

# RELIABILITY MODEL BASED COST COMPUTATION TOOL APPLIED TO 4R PROCESS (ROBUST DESIGN, REPAIR, REMANUFACTURE & RECYCLE)

Kevin Boissie – Valeo, Circular Electronic Laboratory, Nevers, France

Fabrice Blasenbauer – Valeo SC2N, Mondeville, France

Thomas ILLING – Valeo Brain, Bietigheim, Germany

Liam Garvey – Valeo Brain, Tuam, Ireland

## Abstract

In rework and repair operations, early-stage estimation of risk assessment costs is hindered by uncertainty in the nature of the operations, variability in reliability targets, and the complexity of underlying failure mechanisms. At a point when budgeting for quality control is essential, the lack of foundational data often leads to inaccurate cost projections. This paper introduces a configurable framework that integrates accelerated testing models with a project-planning tool to reduce cost uncertainty in repair and remanufacturing processes. Project managers can define the desired level of complexity and reliability based on customer requirements, and the tool then evaluates viable cost scenarios accordingly. By leveraging models such as Arrhenius, Coffin-Manson, and Hallberg-Peck—along with internal rules for activation energies and sample sizing—the system calculates the testing effort required to demonstrate a specified reliability objective. The reliability target, chosen by the project manager, acts as a key input in the overall cost evaluation. The result is a structured cost range that accounts for different warranty levels and failure physics, enabling more informed decision-making early in the project lifecycle. This methodology supports design-for-repair strategies by improving predictability in quality planning and enhancing transparency in cost-risk tradeoffs. It also aligns with circular economy goals by optimizing resource use and supporting more sustainable product life cycles.

## Introduction and Motivation

In industrial repair, refurbishment, and remanufacturing of electronic assemblies, a major challenge in early-stage planning is cost estimation under uncertainty—especially with limited data on failure modes, post-repair service life, and reliability targets. This study is framed within the 4R concept—Robust Design, Repair, Remanufacture, and Recycle—a lifecycle strategy aligned with circular economy principles aiming to extend product life and reduce waste. Rework operations often involve assemblies with unknown degradation patterns, complicating testing and qualification. This leads to either under-budgeted quality assurance or overly conservative plans. In high-reliability sectors like automotive, aerospace, or defense, failure of a repaired unit can cause costly warranty issues and damage reputation. Moreover, repair activities introduce stressors (e.g., localized heating, mechanical disruption), complicating reliability assurance. Boissie et al. introduced the “Repair Index” to assess Printed Circuit Board Assembly (PCBA) repairability during design, considering factors like component spacing and rework stress [1], highlighting that repair cannot be equated with new manufacturing in terms of cost and reliability. Though various reliability models exist (Arrhenius, Coffin–Manson, Hallberg–Peck), applying them to repaired systems is limited by lack of input data (e.g., activation energy, stress profiles) and unclear reliability targets [2]. As a result, planners rely on heuristics or outdated data that may not reflect rework-induced failures. Repairability is gaining economic and regulatory traction, with benefits in extended product life and waste reduction—if post-repair reliability is sufficient. A product easier to repair may lower costs and downtime, but if less reliable, these gains are lost to early failures or warranties. Directive (EU) 2024/1799 promotes repair and product lifetime extension, pressing for better cost-risk anticipation in remanufacturing [3]. This dual pressure—extending use per circular economy goals while meeting reliability at acceptable cost—requires robust planning. LCA studies show that adding five years to a module’s life via repair can cut lifecycle emissions by 20%, mainly by avoiding new component production [4]. Thus, project managers and reliability engineers need tools to (1) set reliability goals from the outset, (2) simulate test/qualification paths per repair complexity, and (3) define cost-risk scenarios linked to failure physics. Boissie et al.’s “Repair Index” aids the design phase [1], but comprehensive frameworks tying together reliability modeling, test planning, and cost estimation remain rare. This work proposes such a framework: letting managers choose reliability targets, classify repair complexity, and apply standard models (Arrhenius, Coffin–Manson, Hallberg–Peck) using embedded heuristics (e.g., sample sizes, failure rules) to determine test effort and derive cost scenarios. This reduces early-stage budget uncertainty, supports design-for-repair strategies, and aligns with circular economy goals through transparent cost-

reliability tradeoffs. In sum, this study aims to bridge early planning with the realities of repair. Repair projects need data-driven tools to translate reliability goals into cost-aware plans. While the methodology is rooted in reliability engineering, it provides decision-making tools that are accessible to circular economy stakeholders. By translating technical repair characteristics into quantifiable cost and risk scenarios, the framework empowers sustainability professionals to evaluate the trade-offs between lifecycle extension and qualification burden.

## Current State of the Technology Industry Uses

As electronics repair and requalification gain momentum in the context of the circular economy and regulatory pressure, the industry continues to face structural limitations in how reliability and cost are managed throughout the 4R lifecycle (Robust Design, Repair, Remanufacture, Recycle(d)). While the need to extend product life and reduce electronic waste is now widely acknowledged, the methodologies used to evaluate and qualify repaired systems remain fragmented, inconsistent, and often disconnected from failure physics. This section explores the current state of practice in industrial repair, highlighting both the strategic role of rework and the risks associated with insufficient quality validation. It also reviews the challenges inherent to cost estimation in reliability-driven repair programs, outlines key regulatory and sustainability drivers shaping future requirements, and discusses existing initiatives that begin to bridge some of these gaps. Despite progress, there remains a lack of structured frameworks linking reliability targets with simulation-based cost assessments. The remainder of this section is structured into four subsections: industrial practices, modelling challenges, regulatory constraints, and a discussion of conceptual and methodological gaps.

## Industrial Practices in Repair and Remanufacturing

In the electronics sector, repair and remanufacturing play a pivotal role in extending product lifespans, reducing electronic waste, and aligning with circular economy goals. However, current industrial practices in validating post-repair reliability remain highly variable and, in many cases, insufficient. A widely adopted yet minimal approach consists of functional-only testing, which returns assemblies to service after a simple visual or electrical verification. While cost-effective, this method leaves significant residual risk, as latent defects such as micro-cracks, solder fatigue, or thermal degradation introduced during rework often go undetected [5]. To mitigate this, some manufacturers incorporate basic visual inspections and electrical tests post-repair, aimed at identifying obvious rework-induced defects like misalignment or poor solder wetting.

Table 1. Comparison of Current Industrial Repair Practices

| Practice type                                                            | Typical cost implication | Reliability gap / residual risk                                           | Level of process control                                     |
|--------------------------------------------------------------------------|--------------------------|---------------------------------------------------------------------------|--------------------------------------------------------------|
| Functional test only (post-repair)                                       | Low immediate cost       | High: latent damage undetected may lead to early failure                  | Low – Visual inspection or functional test only              |
| Visual inspection + basic functional                                     | Moderate cost            | Moderate: some failure modes caught, but accelerated ageing not addressed | Medium – Basic rework standards applied                      |
| Accelerated life test (generic)                                          | Higher cost              | Reduced risk, but may not target repair-specific failure modes            | Medium-High – Generic testing program                        |
| Qualification including detailed reliability modelling and sample sizing | High cost                | Low risk: reliability targets aligned with physics of failure             | High – Structured process, traceability, advanced simulation |

At the upper end of the spectrum, some organizations implement qualification programs grounded in reliability modelling. These include sample sizing and stress modeling based on physics-of-failure approaches, such as defining activation energies for the Arrhenius model or fatigue life parameters for Coffin–Manson. Though offering high confidence in post-repair reliability, such methods are resource-intensive and typically reserved for high-risk or safety-critical systems. Table 1 summarizes how these different approaches compare in terms of cost, residual risk, and process control; where in this context, “process control” refers not to PID or closed-loop feedback systems, but to the structured control and traceability of qualification steps, test coverage, and process robustness applied during repair validation. Despite the availability of more robust methods, many organizations rely on basic testing due to cost constraints or high product volumes. This can lead to under-qualified repairs and poorly scoped budgets. As Cordella et al. point out, decisions around reliability and repairability are often made without formal quantitative foundations [7]. The sector lacks standardized frameworks linking repair complexity with reliability targets and qualification cost. Addressing this gap is the objective of the framework proposed in this study.

## Challenges in Reliability-Based Cost Forecasting

Forecasting the cost of reliability qualification for repaired electronics presents several interrelated challenges. Chief among them is the absence of clearly defined post-repair reliability targets. While new product development typically includes quantified objectives—failure rates, MTTF, or warranty returns—repair programs often rely on vague assertions like “as good as new” without measurable benchmarks. This absence prevents meaningful test design, sample sizing, or risk-cost estimation. In maintenance-oriented models, the lack of reliability objectives has been shown to impair decision-making efficiency [8]. Compounding this issue is the high variability in failure modes and usage conditions after repair. Thermal and mechanical stresses introduced during rework—such as local reheating, reflow cycles, and manual handling—can initiate new degradation pathways not present in original manufacturing. Manual operations introduce inconsistent stress levels, increasing uncertainty. Additionally, post-repair units often operate in environments that differ from their original deployment, with service conditions either undocumented or unpredictable. These uncertainties directly affect cost forecasting, as repair qualification must account for a broader range of scenarios, or risk overlooking potential failure modes. Gavidel and Rickli emphasize that in remanufacturing, variability in return conditions and core quality can significantly skew cost projections [9]. Traditional cost-estimation models, inherited from manufacturing or scheduled maintenance, are ill-suited to the specific context of repair. Most assume homogeneity in component history, known failure distributions, and consistent usage—all of which are incompatible with the partially degraded, manually reworked, and operationally diverse nature of repaired units. Xu and Feng argue that cost models for remanufacturing must be process-specific to yield meaningful results [10]. Translated into the repair context, this means accounting for sample sizing, tailored testing, and failure-risk simulations—none of which are standard in most repair cost frameworks. In the absence of structured methods, project planners’ resort to heuristic decisions or analogical reasoning — “we did something similar last year”—resulting either in overqualification with inflated costs, or in underqualification with hidden reliability risks. What is lacking is a methodological tool that integrates reliability targets, repair complexity, and physical degradation mechanisms to yield realistic cost and qualification scenarios. The framework introduced in this work aims to fill that gap, enabling repair project managers to initiate planning based on defined reliability objectives and simulate the required qualification effort using established models like Arrhenius, Coffin–Manson, and Hallberg–Peck.

## Regulatory and Sustainability Driver

Regulatory momentum and sustainability imperatives are increasingly shaping repair strategies in the electronics sector. Repair, once seen as an operational decision, is now embedded within broader legislative and environmental frameworks. At the European level, the Circular Economy Action Plan and the Sustainable Products Initiative advocate for design strategies that prioritize reparability, reusability, and lifetime extension. These initiatives mandate integration of durability and repairability into both technical and economic planning [11]. The recent Directive (EU) 2024/1799, commonly known as the Right to Repair directive, marks a significant regulatory shift. Effective since June 2024, it obliges manufacturers and service providers across the EU to facilitate repair even beyond the legal

guarantee period. This includes making spare parts and documentation available, ensuring repair services are accessible and affordable, and clearly informing consumers of their options. It also introduces the notion of a “repair score,” which will impact regulatory compliance and market behavior [12]. Complementary tools like the French Repair Index provide scoring criteria based on disassembly ease, spare part availability, and documentation. These tools not only serve regulatory goals but also exert market pressure on manufacturers to quantify repair costs—including warranty risks and lifecycle impacts. As Meysner notes, the integration of repairability assessments into design and budgeting is rapidly becoming an industrial necessity [13]. Extending electronics’ service life by five years can reduce lifecycle emissions by 15–20% [14]. However, such benefits are only realized if post-repair reliability is sufficient to prevent premature failure. Hence, simulated reliability and cost assessments are now essential—not only as best practices, but as compliance tools under evolving EU legislation. Table 2 outlines the key policy instruments currently shaping repair planning strategies.

Table 2. Regulatory and Sustainability Constraints Influencing Repair Planning

|                                                                              |                                                              |                                                                                              |
|------------------------------------------------------------------------------|--------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Circular Economy Action Plan / Sustainable Products Initiative               | Extension of product lifetime, encouragement of reuse/repair | Repair must align with sustainability targets; cost of repair justified by extension of life |
| Directive (EU) 2024/1799 (Right-to-Repair) [15]                              | Common rules promoting repair of goods                       | Need for transparent cost structures, repair access, documentation                           |
| Affordability of repair & consumer protection [16]                           | Repair cost must be “reasonable and non-discriminatory”      | Project planners must include repair cost-risk trade-offs early                              |
| Material efficiency / repairability indices (e.g., French Repair Index) [17] | Metrics for durability, reparability, robustness             | Design-for-repair must feed into cost modelling and process design                           |
| Circular Economy Action Plan / Sustainable Products Initiative [17]          | Extension of product lifetime, encouragement of reuse/repair | Repair must align with sustainability targets; cost of repair justified by extension of life |

## Existing Approaches and Gaps

Despite regulatory advances and increasing emphasis on repairability, existing qualification practices for repaired electronics remain fragmented and empirically driven. Most repair programs prioritize functionality and basic inspection, occasionally supported by generic ALT. However, these methods rarely integrate physics-based reliability modelling and fail to offer meaningful cost-risk insights. A core limitation is the disconnect between degradation modeling and cost planning. Models like Arrhenius and Coffin–Manson are well-established in product qualification but rarely adapted for repair contexts due to the lack of structured input parameters, such as post-repair activation energy or new stress profiles. Moreover, traditional cost models often assume fixed operating conditions, which do not hold for reworked assemblies with partial histories. Consequently, many organizations either over-engineer their qualification efforts or under-prepare for warranty risk, as few methods support the joint evaluation of repair complexity, reliability objectives, and cost implications. While some design-stage tools score reparability based on accessibility and part availability, they typically overlook post-repair reliability and associated testing burdens. This creates a methodological blind spot, especially in early planning phases where budget, risk tolerance, and qualification scope must be defined. Moreover, the correlation between repairability and qualification effort is often non-linear. More accessible components may also be more fragile or thermally sensitive, requiring more extensive validation. This underlines the need for simulation-based planning tools that can evaluate test burdens and cost ranges based on technical realities. The framework presented in this paper addresses this gap by offering a structured method to simulate qualification effort, define cost scenarios, and align reliability objectives with rework complexity and environmental constraints.

## Technology Approach

The proposed framework addresses a key industrial challenge: estimating qualification effort and cost for electronic assembly repair, rework, or remanufacturing at early project stages, when reliability targets, failure mechanisms, and cost exposures must be aligned. Figure 1 below illustrates the overall framework used in this study, structured around four sequential operations: Risk Assessment, Test Suite Selection, Test Duration Calculation, and Cost Estimation.

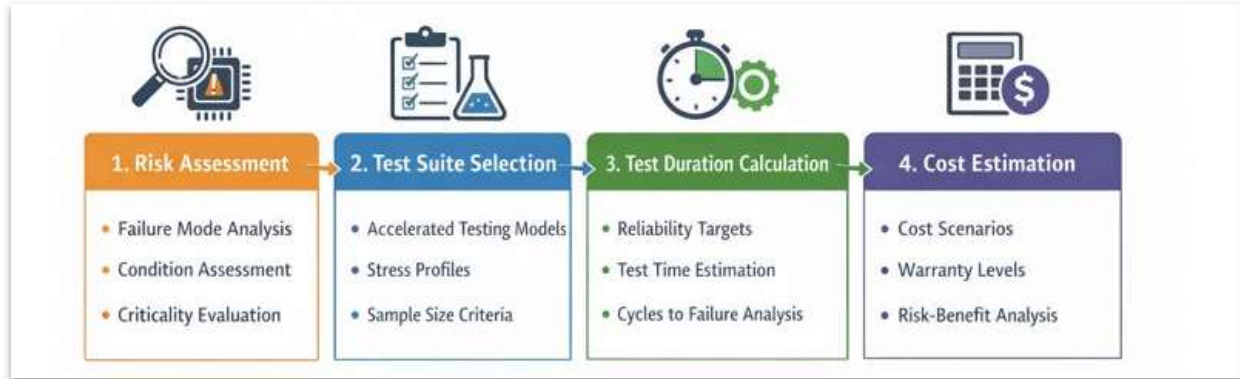


Figure 1. Overview of the Cost Estimation Framework for Repair & Remanufacturing

This is critical in sectors with high reliability expectations and constrained budgets. The tool transforms a reliability target into an actionable qualification plan, defining sample sizes, test durations, and cost ranges—particularly important in scenarios where reworked units differ significantly from new assemblies due to prior stress, altered material states, or non-uniform degradation. By integrating accepted accelerated life test (ALT) models, a tailored classification of repair complexity, and a cost calculation engine, the framework ensures qualification strategies are both technically robust and economically scalable. Three main inputs initialize the tool: the product type (e.g., camera, domain controller), production volume, and Bill-of-Materials (BOM) cost. These act as proxies for product complexity, safety relevance, and rework effort. Mapped into a two-dimensional classification space, they yield a discrete risk level (low, medium, or high), which governs the selection of failure models, test types, and cost computations. The tool then triggers a corresponding test plan. For Risk Level 1, process-qualification tests validate baseline reliability on bare PCBAs using thermal cycling (PTCE), humidity exposure (HTHE), and thermal shocks with minimal monitoring. At Risk Level 2, reliability-demonstration tests are applied to fully assembled products to capture rework-induced failures (e.g., corrosion, mechanical fatigue, long-term humidity exposure). DVP/PV warranty-coverage tests are added to ensure customer compliance. For high-risk Level 3 applications, HALT-based robustness tests and screening tests near operating limits detect latent margin reductions. Thermo-mechanical simulation complements all levels to refine scope and stress relevance.

Table 3 Reliability Models and Associated Parameters

| Model         | Equation                                                                         | Applicable Stress Type           |
|---------------|----------------------------------------------------------------------------------|----------------------------------|
| Arrhenius     | $AF = \exp(E_a/k \times (1/T_{use} - 1/T_{test}))$                               | Temperature                      |
| Coffin–Manson | $Nf = C \times (\Delta\epsilon)^{-b}$                                            | Thermo-mechanical fatigue        |
| Hallberg–Peck | $AF = \exp(E_a/k \times (1/T_{use} - 1/T_{test})) \times (RH_{test}/RH_{use})^n$ | Temp. + Humidity combined stress |

Where  $AF$ : acceleration factor;  $E_a$ : activation energy (in eV);  $k$ : Boltzmann constant ( $8.617 \times 10^{-5}$  eV/K);  $T_{use}, T_{test}$ : temperatures in Kelvin;  $\Delta\epsilon$ : strain range;  $n$ : humidity exponent in Hallberg–Peck;  $RH$ : relative humidity (as %)

To calculate test duration, the tool uses the zero-failure binomial model, combining the specified reliability target (e.g., 3–10 years), confidence level (typically 75–90% for critical systems), sample size (bench-limited or adjusted), activation energy, and the mission profile. These parameters yield an acceleration factor (AF), which is then used to compute required stress durations. Repair complexity is also considered, with the tool adjusting duty cycles, loads, and sample sizes depending on component accessibility, thermal sensitivity, and interconnection density. A basic passive rework differs significantly from a BGA repair on a high-density board, and the classification adapts accordingly. Scientifically, the framework rests on standard ALT models presented in Table 3. Failure model selection is rule-based and depends on dominant degradation mechanisms. Parameters are sourced from internal datasets, industry databases, or LV124 standards. Test durations are calculated using these models and adjusted through AF scaling.

The overall workflow consists of four operations. Operation 1 computes product risk from basic early-stage data such as BOM, manufacturing site, and product family. The resulting risk rating informs test scope without needing expert input, supporting early cost estimation. Operation 2 automatically selects the appropriate test suite (e.g., PCBA inspection, reliability demo, robustness or screening) based on the risk level. These selections embed both internal standards and published industrial practices. Operation 3 computes test durations using mission profiles, model parameters, and sample sizes. Mission profiles can be standard or probabilistically generated from historical usage data, following approaches proposed by Delaux [18]. Operation 4 converts sample count, test duration, and engineering workload into a cost estimate, normalized to a reference unit (e.g., €10k = 1.0) for consistent comparison.

## Computation Workflow

The tool estimates reliability impact, test duration, and engineering effort for repaired electronics. It operates through four integrated operations, transforming early technical inputs into qualification outputs aligned with risk, cost, and performance constraints. The first operation consists of a high-level risk rating based on general product descriptors available in the early design phase. Inputs such as the electronic Bill of Materials, manufacturing site, and product family are combined with historical indicators like warranty return rates and board complexity to produce a discrete risk level—low, medium, or high. This classification is derived from a bidimensional mapping that correlates production volume with unit cost, the latter serving as a proxy for potential warranty exposure. In the second operation, the tool automatically determines the appropriate qualification test suite for the assigned risk level. Test selection draws from internal standards and published methodologies to ensure consistency across projects. The output is a complete test plan adapted to the product’s criticality and rework severity. Lower-risk categories activate process qualification at the PCBA level, using thermal cycling, humidity exposure and thermal shock. Medium-risk cases require reliability demonstration on fully assembled units, including corrosion and temperature endurance tests with continuous functional monitoring, and warranty compliance validation on mixed populations. For high-risk classifications, additional robustness and screening procedures such as HALT and stress ramps up to 80% of functional thresholds are deployed. Simulation-based analyses, particularly those addressing thermo-mechanical ageing, complement physical tests across all levels to refine scope definition and stress assumptions. The third operation computes test durations by combining mission profile selection, failure model parameterization, and sample size allocation. Mission profiles can follow a standard usage assumption or be probabilistically generated from field data distributions, as described in approaches like those proposed by Delaux [18]. Acceleration factors are calculated using physics-of-failure models—typically Arrhenius for thermally activated processes, Coffin–Manson for cyclic fatigue, and Hallberg–Peck for combined temperature-humidity stress. Model parameters such as activation energy, humidity exponent, and strain range are selected based on internal datasets or LV124 reference values. With the reliability target, confidence level, and sample size defined, the tool applies binomial law to compute the required test duration to demonstrate compliance under zero-failure conditions. The final operation converts the test plan and duration into cost outputs by computing the engineering and equipment workload. These are normalized against a standard baseline, for example 1.0 corresponding to €10,000, to ensure cross-project comparability. Outputs include stress duration, sample count, and resource occupancy, forming the basis for technical and economic evaluation. The tool supports scenario simulation, allowing users to adjust reliability objectives or repair complexity and instantly observe how test effort and costs shift in response. Because qualification effort depends non-linearly on both reliability targets and technical complexity, the tool facilitates early trade-off decisions between budget, time, and risk—an essential feature in regulated environments where warranty liability and compliance depend on demonstrable qualification integrity. By integrating standard test models, probabilistic mission profiles, and cost normalization, the tool provides a coherent

methodology for assessing requalification strategies in the context of repair and circular economy goals. All outputs remain traceable, data-driven, and aligned with the physics of failure that govern electronic assembly degradation.

Table 4 – Block Diagram of the Cost Computation Tool

| Inputs                                                                                                                                                                                                                                                                                                                                             | Operation 1 - <b>PRODUCT RISK Rating</b>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Output                                                                                                                                  |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| <ul style="list-style-type: none"> <li>- Electronic bill of materials</li> <li>- Manufacturing Site</li> <li>- Product Type / Family</li> <li>- Product Risk rating chat</li> </ul>                                                                                                                                                                | Risk Assessment based on two-dimensional mapping                                                                                                                                                                                                                                                                                                                                                                                                                                                                         | Risk Rating 1 : low<br>Risk Rating 2 : medium<br>Risk Rating 3: high                                                                    |
| Inputs                                                                                                                                                                                                                                                                                                                                             | Operation 2 - <b>TEST SELECTION</b>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | Output                                                                                                                                  |
| <ul style="list-style-type: none"> <li>- Risk Rating</li> <li>- Test list according to risk ratings</li> <li>- Recover levels</li> </ul>                                                                                                                                                                                                           | Selection of tests out of: <ul style="list-style-type: none"> <li>- PCBA tests (internal standard)</li> <li>- Reliability demonstration on full product (internal standard)</li> <li>- Warranty coverage (PV test at 0 failure)</li> <li>- Robustness Test (back-to-back functional margins loss)</li> <li>- Quality Screening tests</li> <li>- Simulation computations</li> </ul>                                                                                                                                       | List of tests                                                                                                                           |
| Inputs                                                                                                                                                                                                                                                                                                                                             | Operation 3 - <b>TEST DURATION</b> computation                                                                                                                                                                                                                                                                                                                                                                                                                                                                           | Output                                                                                                                                  |
| <ul style="list-style-type: none"> <li>- Test list</li> <li>- Customer Specification</li> <li>- LV124 specification</li> <li>- Ea catalogue</li> <li>- Model parameters (probability density functions)</li> <li>- Failure mechanism list</li> <li>- Sample Size by test bench</li> <li>- Reliability target</li> <li>- Warranty target</li> </ul> | <u>Step 1: mission profile selection</u><br>Option 1: user forces the use of “standard” mission profile<br>Option 2: user select a computed set of values (probabilistic approach)<br><u>Step 2: physics of failure selection</u><br>Option 1: default values from LV124<br>Option 2: definition of Ea based on probabilistic approach<br><u>Step 3: Sample size according to bench capacity</u><br>Option 1: default values set at test bench capacity<br>Option 2: extra investment allows to increase the sample size | Acceleration factor computed, then Test duration according to Binomial law computed for Reliability demonstration and warranty coverage |
| Inputs                                                                                                                                                                                                                                                                                                                                             | Operation 4 - <b>COST</b> computation                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | Output                                                                                                                                  |
| <ul style="list-style-type: none"> <li>- Test list</li> <li>- Test duration</li> <li>- Mission profile option</li> <li>- Physics of failure option</li> <li>- Sample size option</li> <li>- Product Site Location</li> </ul>                                                                                                                       | <u>Computation of Machine workload</u><br>Sample size (from options)<br><u>Computation of Engineering workload</u><br>Sample size (from options)<br>Set of analysis (default values)                                                                                                                                                                                                                                                                                                                                     | Engineering duration range<br>Test duration range                                                                                       |

### Example Scenario

Consider a repair project on a high-density power electronics control board, requiring a reliability target of  $\leq 0.1\%$  failures over 3 years. The product includes BGA-mounted semiconductors on an HDI substrate, assigning it to complexity Level 3. Using internal modelling rules, the tool selects the Coffin–Manson model (fatigue driven by thermal cycling) and applies an activation energy of 0.8 eV (consistent with solder-joint degradation databases). Given the reliability target and complexity, the simulation computes a required sample size of 60 units and a test profile of 1,000 thermal cycles at accelerated conditions ( $-40\text{ }^{\circ}\text{C}$  to  $+125\text{ }^{\circ}\text{C}$ ). The normalized cost output is 4.5 units (i.e., €45 k if baseline = €10k), and the test duration is estimated at six weeks. Running a second scenario with the same complexity but relaxing the reliability target to  $\leq 1.0\%$  failures reduces the sample size to  $\sim 20$  units, lowers test duration and yields a normalized cost of 1.8 units ( $\approx$  €18 k). This dual-scenario calculation demonstrates how project teams can use the tool to visualize cost implications of reliability decisions and repair-complexity choices. By

delivering normalized metrics, the tool allows meaningful comparison across projects irrespective of absolute budget scales. It thereby supports data-driven trade-off decisions between cost, schedule, and risk.

## Discussion

The tool offers substantial benefits across project management, quality assurance, procurement, and sustainability. For project managers, its key advantage lies in rapidly producing budget-aligned estimates, allowing early integration of cost, schedule, and risk. An exhaustive test catalogue links each risk level to specific qualification steps, reducing omissions and improving consistency. For quality teams, the tool enhances transparency: all assumptions, physics-of-failure selections, and parameters are fully exposed. This traceability ensures that validation plans remain technically defensible. Procurement gains from standardized cost outputs and reproducible estimates that support early quotation, supplier benchmarking, and negotiation. Presenting cost as a range helps quantify reliability and test duration impacts. Sustainability teams benefit from structured alignment between test effort and reliability goals. The framework can be adapted to meet either state-of-the-art reliability requirements or acceptable levels suited for circular-economy contexts. This flexibility is especially valuable in constrained or scalable repair scenarios. However, limitations remain. The tool prioritizes speed and early visibility, but its accuracy diminishes when inputs are immature. Conservative assumptions may lead to oversized estimates. Furthermore, warranty data often cover only 2–5 years, limiting the model’s ability to capture long-term degradation risks. Failure analysis introduces additional uncertainty: high-risk repairs may require advanced diagnostics (e.g., microscopy, ionic analysis) that are costly and hard to predict. The tool also presumes test-bench availability, while in practice, scheduling conflicts or bench duplication may incur unaccounted costs. A deeper constraint lies in using apparent activation energies per failure mechanism. These values, though based on industry knowledge, average out complex degradation processes. Excessive user margins to compensate for uncertainty can degrade accuracy. To ensure coherence, real-world demonstration tests must validate failure modes, and parameter sets must be consolidated in a controlled knowledge base. The embedded mission profiles also stem from conventional usage assumptions. As usage patterns evolve—such as EV charging or shared mobility—stress profiles shift, making periodic recalibration essential. Without this, predictions may not represent current field conditions. Still, the framework marks a notable advance in repair qualification for electronics. Historically, cost estimation in repair has lacked formal linkage between technical parameters and financial planning. The proposed simulation method closes this gap by linking repair complexity with reliability targets, enabling risk mitigation from project inception. This is vital in contexts with tight warranty or budget constraints. The structured outputs also facilitate customer communication. Rather than vague statements like “tested to industry standards,” project teams can now present quantified scenarios (e.g., 0.1% failure rate at 90% confidence), aligning expectations and enhancing trust. For modular, lower-risk products (Complexity Levels 1–2 in Table 3), minimal qualification may suffice. For critical systems, higher-complexity operations (Level 3) justify extended test campaigns through cost-risk balancing. Compared to conventional methods, the model enables robust cost-time-risk analysis. Traditional plans tend to over test, inflating costs, or undertest, leading to reliability exposure. Both are suboptimal. Table 6 contrasts tool-based and traditional cost projections from past repair programs. In one instance, traditional over-testing led to a 40% cost overrun due to conservative test planning. In another, insufficient qualification effort caused early warranty returns, resulting in reputational damage and additional field campaign costs. The tool helps avoid both extremes by offering calibrated cost projections aligned with reliability science and actual complexity of the repair. The broader industrial relevance of the tool lies in its contribution to circular product strategies. In the context of the 4R framework (Robust design, Repair, Remanufacturing, Recycle), the ability to reliably requalify electronics is a linchpin of lifecycle extension. The methodology ensures that post-repair reliability is predictable, which is essential for sustainability claims and carbon-footprint reduction assessments. Table 7 summarizes the perceived benefits across functions. For engineering, it links design decisions to requalification burden; for quality teams, it produces transparent validation protocols; for procurement, it offers early cost visibility; and for sustainability, it supports traceable impact reporting, including alignment with EU Taxonomy or Digital Product Passport (DPP) initiatives. By establishing a shared technical-financial language, the tool improves alignment between design, quality, and procurement decisions, ensuring technical feasibility and economic realism across the repair chain. Nonetheless, key limitations persist. The model’s accuracy hinges on parameter assumptions, such as activation energy values and stress multipliers. While grounded in literature and databases (Table 4), product-to-product variation requires calibration. Especially for novel assemblies, simulation outputs must be interpreted with caution. Another gap is the lack of field data integration. Without feedback from warranty or monitoring systems, predictions remain partially speculative. Closing this loop would enable refinement of input distributions and enhance accuracy.

Table 6 - Comparison of Estimated vs. Actual Qualification Costs

| Stakeholder Function | Transparency | Budget Accuracy | Risk Reduction | Strategic Value   |
|----------------------|--------------|-----------------|----------------|-------------------|
| Project Management   | High         | High            | Medium         | Planning support  |
| Quality Assurance    | High         | Medium          | High           | Test scoping      |
| Procurement          | Medium       | High            | Medium         | Quotation logic   |
| Sustainability       | Medium       | Medium          | High           | Lifecycle metrics |

Table 7 - Benefits across Stakeholders

| Scenario Type           | Traditional Estimate | Tool-Based Estimate | Actual Incurred | Error Gap (vs Actual)         |
|-------------------------|----------------------|---------------------|-----------------|-------------------------------|
| Case A – Medium Repair  | €22,00               | €18,00              | €19,00          | Traditional: +16%, Tool: -5%  |
| Case B – Complex Repair | €60,00               | €45,00              | €47,00          | Traditional: +28%, Tool: -4%  |
| Case C – Low Risk       | €12,00               | €9,00               | €10,00          | Traditional: +20%, Tool: -10% |

A promising avenue involves linking the tool to digital twin platforms or future DPP systems. These would embed rework history, qualification data, and stress profiles into a digital traceability layer—supporting automated inputs, auditable records, and regulatory transparency. Such integration would not only enhance the tool’s utility but respond to growing OEM and policy demands for lifecycle accountability in electronics. The proposed tool supports circular economy goals by quantifying the cost and effort needed to ensure the reliability of repaired products. This enables life extension strategies through informed qualification decisions. For instance, by simulating reliability scenarios (as seen in Section 3.5), planners can balance sustainability benefits (e.g., 20% GHG emission reduction [4]) with qualification efforts. Furthermore, the tool aligns with policy instruments such as the EU Directive 2024/1799, reinforcing the technical-economic integration of durability and reparability.

## Conclusions & Recommendations

The framework bridges cost modeling and reliability planning in early-stage repair projects. By providing a configurable simulation environment, the tool enables project managers and reliability engineers to define target reliability levels and immediately derive the qualification effort, sample size, and associated cost implications. This model-based approach brings structure and transparency to a domain traditionally governed by empirical practices and heuristic assumptions. Importantly, the methodology is fully aligned with sustainability and circular economy objectives. It enables lifecycle extension by quantifying the cost and reliability impact of repair decisions. For example, in Case B (Table 6), the tool produced a 4% error margin versus actual costs—versus a 28% error for traditional methods—while ensuring post-repair reliability compliance. These quantifiable outputs are crucial for validating sustainability claims in circular product strategies. To maximize industrial value, the tool should be embedded early in the design-for-repair process, particularly during the quotation and development phases where quality plans and risk provisioning must be scoped. Integration with scoring systems like the Repair Index links design with qualification cost. Looking forward, the framework offers a strong foundation for expansion into advanced capabilities, including AI-based reliability prediction engines and tighter coupling with thermo-mechanical simulation environments. Such developments would further improve predictive accuracy and enable real-time adaptation to complex stress profiles or emerging field conditions. Additionally, the methodology holds strong potential for cross-sector adaptation in high-stakes industries such as medical devices, energy systems, and railway applications, where the cost of failure demands rigorous requalification and traceability. Such tools will be central to balancing technical, economic, and environmental goals.

## References

- [1] Boissie, K., Prono, J.-B., Marzelière, M., Aznar, P. *Repair Index: A Tool for Assessing PCBA Repairability During the Design Phase*, Remade Conference 2025.
- [2] Motalab, M., Mustafa, M., Suhling, J. C., Zhang, J., Evans, J., Bozack, M. J., & Lall, P., *Correlation of reliability models including aging effects with thermal cycling reliability data*, 2013 IEEE 63rd Electronic Components and Technology Conference, pp. 986–1004. Las Vegas, NV, USA, 2013.
- [3] Directive (EU) 2024/1799 of the European Parliament and of the Council of 13 June 2024 on common rules promoting the repair of goods and amending Regulation (EU) 2017/2394 and Directives (EU) 2019/771 and (EU) 2020/1828, 2024.
- [4] Chauhan, D., Mewada, H., Gondalia, V., Almalki, F. *Balancing Technological Innovation and Environmental Sustainability: A Lifecycle Analysis of 6G Wireless Communication Technology*. *Sustainability*, 16 (15), 6533, 2024.
- [5] T. T. Mattila, “Toward comprehensive reliability assessment of electronic assemblies under different loading conditions”, *J. Mechanical Science and Technology*, 36, 4895–4903, 2022.
- [6] Pecht, Michael, and Jie Gu. "Physics-of-failure-based prognostics for electronic products." *Transactions of the Institute of Measurement and Control* 31.3-4 (2009): 309-322.
- [7] M. Cordella, “Durability of smartphones: reliability & repairability analysis”, *Sustainability*, 13(9):4922, 2021.
- [8] G. Si, “A reliability-and-cost-based framework to optimize remanufacturing service costs whilst controlling machine reliability”, *Reliability Engineering & System Safety*, Vol. 226, 2022.
- [9] S. Z. Gavidel, J. L. Rickli, “Remanufacturing cost analysis under uncertain core quality and return conditions: extreme and non-extreme scenarios”, *arXiv preprint arXiv:1801.10497*, 2018.
- [10] Y. Xu & W. Feng, “Develop a cost model to evaluate the economic benefit of remanufacturing based on specific technique”, *Journal of Remanufacturing*, 4:4, 2014.
- [11] Chauhan, D., Mewada, H., Gondalia, V., Almalki, F. *Balancing Technological Innovation and Environmental Sustainability: A Lifecycle Analysis of 6G Wireless Communication Technology*. *Sustainability*, 16(15), 6533, 2024..
- [12] European Commission. *Directive (EU) 2024/1799 of the European Parliament and of the Council of 13 June 2024 on common rules promoting the repair of goods and amending Regulation (EU) 2017/2394 and Directives (EU) 2019/771 and (EU) 2020/1828*, Official Journal of the European Union, 2024.
- [13] Meysner, A. *The “Right to Repair”: Potential Impacts of EU Directive (EU) 2024/1799*. Institute for European Environmental Policy (IEEP), Policy Brief, 2022.
- [14] Glöser-Chahoud, S., Pfaff, M., & Schultmann, F. (2021). The link between product service lifetime and GHG emissions: A comparative study for different consumer products. *Journal of Industrial Ecology*, 25(2), 465-478.
- [15] European Commission. *Directive (EU) 2024/1799 of the European Parliament and of the Council of 13 June 2024 on common rules promoting the repair of goods and amending Regulation (EU) 2017/2394*
- [16] *Directives (EU) 2019/771 and (EU) 2020/1828*. Official Journal of the European Union, 2024. European Commission. *Circular Economy Action Plan – For a cleaner and more competitive Europe*, 2020.
- [17] Meysner, A. *The “right to repair”: Potential impacts of EU Directive (EU) 2024/1799*. Institute for European Environmental Policy (IEEP) Policy Brief, 2022.
- [18] Delaux, D., Illing, T., & El Hami, A. (2020). Reliability Climatic Test for Composite based on Probabilistic Arrhenius model. *Proceedings of the 17th IMEKO TC*, 10.

## About the Authors

Dr. Kevin Boissié, Circular Electronic Laboratory Leader, Senior Expert in Repair & Obsolescence Engineering, Vice Chair at International Institute of Obsolescence Management. Working in Valeo Brain, since 2005.

Fabrice Blasenbauer, Expert in reliability, Reliability & NVH Manager at Valeo SC2N, Mondeville, France. Working in Valeo, since 2010

Dr. Thomas Illing, Director of Validation Laboratories in Valeo Brain Division, Master Expert in Experimental Reliability, since 2000

Liam Garvey, Valeo Expert in Environmental Tests and Environmental and Reliability Test Leader, Valeo Brain in Tuam Ireland, working in Valeo/CEL since 2001.