The Use of “Canaries” for Adaptive Health Management of Electronic Systems

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Abstract - **Reliability concerns in state-of-the-art electronic systems have led researchers and engineers to develop innovative real-time prognostics and adaptive health management methods to assure desired availability. Prognostics techniques described here use a novel concept of *canaries*, along with data analysis, failure mechanism models and integrated fusion techniques to determine the remaining useful life of a system. A *canary* is a device that provides data to generate early warning of functional degradation and impending functional failure. Three types of *canaries* are discussed. Expendable *canaries* experience accelerated degradation (compared to functional degradation) by design, so that early warning of impending failure can be generated. Sensory *canaries* provide early warning by observing nonfunctional manifestation of functional degradation. Conjugate-stress *canaries* provide measurement of life-cycle stress history so that failure models can be used to estimate consumed life and remaining life. This paper focuses on expendable canaries, in particular, and provides three examples to illustrate the underlying design concepts.**

Keywords – canary; electronic systems; failure mechanisms; precursors; prognostics; reliability; remaining useful life.

I. INTRODUCTION

Cost effective methods for assuring high availability and safety are a key need in many critical electronics-rich systems, such as in medical devices, military products, aviation controllers and avionics, information management systems and in energy generation and distribution systems, especially in nuclear power plants [1]. Functional failure of such critical products during performance in the field can have catastrophic and costly consequences. The prevention of failures in cutting-edge electronics is very challenging because of the extremely high density and functionality, small length-scales, multitude of competing multi-physics degradation mechanisms and failure mechanisms, rapid turnover of technology and highly diverse global supply chain.

Current predictive methods in the industry for predicting failures, based on reliability handbooks, have been shown to be very inadequate. Some of the key causes for prediction inaccuracies are model inaccuracy and uncertainties in the inputs to the models. The most important input is the life cycle loading history and uncertainty arises in this input users. Another important source of uncertainty is in input model constants that represent material behavior, because of the wide variability in defect levels and manufacturing tolerances in specimen populations. These variabilities are difficult to quantify *apriori* in new emerging technologies, making it difficult to make accurate proactive failure predictions. Corrective and preventive maintenance can, to some extent, mitigate failure risks [2]. However, mandatory maintenance on an inflexible predetermined schedule is not always the most cost-effective way to ensure availability and safety. Prognostics and health management (PHM) methodology is based on monitoring the performance of a system *in-situ* in its actual life-cycle conditions to identify early signs of degradation, providing advance warnings for future failures, and implementing timely corrective action to mitigate the failure risk. As an important aspect of PHM, the technology of embedded *canaries* has attracted more and more attention from industry due to their intrinsic capability to provide early warning of host degradation and impending failure, under actual life-cycle conditions.

The use of the term *canary* in PHM is derived from the historic concept of using canary birds in coal mines in order to detect the presence of hazardous gases. Because canaries are more sensitive to hazardous gases than humans, the death or sickening of the canaries provided early warning to miners to take corrective action and exit the mine-shaft. In this paper, we use the word *canary* to refer to a family of technologies that are embedded in functional electronic systems, to give early warning of functional degradation, and to provide estimates of the remaining useful life of the host system. In a classical context, the word *canary* was used to refer to a device that changes its functional characteristics ahead of similar functional parameters that indicate system performance degradation when the product is subjected to life cycle stress conditions. If the acceleration factors are known, their time-to-failure estimates can be used to quantify the remaining useful life of the system. The early warning provided opportunities to implement timely risk-mitigation actions and avert danger. The use of *canaries* is an integral part of the prognostics approach described in this paper, and the concept is generalized and extended well beyond the classical definition, as discussed later in this paper.

Canaries have been applied to several system-level applications to predict failures and the resulting changes in the performance of systems. In system-level applications they have had a significant impact in failure prediction by providing advance warning about the initiation and growth of defects and their correlation to system parameters. Researchers have been working on applying *canaries* to the prognostics of both components and systems. Han et al. [3] proposed a concept of developing a "*canary*-containing" packet that can be attached externally to weapon casings. In this process, the *canaries* received environmental loading identical to what the casings experienced. The *canary* material was configured to deteriorate at a faster rate than the system's parameters. Energetic materials that have a faster rate of initiation of failure mechanisms compared to semiconductors materials have been applied to semiconductor systems to evaluate their failures and manage their health by applying pre-calibrated circuits to the host chip (Mishra et al. [4]).

Ridgetop Group has developed sentinels for advance warnings of device failures [5]. Wang et al. [6] demonstrated a 90nm 128Kb SRAM test chip on which the *canary* cells track changes in temperature and data retention voltage, which is the minimal value of positive supply voltage (V_{DD}). These *canary* cells ensure a reliable function of the host chip by protecting core cells in a closed loop V_{DD} scaling system. Calhoun et al. [7] proposed a closed-loop approach using *canary* flip-flops to enable power savings of over 40 times in a 0.13-um, dual-test chip. Anderson et al. [8] used low cycle fatigue solder joints and corrosion-susceptible circuits on the host printed circuit board as *canaries* and identified prospective failure mechanisms. Goodman et al. [9] used a prognostic cell to monitor time-dependent dielectric breakdown (TDDB) of the metal oxide semiconductor field-effect transistor (MOSFET) on integrated circuits.

In this paper, we present several examples of *canaries* for electronic systems, but first provide the context of the prognostics framework that *canaries* are a part of. The prognostics framework to monitor and predict the remaining life of systems is reviewed in Section II. A detailed review of *canary* design and application is presented in Section III. Examples of *canaries* and their applications are provided in Section IV. In Section V conclusions are provided, including future functional goals for *canaries*.

II. PROGNOSTICS METHODOLOGY

To improve the availability of a system, we need to ensure that the system can perform as intended (i.e., without failure and within specified performance limits) for a specified period of time, in its life-cycle environment [10]; within a specified confidence level. Unfortunately, traditional reliability assessment methods using Telcordia [11], PRISM [12], and FIDES [13] fall short in performance, since they fail to provide accurate failure predictions, which can result in poor design and logistic decisions [14] [15]. The central idea in prognostics is to assess the reliability in real-time, under its actual application conditions, so that timely corrective action can be implemented and availability can be improved. The general prognostics methodology is shown in Figure 1 [16]. Prognostics techniques combine sensing, recording, and interpretation of environmental, operational, functional and relevant non-functional parameters, to determine failure precursors that are indicative of a system's health. A failure precursor is a data event or trend that signifies impending failure. A precursor indication is usually a change in a measurable variable that can be associated with system degradation and subsequent failure. For example, a shift in the output voltage of a power supply might suggest impending failure due to a damaged feedback regulator and damaged opto-isolator circuitry. Pecht et al. [18] presented a guideline for selecting measurable parameters that can be used as failure precursors for electronic products.

The first step in Prognostics involves a virtual life assessment where design data, expected life-cycle conditions, the results of failure modes, mechanisms, and effects analysis (FMMEA), and Physics of Failure (PoF) models are the inputs. Based on the virtual life assessment, it is possible to prioritize the critical failure modes and failure mechanisms. The existing functional data, bus monitor data, BIT, IETM, *canary* data, maintenance and inspection records can be used to identify potential the abnormal conditions and parameters. Based on this information, PHM engineers select the functional parameters to be monitored for health assessment and relevant sensor locations as well as relevant *canary* designs. Based on the collected functional and *canary* data, the health status of the products can be assessed [10]. The different approaches to prognostics are highlighted in yellow boxes in Figure 1. Three current approaches for Prognostics include: (A) Data-driven Prognostics; (B) Model-based Prognostics; and (C) Prognostics based on fusion of model and data.

A. Data-driven Prognostics: This approach is based on trend analysis of the precursor data from the functional system and the *canaries*. The monitored data is analyzed to see if there is a significant change in the previous trends observed with this data. Trends are detected by extracting key features which are then classified as recurring anomalies or transient soft events, using machine learning methods. Time series techniques and logic-reasoning techniques are used for state estimation, to diagnose the underlying cause and source of degradation. Since the data is highly multi-dimensional, *canary* data can help to deconvolve them for insights about dominant failure mechanisms. Forecasting methods and dynamic state tracking methods are used to extrapolate this data and provide predictions of when failure is likely to occur and hence provide an estimate of the remaining useful life of the system. Techniques such as parametric curve fit, expert system, neural networks, and Bayesian inference are often used for this task [19]-[28]. Methods, such as FMMEA [29], are used to determine parameters that need to be monitored.

B. Model-based Prognostics: Life-cycle loads (thermal, mechanical, chemical, electrical, and so on) on a product can arise from the manufacturing, shipment, storage, handling, and operating and non-operating conditions, and may lead to performance or physical degradation of the product and reduce its service life [16]. Physics-of-Failure (PoF) models provide quantitative stress-damage relationships, based on the root causes of the failure of *canaries* and functional components and provide insights about how fast the system degrades and when failure can be expected, when used in conjunction with the precursor data from the functional systems and from the *canaries*. PoF models are typically based on fundamental physics and may take a relatively simple approach at the continuum length-scale or a more complex *ab-initio* approach at the molecular and atomistic length scales [17].

C. Fusion Prognostics This approach provides an intelligent combination of the model-based and data-driven methods to improve the accuracy and speed of diagnostics and prognostics. Data-driven approaches have the drawback that they require vast amounts of training data and are difficult to extrapolate to new use conditions. Methods based purely on PoF models have the drawback that real-time calculation of failure models for a complex system may be computationally very cumbersome. Fusion between the two provides valuable synergy and also provides the ability to discriminate between real failure trends vs. transient false-positives.

Self-checking circuitry and built-in-tests (BITS) can also be incorporated, in addition to *canaries*, to sense abnormal changes in system functions and to activate autonomous reconfiguration, to compensate for the malfunction [30].

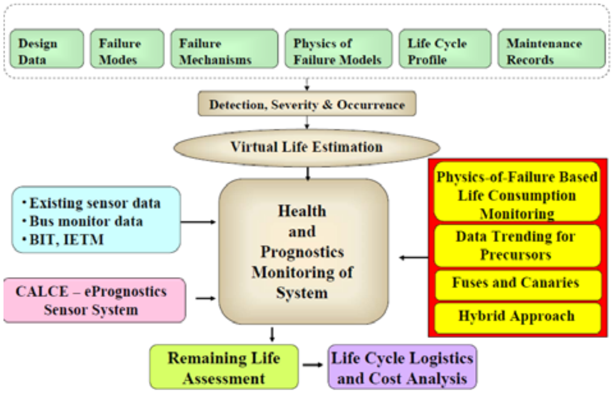

Figure 1. Prognostics methodology.

III. DESIGN OF CANARIES

Canaries are embedded in products and are used to identify changes in failure mechanisms as a precursor to predict the future effects of similar mechanisms on system parameter changes. *Canaries* are integrated into components or devices during the system design phase. These embedded *canary* devices (also called prognostic cells) are non-critical elements in overall system performance [31].

Figure 2 shows the failure probability density distributions for functional products and corresponding *canaries*, showing the concept of remaining useful life (RUL) or 'prognostic distance.'

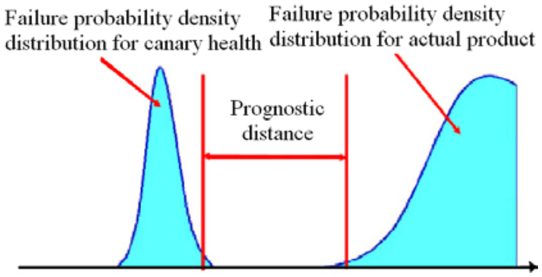

Figure 2. Failure probability density distributions for *canaries* and actual products, showing prognostic distance or remaining useful life (RUL).

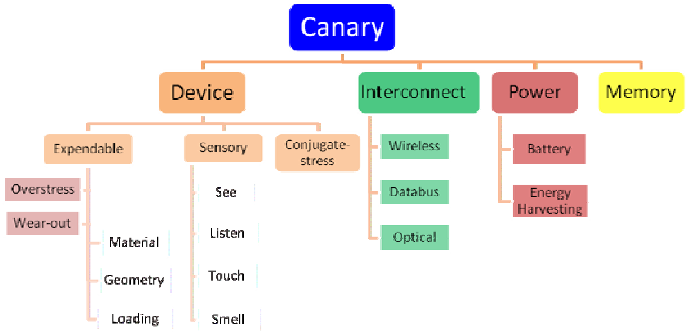

Figure 3. Classification of *canaries.*

The term *canaries*, as used in an extended generalized context in this paper, refers to three main types of devices (see Figure 3): expendable *canaries*, sensory *canaries*, and conjugate-stress *canaries*.

A. Expendable canaries: They are based on controlled acceleration of failure precursor signatures, using error-seeded, sacrificial, nonfunctional elements (*canaries*). The error-seeding in *canaries* includes three inter-related techniques that will be used individually or synergistically to enhance the degradation rates in the *canaries*: geometry error-seeding, material error-seeding, load error-seeding. Section IV will discuss these three error-seeding methods in detail. Based on their dominant failure mechanisms, expendable *canaries* can be further categorized into overstress *canaries* and wear-out *canaries*. Overstress *canaries* come into play when loaded stress exceeds its strength. Some of the overstress failures are dielectric breakdown, electrostatic discharge (ESD), interconnect fracture, pin buckling. Wear-out failure, which is caused by gradual increase of cumulative damage, includes electromigration, fatigue, Tin whisker growth, interconnect corrosion, time dependent dielectric breakdown caused by tunneling mechanisms, etc.

B. Sensory canaries: Inspired by biological system, these *canaries* can detect non-traditional signatures of system degradations. They will be able to "look," "listen," "smell," and "feel" for signs of degradation and impending failure just as an animal does. By collecting and analyzing these signs, early warnings of failure can be achieved. Examples include: infrared *canaries* to "look" for degradation in microprocessors based on changes in the thermal dissipation; Impedance spectroscopy and time domain reflectometry to "listen" for defects in signal traces and wiring harnesses. Micro Electro-mechanical System (MEMS)-based chemical *canaries* to "smell" for outgassing products; Piezoelectric or piezoresistive *canaries* to "touch" for signs of delamination, which is a common failure mechanism of laminated material subjected to repeated cyclic stresses or impact, with significant loss of mechanical toughness.

C. Conjugate-stress canaries: These *canaries* can provide model-based fusion prognostic assessments of remaining useful life based on simultaneous identification of conjugate-stress pairs, which is a novel concept because most conventional detectors provide a single stress metric, rather than a conjugate pair. For example, a conventional stress monitoring *canary* such as a thermocouple can measure only temperature. In many cases, it cannot provide sufficient information to health condition. However, the conjugate-stress approach will simultaneously measure temperature and heat flux at the same site by using a pair of collocated detectors.

These three classes of *canaries* will provide unprecedented levels of synergistic prognostic and health information of systems to minimize uncertainties in remaining useful life assessment. In this paper we discuss only the first type, viz. expendable *canaries*. Discussion of the two remaining types of *canaries* is deferred to a future paper

Expendable *canaries* can be designed based on controlled error-seeding, which provides controlled acceleration of degradation rates and failure precursor signatures. Technically, an expendable *canary* can be any device that wears out faster than the actual product under the same environmental and operational loading conditions. An example is a dummy filament in a light bulb, which is designed to age faster than functional filament can be used as an expendable *canary* to provide early warning of impending failure of the bulb. The methods to make the filament fail faster than normal one can be either scaling its physical dimension, or subjecting it to higher current stress, or utilizing material of less susceptibility to melting. We called these methods geometry error-seeding, material error-seeding, load error-seeding.

A. Material error-seeding

Material error-seeding takes advantage of the greater sensitivity of the materials to failure modes (physical or chemical),in *canaries* compared to that in the functional system so that degradation and failure of *canaries* can be used as an early warning of the degradation and future failure of of the functional host, before experiencing catastrophic loss. Since there are various properties a material has, many types of *canaries*, in theory, can be designed. These properties include, but are not limited to, the following: mechanical, thermal, electrical, magnetic, optical and photonic, chemical, biological, reaction to gases, and reaction to humidity. Each category has quite a few material properties; for example, the mechanical properties include Young's modulus, specific modulus, tensile and compressive strength, ductility, Poisson's ratio, etc. Thermal properties include thermal conductivity, thermal diffusivity, coefficient of thermal expansion, specific heat, glass transition temperature, melting point, Curie point, etc. Electrical properties include electrical conductivity, permittivity, dielectric constant, dielectric strength, Seebeck coefficient, etc. The selection of material properties is determined by the application of *canaries* and other concerns, such as the effectiveness of providing early warning, ease of fabrication, and low cost.

B. Geometry error-seeding canaries

This kind of *canary* is designed to change in shape, or geometry in response to changes in failure mechanisms induced by a stimulus. Ridgetop Group's commercialized prognostic cells can provide an early-warning sentinel for device failures [5]. Their prognostic cells are available for 0.35, 0.25, and 0.18 micron CMOS processors. The time to failure of these prognostic cells depends on the stress on the circuit, including voltage, current, temperature, humidity, and radiation. The earlier failure of these prognostic cells is achieved by the controlled shrinking of the cross-sectional area of the circuits inside the cells. With the same amount of current passing through host circuits and *canary* circuits, the *canary* circuits withstand a higher current density than host circuits. Currently, the prognostic cells are available for semiconductor failure mechanisms such as electrostatic discharge (ESD), hot carrier, metal migration, dielectric breakdown, and radiation effects. Other examples are presented in Section IV of this paper.

C. Load error-seeding canaries

Failure mechanisms initiate and grow in *canaries* when they are exposed to changes in environmental and usage loading conditions. Due to the exposure to different load level, materials or elements can deteriorate at different rates. In most cases, critical components at high-risk are assembled at a position close to the corner of a substrate. They fail to perform to set specifications in comparison to those components assembled at normal positions.

IV. DEMONSTRATION OF EXPENDABLE *CANARIES*

Three examples of expendable *canaries* are presented in this paper: (A) Thermal aging of filaments; (B) thermomechanical fatigue of solder joints; (C) electrochemical migration (ECM) on a printed wiring board.

A. Filament *Canary:* Filaments are used in incandescent light bulbs and in X-Ray tubes to utilize electrical energy to generate photons of desired frequency range. However, some of the input electrical energy is also converted to thermal energy which results in long-term degradation and failure of the filament. In this example we explore the concept of an error-seeded *canary* that is designed to age faster than the functional filament. The test vehicle in this simple demonstration is a commercial 100mA electrical fuse. As shown in Figure 4, the *canary* is error-seeded by compromising the hermetic seal of the glass housing with a small crack which exposes the filament to oxygen in the external atmosphere.

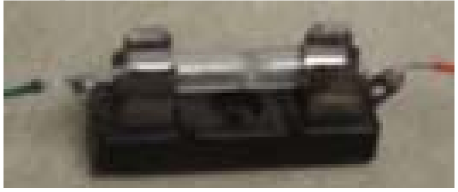

Figure 4. *Canary* fuse with cracked glass housing.

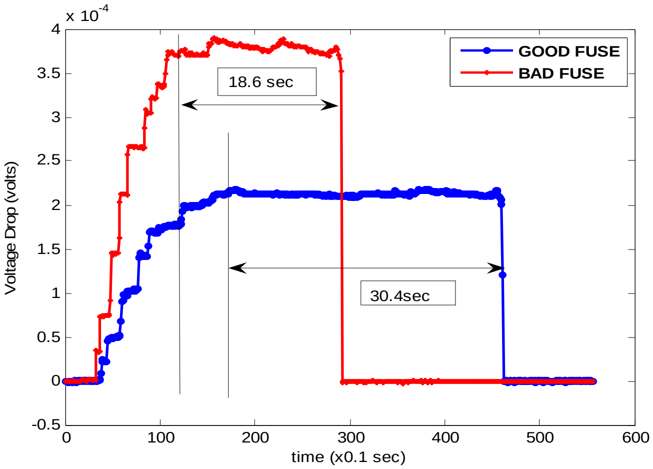

Figure 5. At 1.4 Amps: Functional filament fails at t_1= 30.4 secs, *canary* filament fails at t_2 =18.6 secs.

The flow of current causes the *canary* filament to oxidize faster than the functional filament, causing an increase in the resistivity of the material. Thus, this is an example of load error-seeding. (i.e. the *canary* filament experiences a more harsh chemical environment than the functional filament does). A constant current is supplied to both the test filament and the *canary* filament, causing increased Joule heating and faster melt-down of the *canary*. Figure 5 shows that the *canary* degrades 60% faster than the functional filament in this case, under a constant 1.4 Amps supply. In other words, when the *canary* fails, the RUL (or prognostic distance) is approximately 66% of the *canary* life.

B. Solder Joint *Canary*

Solder interconnections of electronic equipment are subjected to cyclic thermomechanical loading caused by thermal expansion mismatches during environment and operational temperature excursions. This cyclic loading can degrade solder interconnects by cyclic fatigue and eventually lead to a wearout failure. PoF models have been developed to accurately predict solder joint interconnect reliability under imposed test conditions [32-34]. However, in actual use, conditions may vary from anticipated design criteria and across field electronic equipment. In this example, two solder *canaries* are discussed: one by load-seeding and the other by geometric error-seeding [8].

The solder interconnect *canaries* presented here are specially designed to fail by the same failure mechanism and at a pre-defined prognostic distance from the failure of the functional solder joint. The proposed *canary* structures can be an extra non-functional error-seeded interconnect on a BGA device (as depicted in 6). Alternatively, it can be an additional nonfunctional component with error-seeded interconnects, such as the leadless ceramic chip resistor (LCR) depicted in Figure 7.

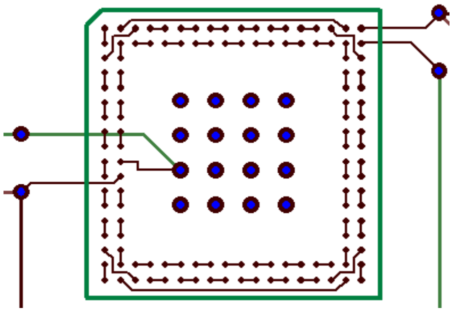

Figure 6. Example of a BGA Test Vehicle.

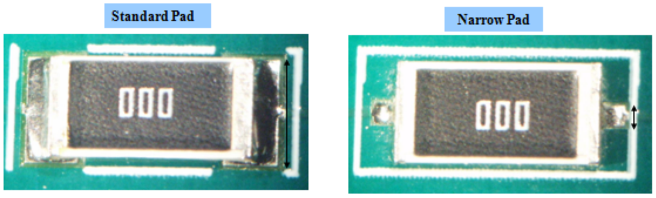

Figure 7. Resistor *Canary* Structure.

The BGA *canary* uses load seeding (due to increased distance from the component center) while the LCR *canary* uses geometric seeding by using a narrower joint pad.

Testing of BGA structure has demonstrated that in many BGA architectures, the outer solder joints may fail sooner than interior solder joints. Figure 8 shows the probability density functions of the time to failure data for the BGA depicted in Figure 6, subjected to a defined temperature cycle loading condition. Comparing the distributions reveals a less than 1% probability that an inner net will fail prior to an outer net. Comparing the mean cycles to failure reveals a prognostic distance of 1360 cycles for the given BGA test specimen and given loading condition.

Thermal cycling tests on LCRs with standard and narrow pads demonstrates a reduced life expectancy for the *canary* LCR. The proability density functions of the failure data for standard and *canary* LCRs under a defined temperature cycling test is presented in Figure 9. A comparison of distributions reveals the probability of a standard pad failure prior to a *canary* pad failure to be less than 0.01%. Examination of mean cycles to failure reveals a prognostic distance of approximately 1660 cycles.

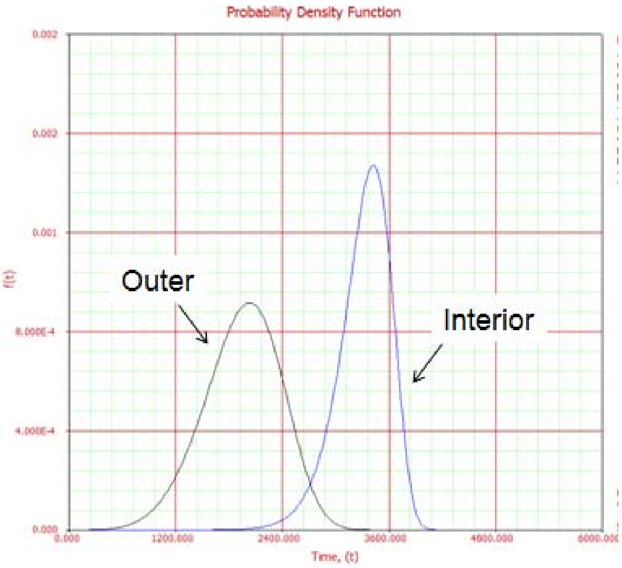

Figure 8. Probability Density Function of Cycles to Failure for an outer net and interior nets of a BGA.

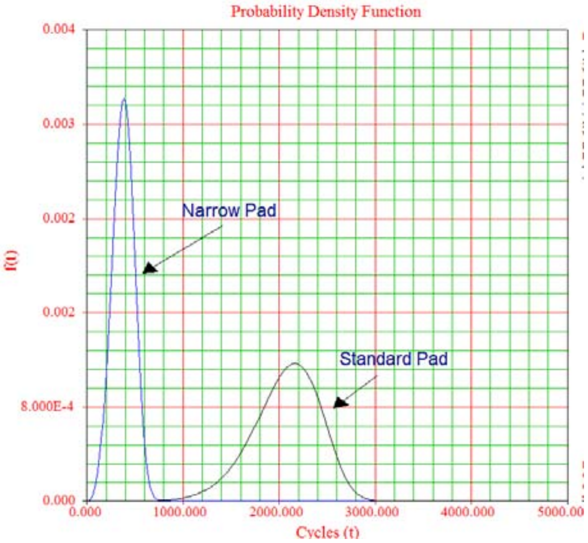

Figure 9. Probability Density Function Plot of Functional and *Canary* LCRs.

While the presented test data shows promise for solder joint *canaries*, more work is required. Testing of large IO BGAs has demonstrated that the corner solder joints are not always the first to fail. Figure 10 depicts a quarter of a 1500 I/O BGA subjected to a specific temperature cycling test. Different solder joints at different distances from the center were monitored in different daisy-chain nets shown by the different color codes. Figure 10 also depicts the frequency of first failures. As can be observed, a *canary* that only includes the three corner solder interconnects in this case would frequently miss failure prior to functional interior solder interconnects [35].

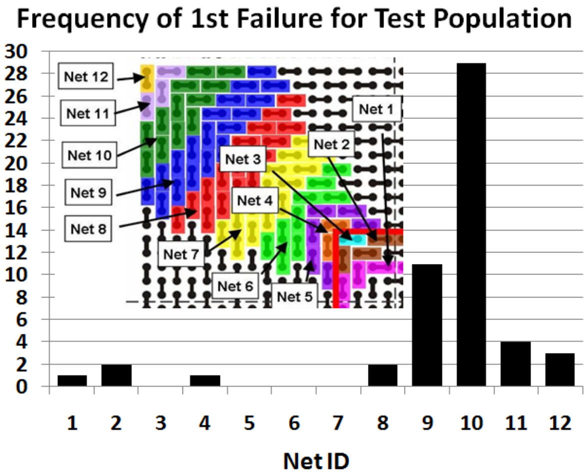

Figure 10. Frequency of First Failure in large BGA.

C. PWB Metallization *Canaries*:

Electronic products whose usage conditions include operation in environments with elevated levels of humidity are known to exhibit failures involving reduced surface insulation resistance (SIR). This can result in leakage currents or short circuits between portions of the circuit that are at different potential levels and are intended to be electrically isolated from one another, such as between a signal or power circuit and ground. One of the mechanisms by which the SIR of a printed circuit board (PCB) can degrade is known as electrochemical migration (ECM). The most visible manifestation of ECM is the presence of conductive metallic dendrites spanning the dielectric gap between differently biased leads, traces, or electrodes on the surface of a PCB. ECM occurs by the following sequence of steps [36]: formation of a path for ion migration between electrically biased metallic conductors, ingress into the path of a layer of electrolyte with dissolved ions typically in an adsorbed or condensed layer of water; ionization and dissolution of metal from the more positively charged conductor (anode); migration of metal cations through the electrolyte; deposition and reduction of metal cations onto the more negatively charged conductor (cathode); and growth of conductive metallic filaments towards the anode as more metal is deposited on the cathode.

Canaries for ECM can be incorporated into printed circuit boards and monitored for accelerated degradation in surface insulation resistance that will precede a functional failure of the circuit. The error-seeding for the *canary* design would thus need to be based on one or more known acceleration factors for this mechanism. Factors which could be used to accelerate ECM of *canary* structures include load parameters such as voltage, adsorbed moisture, and ionic contamination; geometric parameters such as spacing between conductors, and length of interface between conductors; and material parameters such as the presence of absence of a solder mask. Choice of suitable factor(s) should be based upon the achievable degree of control or repeatability, their sensitivity to specific processing or environmental risks, and their ease of integration into a product based on available space, voltage, and processing limitations.

One example of a structure which could serve as an effective ECM *canary* is a comb structure in which interdigitated conductors would be biased at similar or higher voltages than the functional circuit (Figure 11a). Acceleration of ECM failure relative to the functional circuit would be obtained due to the extended length of the interface between the conductors as well as the spacing of the conductors in the comb structure compared to the smallest spacing between biased conductors present in the circuit. This is geometric error-seeding. A source of material error-seeding is the elimination of the solder mask in the *canary* (Figure 11b), as it changes reduces the time taken for moisture to diffuse to the failure site (PWB metallization). Further acceleration could be obtained by load error-seeding, such as elevating the voltage applied across the adjacent conductors. A cross-hatched solder mask pattern across the comb could accentuate sensitivity to trapped contaminants associated with solder assembly or handling and anticipate circuit failures resulting from sub-standard processing procedures. These *canary* concepts are currently under investigation in this study and results will be presented in a future paper.

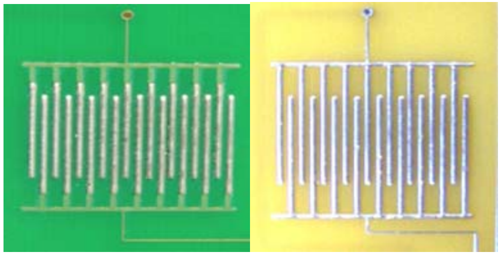

Figure 11. ECM *canaries* consisting of comb structures patterned from metallization on a PCB: (a) with solder mask between conductors; (b) with no solder mask.

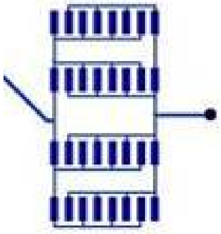

Figure 12. Conductor pattern for ECM *canary* for use with a pair of surface mount leaded packages.

Another example of a *canary* suitable for ECM is one in which the opportunity exists for dendritic growth next to or under surface mount components (Figure 12). In this case, acceleration of ECM failure can be obtained due to entrapment of moisture or ionic contaminants under the components, such as by residues of a no-clean solder flux; and/or by voltage and spacing, as well as total length of interface between the multiple adjacent solder pads connected in parallel.

V. CONCLUSIONS

Prognostics and health management is emerging as a popular alternative to traditional reliability assessment methods, for assuring product availability. As an important approach to prognostics, *canaries* have attracted more and more attention from industry. The definition of three different types of *canaries* has been presented: expendable *canaries*, sensory *canaries* and conjugate-stress *canaries*. Three main design methods for expendable *canaries* have been described, and three examples have been presented. In the interest of space, discussion of other types of canaries is deferred to a future paper. However, there remain unanswered questions of *canaries* for PHM. For instance, PoF knowledge is needed to ensure that a *canary* will behave in the same manner as host devices and fail due to the same failure mechanisms as host devices. Since manufacturers already have mature and standard assembly lines for existing products, affordably retrofitting *canary* devices, especially with different scaling, is a big challenge. Another big challenge is the invasiveness of *canaries*, based on their impact on degradation rates of the functional host.

Research on *canary* approaches for PHM is extremely critical for electronics that must meet high availability targets. By gaining a better understanding of the design rules of *canaries*, PHM will gain more momentum and more penetration into our daily life, and ensure higher availability for commercial and military products.

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REFERENCES

1. K. Keller, K. Swearingen, J. Sheahan, M. Bailey, J. Dunsdon, K.W.Przytula, and B. Jordan, “Aircraft Electrical Power Systems Prognostics and Health Management,” *IEEE Aerospace Conference Proceedings*, Big Sky, MT, March 2006.
2. A.H.C. Tsang, “Condition-based Maintenance: Tools and Decision Making”, *Journal of Quality in Maintenance Engineering*, 1(3), pp. 3-17, 1995.
3. D. K. Han, M. G. Pecht, D. K. Anand, and R. Kavetsky, “Energetic Material/Systems Prognostics,” *53rd Annual Reliability & Maintainability Symposium (RAMS)*, 2007.
4. S. Mishra and M. Pecht, “In-situ sensors for product reliability monitoring,” *Proceedings of the SPIE 2002*; 4755, pp. 10–19.
5. Ridgetop Semiconductor-Sentinel Silicon™ Library, “Hot Carrier (HC) Prognostic Cell,” 2004; August.

6. J. Wang and B. Calhoun, “Canary Replica Feedback for Near-DRV Standby VDD Scaling in a 90nm SRAM,” *IEEE 2007 Custom Integ Circuits Conf* (CICC), pp. 29-32.
7. B.H. Calhoun and A. Chandrakasan, “Standby Power Reduction Using Dynamic Voltage Scaling and Canary Flip-Flop Structures,” *IEEE J. Solid State Circuits*, vol. 39, no. 9, Sept. 2004.
8. N. Anderson and R. Wilcoxon, “Framework for prognostics of electronic systems,” *Proceedings of International Military and Aerospace/Avionics COTS Conference*, Seattle, WA, 2004; August 3–5.
9. D. Goodman, B. Vermeire, J. Ralston-Good, and R. Graves, “A Board-Level Prognostic Monitor for MOSFET TDDB,” *IEEE Aerospace Conference*, March 2006.
10. M. Pecht, *Prognostics and Health Management of Electronics*, Wiley- Interscience, August 2008.
11. Telcordia Technologies, Special Report SR-332, “Reliability Prediction Procedure for Electronic Equipment,” *Issue 1, Telcordia Customer Service*, Piscataway, NJ, 2001.
12. W. Denson, “A Tutorial: PRIS,” *RAC Journal*, 1999, pp. 1-6.
13. FIDES Group, “*FIDES Guide issue A, Reliability Methodology for Electronic Systems*,” 2004.
14. M. Cushing, D. Mortin, J. Stadterman, and A. Malhotra, “Comparison of Electronics-Reliability Assessment Approaches,” *IEEE Transactions on Reliability*, Vol. 42, No. 4, 1993, pp. 542-546.
15. S. F. Morris, “Use and Application of MIL-HDBK-217,” *Solid State Technology*, 1990, pp. 65-69.
16. J. Gu and M. Pecht, “Prognostics and Health Management Using Physics-of-Failure,” *54th Annual Reliability & Maintainability Symposium*, Las Vegas, NV, 2008.
17. A. Strachan, E. Kober, A. van Duin, J. Oxgaard, and W. Goddard III, “Thermal Decomposition of RDX from Reactive Molecular Dynamics,” *Journal of Chemical Physics*, 122, 054502, 2005.
18. M. Pecht, R. Radojcic, and G. Rao, *Guidebook for Managing Silicon Chip Reliability*, CRC Press, Boca Raton, FL, 1999.
19. P. Wang, and G. Vachtsevanos, “Fault prognostics using dynamic wavelet neural networks,” *Artificial Intelligence for Engineering Design and Manufacturing*, 15, 2001, pp. 349-365.
20. T. Brotherton, J. Jahns, J. Jacobs, and D. Wroblewski, “Prognosis of Faults in Gas Turbine Engines,” *Proceedings of the IEEE Aerospace Conference*, IEEE, New York, Vol. 6, 2000, pp. 163 –171.
21. B. Parker, Jr., T. Nigro, M. Carley, R. Barron, D. Ward, H. Poor, D. Rock, and T. DuBois, “Helicopter gearbox diagnostics and prognostics using vibration signature analysis,” *Proc. SPIE—The International Society for Optical Engineering*, Vol. 1965, 1993, pp. 531–542.
22. C. Byington, P. Kalgren, R. Johns, and R. Beers, “Embedded diagnostic/prognostic reasoning and information continuity for improved avionics maintenance,” *Proceedings of AUTOTESTCON 2003: IEEE Systems Readiness Technology Conference*, 2003, pp. 320-329.
23. W. Fenton, L. Maguire, and T. McGinnity, "Fault diagnosis of electronic systems using intelligent techniques: A review," *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, vol 31, no 3, August, 2001, pp. 269-281.
24. N. Dev and B. Anderson, "Pimtool: An expert system to troubleshoot computer hardware failures," *Proc. Innovative Applicat. Artif. Intell.*, 1997.
25. O. Duffaut and C. Castel, "A method to aid test-tree generation for hardware fault isolation in automotive electronic control systems," in *Proc.TOOLDIAG Int. Conf. Fault Diagnosis*, 1993, pp. 230-237.
26. A. Siddique, G. Yadava, and B. Singh, "Applications of artificial intelligence techniques for induction machine stator fault diagnostics: review," *4th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives*, 2003, pp. 29- 34, 24-26 Aug. 2003.
27. K. Przytula and D. Thompson, "Development of Bayesian diagnostic models using troubleshooting flow diagrams," *Proc. SPIE*, Vol. 4389, p. 110-120, July 2001.
28. A. AL-Jumah and T. Arslan, "Artificial neural network based multiple fault diagnosis in digital circuits," in *Proc. ICCAS*, vol. 2, pp. 304-307, 1998.
29. S. Ganesan, V. Eveloy, D. Das, and M. Pecht, “Identification and Utilization of Failure Mechanisms to Enhance FMEA and FMECA,” *Proceedings, IEEE Workshop on Accelerated Stress Testing and Reliability (ASTR)*, Austin, TX, October 3-5, 2005.
30. A. Ramakrishnan, T. Syrus, and M. Pecht, “Electronics Hardware Reliability,” Avionics handbook, CRC Press, Boca Raton, FL, pp.22.1-22.21, December 2000,.
31. N. Vichare, and M. Pecht, “Prognostics and Health Management of Electronics,” IEEE Transactions on Components and Packaging Technologies, Vol. 29, No. 1, March 2006, pp. 222-229.
32. Q. Zhang, A. Dasgupta, P. Haswell, “Partitioned viscoplastic-constitutive properties of the Pb-free Sn3.9Ag0.6Cu solder,” *J Electronic Materials* 2004; 33(11), pp,1338–49.
33. M. Osterman and M. Pecht, “Strain Range Fatigue Life Assessment of Lead-free Solder Interconnects Subject to Temperature Cycle Loading**,”** *Soldering & surface Mount Technology*, Vol. 19, No. 2, 2007, pp. 12-17.
34. A. Dasgupta, C. Oyan, M. Pecht and D. Barker, “Solder Creep-Fatigue Analysis by an Energy-Partitioning Approach**,”** *AMSE Journal of Electronic Packaging*, Vol. 144, June 1992, pp. 152-160.
35. S. London, D. Fricano, A. Dasgupta, T. Reinikaininen, G. Freitas, and C. Pagliosa, “Probabilistic effects in thermal cycling failures of high-I/O BGA assemblies,” *10th International Conference on Thermal, Mechanical and Multi-Physics simulation and Experiments in Microelectronics and Microsystems, Proc. IEEE EuroSimE*, April, 2009, pp. 26-29, DOI 10.1109/ESIME.2009.4938418.
36. S. Zhan, M. Azarian, and M. Pecht, "Surface Insulation Resistance of Conformally Coated Printed Circuit Boards Processed With No-Clean Flux," *IEEE Transactions on Electronics Packaging Manufacturing*, Vol. 29, Issue 3, July 2006, pp. 217 - 223.