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# A Conceptual Framework for Reliability-Centered Design and Failure Prevention in Precision Electromechanical Systems

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**Abstract**

Precision electromechanical systems such as positioning stages, servo actuators, optical scanners and metrology instruments rarely fail by sudden fracture. Far more often they drift: accuracy, repeatability and dynamic response erode until the system can no longer meet its specification even though it still operates. Conventional reliability practice, built around binary failure definitions and constant failure rate prediction, captures this behavior poorly, and Reliability-Centered Maintenance (RCM), although rich in functional logic, is applied after design decisions have already fixed most of the life-cycle risk. Using a conceptual, theory-building methodology based on an integrative synthesis of 58 sources from the reliability, maintenance, precision engineering and applied engineering literature, this paper develops a conceptual model that carries RCM's function-first reasoning upstream into design and couples it with physics-of-failure modeling and degradation-based reliability. The framework consists of seven phases: mission profile definition, functional decomposition with an explicit precision budget, physics-of-failure failure modes, mechanisms and effects analysis, a precision-weighted criticality index, a hierarchy of design countermeasures, accelerated verification, and a closed feedback loop through prognostics and health management. A degradation-threshold formulation of reliability is presented that treats loss of precision as a failure in its own right. An illustrative application to a ball-screw-driven linear positioning stage shows how the framework moves attention from components with high nominal failure rates to the slow wear mechanisms that actually govern useful life, and how a targeted design change roughly doubles predicted reliability at the intended service life. Four testable propositions are derived from the model, and its theoretical, practical and managerial implications, limitations and directions for future research are discussed. The framework is intended as a structured basis for design reviews and for future empirical validation.

**Keywords:** reliability-centered design; physics of failure; FMMEA; degradation modeling; precision engineering; electromechanical systems; prognostics and health management

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## 1. INTRODUCTION

Precision electromechanical systems combine mechanical structures, actuators, sensors, power electronics and embedded control to produce motion or measurement at micrometre and sub-micrometre levels. They sit at the core of semiconductor lithography and inspection, machine tools, medical robotics, satellite pointing mechanisms, optical communication and coordinate metrology. In each of these settings the economic and safety consequences of unreliability are large, yet the nature of failure differs in an important way from that of conventional machinery. A precision stage that has lost two micrometres of repeatability has failed its mission while appearing, to a casual observer, to work perfectly.

Interest in structured reliability management is not confined to aerospace and defense. Predictive maintenance and condition monitoring have been examined for critical power and energy infrastructure (Adaramola et al., 2018), risk-based inspection and fitness-for-service assessment have been proposed for ageing offshore pressure vessels (Obetta, 2018), and condition-based maintenance has been applied to bearings and swivels in offshore crude export systems (Obetta & Ninduwezuor-Ehiobu, 2018). These studies show that life-cycle reliability thinking is spreading across engineering sectors; what they leave open is how it should shape design decisions in the first place.

Reliability engineering has developed two broad traditions that are relevant here. The first is design-stage reliability prediction and analysis, exemplified by handbook methods such as MIL-HDBK-217F, failure mode and effects analysis (FMEA) and fault tree analysis (International Electrotechnical Commission, 2006a; International Electrotechnical Commission, 2006b; U.S. Department of Defense, 1991). The second is Reliability-Centered Maintenance, which originated in commercial aviation in the work of Nowlan and Heap (1978) and was later generalized by Moubray (1997). RCM asks, for each function of an asset, how that function can fail, what causes each functional failure, what happens when it occurs, and what can be done to predict or prevent it. Its strength is that it begins with function rather than with hardware. Its weakness, from a design standpoint, is that it is normally applied to assets that already exist, when the cost of change is highest.

A parallel development, physics of failure (PoF), argues that reliability should be built from an understanding of the mechanisms that cause degradation, such as fatigue, wear, corrosion, electromigration and creep, rather than from statistical failure rates collected from dissimilar equipment (Kapur & Pecht, 2014; Pecht, 2008). PoF provides the mechanistic link that both FMEA and RCM often lack, but it is typically applied to individual components rather than to system functions.

This paper argues that the three traditions are complementary and that precision electromechanical systems are a domain where their integration is particularly valuable. The contribution is a conceptual framework, here called Reliability-Centered Design (RCD), that (i) begins with functional requirements expressed as precision budgets, (ii) identifies degradation mechanisms with PoF methods, (iii) ranks them with a criticality measure that treats loss of precision on equal terms with loss of function, (iv) selects countermeasures through an explicit hierarchy, and (v) closes the loop through accelerated testing and

field health monitoring. The framework is conceptual: it is offered as a structured method and a vocabulary, illustrated with a worked example, rather than as a validated industrial standard.

The remainder of the paper is organized as follows. The research method is described first. The results and discussion then present the literature synthesis and the research gaps it reveals, the conceptual model with its constructs, propositions and seven phases, its quantitative formulation, an illustrative application to a linear positioning stage, and the discussion, implications, limitations and directions for future research. The final section concludes.

## 2. RESEARCH METHOD

This study adopts a conceptual, theory-building research design. Its aim is not to test hypotheses against field data but to integrate existing bodies of knowledge into a coherent model that can later be tested. The guiding research question is: how can the functional logic of Reliability-Centered Maintenance, the mechanistic logic of physics of failure and the statistical logic of degradation modeling be combined into a design-stage method that treats loss of precision as a failure in its own right? The approach follows the integrative literature review tradition, in which a body of literature is critically reviewed and synthesized so that new frameworks and perspectives emerge (Torraco, 2005), and the concept-centric style of synthesis in which the literature is organized by concepts rather than by authors (Webster & Watson, 2002). Table 1 summarizes the stages of the research design.

**Table 1.** Summary of the research design

| Stage | Activity | Output |
|---|---|---|
| 1. Problem framing | Define scope (precision electromechanical systems, parametric or soft failures) and the research question | Research question and boundaries |
| 2. Literature identification | Assemble foundational texts, standards and reviews, and screen a corpus of applied peer studies against inclusion criteria | 58 sources published to date |
| 3. Thematic synthesis | Concept-centric coding of sources into themes; extraction of insights and gaps | Synthesis matrix (Table 2) and gap analysis (Table 3) |
| 4. Model building | Integrate constructs into a phased model, state propositions, and formalize key relationships | Conceptual model (Figure 1), propositions, Equations (1)-(5) |
| 5. Illustrative evaluation | Apply the model to a representative linear positioning stage using stated, plausible parameters | Tables 7 and 8, Figure 2 |

Sources were drawn from three pools. The first comprised foundational texts and standards in reliability engineering, reliability-centered maintenance and precision engineering, including reliability prediction and analysis standards (International Electrotechnical Commission, 2006a; International Electrotechnical Commission, 2006b; U.S. Department of Defense, 1991), the original and later formulations of RCM

(Moubray, 1997; Nowlan & Heap, 1978; SAE International, 1999), reliability engineering texts (Bertsche, 2008; Kapur & Pecht, 2014; O'Connor & Kleyner, 2012; Yang, 2007) and precision machine design (Slocum, 1992). The second comprised peer-reviewed articles on FMEA risk evaluation, physics-of-failure modeling, degradation analysis, accelerated testing and prognostics (Black, 1969; Escobar & Meeker, 2006; Hobbs, 2000; Jardine et al., 2006; Lei et al., 2018; Liu et al., 2013; Lu & Meeker, 1993; Meeker & Escobar, 1998; Pecht, 2008; Tinga, 2010). The third was a consolidated corpus of applied studies by peer researchers spanning engineering, energy, safety, information systems and related fields.

Three inclusion criteria were applied. A source had to be published to date, consistent with the timing of this study; it had to address reliability, maintenance, failure mechanisms, condition monitoring, electrical machines and supply, safety and risk management, or the data and information infrastructure on which monitored systems depend; and it had to contribute a concept, method or empirical observation usable in the model. Studies from unrelated domains, such as livestock nutrition, housing affordability, tax administration and pedagogy, were excluded. Of the 53 applied studies in the corpus that met the date criterion, 35 met the relevance criteria after title screening. Together with the 21 foundational and review sources and the two methodological sources, the final set comprised 58 sources.

Each source was read for the concepts it contributes and coded against a set of themes that emerged iteratively: reliability-centered maintenance, design for reliability and FMEA, physics of failure, degradation modeling and prognostics, precision engineering, accelerated testing and verification, electrical machines and power supply, data infrastructure and security, safety and logistics, and the field environment. For each theme, the synthesis recorded the main insight, the representative sources and the contribution of the theme to the model; the result is the synthesis matrix in Table 2. The approaches were then compared against criteria that matter for precision electromechanical systems to identify gaps (Table 3).

The constructs identified in the synthesis were integrated into a seven-phase model with a closed feedback loop, and the expected relationships among them were stated as propositions. Two relationships central to the model, reliability with respect to a precision threshold and the ranking of failure mechanisms, were formalized mathematically. Because the study is conceptual, the model was evaluated for internal consistency and practical usefulness through an illustrative numerical application to a ball-screw-driven linear positioning stage. The parameters of that application are representative of the system class but are not measurements from a specific product, and the evaluation is therefore a demonstration of the model's logic rather than an empirical validation.

## 3. RESULTS AND DISCUSSION

Nowlan and Heap's (1978) study of airline maintenance overturned the assumption that most equipment wears out on a predictable schedule. Their analysis of failure patterns showed that only a minority of components exhibited a clear wear-out zone, and that scheduled overhaul frequently increased failure rates

by introducing infant mortality. RCM's response was a decision logic that selects, for each failure mode, the most effective task among condition-based monitoring, scheduled restoration, scheduled discard, failure finding, redesign or run-to-failure (Moubray, 1997). The standard SAE JA1011 later codified the minimum criteria for a process to be called RCM (SAE International, 1999). Two RCM concepts are central to this paper: the definition of failure as the inability to meet a stated performance standard, and the P-F interval, the time between the point at which a developing failure becomes detectable (P) and the point at which functional failure occurs (F).

Recent applications illustrate both the reach and the limits of this logic. Condition-based maintenance concepts for offshore bearings and swivels (Obetta & Ninduwezuor-Ehiobu, 2018), risk-based inspection of pressure vessels (Obetta, 2018) and predictive maintenance in power infrastructure (Adaramola et al., 2018) apply function-first reasoning to existing assets, while studies of inventory availability and plant uptime (Okonkwo et al., 2018b) and strategic procurement optimization in oil and gas operations (Okonkwo et al., 2018a) show how maintenance outcomes depend on the logistics that support them. In each case, however, the design of the asset is taken as given.

Design for reliability (DfR) seeks to ensure that reliability requirements are met through design decisions rather than through screening and repair (O'Connor & Kleyner, 2012; Yang, 2007). FMEA, standardized in IEC 60812 (International Electrotechnical Commission, 2006a), remains the most widely used DfR tool. Its conventional risk priority number (RPN), the product of severity, occurrence and detection ratings, has well-documented shortcomings: the ordinal scales are multiplied as if they were ratio scales, different combinations produce identical RPNs with very different risk profiles, and the method gives no account of how failures develop over time (Liu et al., 2013). Numerous refinements, including fuzzy and multi-criteria approaches, have been proposed (Liu et al., 2013), but most retain a binary view of failure.

FMEA also sits within a wider body of quality and operations practice. Reviews of digital transformation in operations management describe how automation, analytics and process redesign change the way failure data are gathered and acted on (Agboada et al., 2018), and work on diagnostic quality systems shows that the reliability of a measurement depends as much on procedure and quality control as on instrumentation (Yusuf & Abdulrazaq, 2018). Studies of laboratory spatial planning make a similar point about how layout and workflow design affect accuracy and safety (Ogbete et al., 2018). The common lesson is that a failure analysis is only as good as the discipline with which its findings are turned into controlled changes.

Physics of failure models relate stress, material properties and geometry to time to failure. Classical examples include Basquin and Coffin-Manson relations for fatigue, Archard's wear law, Arrhenius and Eyring models for thermally activated processes, and Black's equation for electromigration (Bertsche, 2008; Black, 1969). Failure modes, mechanisms and effects analysis (FMMEA), developed at the Center for Advanced Life Cycle Engineering, extends FMEA by requiring that each failure mode be linked to an

identified mechanism and model, and by prioritizing mechanisms according to the life-cycle loading profile (Pecht, 2008). Tinga (2010) showed how such models enable usage-based rather than calendar-based maintenance.

Mechanism-based thinking also appears in applied studies of degradation and protection. Reviews of green corrosion inhibitors for mild steel in acidic and alkaline media (Atta et al., 2018) and risk-based fitness-for-service assessment of ageing pressure vessels (Obetta, 2018) show how knowledge of a specific degradation mechanism informs material choice and inspection intervals.

When a performance characteristic degrades gradually, reliability can be estimated from degradation paths rather than from failure times, an approach that is especially useful when few or no failures are observed during testing (Lu & Meeker, 1993; Meeker & Escobar, 1998). Prognostics and health management (PHM) uses sensor data to estimate the current state of degradation and the remaining useful life (RUL) (Jardine et al., 2006; Kapur & Pecht, 2014). Recent reviews summarize the range of model-based, data-driven and hybrid prognostic methods for machinery (Lei et al., 2018).

Applied condition monitoring has been reviewed for critical power and energy infrastructure, where the case for moving from time-based to predictive maintenance is well established (Adaramola et al., 2018). Data-driven prediction frameworks developed in other fields, such as forecasting subsurface contamination pathways (Azeez & Badmus, 2018) and spatially explicit risk modeling at data-limited sites (Lamidi & Olamide, 2018), address a problem familiar to prognostics: estimating the evolution of a hidden state from limited observations.

Precision engineering principles, including kinematic design, thermal symmetry, error budgeting and the separation of structural and metrology loops, are well established (Slocum, 1992). Several features distinguish these systems from a reliability standpoint. First, the performance margin is small relative to the magnitude of drift mechanisms: a few micrometres of wear or thermal growth can consume the entire error budget. Second, failure is strongly multi-physical, with mechanical, thermal, electrical and control effects interacting; a worn bearing raises friction, which raises motor current and heat, which causes thermal expansion and degrades accuracy. Third, closed-loop control can mask degradation for long periods by compensating for it, then fail abruptly when actuator or sensor limits are reached. Fourth, many failure modes are soft: they reduce accuracy, repeatability, bandwidth or settling time rather than stopping motion.

The electrical side of electromechanical systems has its own literature. Multi-algorithm optimization of the loss, weight and single objective functions of single-phase induction motors (Amayo, 2017; Amayo & Popoola, 2017a; Amayo et al., 2015) shows how design objectives for electrical machines can be traded against one another, and voltage control in networks with distributed generation (Oshevire et al., 2017) describes part of the supply environment from which drive stresses originate. Work on integrating solar power in small-scale manufacturing (Sunday & Omoegun, 2018) and on statistical estimation of daily solar radiation (Odejobi & Ahmed, 2018a) is relevant where equipment runs on hybrid or renewable

supplies, and studies of telecommunication deployment for network quality (Amayo & Popoola, 2017b) bear on the links over which monitoring data travel.

Because monitored systems are connected systems, the reliability of health data also depends on information infrastructure and security. Energy-efficient virtual machine placement in data centers (Ahmed & Odejobi, 2018b), scalable and secure cloud architectures (Ahmed & Odejobi, 2018a), performance evaluation of multi-tenant deployments under high concurrency (Odejobi & Ahmed, 2018b) and offline-first design for low-connectivity environments (Unamma et al., 2018) address how monitoring data can be stored and processed dependably. Insider threat classification and risk modeling in complex digital systems (Akeju et al., 2018), lessons from offline assessment of security-critical systems (Ladapo et al., 2018) and legal and ethical risk modeling in data protection governance (Mbonu et al., 2018) show that the integrity of the data on which prognostics depend cannot be assumed.

Table 2 brings the themes together. Read across its rows, the literature supplies most of the ingredients a design-stage reliability method needs: a function-based definition of failure, mechanism models, degradation-based reliability, verification methods and a growing practice of condition monitoring. Read down its last column, it also shows that these ingredients are scattered across communities that rarely meet, which is the opportunity the conceptual model presented below takes up.

Table 3 compares the main approaches against criteria that matter for precision electromechanical systems. Four gaps emerge.

**Table 2.** Literature synthesis matrix

| **Theme** | **Key insight** | **Representative sources** | **Contribution to the model** |
|---|---|---|---|
| Reliability-centered maintenance | Failure is defined against a performance standard; tasks are chosen by consequence; the P-F interval governs whether there is time to act | (Moubray, 1997; Nowlan & Heap, 1978; Obetta, 2018; Obetta & Ninduwezuor-Ehiobu, 2018; SAE International, 1999) | Function-first definition of failure (P1); latency rating in the criticality index (P4) |
| Design for reliability, FMEA and quality | Structured cause analysis is essential, but the RPN is ordinal and time-blind; quality discipline determines whether findings become controlled changes | (Agboada et al., 2018; International Electrotechnical Commission, 2006a; Liu et al., 2013; O'Connor & Kleyner, 2012; Ogbete et al., 2018; Yang, 2007; Yusuf & Abdulrazaq, 2018) | Precision-weighted criticality index (P4); countermeasure discipline (P5) |
| Physics of failure | Life follows from loads acting through identifiable mechanisms; mechanism | (Atta et al., 2018; Bertsche, 2008; Black, 1969; Pecht, 2008; Tinga, 2010) | Mechanism library and PoF-FMMEA (P3) |

| Theme | Key insight | Representative sources | Contribution to the model |
|---|---|---|---|
| | models enable usage-based maintenance | | |
| Degradation modeling and prognostics | Reliability can be estimated from degradation paths; health monitoring estimates state and remaining life | (Adaramola et al., 2018; Azeez & Badmus, 2018; Jardine et al., 2006; Lamidi & Olamide, 2018; Lei et al., 2018; Lu & Meeker, 1993; Meeker & Escobar, 1998) | Degradation-threshold reliability (Equations 1-3); PHM feedback (P7) |
| Precision engineering | Error budgets allocate allowable error among contributors; structural and metrology loops should be separated | (Slocum, 1992) | Precision budget over life (P2) |
| Accelerated testing and verification | HALT reveals margins; ALT and ADT estimate model parameters; software pipelines need continuous verification | (Badmus et al., 2018; Escobar & Meeker, 2006; Hobbs, 2000) | Accelerated verification (P6) |
| Electrical machines and supply | Machine design involves competing objectives; supply conditions impose electrical stresses | (Amayo, 2017; Amayo & Popoola, 2017a; Amayo et al., 2015; Odejobi & Ahmed, 2018a; Oshevire et al., 2017; Sunday & Omoegun, 2018) | Electrical mechanisms and mission profile (P1, P3) |
| Data infrastructure and security | Monitoring data must be stored, transmitted and protected dependably for prognostics to be trusted | (Ahmed & Odejobi, 2018a; Ahmed & Odejobi, 2018b; Akeju et al., 2018; Amayo & Popoola, 2017b; Ekemezie et al., 2018; Ladapo et al., 2018; Mbonu et al., 2018; Odejobi & Ahmed, 2018b; Unamma et al., 2018) | Knowledge base and field feedback (P7) |
| Safety, risk and logistics | Severity must be calibrated to wider safety practice; restoration depends on parts availability | (Adeyelu, 2018; Akomolafe & Agu, 2018; Nwangwu et al., 2018; Obriki & Arumosoye, 2018; Okonkwo et al., 2018a; Okonkwo et al., 2018b) | Severity scale (P4); restoration level of the hierarchy (P5) |
| Field environment and inspection | Climate and operating conditions drive loads; remote inspection can document them | (Arumosoye & Obriki, 2018; Dagodzo, 2018a; Dagodzo, 2018b; Nwafor et al., 2018) | Mission profile (P1) |

**Table 3.** Comparison of reliability approaches for precision electromechanical systems

| **Criterion** | **Handbook prediction** | **Classical FMEA** | **RCM** | **PoF / FMMEA** |
|---|---|---|---|---|
| Life-cycle stage | Design | Design | Operation | Design |
| Function-oriented | No | Partly | Yes | Partly |
| Treats loss of precision as failure | No | Rarely | Yes, if standard is set | Possible |
| Mechanism-based | No | No | No | Yes |
| Time-dependent degradation | No (constant rate) | No | Yes (P-F interval) | Yes |
| Multi-physics interaction | No | Weak | Weak | Moderate |
| Feedback from field data | Indirect | Indirect | Yes | Possible |

**Gap 1: Timing.** RCM's functional reasoning is applied mainly during operation, when most life-cycle cost and risk are already committed. Commonly cited estimates suggest that the large majority of life-cycle cost is fixed during conceptual and detailed design.

**Gap 2: Binary failure definitions.** Handbook prediction and conventional FMEA define failure as cessation of function. For precision systems the dominant failures are parametric, and their omission leads to misplaced design effort.

**Gap 3: Missing mechanisms.** FMEA and RCM identify causes qualitatively. Without PoF models, the design team cannot estimate how a change in preload, lubricant, material or duty cycle alters life.

**Gap 4: Open loops.** Design-stage analyses are seldom updated with test and field data, so the same errors in assumed loads and mechanisms recur across product generations.

Experience with technology-enabled risk assessment in internal auditing points the same way: risk is managed more effectively when assessment is built into the system rather than applied after the fact (Akomolafe & Agu, 2018).

The Reliability-Centered Design framework is shown in Figure 1. It has a forward path of five design phases (P1 to P5), a verification phase (P6), and a field phase (P7) whose data return to the design phases through a shared knowledge base. The framework is deliberately iterative: findings in later phases are expected to revise assumptions made earlier.

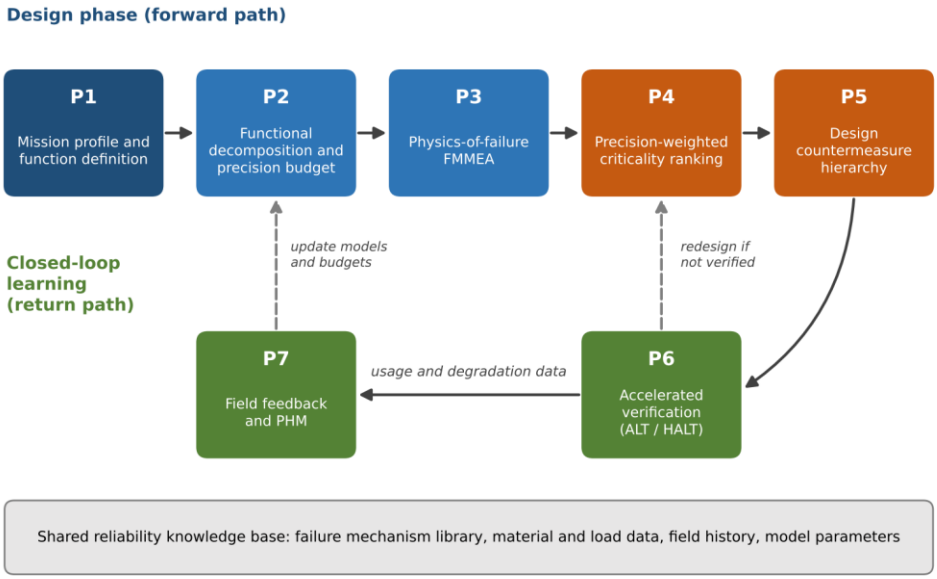



**Figure 1.** The Reliability-Centered Design framework for precision electromechanical systems.

The model rests on five constructs drawn from the synthesis: the life precision requirement, which defines failure as crossing a precision threshold; mechanism exposure, the set of degradation mechanisms activated by the mission profile; precision-weighted criticality, which ranks those mechanisms; countermeasure strength, the level of the design hierarchy at which each mechanism is addressed; and learning feedback, the flow of test and field data back into design assumptions. The expected relationships among these constructs are stated as four propositions for future empirical testing.

**Proposition 1.** Defining failure against a life precision budget, rather than against cessation of function, increases the share of design effort directed at wear, drift and thermal mechanisms.

**Proposition 2.** Criticality rankings based on mechanism models evaluated over the mission profile correspond more closely to field experience than rankings based on handbook failure rates.

**Proposition 3.** Countermeasures taken at higher levels of the design hierarchy produce larger and more durable reliability gains per unit cost than countermeasures taken at lower levels.

**Proposition 4.** Systematic updating of the reliability knowledge base with test and field data reduces the error in predicted useful life across successive product generations.

The process starts by stating what the system must do, under what conditions and for how long. Following RCM, each function is written with a measurable performance standard, for example "position the payload to within ±1.5 µm of the commanded point over a 300 mm stroke, at 20 ± 2 °C, for 25,000 operating hours." The mission profile records the life-cycle environment: duty cycle, stroke distribution, velocity and acceleration spectra, payload, ambient temperature range, humidity, contamination, shock

and vibration during transport, and storage periods. Because PoF models are driven by loads, an inaccurate mission profile propagates directly into inaccurate life estimates; this phase therefore deserves effort proportional to its influence.

Environmental loads deserve particular care where equipment operates outside controlled facilities. Studies of the effect of climatic variables on building envelope design in humid regions (Nwafor et al., 2018) and of heat stress in industrial operations in extreme environments (Arumosoye & Obriki, 2018) illustrate the conditions a mission profile may need to capture. Field inspection is another source of load data: UAV-based inspection of power grids and transmission lines (Dagodzo, 2018a; Dagodzo, 2018b) shows how remote sensing can document the actual operating environment of distributed equipment.

The top-level functions are decomposed into subfunctions and allocated to physical subsystems: guidance, drive, actuation, sensing, power conversion, control and structure. In parallel, the error budget of precision engineering (Slocum, 1992) is extended into a **precision budget over life**. The conventional error budget allocates the total allowable error among contributors at the beginning of life. The life budget additionally reserves a degradation allowance for each contributor, so that the sum of initial errors and expected drift remains within specification at end of life. Formally, the budget requires that a combined end-of-life error, typically computed as a root-sum-square of random contributors plus a linear sum of systematic contributors, stays below the specification limit with a stated margin. The degradation allowances become the thresholds used in Phase 4 and in Equations (1) to (3).

For each subfunction, the team identifies potential failure modes, including parametric modes such as loss of repeatability, increased hysteresis, reduced bandwidth, increased settling time and thermal drift, as well as hard modes such as seizure, open circuit and loss of encoder signal. Each mode is linked to one or more mechanisms, the loads that drive them, and an appropriate model. Table 4 summarizes mechanisms commonly encountered in precision electromechanical systems.

**Table 4.** Representative failure mechanisms in precision electromechanical systems

| **Subsystem** | **Mechanism** | **Driving loads** | **Typical model** | **Failure character** |
|---|---|---|---|---|
| Ball screw, guides | Abrasive and adhesive wear, preload loss | Contact load, sliding distance, contamination | Archard wear law | Gradual (soft) |
| Rolling bearings | Rolling contact fatigue | Load, revolutions, lubrication film | Lundberg-Palmgren / ISO 281 | Gradual then rapid |
| Flexures | High-cycle fatigue | Stress amplitude, cycles | Basquin, Goodman | Sudden (hard) |
| Motor windings | Insulation thermal ageing | Temperature, voltage | Arrhenius | Gradual then hard |

| **Subsystem** | **Mechanism** | **Driving loads** | **Typical model** | **Failure character** |
|---|---|---|---|---|
| Permanent magnets | Thermal demagnetization | Temperature, reverse field | Material curves | Gradual (soft) |
| Optical encoder | Scale contamination, LED ageing | Particulates, temperature, current | Empirical, Arrhenius | Gradual (soft) |
| Solder joints, PCBs | Thermomechanical fatigue | Temperature cycling | Coffin-Manson, Engelmaier | Intermittent then hard |
| Power electronics | Wire bond lift-off, capacitor ageing | Junction temperature swing, ripple current | Coffin-Manson, Arrhenius | Gradual then hard |
| Structure | Creep, stress relaxation, thermal distortion | Sustained stress, temperature gradients | Norton creep law | Gradual (soft) |
| Controller | Loop detuning from plant drift | Friction, stiffness and inertia changes | Plant model sensitivity | Gradual then unstable |

Interactions are recorded explicitly. A coupling matrix lists, for each mechanism, which other mechanisms it accelerates; for example, guide wear raises friction, which raises motor current, which raises winding temperature and so accelerates insulation ageing and thermal drift. These couplings are what make precision systems fail in ways that component-level analyses do not predict.

The mechanisms are ranked using a precision-weighted criticality index (PCI) that addresses the limitations of the conventional RPN for soft failures. It is defined formally in Equation (5). In essence, it assigns separate severity ratings to loss of function and loss of precision, uses the larger as the effective severity, estimates occurrence from the PoF model over the mission profile rather than from generic tables, and replaces the detection rating with a rating of the P-F interval relative to the planned monitoring interval. A coupling factor raises the rank of mechanisms that accelerate others. Table 5 shows the precision severity scale used in the illustrative case.

**Table 5.** Precision severity scale $S_p$ (illustrative)

| **Rating** | **Effect on precision performance** |
|---|---|
| 1-2 | Drift below 10 % of the degradation allowance at end of life; not noticeable to the user |
| 3-4 | Drift consumes 10-50 % of the allowance; within specification, may require recalibration |

| Rating | Effect on precision performance |
|---|---|
| 5-6 | Drift consumes 50-100 % of the allowance; specification margin lost near end of life |
| 7-8 | Specification exceeded before planned end of life; product output degraded or scrapped |
| 9-10 | Specification exceeded without warning, causing undetected nonconforming output or a safety hazard |

Severity ratings should be calibrated against the organization's wider safety and risk practice, so that a precision failure that can create a hazard is rated consistently with other hazards. Frameworks for operational integrity in high-risk drilling that balance productivity and safety compliance (Nwangwu et al., 2018), data-driven occupational risk control in large energy infrastructure projects (Obriki & Arumosoye, 2018) and predictive compliance monitoring for systemic safety risks in aviation (Adeyelu, 2018) offer models for doing so.

Analogous to the hierarchy of controls in safety engineering, countermeasures are selected in a fixed order of preference, shown in Table 6. Higher levels remove or weaken the mechanism; lower levels manage its consequences. A design review should be able to show, for each critical mechanism, why a higher level was not feasible before a lower one was accepted. Only at the lowest levels does the framework hand over to RCM-style maintenance tasks, and those tasks are then designed into the product (access, sensors, diagnostic routines) rather than added afterwards.

**Table 6.** Design countermeasure hierarchy

| Level | Strategy | Description | Example |
|---|---|---|---|
| 1 | Eliminate the mechanism | Change the physical principle so the mechanism cannot act | Replace sliding contact with flexure or air bearing guidance |
| 2 | Reduce the driving stress | Derate, redistribute loads, control environment | Lower contact stress through larger balls or more circuits; seal against contamination |
| 3 | Increase strength or tolerance | Improve materials, surfaces, lubrication; widen the allowance in the precision budget | Hardened and coated raceways; lubricant with higher film thickness |
| 4 | Make the system insensitive | Compensate or decouple the effect from the output | Direct linear encoder on the payload instead of rotary encoder on the motor; thermal symmetry |
| 5 | Add redundancy | Provide parallel paths for hard failures | Dual encoder read heads; redundant windings |

| Level | Strategy | Description | Example |
|---|---|---|---|
| 6 | Detect and predict | Monitor degradation to act within the P-F interval | Motor current signature analysis; periodic repeatability self-test |
| 7 | Restore or replace | Planned maintenance designed into the product | Preload adjustment; quick-change lubrication cartridge |

Lower levels of the hierarchy depend on logistics as much as on engineering, because restoration and replacement only work if parts are available before the P-F interval runs out. Models for inventory availability and plant uptime in energy facilities (Okonkwo et al., 2018b) and strategic procurement optimization in oil and gas operations (Okonkwo et al., 2018a) provide the operational counterpart to the design countermeasures described here.

Verification must demonstrate that the life estimates and countermeasures hold. Two complementary test types are used. Highly accelerated life testing (HALT) applies step-stressed temperature, vibration and electrical loads to discover weaknesses and operating margins quickly, without aiming to estimate life (Hobbs, 2000). Quantitative accelerated life and accelerated degradation testing (ALT and ADT) apply elevated but realistic stresses to estimate the parameters of the PoF and degradation models (Escobar & Meeker, 2006; Meeker & Escobar, 1998). For precision systems, ADT is usually more informative than ALT, because degradation in positioning error can be measured long before any hard failure occurs. Care is needed that acceleration does not activate mechanisms that are absent in service, for example lubricant breakdown at temperatures the product never sees. A test that reveals an unmodeled mechanism returns the design to Phase 3 or Phase 4.

Software verification belongs in Phase 6 as well, since firmware and motion control code change throughout the product life. Systematic reviews of continuous integration and delivery pipeline strategies (Badmus et al., 2018) describe practices that can be adapted to embedded control software.

In service, the monitoring provisions designed in Phase 5 generate data on loads and degradation. These data serve two purposes. Operationally, they support condition-based maintenance within the P-F interval and remaining useful life estimation (Jardine et al., 2006; Lei et al., 2018). For design, they correct the mission profile and model parameters held in the knowledge base, so that the next generation begins with better assumptions. The knowledge base is thus the mechanism by which the framework learns; without it, the closed loop in Figure 1 exists only on paper.

The value of the knowledge base depends on data quality. Evaluations of surveillance data quality and reporting capacity (Ekemezie et al., 2018) and technology-enabled risk assessment frameworks (Akomolafe & Agu, 2018) offer models for how field data can be made fit for decision-making.

Let $D(t)$ denote a precision performance measure, such as bidirectional positioning error, that grows with operating time $t$. A precision failure occurs when $D(t)$ first exceeds the threshold $D_{th}$ defined by the life precision budget. Reliability with respect to that function is then

$$R(t) = P[\, D(\tau) < D_{th} \text{ for all } \tau \leq t \,] \tag{1}$$

For monotonically increasing paths this reduces to $R(t) = P[D(t) < D_{th}]$. A flexible general path model, consistent with many wear processes, is

$$D(t) = D_0 + \beta\, t^{\gamma} \tag{2}$$

where $D_0$ is the initial (as-built) error, $\beta$ is a unit-to-unit rate parameter that captures variation in materials, assembly and usage, and $\gamma$ describes the curvature of the path ($\gamma = 1$ for linear wear; $\gamma > 1$ for accelerating degradation). If $\beta$ is lognormally distributed with log-mean $\mu$ and log-standard deviation $\sigma$, reliability has the closed form

$$R(t) = \Phi(\, [\, \ln((D_{th} - D_0) / t^{\gamma}) - \mu \,] / \sigma \,) \tag{3}$$

where $\Phi$ is the standard normal cumulative distribution function. Equation (3) makes the design levers explicit: reliability increases if the initial error $D_0$ is reduced (better manufacturing), if the allowance $D_{th} - D_0$ is enlarged (a more favourable precision budget), if the median degradation rate $\exp(\mu)$ is lowered (reduced stress or stronger materials), or if variability $\sigma$ is reduced (tighter process control). This direct mapping from design parameters to reliability is the main advantage of the degradation view over a constant failure rate.

Hard failure mechanisms are modeled with conventional life distributions, for example a Weibull distribution for bearing fatigue or flexure fracture. If mechanisms are treated as competing and approximately independent, system reliability for a function is the product of the survival probabilities of all mechanisms that can cause it to fail:

$$R_{sys}(t) = \prod_{k=1}^{m} R_k(t) \tag{4}$$

Where coupling identified in Phase 3 is strong, the independence assumption is not conservative, because one mechanism raises the stress on another. In those cases the coupled mechanisms should be simulated jointly, for example by letting the friction term from guide wear feed the thermal model of the motor in a Monte Carlo analysis.

For ranking in Phase 4, each mechanism $k$ receives the index

$$PCI_k = \max(S_{f,k}, S_{p,k}) \times O_k \times L_k \times \kappa_k \tag{5}$$

where $S_f$ and $S_p$ are severity ratings (1 to 10) for loss of function and loss of precision respectively; $O$ is an occurrence rating (1 to 10) mapped from the PoF-estimated probability of reaching the failure threshold within the design life; $L$ is a latency rating (1 to 10) that is high when the P-F interval is short relative to the feasible monitoring interval, so that the failure is likely to arrive unannounced; and $\kappa$ is a coupling factor equal to 1.0 for isolated mechanisms, 1.25 for mechanisms that accelerate one other mechanism,

and 1.5 for those that accelerate two or more. Using the maximum of the two severities prevents a parametric failure from being under-ranked merely because the system continues to move. Using latency rather than detection reflects the RCM insight that what matters is whether there is time to act, not simply whether the condition can be observed. Like all ordinal indices, PCI is a ranking aid, not a measure of risk, and ties or near ties should be resolved by examining the underlying ratings.

To show how the framework operates, it is applied to a representative single-axis linear stage of the type used in wafer inspection and laser processing equipment. The numerical values below are illustrative, chosen to be plausible for this class of system; they are not measurements from a specific product.

The stage carries a 4 kg payload over a 300 mm stroke with a peak acceleration of 5 m/s² and a duty cycle of 70 %. It is driven by a brushless DC servo motor through a preloaded ball screw, supported on two recirculating ball linear guides, and its position is measured by a rotary encoder on the motor shaft. The primary function is stated as: maintain bidirectional positioning error below 5.0 µm over the full stroke for 25,000 operating hours at 20 ± 2 °C. The life precision budget allocates an as-built error of 0.8 µm, leaving a degradation allowance of 4.2 µm, so that $D_{th}$ = 5.0 µm and $D_0$ = 0.8 µm.

The FMMEA produced a list of fourteen mechanisms; the six highest-ranked are shown in Table 7. A conventional handbook prediction for the same stage is dominated by the drive electronics and motor, which have the highest nominal failure rates. The PCI ranking instead places ball screw wear and preload loss first. Because position is measured at the motor rather than at the payload, wear in the screw and nut appears directly as lost motion that the control loop cannot see or correct. This mechanism is gradual, so it would rate low on a conventional RPN as easy to detect in principle, but in practice its P-F interval is not observed unless periodic laser interferometer checks are performed, which are rarely scheduled in production.

**Table 7.** Highest-ranked mechanisms for the baseline stage design (illustrative)

| **Mechanism** | **S_f** | **S_p** | **O** | **L** | **κ** | **PCI** | **Rank by handbook rate** |
|---|---|---|---|---|---|---|---|
| Ball screw wear, preload loss | 3 | 8 | 7 | 8 | 1.25 | 560 | 9 |
| Linear guide wear | 2 | 6 | 5 | 7 | 1.25 | 263 | 11 |
| Thermal growth of screw | 1 | 7 | 6 | 4 | 1.0 | 168 | not listed |
| Servo amplifier capacitor ageing | 8 | 3 | 3 | 6 | 1.0 | 144 | 1 |
| Encoder LED degradation | 7 | 4 | 3 | 5 | 1.0 | 105 | 3 |
| Motor bearing fatigue | 7 | 3 | 2 | 4 | 1.5 | 84 | 4 |

The degradation of positioning error due to screw and guide wear was represented with Equation (2), taking $\gamma = 1.35$ and a lognormal rate parameter with median 0.055 µm per (thousand hours)$^{1.35}$ and $\sigma = 0.32$. Figure 2 shows twenty-five simulated degradation paths together with the threshold and an alert level at 80 % of it.

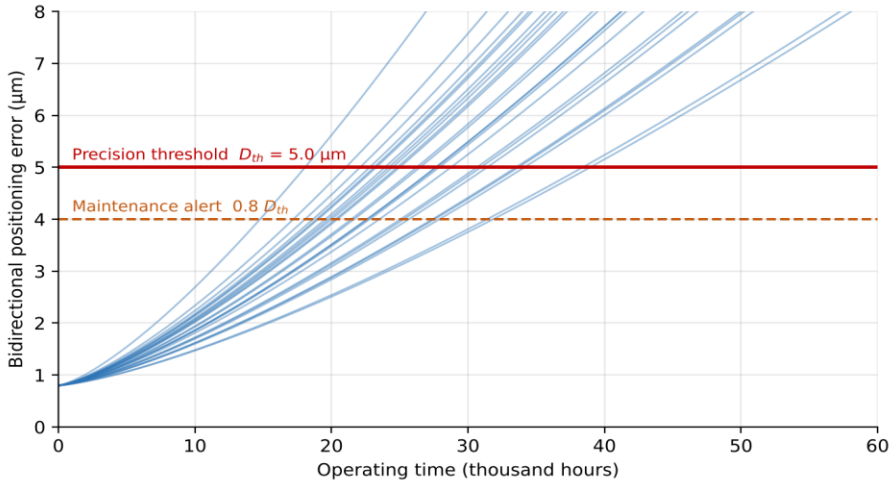



**Figure 2.** Simulated degradation paths of positioning error for the baseline design, showing the precision threshold and a maintenance alert level (illustrative parameters).

Evaluating Equation (3), the baseline design has a B10 life (the time by which 10 % of units exceed the threshold) of about 18,300 hours and a median life of about 24,800 hours. Reliability at the 25,000-hour design life is only about 0.49, and even at 20,000 hours it is about 0.82. The baseline therefore fails its life requirement through a mechanism that a failure-rate-based analysis would not have emphasized.

Working down the hierarchy in Table 6, Level 1 (replacing the ball screw with a linear motor) was considered but rejected for cost and heat load. At Level 2 and Level 3, the design team increased the screw diameter to reduce contact stress, added wiper seals and a sealed lubrication reservoir to limit contamination, and specified a lubricant with greater film thickness. At Level 4, a linear encoder was added on the payload so that residual screw wear and thermal growth are compensated by the control loop rather than appearing as position error; the screw wear then affects mainly stiffness and settling time, which have their own wider allowances. At Level 6, a motor current monitoring routine was added to detect friction changes caused by preload loss.

For the purpose of illustration, the Level 2 and 3 measures alone are assumed to reduce the median wear rate parameter from 0.055 to 0.030 with unchanged variability. Under this assumption the B10 life rises to about 28,700 hours and the median life to about 38,900 hours, and reliability at 20,000 hours rises from 0.82 to above 0.99. The Level 4 measure further decouples the remaining wear from the precision output, so that these figures are conservative for the final design. Table 8 summarizes the comparison.

**Table 8.** Predicted precision reliability before and after countermeasures (illustrative)

| **Metric** | **Baseline design** | **After Level 2 and 3 measures** |
|---|---|---|
| Median wear rate parameter exp(μ) | 0.055 | 0.030 |
| B10 life (hours) | ≈ 18,300 | ≈ 28,700 |
| Median life (hours) | ≈ 24,800 | ≈ 38,900 |
| R(20,000 h) | ≈ 0.82 | ≈ 0.998 |
| R(25,000 h) | ≈ 0.49 | ≈ 0.97 |

The verification plan specifies an accelerated degradation test in which stages run at 1.6 times nominal payload and twice the nominal duty rate, with positioning error measured by laser interferometer every 500 hours. A stress-life relation for the wear rate, calibrated from at least two stress levels, allows the median rate under nominal conditions to be estimated and compared with the design assumption. In the field, the motor current monitor and an automatic repeatability self-test against a reference mark supply degradation data, which are used to refine $\mu$, $\sigma$ and $\gamma$ for the next product generation.

The illustrative case highlights the framework's central claim: in precision systems, the mechanisms that determine useful life are often not those with the highest nominal failure rates. Treating precision as a function with its own failure threshold redirects design attention to wear, drift and thermal effects, and the degradation formulation turns those effects into quantities that can be traded against cost. The hierarchy of countermeasures adds discipline to design reviews by requiring that monitoring and maintenance be justified as choices rather than accepted as defaults. The framework also gives RCM a natural place in product development: the maintenance strategy for the field is an output of design, complete with the sensors and access needed to execute it.

These results are consistent with the literature synthesis. Applied studies of condition-based maintenance, risk-based inspection and predictive maintenance in offshore and power settings (Adaramola et al., 2018; Obetta, 2018; Obetta & Ninduwezuor-Ehiobu, 2018) demonstrate the value of function-first and condition-based reasoning, but they take the design of the asset as fixed. Physics-of-failure work (Pecht, 2008; Tinga, 2010) supplies the mechanism models, and degradation analysis (Lu & Meeker, 1993; Meeker & Escobar, 1998) supplies the statistics, yet neither on its own defines what failure means for a precision function. The conceptual model connects these strands: the precision budget defines the threshold, the mechanism models predict how quickly it is approached, and the RCM logic decides what to do about it.

Equation (3) also clarifies where design effort pays off. Reliability rises when the as-built error is reduced, when the degradation allowance is enlarged, when the median degradation rate is lowered and when unit-to-unit variability is narrowed. In the illustrative case, lowering the median wear rate alone

moved predicted reliability at 25,000 hours from about 0.49 to about 0.97, a change that a constant failure rate model would not have revealed because it would not have ranked the mechanism as critical in the first place.

This view aligns with practice in other asset-intensive sectors, where predictive maintenance (Adaramola et al., 2018), risk-based inspection (Obetta, 2018), condition-based maintenance (Obetta & Ninduwezuor-Ehiobu, 2018) and uptime-oriented inventory management (Okonkwo et al., 2018b) are increasingly treated as parts of one life-cycle strategy.

The model makes three contributions to reliability theory. First, it reframes failure for precision systems as the first crossing of a precision threshold, which unifies hard and soft failures within one reliability definition and allows them to be combined through Equations (1) to (4). Second, it shows how three traditions that have developed largely in parallel, RCM, physics of failure and degradation modeling (Meeker & Escobar, 1998; Moubray, 1997; Pecht, 2008), can be integrated without loss of their distinctive strengths. Third, the four propositions stated with the model convert the model into testable claims, giving future empirical work a clear agenda.

For design teams, the model offers a set of tools that can be adopted incrementally: a precision budget over life that reserves explicit degradation allowances; a precision-weighted criticality index that prevents parametric failures from being under-ranked; and a countermeasure hierarchy that asks, for every critical mechanism, whether it can be eliminated or its stress reduced before monitoring is accepted. The model also implies that monitoring provisions, such as sensors, self-tests and access for adjustment, should be specified during design, so that the maintenance strategy is an output of design rather than an afterthought.

For managers, the model implies a shift of resources toward early life-cycle activities, especially mission profile definition and accelerated degradation testing, where the leverage on life-cycle cost is greatest. It also implies closer coordination between engineering and functions that are often managed separately: procurement and inventory planning, since restoration depends on parts availability (Okonkwo et al., 2018a; Okonkwo et al., 2018b); safety and risk management, since severity ratings must be consistent with wider hazard practice (Nwangwu et al., 2018; Obriki & Arumosoye, 2018); and data governance, since prognostic decisions are only as reliable as the data and systems behind them (Akeju et al., 2018; Ekemezie et al., 2018). Finally, the knowledge base at the center of the model is an organizational asset that needs an owner, a budget and procedures for keeping it current.

Several limitations should be acknowledged. First, the framework is conceptual and has been demonstrated only with an illustrative example; its benefits relative to existing practice must be established through industrial case studies and controlled comparisons. Second, PoF models require material and load data that are often unavailable early in design, so early estimates will carry wide uncertainty; the framework mitigates but does not remove this by encouraging explicit uncertainty in model parameters and by updating them through Phases 6 and 7. Third, the PCI, like the RPN, combines ordinal ratings by multiplication, and its weights and scales are judgments that teams should calibrate to

their own products. Fourth, the independence assumption in Equation (4) can be unconservative where coupling is strong, and joint simulation adds modeling effort. Finally, the effort required is substantial and should be scaled to the consequences of failure; a full application is justified for high-value or safety-related systems, while a reduced version focused on the top-ranked mechanisms may suffice elsewhere.

The methodology has its own limitations. The literature synthesis is integrative rather than systematic: sources were selected for relevance and contribution rather than through an exhaustive database search, the applied corpus was screened by title, and the date criterion excluded more recent developments in prognostics and data-driven maintenance. The synthesis matrix and gap analysis therefore reflect a purposive sample, and other researchers might weight the themes differently. In addition, the illustrative application uses representative parameters rather than measured data, so its numerical results demonstrate the logic of the model and should not be read as predictions for any particular product.

The most immediate need is empirical testing of the four propositions. Proposition 1 could be examined by comparing the allocation of design effort in projects that use a life precision budget with matched projects that do not. Proposition 2 calls for retrospective studies that compare handbook and mechanism-based rankings against field return data. Proposition 3 could be tested through case studies that record the cost and reliability effect of countermeasures at different levels of the hierarchy, and Proposition 4 through longitudinal studies of prediction error across product generations.

Promising directions include: Bayesian updating of degradation parameters from mixed test and field data; multi-physics co-simulation that propagates mechanism coupling into reliability estimates; formal methods for allocating degradation allowances within precision budgets to minimize life-cycle cost; integration of the framework with model-based systems engineering tools so that functional models, FMMEA and reliability models share a single source of truth; and the use of data-driven prognostics trained on fleets of instrumented systems to complement physics-based models.

Further work could also extend the literature base through a systematic review, refine the severity and latency scales through expert elicitation, and apply the model to other classes of precision electromechanical systems, such as galvanometer scanners, piezoelectric positioners, satellite pointing mechanisms and coordinate measuring machines, to establish how far its phases and scales generalize.

## 4. CONCLUSION

This paper has proposed a conceptual framework for reliability-centered design and failure prevention in precision electromechanical systems. It moves the function-first logic of Reliability-Centered Maintenance into the design phase, grounds failure analysis in physics-of-failure mechanisms, and treats loss of precision as a failure on equal terms with loss of function. Its seven phases connect mission definition and precision budgeting to mechanism analysis, criticality ranking, a hierarchy of

countermeasures, accelerated verification and field feedback. A degradation-threshold formulation provides a direct link between design parameters and reliability, and a precision-weighted criticality index supports ranking of soft and hard failure mechanisms together. The illustrative application to a linear positioning stage shows that the approach can expose life-limiting mechanisms that conventional methods underweight and can quantify the benefit of targeted design changes. Empirical validation across a range of products is the essential next step.

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