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Capitalisation of rex data for use in predictive reliability databases for the distribution of failure modes

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The failure mode catalogue is a common data set used in reliability studies. It lists the failures and symptoms of failure for each type of component and suggests occurrence ratios. These lists are particularly useful for conducting FMECA or fault trees, for electronic card designers to make designs more robust against the most predictable faults, or for diagnostic in case of failure observation. However, the main limitation of these catalogues is their static nature. Failure modes and their occurrence distributions are highly dependent on the context in which the component is used, i.e. its life profile and the environmental stresses it is subjected to. As a result, the predominant failure mechanisms and modes vary. For a more accurate assessment, the FIDES methodology already proposes evaluating the failure rate by integrating environmental stresses via a detailed mission profile for each component family. In this article, we propose a method for capitalising on test data or data from operational feedback for use in predictive reliability databases. This method is based on two main approaches: The use of FMMEA (Failure Modes, Mechanisms, and Effects Analysis) based on the physics of failure and the design of Bayesian networks to update predictive reliability data. This statistical technique refines initial estimates by integrating new observed data. This methodology is then illustrated by an application to ceramic capacitors, where accelerated test data is used to update an existing predictive reliability study.

Keywords: Failure mode, PoF, Predictive reliability, FIDES, FMMEA.

1. Introduction et contexte

Failure mode distribution catalogues, such as (Quanterion Solutions Incorporated 2016), representing the ratio of different modes observed on an electronic component, are used to provide input into reliability/safety analyses during the design phase, such as Failure Mode, Effects and Criticality Analysis (FMECA). This also helps to guide testing and validation or post-test investigations towards the most likely failure modes. It can even help to anticipate diagnostic solutions. However, it is now accepted that the predominant failure modes observed on the same component differ depending on the mission profile (e.g. automotive, aeronautical or medical).

In electronics, there has been a change in approach to expressing reliability with work on the FIDES methodology (AFNOR 2011) and then (*Méthodologie d'évaluation de la fiabilité des systèmes électroniques - Guide FIDES 2022 Edition A* 2023).

While the FIDES methodology makes it possible to efficiently assess the predicted reliability of electronic systems by expressing a failure rate associated with environmental constraints, it also provides access to certain equations that were not explicit in older electronic reliability methodologies. Based on knowledge of the predominant failure mechanisms of the technological families covered and knowledge of the Physics of Failures (PoF) related to these predominant failure mechanisms, the FIDES method provides a quasi-physical link between the stress on the mechanism and the environmental stress, covered by the description of a life profile, an essential element of the methodology itself.

Common failure mode distribution catalogues, including (Quanterion Solutions Incorporated 2016) and RDF 2000 (TR 62380 - Equipment Reliability - Reliability Assessment Methods, 2004), provide lists based on component operation, but their distribution remains static. This distribution of failure modes is not modified by the product's life profile.

Based on the FIDES methodology, the next section presents the dynamic approach using a static Bayesian network, which depends on the life profile of the electronic system and is based on Failure Mode, Mechanism and Effect Analysis (FMMEA). In the following section, formalism is defined for learning the conditional probabilities of the Bayesian network from new test data. Finally, the last section develops an application case on ceramic capacitors based on an initial study and then on test data.

2. Distribution of failure modes according to life profile

The next two subsections describe the FIDES model, as outlined in the corresponding guide, and the use of FMEA to express the links between stress factors, failure mechanisms and failure modes. These elements are detailed in previous works.

2.1. *FIDES model and distribution of physical contributions*

The assessment of predictive reliability proposed by FIDES is formulated in Eq.(1) completed by Eq.(2).

$$\lambda_{Product} = \lambda_{Physical} \times \pi_{PM} \times \pi_{Process} \qquad (1)$$

With :

- $\lambda_{Product}$: failure rate of the item (electronic component, subassembly, COTS cards, etc.),
- $\lambda_{Physical}$: physical failure rate of the item, based on the laws selected by family and accelerated by the applied life profile as described in Eq.(2),
- π_{PM} : factor of the quality and technical control of the item's manufacturing,
- $\pi_{Process}$: process factor representing the process control reliability throughout the product life cycle.

$$\lambda_{physical} = \left[\sum_{Physical\ factors}(\lambda_0 \times \pi_{Acceleration})\right] \times \pi_{Induced} \qquad (2)$$

With :

- λ_0 : basic failure rate of the item in relation to the physical contribution,
- $\Pi_{Acceleration}$: acceleration factor based on data entered in the life profile, with regard to the physical contribution,
- $\Pi_{Induced}$: factor induced by electrical, mechanical and thermal overstress, taking into account its environment or use.

Certain failure mechanisms or modes are associated with quality defects and are therefore related to factors induced by part manufacturing or processes.

In FIDES, however, the decision was made to consider all these multiplicative factors as simple acceleration factors of failure mechanisms and failure modes already intrinsically present in the component (promoted by λ_0 and $\pi_{Acceleration}$). This remains acceptable initially, given that the findings indicate a high proportion of accelerated “intrinsic” fragility. This could be an interesting area for improvement in the breakdown of the FMMEA.

2.2. *Exploitation de la FMMEA*

In the life cycle of an electronic component, several failure mechanisms can be triggered by different environmental and operational parameters acting at different stress levels. The study of failure mechanisms enriches the standard FMEA by developing the Failure Mode, Mechanism and Effects Analysis (FMMEA) methodology (Cassanelli et al. 2006). This method is based on PoF to assess the root causes of failures and failure mechanisms of a given product, and is described in (Kapur et Pecht 2014) and (Hendricks et al. 2015).

In the case of an electronic component, the FMMEA allows at least the information in Table 1. below to be extracted. Environmental factors are deduced from the failure mechanisms based on the PoF.

Table 1. Example of FMMEA header.

Failure mode type	Failure mode	Failure causes	Failure mechani sms	Environ emental factors
[…]				

2.3. Bayesian network between failure modes and stress factors

The objective is to model the influence of stress conditions on the state of a mechanism, and then on failure modes, within a consistent probabilistic framework, integrating both:

- a priori knowledge (feedback, expertise),
- uncertain information relating to operating conditions.

To do this, we use a discrete static Bayesian network, which allows for explicit representation of conditional dependencies and learning from new data.

2.3.1. Bayesian network structure

A static discrete Bayesian Network (BN) is used to model the propagation of operational stress towards failure modes through the degradation state of a mechanical system.

The BN is defined by a directed acyclic graph where each node represents a discrete random variable:

- S: operational stress level (*m* states),
- M: mechanical state (*n* states),
- F: failure mode (*p* states).

The retained causal structure is on Fig. 1:

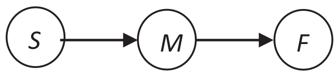

Fig. 1. Bayesian network structure modelling the propagation of operational stress through the mechanical state to failure modes.

This structure reflects the assumption that operational stress affects the internal mechanical state, which in turn determines the activated failure mode, as indicated by an FMMEA study. Conditional independence is assumed between stress and failure mode given the mechanical state.

2.3.2. Joint probability distribution

According to Bayesian network theory, the joint probability distribution factorizes as:

$$P(S, M, F) = P(S)\,P(M \mid S)\,P(F \mid M) \quad (3)$$

where:

- $P(S)$ is a priori distribution of stress,
- $P(M \mid S)$ is the conditional probability table (CPT) combining stress and mechanism condition,
- $P(F \mid M)$ is the CPT linking the state of the mechanism and the failure mode.

2.3.1. Prior distribution of stress

The stress node S is an input data representing a probability vector associated with the contribution of the failure rate of each stress accelerated by the FIDES Life Profile for a given family of components.

When assessing a predicted failure rate using the FIDES methodology, the following steps are essential:

- Identify and characterize a complete life profile.
- Evaluate all the factors required by the methodology,
- Enter a list of components and their respective stresses.

Once this has been done, the value of each stressor is evaluated for each component (e.g. using the FidesLab 1.5.5 software provided with (« A methodology for components reliability | FIDES », s. d.)), by phase, before combining them and calculating the failure rate. It is then possible to obtain a vector, component family by component family, describing the sensitivity of the family to each identified stressor.

An example of an $P(S)$ distribution of stress vector is presented in Table 6.

2.3.2. Stress–mechanism relationship

Using an FMEA, it is possible to create a relational matrix between failure mechanisms and stress factors, as shown in Table 1. This makes it possible to identify a relationship between failure mechanisms and environmental stressors. In addition, an expert opinion approach and the processing of feedback from manufacturers make it possible to build a set of statistical assumptions, which can be used to assign relative weight to the activation of a mechanism if the component is subjected to a particular stressor.

This approach can also be consolidated and enhanced by taking into account the expertise of component analysis companies and laboratories with experience that can be shared (Kevin Zurbuch, Michel Giraudeau, Stéphanie WONG 2012) in order to develop an initial statistical version of the CPT $P(M \mid S)$.

A example of the CPT for a given component family is given in Table 3.

The conditional probability $P(M \mid S)$ is defined by a CPT of size $m \times n$:

$$P(M = m_j \mid S = s_i) \qquad (4)$$

Each column corresponds to a stress level and satisfies: $\sum_{j=1}^{n} P(M = m_j \mid S = s_i) = 1 \quad \forall i$

2.3.3. Mechanism–failure relationship

Similarly, the conditional probability table $P(F \mid M)$ between failure mechanisms and failure modes can be compiled from the FMMEA, but also through testing or feedback from analysis laboratories responsible for investigating technical incidents that have occurred during operation. An example for the ceramic capacitor component family is given in Table 4.

The conditional probability $P(F \mid M)$ is represented by a CPT of size $p \times n$:

$$P(F = f_k \mid M = m_j) \qquad (5)$$

Each mechanical state is assumed to activate exactly one failure mode with a given probability distribution. By hypothesis, the CPT between failure mechanisms and failure mode remains unchanged regardless of the mission profile.

3. Update based on test data

The set of statistical assumptions, based on expert opinion or even feedback from failure analyses, used to establish conditional probabilities is influenced by the field of application and even by the rationalized industrial choice of components used in electronic designs. It is therefore essential that these CPTs can be updated using a larger data set. The various tests carried out according to a test profile therefore enable CPT updates to be made, considering the initial CPTs as a priori information within the framework of Bayesian networks. It is therefore necessary to first formalize the test results to enable consistent learning and then define the update of the Bayesian network with the a priori information.

3.1. *Formalization of feedback data*

Feedback data requires formalization specific to the Bayesian network framework. This data comes either from accelerated reliability and/or qualification tests, or from feedback on operational conditions. Accelerated tests are often associated with a single stress in order to identify the predominant failure mechanisms associated with it. For these tests, it is therefore often possible to specify a single target environmental stress factor. However, for feedback from operational conditions, the mission profile contains several joint environmental stresses.

The test data consists of N observations:

$$\mathcal{D} = \{(s^{(n)}, m^{(n)}, f^{(n)})\}_{n=1}^{N}$$

where:

- $s^{(n)}$and $f^{(n)}$, respectively stress type and failure mode, are observed,
- $m^{(n)}$ the failure mechanism may be partially or totally unobserved.

This framework justifies the use of probabilistic learning with latent.

3.2. Update of Bayesian network from data test data

To update the Bayesian network, it is necessary to define at least one predominant stress factor for each observed failure. When the observed stress is a probability vector, it is then necessary to enter the information by considering each observed factor proportionally and assigning it a relative weight for the observed data in relation to the prior.

Weighting is introduced via a factor $\gamma \geq 0$ applied to the prior data:

$$\alpha_{ij}^{\text{eff}} = \gamma \cdot \alpha_{ij}^{\text{prior}} + N_{ij} \qquad (6)$$

where:

- α^{prior} encodes expert knowledge,
- N^{data} corresponds to counts from test data,
- γ controls the relative influence of the prior.

Boundary cases:

- $\gamma = 0$: learning based purely on data
- $\gamma \gg 1$: model strongly constrained by expertise

To account for heterogeneous confidence levels in experimental data, parameter learning was performed using a Bayesian Maximum A Posteriori approach. Expert knowledge and data reliability were encoded as Dirichlet prior distributions on the conditional probability tables, acting as weighted pseudo-counts during the learning process. Parameter learning was performed using the Bayesian Network Toolbox (BNT) in MATLAB.

4.2. Learning with incomplete data

An interesting point here is that it is not necessary to have information on the failure mechanisms represented by the intermediate node of the Bayesian network. In such cases, the Expectation–Maximization (EM) algorithm is employed to estimate CPTs by iteratively maximizing the likelihood of incomplete data.

4. Application in the case of ceramic capacitors

The FMMEA for ceramic capacitors, based on literature, was carried out as part of the RECOME (Reliability of Electronic Components for MEdical applications) project with a focus on the use of this type of component for active implantable medical devices. It appears that humidity plays a role in the onset of failure mechanisms resulting from manufacturing defects or aging (Donahoe et al. 2006; Saito et al. 2018). These failure mechanisms are not considered in the current FIDES model, which is linked to feedback based on environments from different industrial sectors. We therefore felt it was important to include an acceleration factor associated with humidity, based on the model derived from Peck's law and included in FIDES, particularly for integrated circuits.

4.1. *CPT and initial Bayesian network*

For ceramic capacitors, four stressors have been identified: three using the FIDES methodology (thermoelectric, thermal cycling, mechanical), plus humidity, and 13 failure mechanisms. The first correspondence matrices based on industrial laboratory feedback were established using the FMMEA (Pelloquin, Gaëtan et al. 2024) and gives initial CPT of BNT.

4.2. *Test data performed*

As part of the RECOME project, which aims to provide a guide for qualifying the reliability of electronic components used in active implantable medical devices, with a particular focus on miniature components, accelerated reliability tests were carried out on ceramic capacitors.

In this project, a series of tests was carried out on 12 different types of capacitors (in terms of the technological factors taken into account in FIDES), following five different test profiles (temperature, humidity, voltage) (Indmeskine et al. 2024). This resulted in a set of 60 stress contribution profiles and failure mechanism distribution data, with 24 identical components tested for each combination (Indmeskine 2024). Three test profiles provided sufficient failure information and are presented in Table 2.

Table 2. Stress level of accelerated life test.

	Voltage Ratio	Humidity (%)	Temperature (°C)
ALT1	0	75	30
ALT2	0.4	85	85
ALT4	1.2	0	120

Accelerated testing is often associated with a single stress to identify the predominant failure mechanisms involved. This makes it easy to determine the contributions of the various stress factors.

For ALT1 tests, only the temperature is accelerated, and therefore only this stress is observed at the input. Similarly, for ALT4 tests, without humidity, only thermo-electrical stress is observed. For the ALT2 tests in humid heat, based on the acceleration laws defined in the thesis work of (Indmeskine 2024), humidity and thermo-electrical stresses are defined as observed in equivalent proportions. This gives the following probability distribution of stress in Table 3. The learning of conditional probabilities in the Bayesian network will therefore be carried out on the corresponding stresses, as well as the associated failure mechanisms and modes from the FMMEA.

Table 3. Probability distribution of stress for accelerated life test

	Thermal cycling	Vibration	Humidity	Thermo-electrical
ALT1	0	0	1	0
ALT2	0	0	0.46	0.54
ALT4	0	0	0	1

Based on measurements of degradation in various parameters (capacitance, dissipation factor, and insulation resistance), eight failure mechanisms were observed: avalanche breakdown, thermal runaway, oxygen vacancy migration (for BME), ECM (ion accumulation), ECM (dendrite growth), ECM (solid state), IR degradation, and capacitance aging. In addition, only two failure modes were observed: drift and short circuit. This led to the observation of 2,723 components.

4.3. *Bayesian network update*

Starting in section 3.2, the initial expertise data is set at 1000 values to obtain the relative influence of the prior data. The parameters of the Bayesian network were estimated using the Expectation–Maximization algorithm with a maximum of 30 iterations. Convergence was assessed by monitoring the log-likelihood, which reached a stable plateau before the maximum number of iterations.

4.4. *Results obtained and comparison*

Based on the initial Bayesian network determined using conditional probability tables (Pelloquin, Gaëtan et al. 2024), the learning process yields the a posteriori CPT combining stress and mechanism condition for ceramic capacitors in Table 4. Similarly, a posteriori CPT linking the state of the mechanism and the failure mode for ceramic capacitors is obtained in Table 5.

Table 4. A posteriori CPT combining stress and mechanism condition for ceramic capacitors

Failure mechanisms \ Stress	Thermal cycling	Vibration	Humidity	Thermo-electrical
Flex cracks		0.5		
Thermal cracks	0.5	0.1		
Avalanche breakdown			0.008	0.186
Thermal runaway			0.042	0.216
Oxygen vacancy migration (for BME)			0.132	0.053
ECM (ion accumulation)			0.152	
ECM (dendrite growth)			0.184	0.076
ECM (Solid State)				0.03
IR degradation			0.074	0.037
Crack growth	0.5			0.02
Electro-mechanical resonance		0.400		0.02
Capacitance ageing			0.406	0.363

Table 5. A posteriori CPT linking the state of the mechanism and the failure mode for ceramic capacitors.

Failure mechanisms \ Stress	Drift	Open	Shorted
Flex cracks	1		
Thermal cracks		1	
Avalanche breakdown			1
Thermal runaway	0.698		0.302
Oxygen vacancy migration (for BME)	0.796		0.204
ECM (ion accumulation)	1		
ECM (dendrite growth)	0.599		0.401
ECM (Solid State)			1
IR degradation	1		
Crack growth			1
Electro-mechanical resonance	0.3		0.7
Capacitance ageing	1		

To apply this to a use case involving an electronic board with 60 capacitors. The capacitors were modeled in the FidesLab tool in accordance with the FIDES 2022 methodology, using the default values from the guide for the Process and Part Manufacturing aspects.

This component list use case was then used according to three different mission profiles:

- Helicopter - Avionics bay computer - VIP use - Temperate climate (outside temperature of 15°C),
- Geostationary orbit satellite - platform equipment (computer type),

- Military portable radio.

The three mission profiles are freely available in the FIDES 2022 guide (Methodology for assessing the reliability of electronic systems - FIDES 2022 Guide Edition A 2023).

From there, three mission profile vectors were generated using the tool, to which was added a profile for an electronic card in an active implanted medical device. These profiles are available in Table 6.

Table 6. Distribution of stress probability in % for different mission profiles.

	Thermal cycling	Vibration	Humidity	Thermo-electrical
Helicopter	65.18%	8.3%	0	25,31%
Satellite GEO	1,65%	0,03%	0	98,32%
Military radio	12,74%	5,34%	0	81,92%
Medical implanted	0	0	66%	34%

From the Bayesian network updated by learning with CPTs, failure mode catalogs for ceramic capacitors are obtained by mission profile in Table 7. This difference can be compared, for example, to the failure mode catalog (Quanterion Solutions Incorporated 2016) in Fig. 2.

Table 7. A posterior failure mode distribution in % for each mission profiles and FMD-2016.

Profil	Drift	Open	Shorted
Helicopter	22,08%	33,62%	44,3%
Satellite GEO	63,35%	0,83%	35,82%
Military radio	56,08%	6,9%	37,02%
Medical implanted	79.85%	0%	20.15%
FMD-2016	62,78%	5,98%	31,24%

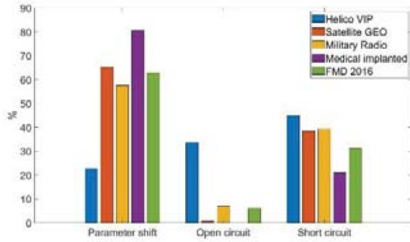

Fig. 2. Comparison of a posteriori failure mode distribution.

5. Conclusion and perspectives

The article presents a methodological framework for expressing the distribution of failure modes based on the mission profile formalized using the FIDES methodology for families of electronic components from a Bayesian network. This framework links the stresses expressed in the life profile to the predominant failure mechanisms and then links the mechanisms to the failure modes. The framework formulated by the Bayesian network allows for learning and updating of conditional probabilities based on REX. The methodology applied to the ceramic capacitor family has shown the variation in failure mode distribution ratios according to industrial mission profiles.

There are still some limitations to the methodology that need to be addressed before it can be generalized. At this stage, the approach considers the multiplicative factors of the FIDES methodology (π_{PM}, $\pi_{Process}$ and $\pi_{induced}$) as accelerators of intrinsic mechanisms, expressed through failure modes that are not necessarily related to quality issues. While this is most likely largely acceptable, it should be demonstrated through a dedicated and representative statistical analysis.

The proposed approach highlights the importance of the feedback and expertise used. While this data is essential, the industrial sectors from which it originates should be specified.

Based on broader feedback, it is possible to develop the method for a catalog of failure modes distribution by including various industrial and academic contributors to expand the representativeness of the method and lay a solid foundation for a new guide to the distribution of dynamic failure modes based on life profiles. This will also require formalizing reliability test data within a standard data framework.

As with many families of electronic components, the technologies used in ceramic capacitors are distinct, which influences the FMMEA by type. It is therefore possible to improve the design of the Bayesian network by adding information on the type of ceramic capacitors. More generally, the Bayesian network framework can be enhanced with input information on component characteristics that influence failure mechanisms.

About ceramic capacitors, the tests carried out as part of the RECOME project reveal some potentially useful additions to the reliability model for certain uses, such as taking humidity into account. Based on the current results, it would be advisable to assess the relevance of updating the FIDES model for ceramic capacitors.

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References

« A methodology for components reliability | FIDES ». s. d. Consulté le 4 février 2026. https://www.fides-reliability.org/.

AFNOR. 2011. *Méthodologie d'évaluation de la fiabilité des systèmes électroniques - Guide FIDES 2009 Edition A*. UTE C80-811.

Cassanelli, G., G. Mura, F. Fantini, M. Vanzi, et B. Plano. 2006. « Failure Analysis-Assisted FMEA ». *Microelectronics Reliability*, Proceedings of the 17th European Symposium on Reliability of Electron Devices, Failure Physics and Analysis. Wuppertal, Germany 3rd–6th October 2006, vol. 46 (9): 1795-99. https://doi.org/10.1016/j.microrel.2006.07.072.

Donahoe, Daniel N., Michael Pecht, Isabel K. Lloyd, et Sanka Ganesan. 2006. « Moisture induced degradation of multilayer ceramic capacitors ». *Microelectronics Reliability* 46 (2): 400-408. https://doi.org/10.1016/j.microrel.2005.05.008.

Hendricks, Christopher, Nick Williard, Sony Mathew, et Michael Pecht. 2015. « A Failure Modes, Mechanisms, and Effects Analysis (FMMEA) of Lithium-Ion Batteries ». *Journal of Power Sources* 297 (novembre): 113-20. https://doi.org/10.1016/j.jpowsour.2015.07.100.

Indmeskine, Fatima-Ezahra. 2024. « Evaluation et qualification de la fiabilité des composants et des procédés d'assemblages électroniques pour applications médicales ». These de doctorat, Angers. https://theses.fr/2024ANGE0029.

Kapur, Kailash C., et Michael Pecht. 2014. *Reliability engineering*. Wiley.

Kevin Zurbuch, Michel Giraudeau, Stéphanie WONG. 2012. « Exploitation de données de retours d'expérience multi-industriels pour la consolidation des modèles FIDES ». Article de colloque presented sur Congrès λμ 18, Tours. octobre.

Méthodologie d'évaluation de la fiabilité des systèmes électroniques - Guide FIDES 2022 Edition A. 2023. juillet. www.fides-reliability.org.

Pelloquin, Gaëtan, Montigaud, Thibault, Saintis, Laurent, et Indmeskine, Fatima-Ezahra. 2024. « Distribution des modes de panne et profils de vie FIDES ». *Congrès Lambda Mu 24 "Les métiers du risque : clés de la réindustrialisation et de la transition écologique" - 24e Congrès de Maîtrise des Risques et de Sûreté de Fonctionnement, Institut pour la Maîtrise des Risques* (Bourges, France), octobre.

Quanterion Solutions Incorporated. 2016. *FMD-2016, Failure Mode/Mechanism Distributions 2016*.

Saito, Yoshito, Tomoyuki Nakamura, Kenichi Nada, et Harunobu Sano. 2018. « Insulation Resistance Degradation Mechanisms of Multilayer Ceramic Capacitors during Highly Accelerated Temperature and Humidity Stress Tests ». *Japanese Journal of Applied Physics* 57 (11S): 11UC04. https://doi.org/10.7567/JJAP.57.11UC04.