Outlook to the Future of Reliability

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Chapter 16
Outlook to the Future of Reliability

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16.1 The (Reliability) Future Is Bright

Reliability is often said to be the "quality over time," but this is not correct. Reliability has its own measures, so-called critical to reliability parameters (CTR), that can have a relation to the critical to quality parameters (CTQ). The link between those two parameters is hidden within two available measures:

1. The number of product recalls
2. The cost of non-quality [CoNQ]

A product recall is a request to return to the maker a batch or an entire production run of a product, usually due to the discovery of safety issues. The recall is an effort to limit liability for corporate negligence (which can cause costly legal penalties) and to improve or avoid damage to publicity. Recalls are costly to a company because they often entail replacing the recalled product or paying for damage caused by use, although possibly less costly than consequential costs caused by damage to brand name and reduced trust in the manufacturer. In the USA, the best source for recalls is http://www.recalls.gov [1]; in Europe it is RAPEX [2]. Both sources

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report a significant increase in the number of recalls over the past 20 years. Even more, in 2022, for the second consecutive year, more than 1 billion units of food, drugs, medical devices, automobiles, and consumer products were recalled in the USA [3]. According to Sedgwick's latest state of the nation recall index report, 2022 was a record-breaking year for the number of units recalled, reaching nearly 1.5 billion [3]. The number of (electronic) consumer product recalls increased by nearly a third (31.2%) in 2022 over 2021, with 23.4 million units recalled in 2022. These are devastating numbers which, if managed poorly, often wreak devastating consequences on a company's reputation, market share, and bottom line. The biggest costs of a product recall event are business interruption, loss of sales, and reputational damage.

The first major recall occurred in the USA in 1959 when General Motors Cadillac's car suffered from a steering linkage (pitman arm) that failed on many cars while making a 90-degree turn at 10 to 15 mph (24 km/h). It turned out to originate from a reliability issue; the arms were made of metal somewhat softer than that usually employed to withstand the stresses of low-speed turns. The most famous recall occurred worldwide in 2006, when all large notebook manufacturers had to recall their computer batteries. Over 7 million batteries were recalled, after several instances where the batteries overheated or caught fire. The root cause turned out to be a short-circuit failure which becomes apparent as the batteries age and perform repetitive charging cycles, a clear example of reliability issue. One of the most recent recalls concerns the grounding of the Boeing 737 MAX passenger airliner worldwide between March 2019 and December 2020—longer in many jurisdictions—after 346 people died in 2 crashes: Lion Air Flight 610 on October 29, 2018, and Ethiopian Airlines Flight 302 on March 10, 2019 [4]. Eventually, a design flaw was discovered in its Maneuvering Characteristics Augmentation System (MCAS), which led to these crashes [5]. It is currently considered as one of the largest recalls as of today, accounting for over $1.0 billion. But brand damage exceeds this amount, as the company estimated a loss of $18.4 billion for 2019 and it reported 183 canceled MAX orders for the year. It is an example of reliability flaws; note there are many examples that have much higher cost values, e.g., the NOx emission scandal accounting for $14.6 billion costs.

Cost of non-quality (CoNQ), also denoted by cost of poor quality (COPQ) or poor-quality costs (PQC), is defined as costs that would disappear if systems, processes, and products were perfect. The term was popularized by IBM quality expert H. James Harrington [6]. The CoNQ has several origins, being yield loss during manufacturing, scrapping costs of parts, costs for rework in manufacturing, repair and/or recall cost, and product liability costs. Warranty Week [7] reports the warranty reserve funds of all semiconductor manufacturers at the end of each calendar year. Warranty reserves for the semiconductor industry exceeded $800 million for the first time in 2022, framing the US-based semiconductor and printed circuit board industry. This is the second year in a row that total claims have risen by around $150 million; in 2020, the industry paid $500 million and, in 2021, $650 million [7]. Figure 16.1 depicts the industry average warranty claims and accrual rates as a % of product sales in the period 2003–2022. Over a period of 20 years,

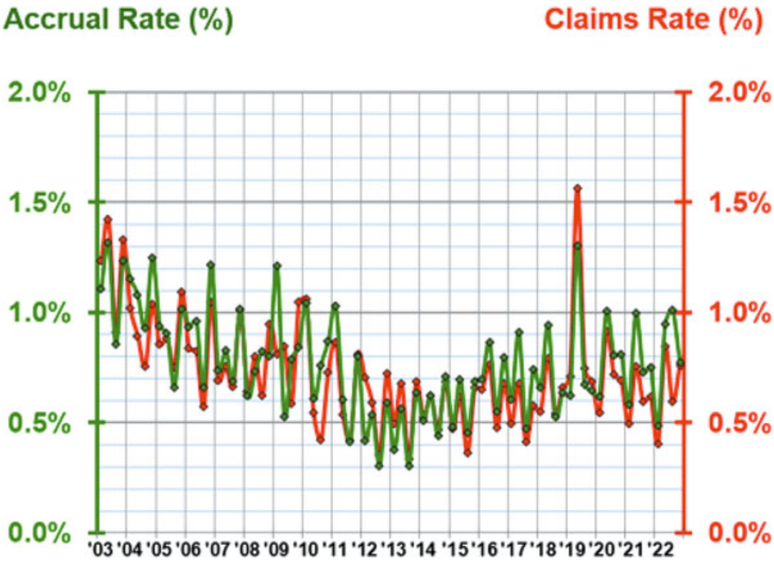


Fig. 16.1 US-based semiconductor industry average warranty claims and accrual rates (as a % of product sales, 2003–2022). (Taken from [7], with permission)

the average claims rate was 0.73%, with a standard deviation of 0.24%, and the average accrual rate was 0.77%, with a standard deviation of 0.24% as well. On the one hand, this is respectful low number accomplished by an industry that is really defined by new and innovative technology. On the other hand, the semiconductor market size was valued at $573 billion in 2022 and will grow to $1380 billion in 2029. With a claims rate of around 1.0%, the semiconductor industry is facing a CoNQ as large as $5 to $10 billion.

It is not straightforward to retrieve that part of the CoNQ that is related to the loss and/or lack of reliability. Repair and/or replacement of products may well be because the product did not perform its intended function within the warrantee period. But manufacturing errors and scrapping parts are not related to reliability. A rough estimate reveals that approximately 40% of the CoNQ are purely reliability related [8]. Of course this differs from industry to industry and strongly depends on the technology used. Still, with the CoNQ as large as $5 to $10 billion, this would give a reliability-related value of approximately $1 billion on annual basis. So truly, the (reliability) future is bright. Bringing down these huge expenses with only 25% would bring a substantial benefit for each company as it impacts directly on the profit.

16.2 Applying Multi-scale and Multi-physics Simulations for Physics of Degradation

Multi-scale and multi-physics applications are now commonplace. A significant number of studies have used and/or are using state-of-the-art simulation techniques for first-time-right development and/or physics-of-failure purposes [9–19]. Different levels of abstraction can define modeling and simulation tools, from circuit simulators such as SPICE to computationally complex models using computational fluid dynamics [9, 10], molecular dynamics [11–13], and finite elements [14–18]. As such, simulation experts undertake these complex analyses, passing on the requirements/constraints to product designers. A mesh-based model such as finite element or computational fluid dynamics cannot be used to address the multi-physics interactions spanning these scales. This is also the case in the time domain, where key electrical effects can take place at ns scales, whereas thermal and mechanical issues can take seconds or even years (in the case of reliability) to appear. To address the issue of dimension and time scaling, modeling techniques based on sub-modeling, compact models, or response surface models are available. For heterogeneous integrated systems, what level of model abstraction is appropriate, and how we exchange data effectively between these is a key challenge. Figure 16.2 details examples of models of different levels of abstraction that are used for electronic systems.

The 2021 edition of the Heterogeneous Integration Roadmap (HIR) modeling and simulation chapter details the key challenges and potential solutions over 5-,

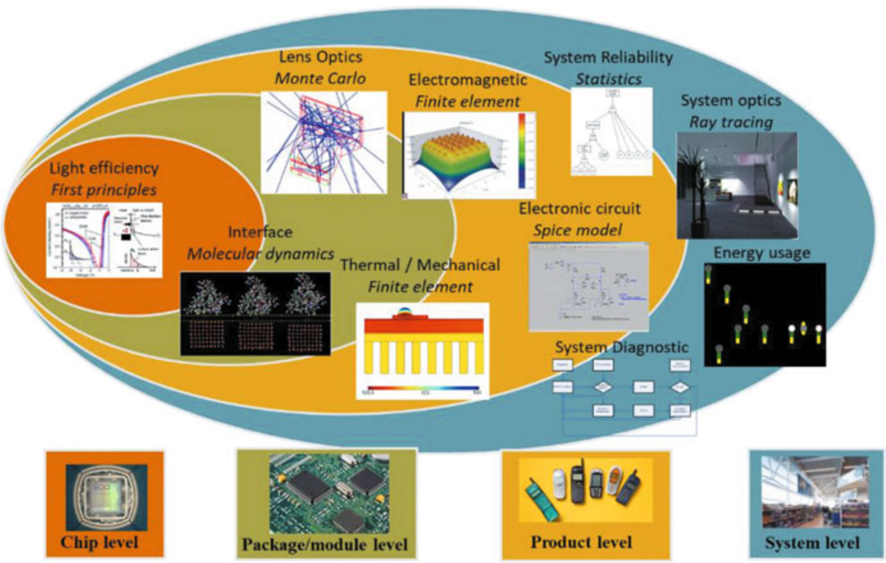


Fig. 16.2 Modeling and simulation landscape for electronic systems

10-, and 15-year horizons and details how these tools will support the knowledge base for electronic systems [20]. Although a lot has been accomplished, still many simulation items are yet impossible, such as (i) accurate, within ±10%, predictions of failure modes; (ii) timely simulations, within 1 h, of multiple failure mode occurrence; and/or (iii) full understanding of all possible failure mechanisms that can occur in microelectronic devices. To accomplish this, we will need breakthrough developments in how engineers are currently using multi-scale and multi-physics tools for predicting electronics reliability. It is not just continuing current improvements; it needs a breakthrough in the way currently these simulation techniques are used. It will need cooperations between tooling vendors, academia, and electronic companies to establish such a breakthrough. Open innovation projects funded by national and international authorities are the only opportunities available that will drive it, with iRel40 an outstanding example.

16.3 Smarter Testing and Characterization

When they were first mass produced, manufacturers expected electronics to last roughly 40 years. By the 1990s, their lifespan was halved. Today, electronics are typically only used for 1.5 to 13 years, with most averaging 4.5 years. Testing schemes started with test-to-failure approaches based on standardized stress-based tests. Examples are thermal cycling, moisture testing, and/or operational tests under combined conditions. Each of these tests got standardized in the semiconductors industry by dedicated bodies, e.g., JEDEC [21], to enable smooth comparison between suppliers and test houses. But as time evolved and qualification costs became substantial, the industry moved over to knowledge-based qualification [22] and application-based qualification [23]. All these developments considered fixed product lifetime requirements, be it in consumer, professional, solid-state lighting, and/or automotive application. But this is changing, mostly driven by the demand for sustainable products. For example, electronics in automobiles are expected to last over 10 years or in terms of milage: 100,000 km or more. In that field period, these electronics exhibit different temperature bins as indicated in Fig. 16.3: 35% of the time, a temperature of 75 °C is felt, 8% a temperature of 60 °C, etc. It is not a continuous loading, rather a variation of loads.

To cover high lifetimes, under variable loads, the current way of testing is not sufficient. As Fig. 16.4 depicts, conventional testing is either stable in temperature (e.g., temperature cycling (TMCL) or temperature shock (TMSK)) or slightly variable by powering the device (power temperature cycling (PTMCL)). Step-stress testing and variable temperature accelerated testing (VTAT) are possible alternative ways of testing. Step-stress testing is a combination of traditional reliability testing and overstress testing [24]. The purpose of step-stress testing is to demonstrate one life of a product and then overstress the product in incremental levels to find failure modes. VTAT is a testing approach that covers the temperature bins as exhibited in

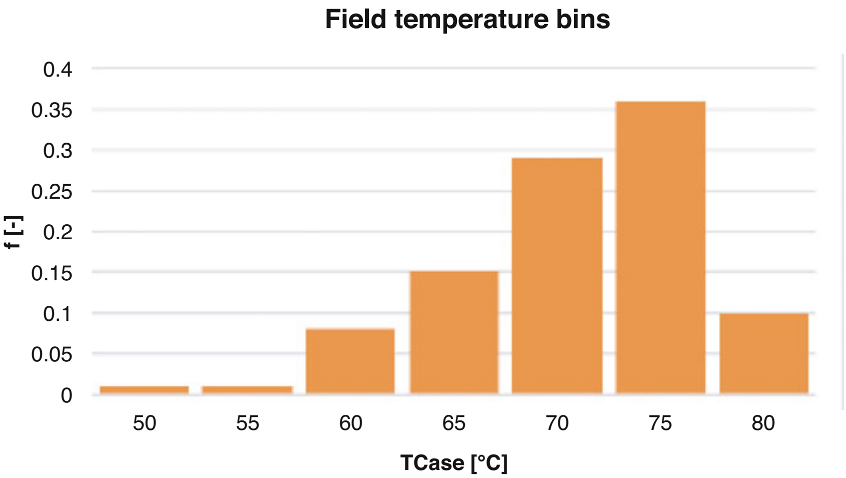


Fig. 16.3 Typical temperature occurrences (frequencies) in electronics

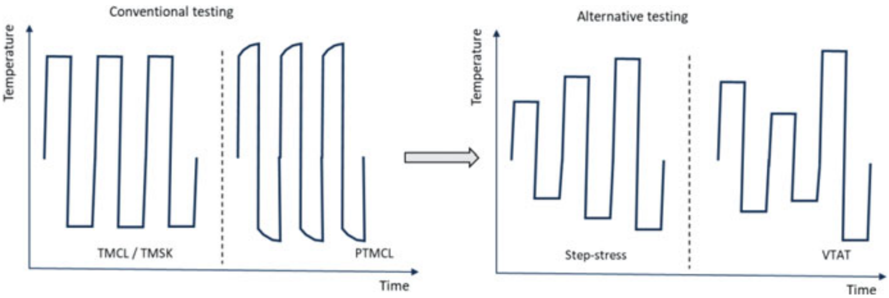


Fig. 16.4 Conventional temperature cycling (TMCL) or temperature shock (TMSK) and power temperature cycling (left) versus alternative temperature testing: step-stress or variable temperature accelerated testing

field application. If combined with monitoring the actual degradation of the product, these alternative approaches should be able to cover high lifetimes.

Accurate materials data and characterization are critical for applying multi-scale and multi-physics simulations for physics of degradation. However, there is a lack of consensus on accurate constitutive models used, for example, for nonlinear materials such as solders. For accurate reliability predictions, processing, miniaturization, and temperature-dependent nonlinear material properties must be used for almost all electronic materials. But, here, neither standard testing nor agreed material models are rarely able to provide the materials data needed for reliability predictions. Alignment between material suppliers, semiconductor manufacturers, test houses, standardization bodies, and academia is a future requirement to achieve accurate materials data in the possession of the simulation experts, just a matter of the right open innovation consortium under national and international funding.

16.4 ML/AI Embedding in Design for Reliability

Machine learning (ML) involves the use of artificial intelligence (AI) theory combined with big data to guide computers for training and learning, with the final goal of developing a prediction model to help researchers make decisions [25]. Machine learning can be applied for regression or classification models using either supervised or unsupervised learning. For electronic reliability predictions where the input datasets are labeled, the learning algorithm for predicting the reliability life is considered supervised and belongs to regression-type model [26–29]. AI knowledge is needed for new degradation physics in complex electronic architectures that are based on advanced semiconductor systems and new emerging packaging material systems [30]. Several machine learning algorithms are suitable, such as artificial neural network (ANN), support vector regression (SVR), K-nearest neighbor (KNN), kernel ridge regression (KRR), recurrent neural network (RNN), random forest (RF), Gaussian process regression (GPR), polynomial regression (PR), and convolutional neural network (CNN). First examples of AI-based design for reliability (DfR) predictions are reported in the literature for wafer-level packages [26, 27, 29] and solid-state lighting devices [28]. The aim of the AI model is to learn and establish a regression model for the relationship between electronics design (input) and the potential failure mode (output). With a trained AI model, it is possible to predict the lifetime of the electronics device for each possible design. Figure 16.5 depicts the process of AI-embedded DfR.

However, machine learning requires big data for training; the main challenge of this AI-assisted DfR technology is the lack of data, e.g., reliability life cycles of packages. There is not a lot of experimental data available to researchers, which makes it difficult to apply the AI-assisted technology. Experimental data mainly lies protected at electronic companies, not willing or not able to share that with academia. As mentioned again, it will need open innovation projects to open a Pandora's box.

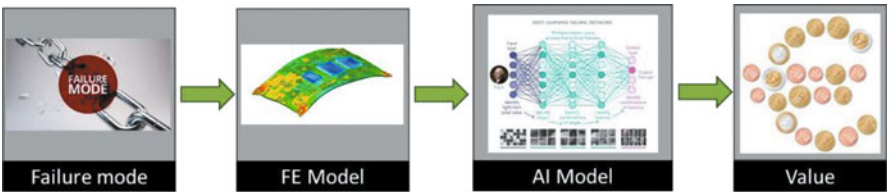


Fig. 16.5 Starting from a failure mode, a finite element analysis will be set up, and results are fed into the AI model which on its turn creates value as it enables lifetime prediction of each possible design

16.5 More Data, More PHM, and More Digital Twin

Today, the volume of remote sensing data has grown considerably. Analyzing, modeling, and interpreting big data through descriptive, predictive, and prescriptive analytics will aid users to make correct decisions in electronic product design.

Prognostics and health management (PHM) is crucial in the life cycle monitoring of a product, especially for, e.g., complex equipment working in a harsh environment and/or products that require long lifetimes ($\geq$10 years). PHM is not just about creating a more reliable product: it is about creating a more predictable product based on real-world usage conditions [31]. Data analytics is a necessary part of this but is not enough. To add value, product insights need to be leveraged into the technologies that are used to differentiate from others. PHM is not about troubleshooting reliability issues; rather, it is a new control point enabled by the transition to a services business. It is the combination of data and deep physical (and technological) insight that will give a unique "right to win" in the industry [32]. The future possibilities for using connected data in reliability applications are unbounded. Lifetime models that are based on this data have the potential to explain much more variability in field data than has been possible before. As of today, rarely any solutions on component or system level are available except from high-end products (e.g., in avionics and energy infrastructure). Search for early warning failure indicators is still at a basic research stage.

Digital twins (DT) have become a groundbreaking concept in the field of electronics packaging and electronic systems [33, 34]. In an era characterized by rapid technological advances and increasing complexity in electronics packaging products, digital twins offer a revolutionary approach. To improve the accuracy and efficiency of PHM, digital twin (DT) is proposed for complex equipment and/or products that require long lifetimes ($\geq$10 years). The combination of PHM with DT by itself should accurately describe the (failure) behavior of the electronic product/device or, from a sustainability perspective, determine its remaining useful life (RUL). The next paragraph presents a use case for this technique.

16.6 Use Case: RUL Estimation for Electronic Devices

Prognostics and health management (PHM) is commonly applied to more complex electronic systems consisting of multiple components including sensors that measure the environmental loads, e.g., temperature, humidity, voltage, current, etc. However, PHM of the sensors measuring these loads is typically reduced to detection of faulty sensors as these do not commonly implement any form of intelligence which is so far left to the higher-level systems that incorporate the sensors. In the worst case, faulty sensors are not detected and provide wrong readouts, e.g., because their sensitivity changes over lifetime. Overall increased wear out or system failures may be the consequence. Therefore, imminent device failure needs to be reliably detected to exchange sensors before they fail.

16.6.1 Mission Profiles and Acceleration Factors

Mission profiles from the robustness validation approach commonly used during part qualification, especially, in an automotive context are one building block of the remaining useful life (RUL) model and system status assessment concept. In robustness validation, the mission profile is used to define standardized testing times and conditions based on different, temperature-induced failure mechanisms [35, 36]. For this approach, the critical failure mechanism that most likely causes a part to fail has to be identified together with the critical environmental load parameters (temperature, humidity, etc.). A range of operating temperatures is defined for each mission profile which is required to cover the whole temperature range the part is subjected to in the later application as well as the times the part experiences these temperatures. Higher temperatures will lead to an earlier failure of the device because the failure mechanism is temperature driven. Hence, the highest temperature of the mission profile is used as the temperature for accelerated part testing and acceleration factors have to be calculated for all other temperatures [35]. For example, the testing temperature is 155 °C, and the part spends 100 h at a temperature of 125 °C, with an acceleration factor of 10, according to the mission profile. Then the equivalent test time of the part at 155 °C is 10 h.

16.6.2 Concept: Remaining Useful Life Estimation and System Status Assessment

The model aims at the assessment of the part (system) health status by a correlation of a consumed time budget to critical system parameters that serve as indicators for failing devices. At least two classifiers are defined for this purpose, one to classify the consumed temperature-time budget, c_{TT}, and further classifiers to assess the critical system parameter(s), $c_{\mathrm{csp},\,i}$, with $i \in [1, \ldots, N]$. With this approach, the purely temperature-driven device failure mode taken from the robustness validation approach is complemented by system-specific device health indicators to obtain an overall system status.

Calculation of c_{TT} is carried out by comparison of the total equivalent operational time, t_{o}, to the available time budget, t_{b}:

$$c_{\mathrm{TT}} = \frac{t_{\mathrm{o}}}{t_{\mathrm{b}}} \tag{16.1}$$

Both times are derived based on the calculation specifications for equivalent test times used, e.g., for qualification of parts/systems according to the AEC-Q100 standard [37]. Hence, the model applies to temperature-induced device failures, and it is crucial for the accuracy of the model to precisely determine the activation energy E_a of the relevant failure mechanism. The reference mission profiles defined during product development yield t_b for a budget temperature T_b which is the highest temperature of the mission profile. Equivalent operational times $t'_{\mathrm{o},T}$ are calculated for the time t spent at temperature T measured during operational time of the part/system using the same acceleration model and factor, A_f, used to determine t_b:

$$t'_{\mathrm{o},T} = \frac{t_T}{A_\mathrm{f}(T)} \tag{16.2}$$

The total operational time is the sum over all $t'_{\mathrm{o},T}$:

$$t_\mathrm{o} = \sum\nolimits_T t'_{\mathrm{o},T} \tag{16.3}$$

Hence, calculation of c_TT requires logging of the temperature of the part/system over its lifetime. Care must also be taken when choosing the minimum/maximum temperatures defined in the reference mission profile which need to be lower/higher than the temperatures the device exhibits in the field to ensure the assumed failure mechanism is valid. An estimation of the remaining useful life (RUL) can be directly carried out with t_b and t_o available:

$$t_\mathrm{RuL} = t_\mathrm{b} - t_\mathrm{o} \tag{16.4}$$

The second classifier $c_{\mathrm{csp},\,i}$, required to assess the system status, cannot be generalized as it is use case-specific. It just needs to be accessible during device operation. An example is given in Sect. 16.6.3 where the signal offset change of a current measurement device is used as an $c_{\mathrm{csp},\,i}$.

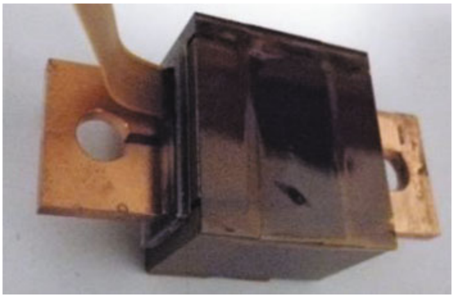
A system status $S(c_\mathrm{TT}, c_{\mathrm{csp},\,i}, \ldots, c_{\mathrm{csp},\,N})$ is defined for distinct combinations of c_TT and the $c_{\mathrm{csp},\,i}$. If, e.g., stored in the form of a look-up table (LUT) on the device hardware, a computationally efficient readout of the system status is feasible.

16.6.3 Use Case: Current Measurement Module

The Current Measurement Module (CMM) prototype shown in Fig. 16.6 holds a PCB with a SO16 current measurement device, in situ condition monitoring circuitry to test the sensor's output signal and a temperature sensor.

Two examples for class III and class IV mission profiles with an operating time of 8000 h are given in Fig. 16.7 (top and bottom, respectively). Time budgets of

Fig. 16.6 Current Measurement Module



Q = activation Energie [eV]		0.7			
Budget-Temp. [°C]		**125**			
Temp. [°C]	Temp. [K]	Time [h]	Duty Cycle	AF	CTT [h]
-40	233	480	0.06	1.89E+06	0
23	296	1600	0.20	1.13E+03	1
76	349	5200	0.65	1.76E+01	296
120	393	640	0.08	1.30E+00	494
125	398	80	0.01	1.00E+00	80
		8000	1.00		871

Q = activation Energie [eV]		0.7	(		
Budget-Temp. [°C]		155			
Temp. [°C]	Temp. [K]	Time [h]	Duty Cycle	AF	CTT [h]
-40	233	480	0.06	7.91E+06	0
23	296	1600	0.20	4.74E+03	0
100	373	5200	0.65	1.64E+01	317
150	423	640	0.08	1.25E+00	511
155	428	80	0.01	1.00E+00	80
		8000	1.00		908

Fig. 16.7 Time budgets for (top) class III and (bottom) class IV mission profiles for an operating time in the field of 8000 h

$t_b = 871$ h and $t_b = 908$ h are calculated for $T_b = 125\ ^\circ$ C and $T_b = 155\ ^\circ$ C, respectively.

Operational times are calculated from logged temperatures according to Eqs. 16.2 and 16.3. Exemplary RUL estimations based on the proposed model for a “Normal” and “Hot” application case are given in Fig. 16.8. The “Normal” case’s total operating time adds up to 20,320 h with $t_o = 190.2$ h resulting in an estimated $t_{RuL} = 709, 8$ h.

On the other hand, the total operating time of the CMM in the “Hot” case only adds up to 6120 h; however, the equivalent operational time is already at $t_o = 561.2$ h yielding $t_{RuL} = 338, 8$ h due to the longer time spent at higher temperatures compared to the “Normal” case. Even without definition of a critical system parameter and the correlation to a system status, this approach already allows

Fig. 16.8 Examples of use cases with different temperature loads

Use-Case "Normal"			
Temp-Class [°C]	Use-Time [h]	AF	Corr. Time [h]
-40	20	7912965.0	0.0
23	20000	4739.9	4.2
100	100	16.4	6.1
150	100	1.3	79.9
155	100	1.0	100.0
		t_o [h]	190.2
		t_b [h]	900
		t_{RUL} [h]	710
		c_{CTT} [%]	**21**

Use-Case "Hot"			
Temp-Class [°C]	Use-Time [h]	AF	Corr. Time [h]
-40	20	7912965.0	0.0
23	5000	4739.9	1.1
100	500	16.4	30.4
150	350	1.3	279.7
155	250	1.0	250.0
		t_o [h]	561.2
		t_b [h]	900
		t_{RUL} [h]	339
		c_{CTT} [%]	**62**

a first indication of the device's health by evaluating exhibited mission profiles rather than just relying on theoretical values defined during product development.

System status assessment relies on only one critical system parameter, the offset change over lifetime, in the discussed use case. The corresponding classifier $c_{\text{csp},1}$ is calculated from the initial signal offset $V_{\text{off},0}$ and the offset voltage at the time of interest:

$$c_{\text{csp},1} = \frac{V_{\text{off,t}} - V_{\text{off,0}}}{V_{\text{off,0}}} \tag{16.5}$$

An exemplary system status table is shown in Fig. 16.9. In the illustrated example, four classes are defined for c_{TT} and three classes are defined for $c_{\text{csp},1}$. The system status ranges from 1 to 10 with low numbers indicating a healthy system and high numbers indicating a system close to its end of life requiring maintenance, e.g., recalibration and/or replacement.

In the case of the investigated CMM, the offset change is the most critical value that indicates a faulty system. Hence, even if all the time budget is consumed and $c_{\text{csp},1}$ is below 0.1%, the device status is 1. The lower the CMM's life value, i.e., the lower c_{TT} is, the more critical a change of the offset voltage is which leads to

Fig. 16.9 Exemplary system status tensor

System Status		$c_{csp,1}$ ±0,1%	$c_{csp,1}$ ±0,2%	$c_{csp,1}$ ±0,4%
c_{TT}	20%	1	6	10
	50%	1	5	10
	80%	1	4	8
	100%	1	3	8

larger values of the system status for lower c_{TT} values at a given $c_{csp,\,1}$. Hence, the evaluation of the system status prevents the presumptuous exchange of devices that are still working within specified parameters but are at their end of life according to c_{TT}. This prevents avoidable downtime of the product a CMM might be part of compared to an approach where devices are exchanged just based on the assessment of their operational time. Consequently, resources of the planet as well as customer's money are saved because the exchange of sensor devices is carried out when device failure becomes imminent, not when device failure is expected.

16.6.4 Conclusions

Due to the increasing importance of device safety and responsible resource management, PHM becomes more and more important for any kind of electronic component/system. The proposed model enables RUL estimation and system health status monitoring directly on a sensor level which is the first step in bringing "intelligence" to these classes of devices. Complexity of the model implementation can be adapted to the use case requirements. A first estimation of the device's RUL is enabled just comparing the overall temperature-time budget defined by the mission profile to the equivalent operational time the part/system spent at the budget temperature. Temperature logging of the device is required for this approach. Additionally, device-specific critical system parameters, e.g., output signal characteristics like an offset change, sensitivity change, resistance thresholds, etc., may be defined and classified. A system status that is defined for distinct combinations of temperature-time and critical system parameter classifiers allows a computational inexpensive and easy to implement way of assessing the device's health. The status can be used as an input, e.g., for predictive maintenance applications.

16.7 Final Remarks

The future of reliability is bright, both from a financial and academic perspective. There are several future developments required to establish fully predictive DfR: (i) improve the simulation skills for physics-of-degradation purposes, (ii) develop smarter testing and characterization concepts, (iii) start embedding AI/ML concepts, and (iv) harvest field/application data and combine that with PHM and DT concepts. This chapter presents further directions for these developments and how it can improve electronic product reliability. A use case is presented that indicates the potential of PHM for remaining useful life prediction.

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