches benefit from the straightforward failure rate calculation, however, all the aforementioned handbook approaches carry some shortcomings despite having updates on their handbooks [77].

Model-based approaches offer better accuracy since the failure rates are calculated based on the results of the real-life accelerated test results and actual physics of the components and their failure modes and mechanisms along with the effect of stresses of the product-level on the reliability of the components. There are also data-driven methods in which models are typically “black boxes” with no explicit system knowledge. Data-driven approaches involve learning statistical relationships and patterns from the failure data to provide valuable decision-making information.

i) MODEL-DRIVEN LIFETIME MODELS

Model-driven lifetime models describe degradation processes through building mathematical models based on accelerated tests using parameterization as empirical methods or based on the failure mechanisms and materials as PoF methods [23]. In theory, all model-based lifetime models have some parameters to be determined and module geometry and material properties are necessary to determine the unknown parameters. Therefore, as some PoF models need parameterization, there no definite borderline between empirical and PoF models.

ii) EMPIRICAL MODELS

Empirical models are deduced from experience and large databases of accelerated aging experimental data collected

over many years for different module technologies. The accuracy of such models can only be guaranteed when used in situations similar to the test conditions from where the models were “born” [29]. They express lifetime in terms of the number of cycles to failure, N_f . These models describe the N_f -dependence on the parameters of accelerated tests, such as maximum, mean, or minimum temperature, cycle frequency, heating and cooling times, load current, and the power module’s properties such as blocking voltage class, and the geometry of bond wires.

Coffin–Manson model is the most widely used approach among the empirical analytical modeling methods [78]. It describes the effect of the junction temperature fluctuation ΔT_j . In this case, the lifetime is inversely proportional to the temperature swing [79].

$$N_f = A \times (\Delta T_j)^{-\alpha} \quad (14)$$

where A and α are the curve fitting parameters which can be fitted using simulation or a cyclic experiment.

The Coffin–Manson model can be enhanced to provide another model by adding the effect of the mean junction temperature T_{jm} known as Coffin–Manson–Arrhenius model, where K_b is the Boltzmann constant and E_a is the activation energy parameter. It is given as [31]:

$$N_f = A \times (\Delta T_j)^{-\alpha} \times \exp\left(\frac{E_a}{K_b \times T_{jm}}\right) \quad (15)$$

Nevertheless, this model does not consider the cycle heating time, which strongly affects the bond wire fatigue. The Norris–Landzberg model takes into account the cycling frequency (f) of the junction temperature, where the β is a curve fitting parameter [31], [80].

$$N_f = A \times f^\beta \times (\Delta T_j)^{-\alpha} \times \exp\left(\frac{E_a}{K_b \times T_{jm}}\right) \quad (16)$$

Bayerer model utilizes a large number of parameters and considers more detailed information derived from the power cycling tests and power module characteristics which makes this approach more complicated than the aforementioned techniques. In this approach, two dominant failure mechanisms have been taken into account: bond wires lift-off and baseplate solder failure. Eq. 17 defines the formula of this model where T_{jm} is the maximum junction temperature, t_{on} is the heating time, V is the blocking voltage, I is the applied dc current, D is the diameter of the bond wire, and the β constants are fitting parameters [81].

$$N_f = A \times (\Delta T_j)^{\beta_1} \times \exp\left(\frac{\beta_2}{T_{jmax}}\right) \times t_{on}^{\beta_3} \times I_{DC}^{\beta_4} \times V_{block}^{\beta_5} \times D^{\beta_6} \quad (17)$$

Semikron model is defined for the advanced power modules with sintered chips in which the soldering process for the die attach is replaced by Ag-diffusion sintering technology. In this model, the bond wire lift-off and heel cracking are the only observed failure modes, so that the developed lifetime

TABLE 4. Model parameters and variables of empirical methods.

Eq.	Lifetime Model	Model Parameters	Variable Considered
(13)	Coffin–Manson	A, α	ΔT
(14)	Coffin–Manson–Arrhenius	A, α, E_a	$\Delta T_j, T_m$
(15)	Norris–Landzberg	A, α, β, E_a	$\Delta T_j, T_m, f$
(16)	Bayerer	A, α, β, E_a	$\Delta T_j, T_{jm}, t_{on}, I_{DC}, V_{block}, D$
(17)	Semikron	$A, \alpha, \beta, C, \gamma, E_a, f_{Diode}$	$\Delta T_j, T_{jm}, t_{on}$

model corresponds only to the failure mechanisms due to thermo-mechanical stress of bond wires [82], [83].

$$N_f = A \times (\Delta T_j)^\alpha \times ar^{\beta_1 \cdot \Delta T_j + \beta_0} \times \left(\frac{C + t_{on}^\gamma}{C + 1}\right) \times e^{\frac{E_a}{K_b \cdot T_{jm}}} \times f_{Diode} \quad (18)$$

where f_{Diode} is a derating factor applied for the test on free-wheeling diodes, ar is the aspect ratio of Al bond wire; β_1 and β_2 are the model coefficients determined together with the other model parameters $A, \alpha, C, \gamma, E_a$, and f_{Diode} , using a least square fitting procedure.

iii) PoF MODELS

Since empirical models lack the description of physical structures of power devices and the actual failure mechanisms, such as the crack propagation of solder layers, some researchers have begun to focus on the POF models of power devices. In this approach, the assessment of a component is done based on investigating the real physics behind the root failure mechanisms, and the impact of stress profiles, manufacturing technologies, and materials are taken into consideration along with any other factor that might affect the product’s Remaining Useful Lifetime (RUL) [29]. Different from the empirical models, the PoF models need to know the failure mechanisms and the deformation mechanisms of power devices in advance so that the stress and strain development within the power module assembly is modeled and directly correlated to the number of cycles to failure.

There are two ways of measuring the stress and strain in electronic packages: One way is direct measurements which demands the usage of high-resolution measuring methods, and the other way is through the stress analysis of materials by experiments or Finite Element Analysis (FEA).

Strain-based models assumes that plastic strain is the main cause of the bond wire lift-off and emphasize on the effects of plastic strain as follows [84]:

$$N_f = C_1 \times (\Delta \varepsilon_p)^{-C_2} \quad (19)$$

where $\Delta \varepsilon_p$ is the average accumulated plastic strain per cycle and C_1 and C_2 are material-specific parameters.

By adding the effect of solder fatigue, Eq. (20) will be obtained:

$$N_f = \frac{L}{a \times (\Delta \varepsilon_p)^b} \quad (20)$$

where L is the length of the solder interconnect and a and b are material-dependent constants.

Stress-based model uses the Basquin equation to describe the damage induced by stress range [85]:

$$N_f = C_1 \times (\Delta \sigma)^{-C_2} \quad (21)$$

where $\Delta \sigma$ is the stress range and C_1 and C_2 are material-specific parameters.

Energy-based approach is consider both stress and strain and are based on the strain–stress hysteresis energy as follows [86]:

$$N_f = \frac{E_f}{E_c} \quad (22)$$

where E_f is the total energy to failure and E_c is the energy per cycle.

Crack-based models are based on the crack propagation within the assembly of a chip soldered on a copper substrate which can be characterized by scanning acoustic microscopy, measurements of the thermal resistance, and FEM for predicting the crack initiation and propagation using the Paris law [87].

$$\begin{aligned} N_0 &= C_1 \times (\varepsilon_a)^{C_2} \\ \frac{da}{dN} &= C_3 \times (\varepsilon_a)^{C_4} \end{aligned} \quad (23)$$

where ε_a is the mean value of the integrated accumulated creep strain along the lines coinciding with the direction of the crack propagation, N_0 is the number of cycles until crack initiation, da/dN is the crack propagation rate, and the constant parameters C_1 , C_2 , C_3 , and C_4 are the material-dependent coefficients, which are determined by means of FEM simulations.

iv) DATA-DRIVEN MODELS

The data-driven methods require less complexity in prediction compared with PoF techniques. The benefit of the remaining time and energy can be used in designing and verification of the algorithm. In this method, the model is built based on the operational data of different periods derived from a large number of experiments [41].

Generally, the data-driven methods fall into two categories: The statistical approaches including Gaussian Process Regression (GPR), the gamma process, the Wiener process, hidden Markov Chains model (MC). There is also Artificial Intelligence (AI) approaches that include Artificial Neural Network (ANN), fuzzy logic, Support Vector Machine (SVM), and Deep Learning (DP). Among these algorithms, ANN and GPR are the most used data-driven approaches [88].

Regression-based models are the most commonly used statistical data-driven techniques. The GPR method is based

on the idea that the higher the similarity of two inputs, the stronger the correlation of the corresponding outputs. It assumes that both predicted and historical parameters follow the multi-dimensional joint Gaussian distribution, and the marginal distribution of the predicted parameter can be obtained using the calculation of the covariance matrix [89]. GPR shows good adaptability in high dimensional, small-sample learning problems as well as nonlinear prediction problems. In addition, it benefits from less adjustable parameters and strong interpretability high computation needed in this approach can be seen as a drawback. Modeling through the Wiener process or Brownian motion with drift is suitable when the degradation develops bidirectionally over time with Gaussian noises. Gamma process models are applied in cases in which the occurrence of the degradation is gradual over time in a sequence of small positive increments. These models take the advantage of having relatively straightforward mathematical calculations along with taking into consideration the temporal variability.

AI modeling methods help reduce the computational burden and the need to store huge loads of lifetime data [90]. Fig. 21 shows all possible machine learning approaches some of which have been used in the reliability assessment of power electronic systems and other techniques have the potential to further be investigated in this field.

One group of AI approaches are neural network methods three of which are Feed Forward Neural Network (FNN), Recurrent Neural Network (RNN), and Convolution Neural Network (CNN). FNN is the fundamental form of neural network which maps the input to output in a forward direction. Another form of Neural Network is RNN which is designed to recognize sequences. This technique has been extended across time by having edges feeding into the next time step instead of into the next layer in the same time step. The third neural network approach is CNN which is based on recognizing images using convolutions inside to identify the edges of an object on the images [91]. For data analysis, FNN is much more suitable, while RNN and CNN are mostly used in the processing and recognition of images, texts, audio, videos, etc., where sequence and spatial features are the important factors.

In the ANN approach in [92], the first step is providing the lifetime data associated with operating conditions using electro-thermal models and stress-strength analysis. As a result, a set of limited lifetime data (L_i) attributed to the active and reactive powers (P_i , Q_i) is generated. In the case of using the data of the manufacturer, providing electro-thermal and lifetime models is not needed which might be confidential in most cases. In the second step, the generated lifetime data is utilized to train the ANN network depicted in Fig. 20. The input for the next layer is generated by processing the information from the neurons of the preceding layer. Thus, the performance index is provided by ANN employing the limited lifetime data.

The final step consists of classifying the active and reactive power profiles and presenting their frequency by a Probability

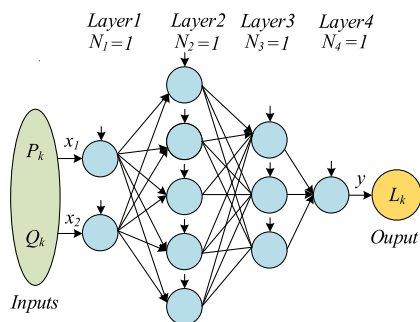


FIGURE 20. Sample ANN structure.

Mass Function (PMF). The converter lifetime associated with each pair of P_i and Q_i is obtained using the performance index curves provided in the third step or predicted by using the ANN trained in the second step. Therefore, the B_n lifetime under a given mission profile can be predicted as Eq. 24, where F_i is the frequency of the active and reactive powers:

$$L(B_n) = \left(\sum F_i/L_i \right)^{-1} \quad (24)$$

A time-delay failure model using ANN is used in [93] in combination with the probabilistic function by utilizing the maximum likelihood technique for IGBT model optimization. In [94], a recurrent neural network approach is employed in the prognostics of the system [88].

In the SVM technique, which is a supervised machine learning method based on classification, structural risk minimization is used instead of empirical risk minimization. It solves the typical ANN problems associated with prediction and classification, non-linear functions, and loss functions. SVM finds a line/hyperplane in multidimensional space to separate the classes and classifies the new data depending on whether it lies on the positive or negative side of the hyperplane depends on the classes to predict [95].

Support Vector Regression (SVR) is another supervised machine learning technique similar to SVM but with the difference that it is based on regression rather than classification [96], [97].

In [98], a deep learning approach is used combined with edge and cloud computing technologies to enable a real-time precise reliability modeling of high-frequency power converter devices. It is based on stacked long short-term memory for collective reliability training and inference across collective MOSFET converters by detecting the change in the drain-source resistance.

d: DAMAGE ACCUMULATION

After the damage caused by each thermal cycle is determined, the total accumulation of damage is calculated, and an initial estimation of the device's lifetime can then be obtained by either linear or nonlinear means [99]. One of the commonly used methods in damage accumulation evaluation is the Palmgren-Miner law [81]. The formula for calculating

the damage accumulation by this method is as follows:

$$D = \sum_{i=0}^N \frac{n_i}{N_i} \quad (25)$$

where D stands for accumulated damage, N stands for the total number of power cycles generated by the rainflow counting algorithm, n_i is the number of cycles for i^{th} power cycle, N_i is the number of cycles to failure at the corresponding ΔT_j and T_m in the i^{th} power cycle [56].

However, this approach has some limitations including considering the damage accumulation rate constant during the lifetime along with being independent of the loading levels leading to reduced lifetime prediction accuracy. More damage would increase the stresses which cause additional physical mechanisms resulting in a different damage accumulation rate [100]. For instance, when the crack propagates, as a result of increased power loss, thermal resistance increases which leads to an accelerated damage accumulation rate in bond wires and solder layers. Hence, the predicted lifetime using linear methods would be impractically longer.

The nonlinear damage accumulation approach reflects the accumulation rate change in different stress levels. A technique based on the double linear damage law analyzes each phase of the loading using the Palmgren-Miner linear damage method. However, it does not take into account the mutual interaction among different stresses [34], [101]. Manson-Halford model addresses this issue by considering both stress sequences and interaction by changing the exponent parameter in the double linear damage model [102], [103]. There are nonlinear approaches that take into account the damage accumulation rate change by placing proper weights onto the affected physical parameters. As detailed experimental data are needed to determine these weights, these techniques are not applied much [34].

Fatemi and Yang [104] in 1998 published a very comprehensive review that categorized cumulative damage models in six categories: (a) linear damage rules, (b) nonlinear damage curve and two-stage linearization methods, (c) life curve modification methods, (d) approaches based on crack growth concepts, (e) continuum damage mechanics models, and (f) energy-based theories. As one of the recent reviews, [105] has reviewed cumulative damage models for high-cycle fatigue.

e: PARAMETER ESTIMATION AND LIFETIME DISTRIBUTION

The basic idea of parameter estimation is modeling the parameters used in the calculation (e.g., stress parameters in a lifetime model) using a certain distribution function ($f(x)$), instead of fixed parameters [50] with a range of variations (e.g., normal distribution with 5% parameter variation). In this way, the parameter variations can be introduced in the calculation to represent uncertainties in practical applications. Then, the lifetime evaluation is carried out with a set of n samples. By doing so, the lifetime distribution (e.g., the

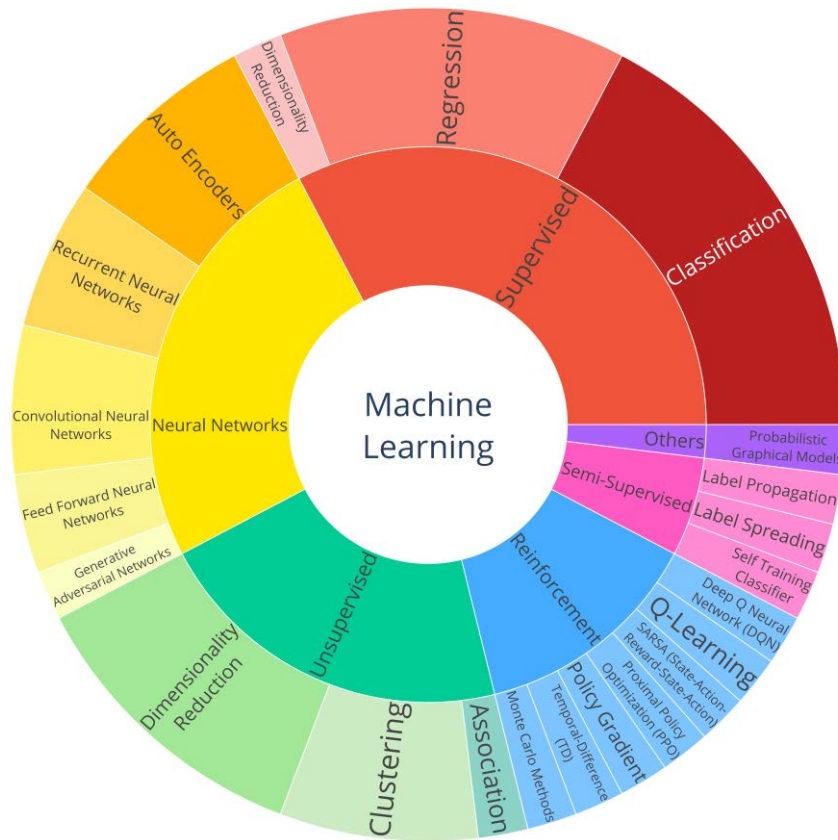


FIGURE 21. Various methods of machine learning [112].

Weibull distribution) of a power electronic component can be constructed from the lifetime yield of n samples [106].

Different distribution methods are defined in Table 5. Weibull distribution is the most popular distribution in lifetime prediction. In this method, the shape parameter β represents the failure mode of the component, where the components that have experienced the same failure mode/mechanism will have similar shape parameter β [107].

Monte Carlo simulations are widely used for analyzing the stochastic behavior of model parameters, which represents uncertainty in the prediction [7]. The Monte Carlo method is based on simulating the model parameters with a certain distribution, representing variation, and randomly selecting them during each simulation [108]. In the next step, if the number of simulations is large enough, the simulation results are expected to converge to the expected value, based on the law of large numbers [109]. In this case, the Monte Carlo simulation (with a large number of simulations) will thus result in a distribution indicating the probability of each of the possible outcomes [110].

After that, the PDF is obtained using a distribution in Table. 5. From the lifetime distribution of the component it is also possible to obtain the component unreliability function $F(x)$, which is the CDF of the distribution (Fig. 22) [111]. The unreliability function can be used to indicate the development of failure overtime. For instance, the time when $x\%$ of the

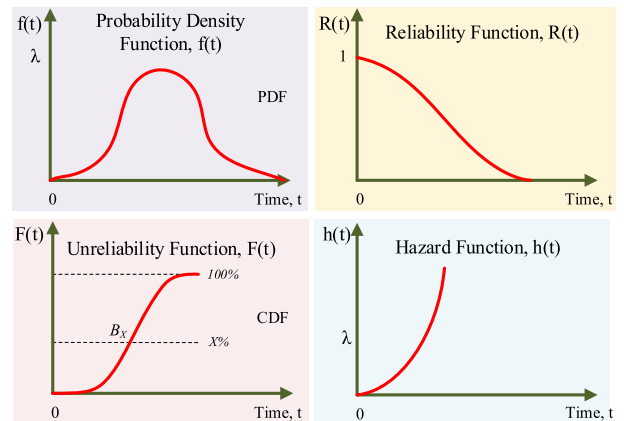


FIGURE 22. Weibull distributions of reliability for wear-out failures.

components failed can be obtained from the unreliability function, and it is normally referred to as the B_x lifetime (Fig. 22(b)) [50].

Comparison of Lifetime Prediction Methods: Lifetime prediction methods are compared in Table 6 mentioning their advantages and disadvantages. Handbook-driven lifetime prediction approaches benefit from the simplicity of usage and using the real field data. However, they are considered to be inaccurate, especially in the presence of new

TABLE 5. PDF and CDF formulas for different distributions [54], [113], [114].

Distribution		CDF	PDF
Uniform		$F(t) = \begin{cases} \frac{t-a}{b-a} & a \leq t \leq b \\ 0 & \text{Otherwise} \end{cases}$	$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{Otherwise} \end{cases}$
Triangular		$F(t) = \begin{cases} \frac{(t-a)^2}{(b-a)(c-a)} & a \leq t \leq c \\ 1 - \frac{(b-t)^2}{(b-a)(b-c)} & c \leq t \leq b \end{cases}$	$f(t) = \begin{cases} \frac{2(t-a)}{(b-a)(c-a)} & a \leq t \leq c \\ \frac{2(b-t)}{(b-a)(b-c)} & c \leq t \leq b \end{cases}$
Normal		$F(t) = \Phi\left(\frac{t-\mu}{\sigma}\right)$	$f(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\right)$
Lognormal		$F(t) = \Phi\left(\frac{\ln t - \mu}{\sigma}\right)$	$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln(t)-\mu)^2}{2\sigma^2}\right)$
Weibull	2 Parameters	$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^\beta}$	$f(t) = \frac{\beta t^{\beta-1}}{\eta^\beta} e^{-\left(\frac{t}{\eta}\right)^\beta}$
	3 Parameters	$F(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^\beta}$	$f(t) = \frac{\beta(t-\gamma)^{\beta-1}}{\eta^\beta} e^{-\left(\frac{t-\gamma}{\eta}\right)^\beta}$
Extreme Value	Min	$F(t) = 1 - \exp\left(-\exp\left(\frac{t-\eta}{\sigma}\right)\right)$	$f(t) = \left(\frac{1}{\sigma}\right) \exp\left(-\exp\left(\frac{t-\mu}{\sigma}\right)\right) \left(1 - \exp\left(-\exp\left(-\frac{t-\mu}{\sigma}\right)\right)\right)$
	Max	$F(t) = \exp\left(-\exp\left(\frac{t-\eta}{\sigma}\right)\right)$	$f(t) = \left(\frac{1}{\sigma}\right) \exp\left(-\exp\left(\frac{t-\mu}{\sigma}\right)\right) \exp\left(-\exp\left(-\frac{t-\mu}{\sigma}\right)\right)$

TABLE 6. Summary of advantages and disadvantages of various component-level lifetime prediction methods.

Method	Advantages	Disadvantages
Handbook-driven	<ul style="list-style-type: none"> ✓ Reflects actual field failure rates and defect densities ✓ Simplicity of usage ✓ Can be a good indicator of field reliability 	<ul style="list-style-type: none"> ☒ Difficult to keep up to date ☒ Difficult to collect good-quality field data ☒ Difficult to distinguish cause vs effect for the correlated variables (e.g., quality vs environment).
Model-driven	<ul style="list-style-type: none"> ✓ Modeling of specific failure mechanisms ✓ Explicitly considers the impact of design, manufacturing, and operation on the end-of-life 	<ul style="list-style-type: none"> ☒ Cannot be used to estimate field reliability ☒ High complex and expensive to apply ☒ Cannot be used to model defect-driven failures
Data-driven	<ul style="list-style-type: none"> ✓ Reflects the actual reliability ✓ Test data can be collected and applied before the system is deployed 	<ul style="list-style-type: none"> ☒ Translations to field stresses are required, which requires acceleration models and adds uncertainty to the estimate

approaches that precisely take into account the wear-out phase of the components and systems.

The main drawback of the PoF lifetime model is the complexity of usage since a deep understanding of the root mechanisms of the failures is needed. However, it has features making it a proper approach for reliability assessment as it explicitly considers the impact of design, manufacturing, and operation on the end-of-life of the products [115].

Data-driven modeling has shown a number of key advantages over its physics-based counterpart, such as substantially reducing the expertise required to use the models.

2) HYBRID LIFETIME PREDICTION

The hybrid models combine at least two of the lifetime prediction methods as shown in Fig. 23 [116]. As an example, [117] combines handbook-driven assessment using MIL-HDBK-217 handbook and model-based method using Coffin-Manson-Arrhenius model in order to take into account both models along with IEC 62380 handbook. Using a hybrid method provides a more precise and comprehensive lifetime prediction and makes it possible to benefit from the merits of each technique and overcome its deficiencies.

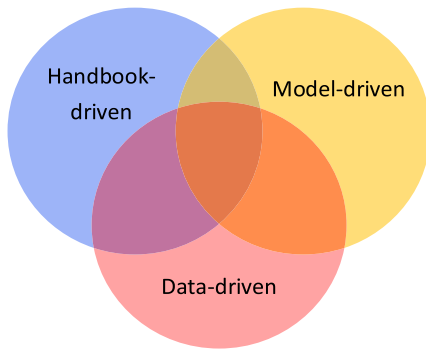


FIGURE 23. Venn diagram of three lifetime prediction methods to create hybrid methods.

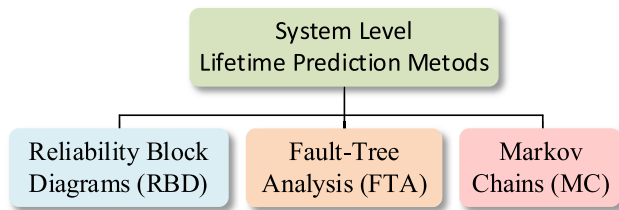


FIGURE 24. System-level lifetime prediction methods.

B. SYSTEM LEVEL LIFETIME PREDICTION

Various methods are used to map the reliability of the components to the systems, including Reliability Block Diagrams (RBD), Fault-Tree Analysis (FTA), and Markov Chains (MC) [118], as shown in Fig. 24.

RBD models the impact of a failure on the system, without necessarily modeling the mechanical structure. Therefore, in this method, the failure of components that are physically present only once in the system may occur at several locations. Fig. 25(a) demonstrates the typical series and parallel RBD diagrams in which the node I is the input and the node O is the output. The system functions whenever there is a path between the input and output nodes formed by the functioning components, otherwise, the system fails [119].

FTA is an analytical technique that applies a top-down approach to analyze the various system combinations of hardware, software, and human failures as sub-events that may cause the system failure as the top event [37], [120]. This method classifies the events as initiating fault events, intermediate events, and top events and uses logic gates such as AND, OR, etc., to transform the component-level lifetime data to the system-level (Fig 26(b)) [19], [25], [61].

MC is a state space analysis method that assumes that the future behavior of the system depends only on the current state and the system is memoryless. Fig. 25(c) depicts a typical MC with three states in which $P(i, j)$ is the transition probability [121]. Compared to the other system-level approaches, MC is well suited to modeling additional system states introduced by fault-tolerance or redundancy, along with the maintenance and repair process. For instance, a simple fault-tolerant system may consist of three states, including

the healthy state, the failure state, and the post-fault state. The healthy and postfault states are both considered as operational states [77]. The MC approach can be simulated as a state space system, in which the state variables are the probabilities that a system will reach each state over time [122].

The state matrix can be provided using the Markov transition rates $P(i, j)$, which in the case of modeling the reliability they can be the summation of the failure rates [25]. The reliability assessment of several dc-dc converters has been done using MC in [60], [122], [123], [124], and [125].

System-level lifetime prediction methods are summarized in Table 7 indicating the elements used in these approaches along with the merits and drawbacks of each technique.

IV. LIFETIME EXTENSION

Although lifetime analysis and prediction are important and fundamental steps of achieving high reliability, performing them is not enough to achieve reliable products. There is a set of other activities involved in an effective reliability plan to achieve reliable products. Achieving a product's reliability goals requires a strategic vision to use a design process that insures reliability. The necessity of taking the advantage of a proper condition monitoring procedure as an efficient, non-intrusive process that has the potential to prevent production loss and guarantee long-term productivity, is inevitable.

A. RELIABLE DESIGN

During the early development stages of the product, reliability analysis tools are used to ensure that the product design meets specific lifetime and safety criteria. Typically, after several design iterations, and only after the reliability requirements have been met, the product can move forward toward more mature product lifecycle stages [126].

1) DESIGN FOR RELIABILITY (DfR)

Design for X (DfX) is a design guideline that proposes an approach with its corresponding methods that may help to provide and apply technical knowledge to control and improve a particular feature of a product [127]. Currently, around 50 different DfX approaches have been proposed and explored in extensive papers by industry experts. DfX approaches can be developed around any feature that is critical to the product and its manufacturer or the organization.

By considering reliability in DfX as an important feature of every product, DfR is obtained. DfR describes a comprehensive set of tools that help to support product and process design from early on in the conception stage through to the point of obsolescence. As a result of this process, the customer can expect full customer satisfaction throughout the life of the product with low overall life-cycle costs [22]. To put it simply, DfR is a systematic, streamlined, concurrent engineering program that incorporates reliability engineering into the design process. To accomplish this, reliability engineering tools must be properly used in conjunction with an understanding of when and how to use them throughout the development cycles. A manufacturer must follow this process

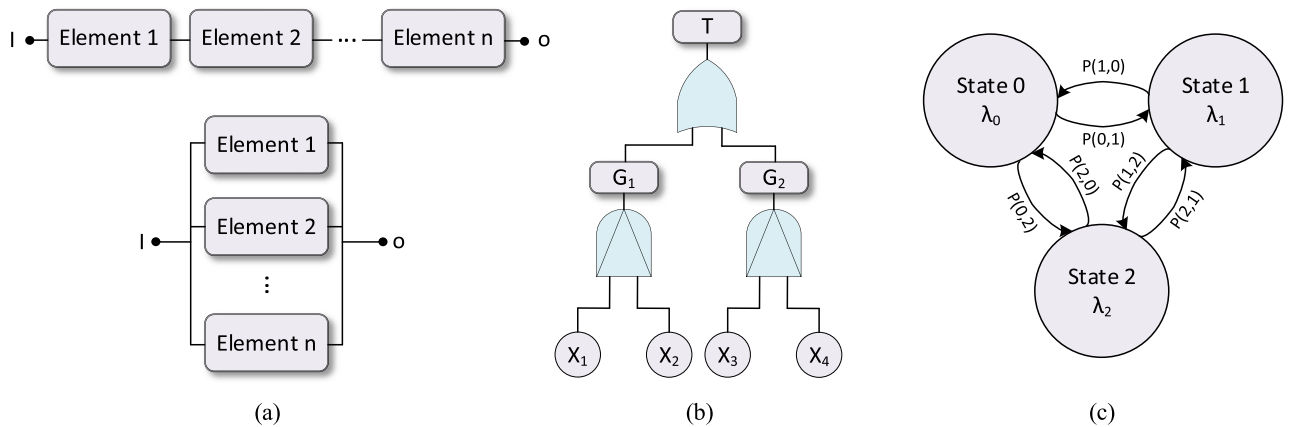


FIGURE 25. Sample diagrams of different system-level lifetime prediction methods. (a) RBD, (b) FTA, (c) MC.

TABLE 7. Summary of various system-level lifetime prediction methods.

Method	Elements	Advantages & Disadvantages
MC	<ul style="list-style-type: none"> ▪ States ▪ Probability transitions between states ▪ Transition rates 	<ul style="list-style-type: none"> ✓ It is dynamic since it represents the state of every component along with the dependences among them at any time. ✓ It can be employed for repairable systems. ☒ A large number of state-based models since the number of states can be 2^n with n components. ☒ Only applied for constant failure and repair rates which neglect the wear-out phase.
RBD	<ul style="list-style-type: none"> ▪ Rectangle blocks ▪ Direction lines ▪ The failure rate of the components or the subsystems represented by each block 	<ul style="list-style-type: none"> ✓ Simplicity and ease of use. ☒ Limitations in considering external events such as the human factor and priority of the events. ☒ Inadequacy of the handling of dependencies between components and subsystems.
FTA	<ul style="list-style-type: none"> ▪ Events ▪ Logic gates ▪ Probability of each event 	<ul style="list-style-type: none"> ✓ Considering all factors including human factors. ✓ Identifying the failure causes and design problems. ☒ Difficult to manage dependencies among components and subsystems.

in order to benefit from a reliable design of its products as it entails using a wide range of tools and practices [128].

A product fails when the stress experienced by the product exceeds its strength according to the Stress-Strength Interference principle [19]. The interference between stress and strength which is the dashed area in Fig. 26, must be reduced to reduce the failure probability. This goal can be accomplished by means of a structured process, such as the DFR process. Fig. 27 represents a flowchart of a sample DFR process used by Reliasoft and its different stages along with the interactions between them. According to the product type and the amount of information available, the sequence of the activities within the DFR process may differ. While this

process is depicted in a linear sequence, in reality, some activities are likely to be performed in parallel or in a loop based on the knowledge gained as the project progresses.

The DfR process can be divided into six main activities to make it general and applicable to varied industries. As shown in Fig. 28, these stages are as follows: 1) Identify, 2) Design, 3) Analyze and Assess, 4) Quantify and Improve, 5) Validate and 6) Monitor and Control [129].

B. CONDITION MONITORING

After designing the power electronic systems, their reliability can be further improved using condition monitoring. The purpose of condition monitoring is to detect a significant

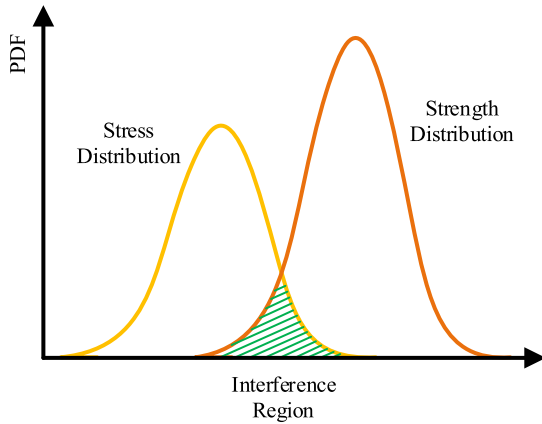


FIGURE 26. Illustration of stress-strength interference.

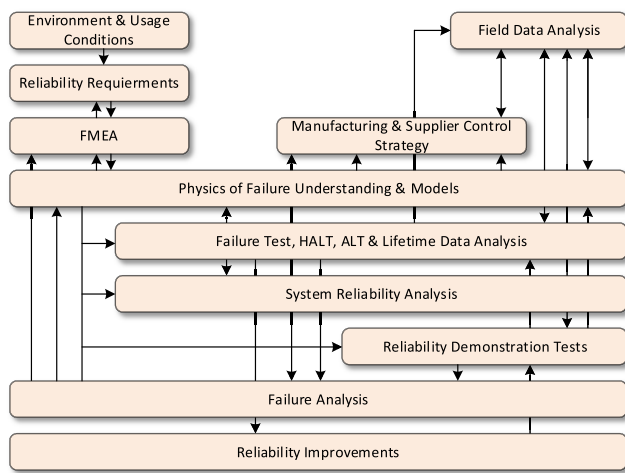


FIGURE 27. Flowchart of a sample DFR process.

change in a parameter such as vibration and temperature with an indication of a developing fault in product [126]. By using condition monitoring, maintenance and other precautions to prevent the failures can be scheduled, in order to minimize the consequences [130]. During the implementation of any control process, monitoring is a crucial function. All the closed loop control approaches rely on the monitoring the output variables of the process. Besides controlling, it is also used to provide information about converter’s failure status. The general diagram of condition monitoring is demonstrated in Fig. 29.

1) DIAGNOSTICS

Diagnostics involves determining a problem or fault in a product, system, or component and analyzing the root causes of the problem [64], [69]. It focuses on existing data to diagnose the failure modes and their pattern.

2) PROGNOSTICS

Prognosis is a technique that makes use of the acquired condition monitored data to predict a variety of useful information

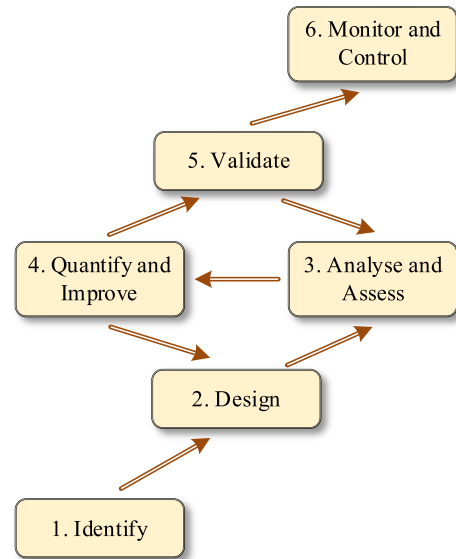


FIGURE 28. General diagram of a typical DFR process.

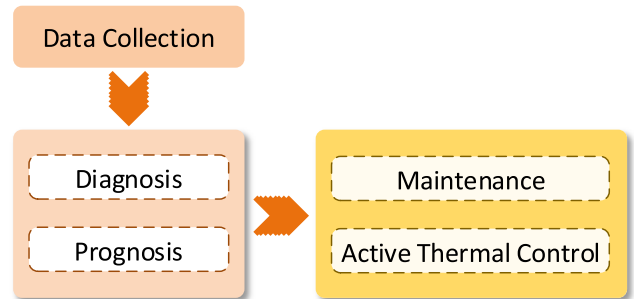


FIGURE 29. General diagram of the condition monitoring process.

relating to the condition of the system or the component [35]. It is an estimation technique for the RUL of a product, the probable condition of the device after the specified time, and the probabilities of reliable operations henceforth [130]. The advantage of the prognostic technique is reducing the repair cost and unforeseen failures since at this stage, faults and failures along with the end-of-life of the product are predicted.

3) MAINTENANCE

The term maintenance refers to recurring and regular processes used to keep a unit or component in a healthy and operating condition so that it is capable of producing the expected outcome without degrading service or decreasing component life. There are four types of maintenance approaches in practice as explained in Fig. 30 including reactive maintenance, preventive maintenance, prescriptive maintenance, and predictive maintenance [39].

4) ACTIVE THERMAL CONTROL

By using degradation indicator data from online condition monitoring, a system lifetime can be passively maintained and actively maintained. There are a number of techniques

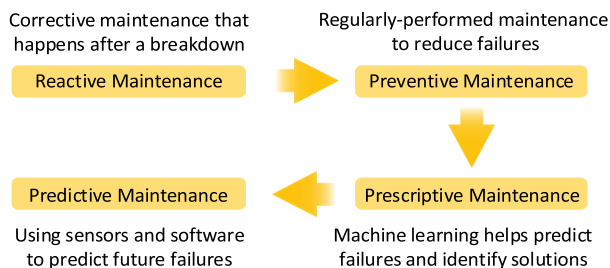


FIGURE 30. Different maintenance methods with arrows showing their evolution direction.

available for component-level active thermal control of power switches, such as switching frequency control, active cooling control, PWM control modification, turn-off delay time control, and hybrid control [131].

V. CONCLUSION

The reliability of power converters can be discussed from two aspects including lifetime management and fault management. The lifetime of power converters is one of the most influential factors on initial investment and economic analysis of a project. If the converters' replacement and maintenance costs exceed the equipment's manufacturing costs, this will generate a negative return on investment.

The first step in the assessing the lifetime of the components, is analyzing the physics of their potential failure mechanisms helps the reliability enhancement efforts to strengthen the lifetime of the converter's stresses caused by temperature increases and abrupt temperature fluctuations are the main mechanisms of failure in power switching devices as one of the main prone-to failure components of converters.

In order to assess the reliability of a converter, handbook-driven methods can be used in the early stages of the design to quickly obtain the lifetime prediction of random failures of power electronic components. However, researchers are shifting away from simple handbook-driven approaches to model-driven and data-driven methods in research on power electronics reliability which consider the wear-out failures. Lifetime prediction of wear-out failures at the component level consists of five steps including electrothermal modeling, cycle counting, lifetime model, damage accumulation, parameter estimation, and lifetime distribution. Among the four cycle counting methods, rainflow counting is considered the best and the most popular method. Model-based lifetime models consider the effect of design, manufacturing, and operation on the end-of-life of the products are considered, while data-driven modeling methods reduce the expertise required to use the PoF models by considering the system as a box without the need for understanding the root failure mechanisms. In model-based lifetime models, since the intrinsic degradation mechanism or empirical knowledge is considered, compared with data-driven methods, model-driven methods can be effective even when the reference data are not sufficient. Using PoF to assess reliability is still an

open topic of research, while interactions between different failure mechanisms will make the analysis more complex. The data-driven strategies especially the approaches based on machine learning are to be further studied. Palmgren–Miner's Law is commonly employed in fatigue damage accumulation. It is encouraged to conduct further research on nonlinear damage accumulation techniques such as the Manson–Halford model instead of only considering the linear approaches. Most of the system-level lifetime modeling for converters has been conducted by using an RBD or MC.

Reliability assessment gives us a valuable understanding of how to extend the lifetime of the converter. The fundamental effort to extend the lifetime happens during the design process using reliable design processes such as DfR. Condition monitoring is crucial after the design process to maintain the lifetime which includes data collection, diagnostics, prognostics, maintenance, and active thermal control.

The combined benefits of lifetime prediction and condition monitoring approaches make it easier for companies to choose when to carry out maintenance operations based on cost considerations.

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