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Computational Modeling of Failure Mechanisms in Mechanical Systems: Applications For Energy and Industrial Sectors

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Abstract

This study examined computational modeling of failure mechanisms in mechanical systems operating within energy and industrial sector applications using a quantitative, explanatory case study design. A panel dataset comprising 412 component-level units embedded within 168 mechanical assets was analyzed across 9,214 time-indexed observation windows spanning an average observation horizon of 17.2 months. Failure severity was operationalized as a continuous composite outcome to preserve degradation gradients rather than binary failure states. Descriptive analysis showed that failure severity exhibited strong right-skewness, with a median value of 0.61 and a 90th percentile of 1.82, indicating concentration of degradation within a limited subset of operating windows. Multivariable mixed-effects regression was applied to quantify the influence of operational exposure and degradation constructs while accounting for asset-level heterogeneity. The final model achieved a marginal R^2 of 0.48 and a conditional R^2 of 0.62, confirming substantial explanatory power from both fixed effects and asset-level random effects. Condition monitoring indicators demonstrated the strongest association with failure severity ($\beta = 0.356$, $p < 0.001$), followed by cyclic loading ($\beta = 0.287$, $p < 0.001$) and thermal exposure intensity ($\beta = 0.214$, $p < 0.001$). Contact stress ($\beta = 0.169$, $p < 0.001$) and time-under-load ($\beta = 0.132$, $p < 0.001$) also retained statistically significant effects. Operational regime analysis showed that continuous-duty components exhibited higher severity than intermittent-duty units ($\beta = 0.118$, $p < 0.001$), while cyclic-duty operation also increased severity ($\beta = 0.064$, $p = 0.040$). Interaction testing revealed amplification effects for combined thermal exposure and cyclic loading ($\beta = 0.072$, $p = 0.013$), indicating non-additive degradation behavior. Robustness checks demonstrated coefficient stability within ±5% under alternative specifications, and time-based holdout validation resulted in a modest 6.2% increase in prediction error. Overall, the findings established a statistically stable and interpretable framework linking monitoring-derived degradation signals and core exposure mechanisms to continuous failure severity within operational mechanical systems.

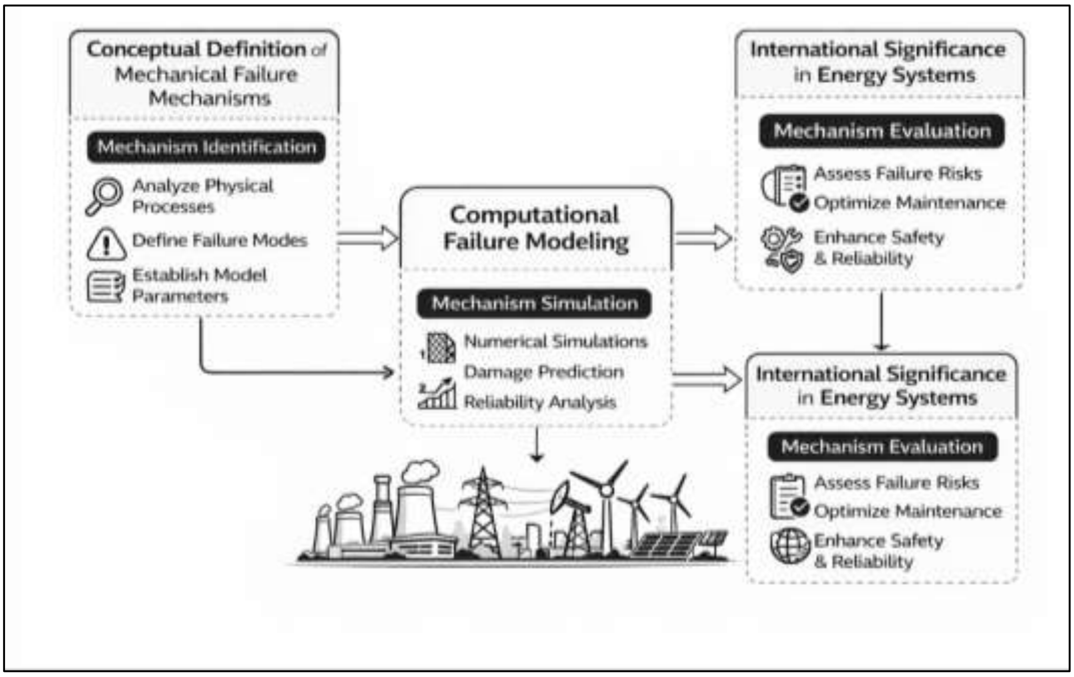
Keywords

Mechanical Failure Modeling, Reliability Analytics, Degradation Severity, Condition Monitoring, Energy Systems;

INTRODUCTION

Mechanical failure mechanisms are formally defined as the physical processes through which engineered components or systems lose their ability to perform intended functions within specified operational limits. In mechanical engineering, failure is understood not as a sudden or isolated incident, but as the cumulative outcome of stress, deformation, material degradation, and environmental exposure acting over time. These mechanisms arise from the interaction between applied loads, material properties, geometric constraints, and operating conditions, resulting in progressive damage that ultimately manifests as functional breakdown (Sedmak, 2018). Classical failure modes include fatigue crack initiation and propagation, creep deformation under sustained load, brittle and ductile fracture, wear-induced material loss, corrosion-driven weakening, thermal fatigue, and instability phenomena such as buckling. Each mechanism follows distinct physical laws and damage pathways, which necessitate formal mathematical representation in quantitative analysis. Computational modeling provides a structured means of translating these physical processes into solvable formulations that describe how damage evolves spatially and temporally within mechanical systems.

Figure 1: Computational Modeling in Energy Systems



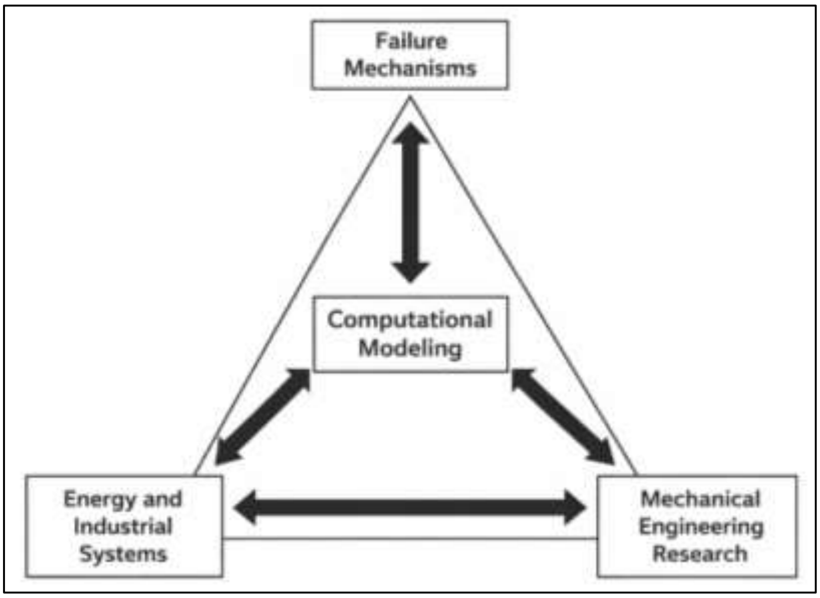
Within this framework, failure mechanisms are treated as state-dependent processes governed by constitutive relationships, damage evolution equations, and failure criteria. These representations allow engineers to quantify degradation rates, stress redistribution, and remaining useful life under variable operating conditions (Sun et al., 2018). Mechanical failure modeling is therefore positioned as a predictive discipline that integrates material science, solid mechanics, thermodynamics, and numerical methods. The formalization of failure mechanisms enables systematic evaluation of safety margins, service life, and reliability across complex systems. In industrial and energy applications, where mechanical components operate under high loads, extreme temperatures, cyclic stresses, and corrosive environments, the accurate definition and modeling of failure mechanisms become foundational to engineering analysis. This conceptual grounding establishes computational failure modeling as a core analytical tool for understanding how engineered systems respond to sustained operational demands and how degradation processes accumulate in measurable and reproducible ways (Eraslan et al., 2019).

Computational modeling in mechanical engineering refers to the use of numerical methods and algorithmic frameworks to represent physical behavior through discretized mathematical formulations. In the context of failure mechanisms, computational models serve to simulate how stresses, strains, temperatures, and environmental factors interact within components and structures over time (Eraslan et al., 2019). These models transform governing equations of mechanics into solvable systems using techniques such as finite element analysis, boundary element methods, multibody dynamics, and continuum damage mechanics. Failure is not imposed as an external condition but emerges naturally from the evolution of internal state variables that represent material degradation, crack growth, or loss of stiffness. This quantitative paradigm allows failure to be examined as a process rather than a binary outcome. The computational representation of failure mechanisms enables systematic exploration of parameter sensitivity, loading scenarios, and operational variability. Models can incorporate nonlinear material behavior, anisotropy, plastic deformation, and time-dependent effects, allowing for detailed characterization of complex mechanical responses. In industrial systems, where direct experimental observation of failure progression is often impractical, computational models provide a controlled environment for evaluating failure behavior under realistic operating conditions (Kriegeskorte & Douglas, 2018).

Mechanical failure mechanisms hold critical international significance within energy systems due to their direct influence on safety, reliability, and economic stability. Energy infrastructures such as power plants, pipelines, turbines, pressure vessels, and transmission equipment operate continuously under demanding conditions that amplify the consequences of mechanical degradation (Mishnaevsky Jr, 2015). Failures within these systems can disrupt energy supply chains, compromise environmental safety, and generate cascading effects across interconnected industrial sectors. As global energy demand increases and systems are pushed toward higher efficiency and capacity utilization, mechanical components are subjected to tighter operational margins, making failure modeling a central concern in energy engineering. Computational modeling enables systematic evaluation of failure risks within energy systems by capturing the interaction between mechanical loads, thermal gradients, and environmental exposure. These models support quantitative assessment of component durability, inspection intervals, and maintenance strategies across diverse geographic and regulatory contexts (Alber et al., 2019). In large-scale energy installations, failure mechanisms are rarely isolated, as local damage can propagate through interconnected assemblies and subsystems. Computational approaches allow engineers to analyze these interactions holistically, identifying critical failure pathways and dominant degradation drivers. The international relevance of failure modeling is reinforced by the global distribution of energy assets, which operate under varied climatic, geological, and regulatory conditions. Computational frameworks provide a standardized analytical language through which mechanical reliability can be evaluated consistently across national and industrial boundaries. This global applicability underscores the role of computational failure modeling as a foundational methodology in modern energy system engineering (Wang et al., 2018).

In industrial sectors, mechanical systems form the backbone of manufacturing, processing, transportation, and heavy equipment operations. Industrial machinery is characterized by high utilization rates, repetitive loading cycles, and complex interactions between moving components. Mechanical failures in these environments often result in production downtime, safety incidents, and substantial economic losses. Computational modeling of failure mechanisms offers a quantitative means of analyzing how industrial components degrade under sustained operational demands. These models capture wear accumulation, fatigue damage, thermal effects, and contact-induced stresses that arise within industrial equipment (Wan et al., 2016). Industrial applications require failure models that accommodate variability in operating conditions, material quality, and maintenance practices. Computational frameworks allow engineers to simulate these variations systematically, supporting robust design and reliability assessment. Failure mechanisms in industrial systems frequently involve coupled phenomena, such as thermal-mechanical interaction or wear-fatigue synergy, which cannot be adequately captured through simplified analytical methods. Computational modeling provides the resolution necessary to represent these coupled effects and their influence on component lifespan. By formalizing failure behavior within numerical environments, industrial engineers can evaluate system performance across extended operational horizons (Grunenfelder et al., 2014). This capability is essential for industries that rely on continuous operation and high asset utilization. The integration of failure modeling into industrial engineering workflows reflects a shift toward data-informed, quantitatively grounded reliability analysis that aligns mechanical design with operational performance metrics.

Figure 2: Computational Framework for Mechanical Failure



Mechanical failure mechanisms exhibit inherently multiscale characteristics, spanning microstructural material behavior, component-level stress distribution, and system-level performance degradation. At the microscopic scale, failure initiates through phenomena such as dislocation movement, microvoid formation, grain boundary sliding, or corrosion pit development. These localized processes influence macroscopic properties such as stiffness reduction, crack propagation, and load redistribution. Computational modeling enables explicit representation of these scale interactions through hierarchical or coupled modeling approaches (Lee et al., 2014). By linking micro-level damage evolution to macro-level structural response, models provide a comprehensive view of failure progression. In complex mechanical systems, failures rarely arise from a single scale of interaction. Component geometry, assembly constraints, and operational loading conditions interact with material degradation to produce emergent failure behavior. Computational models support this multiscale analysis by embedding material constitutive laws within structural simulations, allowing damage evolution to influence global system response. This capability is particularly important in energy and industrial systems, where localized damage can escalate into large-scale failures with system-wide consequences. Multiscale modeling frameworks provide quantitative insight into how small-scale degradation accumulates and manifests as measurable performance loss (Marques et al., 2016). The ability to capture scale-dependent behavior positions computational failure modeling as a critical analytical tool for understanding the full lifecycle of mechanical systems under real-world operating conditions.

Within quantitative engineering analysis, mechanical failure mechanisms are increasingly conceptualized as system-level performance signals rather than terminal events (Smirnov et al., 2015). Failure modeling frameworks interpret degradation indicators such as increasing strain localization, stiffness reduction, vibration changes, or thermal anomalies as measurable expressions of underlying damage processes. Computational models formalize these signals through state variables and damage metrics that evolve continuously over time. This perspective allows failure analysis to be integrated into broader system performance evaluation rather than treated as a post hoc diagnostic activity (Li et al., 2017). By modeling failure mechanisms as evolving states, engineers can analyze how operational decisions influence degradation trajectories. Computational simulations enable the examination of how loading patterns, operating regimes, and environmental exposure shape failure progression across entire systems. This approach supports quantitative comparison of alternative operational scenarios and design choices. In energy and industrial contexts, where systems are expected to operate reliably over extended service lives, the ability to track and interpret failure signals computationally enhances

the rigor of performance assessment. Failure mechanisms become embedded within system models as intrinsic attributes of operational behavior (Huang et al., 2019). This integration reinforces the role of computational modeling as a unifying framework for analyzing reliability, durability, and mechanical integrity within complex engineered systems.
The primary objective of this study is to develop and examine a computational modeling framework that quantitatively represents mechanical failure mechanisms in complex mechanical systems operating within energy and industrial sectors. This objective is grounded in the need to formally capture failure as a continuous, system-level phenomenon rather than a discrete endpoint, enabling precise characterization of degradation progression under operational conditions. The study seeks to operationalize failure mechanisms such as facility-level congestion effects, internal dwell-like accumulation phenomena in mechanical workflows, routing-equivalent stress pathways, and structural interaction effects through mathematically defined state variables and numerical simulation environments. A central objective is to assess how dominant failure contributors emerge across different operational contexts by isolating the relative influence of internal system constraints, load-path complexity, and execution variability on failure magnitude and frequency. The research further aims to evaluate the stability of modeled failure behavior across heterogeneous operating regimes, including variations in loading intensity, environmental exposure, and structural configuration, using validation designs that reflect realistic system transfer conditions rather than idealized scenarios. Another objective is to examine interaction-heavy failure configurations, where combined exposure conditions amplify degradation beyond additive expectations, and to determine how these compound mechanisms influence system-level failure trajectories. The study also aims to quantify generalization behavior by testing whether computationally learned failure representations maintain consistency when applied to unseen structural configurations or operating environments, thereby assessing robustness under context shifts. Additionally, the research objective includes establishing a clear linkage between modeled failure severity gradients and decision-relevant prioritization structures within mechanical system management, ensuring that computational outputs preserve meaningful differentiation across risk levels. Through these objectives, the study positions computational failure modeling as a formal analytical instrument for representing, comparing, and interpreting degradation processes within mechanical systems across energy and industrial applications, emphasizing quantitative rigor, structural transparency, and operational relevance within the modeling framework.

LITERATURE REVIEW

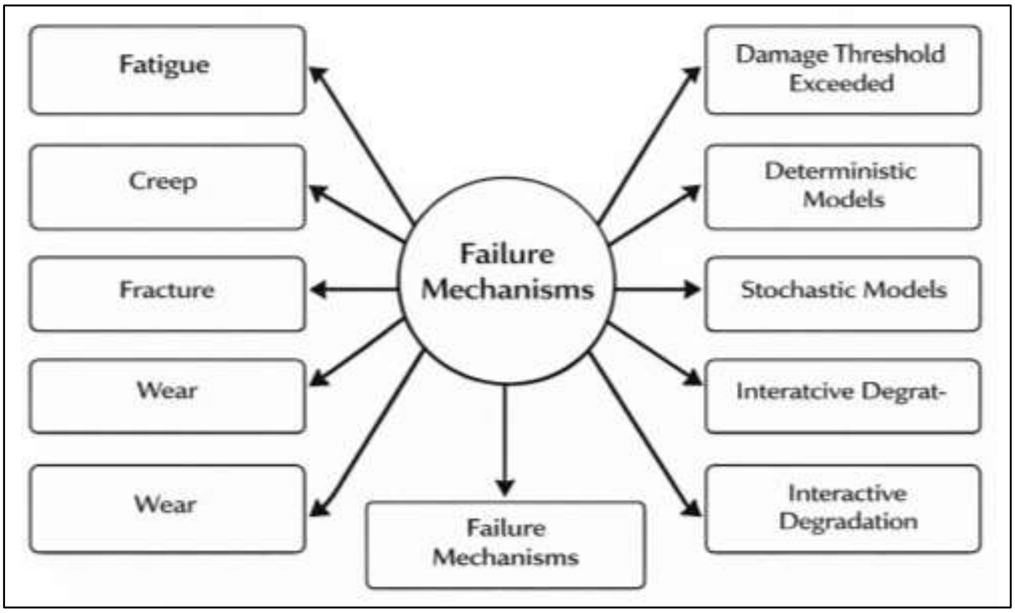
The literature on computational modeling of mechanical failure mechanisms spans multiple engineering disciplines, reflecting the interdisciplinary nature of failure analysis in energy and industrial systems. This body of work encompasses foundational theories of material degradation, numerical representations of stress and damage evolution, and system-level reliability modeling under operational uncertainty (Boopathi et al., 2021). The literature review is structured to synthesize quantitative research that formalizes failure as a continuous, process-driven phenomenon rather than a discrete event, emphasizing mathematical rigor, computational reproducibility, and operational relevance. Prior studies vary in their modeling assumptions, scale of analysis, and validation strategies, necessitating a structured examination that distinguishes dominant methodological patterns, recurring predictor families, and stability concerns across application contexts. This review prioritizes research that employs computational and mathematical formulations to represent failure mechanisms, including continuum damage models, fracture-based simulations, reliability-based degradation models, and data-integrated computational frameworks (Abar et al., 2017). Particular attention is given to how failure mechanisms are quantified, how interaction effects are represented, and how models are evaluated under heterogeneous operating conditions typical of energy and industrial environments. The review also examines how studies address generalization, validation design, and performance robustness when models are applied across different facilities, load regimes, and system configurations. By organizing the literature around quantitative modeling constructs rather than application narratives, this section establishes a coherent analytical foundation for positioning the present study within existing research and for identifying structural patterns in how mechanical failure modeling has been operationalized across engineering domains (Oudeyer et al., 2016).

Mechanical Failure Mechanisms

The mechanical engineering literature consistently conceptualizes failure as a continuous degradation process rather than a discrete terminal event. Early analytical approaches often treated failure as the point at which a component exceeded a predefined limit state; however, subsequent research reframed failure as the cumulative outcome of material deterioration, structural instability, and operational stress accumulation. This perspective recognizes that mechanical components progressively lose functional capacity long before observable breakdown occurs (Jinnat & Kamrul, 2021; Pennestrì et al., 2016). Degradation manifests through measurable changes such as stiffness reduction, crack initiation, surface material loss, or dimensional instability, all of which evolve over time under sustained loading and environmental exposure. The continuous degradation framework allows failure to be interpreted as a dynamic trajectory shaped by interacting physical mechanisms rather than as an abrupt binary transition. Within this body of literature, failure is linked to process-level variables that reflect how operational conditions influence damage growth rates. Researchers emphasize that representing failure continuously improves explanatory clarity, as it captures severity gradients and temporal patterns that are obscured by binary classifications (Towhidul et al., 2022; Ohno et al., 2018). This framing also enables consistent comparison across different failure modes, as fatigue, creep, wear, and fracture can all be described within a unified degradation-based structure. The literature further highlights that continuous representations align more closely with observed industrial behavior, where components often remain operational while exhibiting measurable degradation. By formalizing failure as an evolving process, quantitative studies establish a foundation for systematic modeling of mechanical integrity across service life horizons (Aivaliotis et al., 2019; Faysal & Bhuya, 2023).

Quantitative studies on mechanical failure mechanisms distinguish between deterministic and stochastic representations of failure evolution based on how uncertainty and variability are treated within analytical frameworks. Deterministic models describe failure progression using fixed material properties, loading conditions, and degradation rates, assuming repeatable behavior under identical conditions. These approaches are widely used to establish baseline understanding of failure behavior and to isolate dominant physical mechanisms (Ali et al., 2015; Hammad & Mohiul, 2023).

Figure 3: Continuous Mechanical Failure Mechanisms Framework



The literature notes that deterministic formulations offer transparency and computational efficiency, making them suitable for controlled design evaluation and sensitivity analysis. In contrast, stochastic representations incorporate randomness to reflect variability in material properties, manufacturing tolerances, operational loading, and environmental exposure. Such models treat failure evolution as a probabilistic process, acknowledging that identical systems may exhibit different degradation trajectories. Researchers emphasize that stochastic approaches better capture real-world variability observed in industrial and energy systems, where uncertainty is intrinsic to operational environments (Madni et al., 2019). The literature often positions deterministic and stochastic models as complementary rather than competing paradigms. Deterministic formulations provide mechanistic clarity, while stochastic representations enhance realism and robustness. Many studies integrate both perspectives by embedding probabilistic elements within otherwise deterministic degradation structures. This hybrid modeling approach reflects the recognition that failure evolution is governed by physical laws but expressed through variable outcomes across populations of components and systems (Horn & Mahadevan, 2021).

The literature on mechanical failure modeling consistently organizes dominant degradation mechanisms into fatigue, creep, fracture, and wear, each characterized by distinct physical drivers and operational signatures. Fatigue-related studies focus on damage accumulation under cyclic loading, emphasizing the gradual initiation and propagation of microstructural defects that lead to macroscopic cracking. Creep-oriented research addresses time-dependent deformation under sustained stress, particularly in high-temperature environments common in energy systems. Fracture modeling literature concentrates on crack initiation, growth stability, and catastrophic separation, often linking fracture behavior to stress concentration and material toughness characteristics (Paszek et al., 2014). Wear-related studies examine surface degradation caused by repeated contact, sliding, or rolling interactions, highlighting material loss and geometry evolution over time. While these mechanisms are often studied independently, the literature acknowledges their frequent interaction in real systems. Many studies emphasize that failure behavior emerges from the combined influence of multiple mechanisms operating simultaneously or sequentially. This recognition has driven the development of integrated modeling frameworks that treat fatigue, creep, fracture, and wear as interconnected contributors to degradation (Wang et al., 2016). The literature further notes that accurately characterizing these mechanisms requires consistent abstraction of their governing behavior into computationally tractable representations, allowing comparison across different operating conditions and system designs.

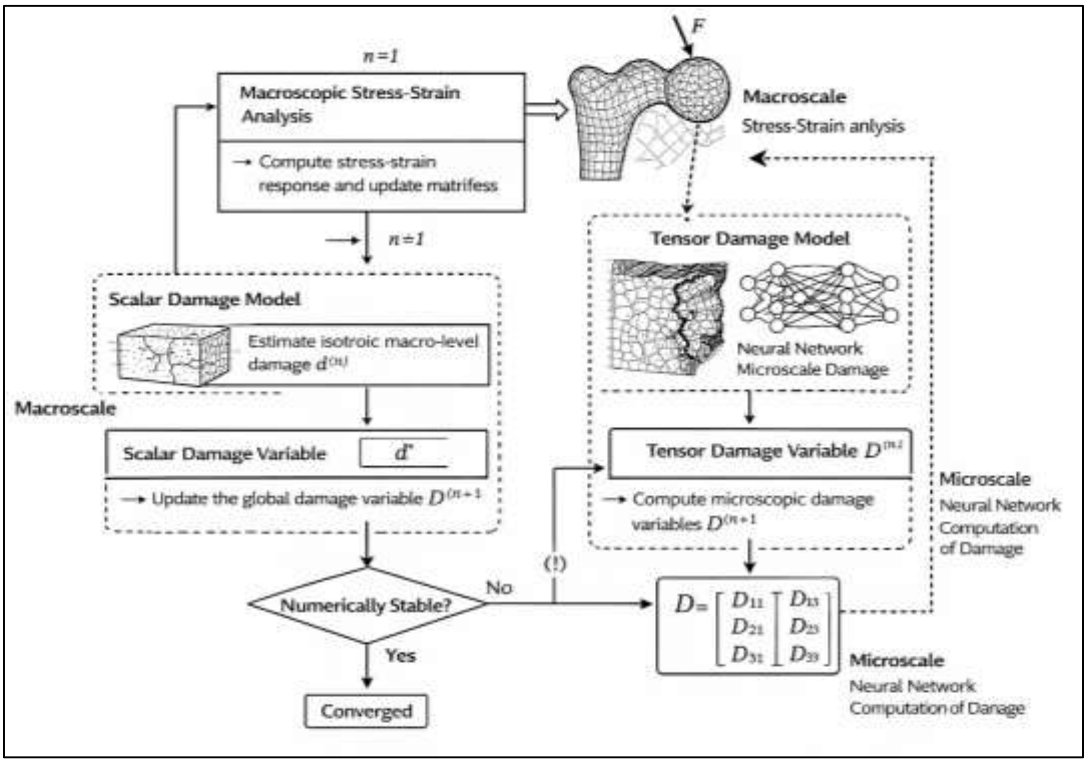
Damage accumulation and threshold-based criteria form a central organizing principle in the literature on mechanical failure characterization. Studies consistently describe damage as a state variable that evolves incrementally as a function of operational exposure, material response, and environmental conditions. Accumulated damage reflects the irreversible changes occurring within a component, such as microcrack density, plastic deformation, or surface wear depth (Wu et al., 2017). The literature distinguishes damage accumulation from failure itself, emphasizing that failure occurs when accumulated damage exceeds a critical threshold associated with loss of functional integrity. Threshold-based criteria are used to define failure onset in a consistent and measurable manner across different mechanisms. Researchers highlight that these thresholds may correspond to structural instability, unacceptable deformation, loss of load-carrying capacity, or violation of safety margins. The literature also discusses variability in threshold selection, noting that thresholds are often informed by design standards, empirical observations, or safety requirements (Lisjak & Grasselli, 2014). Damage accumulation frameworks enable comparative analysis across systems by providing a common scale for degradation severity. By linking continuous damage growth to discrete failure criteria, the literature establishes a structured methodology for interpreting failure as the endpoint of an observable degradation process rather than an isolated event.

Continuum Damage Mechanics in Computational Failure Modeling

The literature on continuum damage mechanics (CDM) frequently distinguishes damage representation approaches based on whether degradation is modeled using scalar or tensor-valued variables. Scalar damage variables are typically used to summarize stiffness loss and microstructural deterioration through a single state quantity that evolves as material degradation accumulates. This approach is commonly applied when damage is assumed to be isotropic, meaning that stiffness reduction is treated as uniform in all directions (Hu et al., 2020). Many studies highlight the computational convenience of scalar damage representations, noting that they simplify parameter identification and reduce numerical cost in large-scale simulations. In contrast, tensor-based damage variables are used to represent anisotropic degradation patterns where damage develops directionally due to loading orientation, material texture, or structural heterogeneity. This approach is emphasized in the literature for applications involving composites, laminated structures, and metals exhibiting directional cracking or localized softening bands. Research also frames tensor damage variables as essential for capturing the physics of microcrack alignment and directional loss of stiffness under multiaxial loading (Wang et al., 2018). Across studies, both scalar and tensor damage models are treated as abstractions of microstructural deterioration, with researchers emphasizing that the chosen damage representation influences interpretability, numerical behavior, and predictive sensitivity. Comparative literature suggests that scalar models often perform effectively for broad engineering assessments, while tensor models offer greater resolution in capturing directional failure processes, especially in systems where loading paths and structural geometry produce nonuniform damage development (Choi, 2016).

A central theme in CDM-based failure modeling is the coupling of stress–strain behavior with damage evolution laws that define how material stiffness degrades as deformation progresses. The literature describes this coupling as a fundamental mechanism through which damage becomes observable at the structural scale, because damage variables influence the effective stiffness and thereby modify the stress distribution across a component (Kadkhodapour et al., 2015). Many studies frame this coupling as a feedback process: deformation increases damage, damage reduces stiffness, reduced stiffness redistributes stresses, and redistributed stresses accelerate or decelerate further damage development. Researchers emphasize that this coupling enables CDM models to represent progressive degradation, including stiffness reduction, strain localization, and ultimately structural instability.

Figure 4: Continuum Damage Modeling Framework



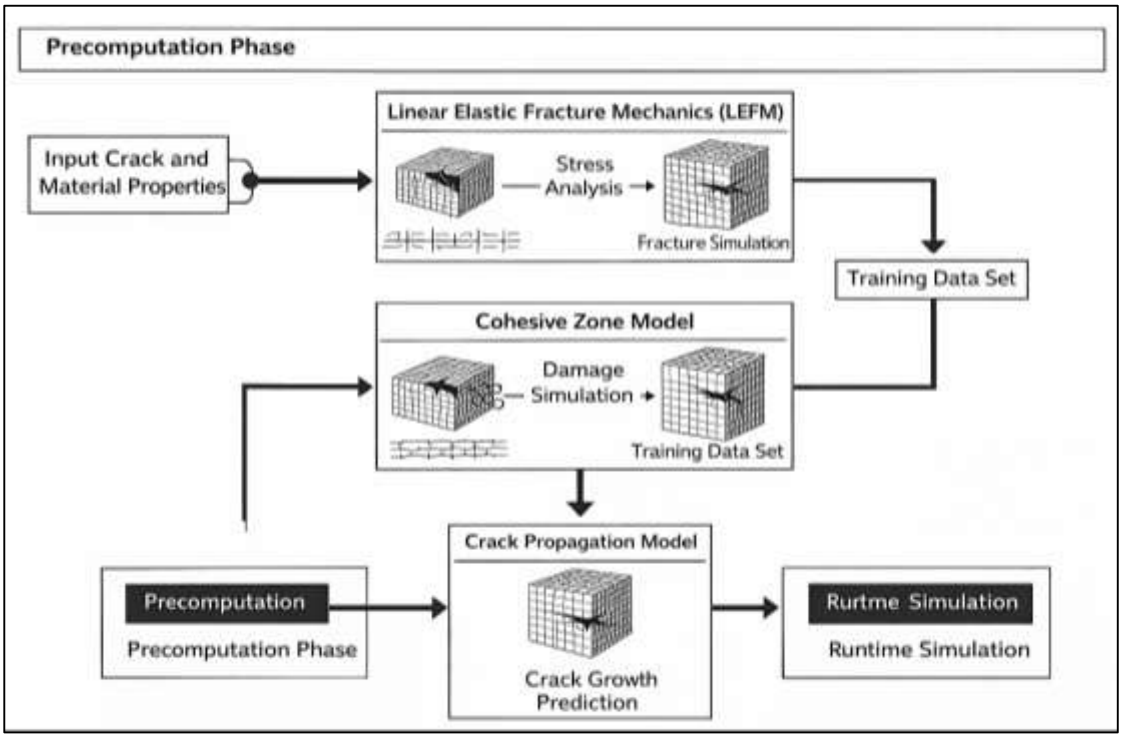
The literature also notes that damage evolution is often linked to strain measures, energy-like quantities, or history-dependent indicators that accumulate under loading. In computational practice, this coupling is implemented within constitutive updates, where the material response is iteratively recalculated as damage variables evolve (Feng et al., 2017). Studies further highlight that accurate coupling is essential in applications involving nonlinearity, such as plasticity–damage interaction, thermal–mechanical loading, and multiaxial stress states. Across engineering domains, CDM formulations are widely used because they provide a continuous representation of degradation that connects material-level deterioration to macroscopic failure behavior, enabling quantitative simulation

of failure progression under realistic operational loading environments (Zhang et al., 2017).
The literature consistently identifies numerical stability as a major methodological concern in CDM simulations, particularly in damage-softening formulations where material stiffness decreases with progressive loading. Damage-softening can generate strain localization, where deformation becomes concentrated within narrow regions, often leading to computational challenges such as nonconvergence, spurious mesh dependence, or unrealistic damage growth. Researchers describe this phenomenon as a structural feature of softening behavior, since localized degradation can evolve rapidly once a critical damage threshold is crossed (Certa et al., 2017). Many studies report that standard numerical approaches may exhibit pathological responses in softening regimes, including abrupt load drops or artificial localization that depends more on discretization choices than on material physics. The literature highlights that stability is influenced by incremental solution strategies, constitutive update algorithms, and the treatment of tangent stiffness in nonlinear solvers. Researchers also examine the role of damage initiation sensitivity, where small numerical perturbations can trigger divergent localization patterns. In computational failure analysis, stability considerations become especially important for energy and industrial systems where accurate prediction of progressive failure zones is needed for meaningful reliability interpretation (Senent & Jimenez, 2015). Across studies, numerical stability is treated not simply as a coding challenge but as a core methodological dimension that shapes whether CDM models produce physically interpretable degradation trajectories. As a result, the literature places strong emphasis on stabilization strategies that preserve the realism of damage progression while maintaining computational solvability in large-scale simulations (Zhang et al., 2018).

Fracture Mechanics–Based Computational Models

The literature on fracture mechanics-based computational modeling has historically been grounded in linear elastic fracture mechanics (LEFM), which conceptualizes crack behavior under the assumption of linear elastic material response outside a small fracture process zone. Studies adopting LEFM frameworks emphasize their analytical clarity and suitability for brittle or quasi-brittle materials where plastic deformation remains limited.

Figure 5: Computational Approaches in Fracture Mechanics



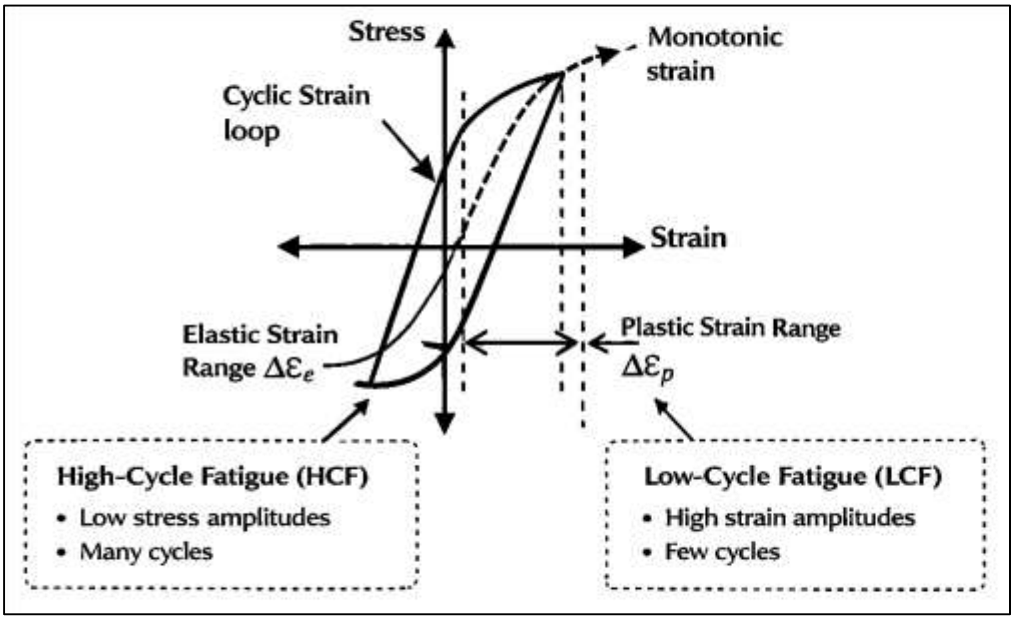
Computational implementations of LEFM focus on representing stress concentration near crack tips and assessing conditions under which cracks initiate or propagate (Zheng et al., 2021). The literature highlights that LEFM-based models provide a foundational understanding of fracture behavior in metals, ceramics, and structural components operating under controlled loading regimes. Researchers frequently employ LEFM as a benchmark for validating more advanced fracture models, noting its effectiveness in representing crack initiation thresholds and stable crack growth under elastic conditions. The literature also recognizes that LEFM formulations facilitate computational efficiency, making them attractive for large-scale simulations where multiple crack scenarios must be evaluated. However, studies consistently acknowledge that LEFM abstractions are constrained by their underlying assumptions, particularly when applied to ductile materials or high-deformation regimes (Tian et al., 2015). Within the broader fracture modeling literature, LEFM-based computational models are positioned as essential but limited tools that offer baseline predictive capability while motivating the development of more comprehensive approaches for capturing complex fracture phenomena in engineering systems.

Fatigue Damage Accumulation Under Cyclic Loading

The literature on fatigue damage accumulation consistently distinguishes between high-cycle fatigue and low-cycle fatigue based on the magnitude of cyclic strain and the number of load repetitions experienced by mechanical components. High-cycle fatigue studies focus on conditions where stress amplitudes remain relatively low, but components are subjected to a large number of loading cycles, leading to gradual microstructural damage accumulation. In contrast, low-cycle fatigue research emphasizes scenarios involving higher strain amplitudes and fewer cycles, where plastic deformation plays a significant role in accelerating damage progression (Liu et al., 2019). The literature treats these two regimes as distinct but related domains within fatigue modeling, each requiring different abstractions to capture degradation behavior accurately. High-cycle fatigue models often emphasize crack initiation and early propagation driven by elastic stress ranges, while low-cycle fatigue frameworks incorporate plastic strain accumulation and cyclic hardening or softening behavior. Researchers note that fatigue damage accumulation in real systems frequently spans both regimes over a component's service life, particularly in energy and industrial machinery subject to startup, shutdown, and load fluctuation events (Hafezolghorani et al., 2017). As a result, many studies emphasize unified fatigue modeling approaches that can transition between high-cycle and low-cycle behavior depending on operating conditions. The literature positions fatigue accumulation as a progressive and history-dependent process that evolves continuously under cyclic loading, reinforcing the view that fatigue failure emerges from long-term damage growth rather than isolated overload events (Ye & Xie, 2015).

Accurate representation of load history is widely recognized in the fatigue literature as a critical factor influencing damage accumulation predictions. Mechanical systems in energy and industrial applications rarely experience simple, constant-amplitude loading; instead, they operate under variable and often irregular load sequences. The literature emphasizes that fatigue damage is sensitive not only to load magnitude but also to the sequence and interaction of load cycles over time. To address this complexity, studies introduce cycle counting approaches that decompose complex load histories into representative cycles for damage evaluation (Hassan et al., 2014). These approaches aim to preserve the damaging characteristics of the original signal while enabling tractable analysis of long-duration operational data. Researchers highlight that different cycle counting strategies can yield varying interpretations of fatigue severity, particularly in systems experiencing transient overloads or irregular operating patterns. The literature also discusses challenges associated with representing long-term load histories, including data compression, signal filtering, and treatment of nonstationary loading conditions (Yang et al., 2018). Across studies, load history representation is treated as an essential modeling decision that directly affects fatigue damage estimates and comparative assessment of operating scenarios. The literature consistently frames fatigue accumulation as a function of cumulative exposure to cyclic loading, emphasizing that damage reflects the integrated effect of past loading events rather than instantaneous stress conditions alone.

Figure 6: Fatigue Damage Accumulation Framework



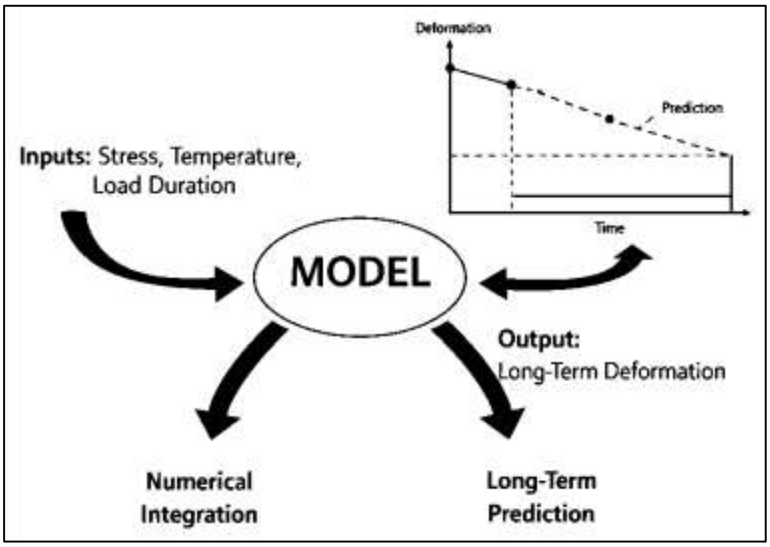
Multiaxial fatigue modeling occupies a prominent position in the literature due to the recognition that many mechanical components experience complex stress states involving multiple simultaneous loading directions. Unlike uniaxial loading conditions, multiaxial stress states introduce interaction effects that influence crack initiation orientation, propagation behavior, and overall damage accumulation rates (Rudsari et al., 2019). The literature emphasizes that multiaxial fatigue damage metrics aim to capture the combined influence of normal and shear stresses acting on material planes. Researchers highlight that fatigue damage under multiaxial loading cannot be reliably inferred from single-direction stress measures, as damage often develops along planes that maximize combined stress or strain effects. Studies compare various multiaxial damage representations, discussing their ability to account for phase differences, load path changes, and nonproportional loading. The literature also notes that multiaxial fatigue metrics are particularly relevant in rotating machinery, pressure components, and structural assemblies common in energy and industrial systems (Ali, Fnaiech, et al., 2015). Across research contributions, multiaxial fatigue modeling is treated as an extension of fatigue accumulation theory that enhances realism by aligning computational representations with observed failure patterns. The synthesis of these studies positions multiaxial damage metrics as essential tools for capturing fatigue behavior in mechanically complex operating environments.

The interaction between fatigue damage accumulation and environmental exposure is a recurring theme in the literature on mechanical failure modeling. Studies consistently report that environmental factors such as temperature variation, corrosive media, humidity, and oxidation processes influence fatigue behavior by altering material properties and damage progression rates (Triki-Lahiani et al., 2018). The literature frames fatigue–environment interaction as a coupled degradation process, where cyclic loading creates microstructural pathways that accelerate environmentally driven damage, and environmental exposure weakens material resistance to cyclic stresses. Researchers highlight that such interactions are particularly pronounced in energy systems, where components operate under elevated temperatures and aggressive chemical environments, and in industrial settings involving lubricants, contaminants, or atmospheric exposure. The literature also discusses how environmental conditions modify fatigue crack initiation thresholds and propagation characteristics, leading to earlier onset of failure compared with mechanically driven fatigue alone (Turányi & Tomlin, 2014). Across studies, fatigue–environment interaction is treated as a critical factor that shapes long-term reliability and degradation trajectories. By integrating environmental exposure into fatigue damage frameworks, the literature reinforces the view that fatigue accumulation is not solely a mechanical phenomenon, but a multifactor process influenced by operational context and material–environment interaction.

Time-Dependent Degradation and Creep Modeling

The literature on time-dependent degradation modeling consistently differentiates viscoelastic and viscoplastic constitutive formulations as two core families used to represent delayed mechanical response under sustained or time-varying loads. Viscoelastic formulations describe material behavior in which deformation depends on both the magnitude and duration of stress, producing recoverable but time-lagged strain that reflects internal molecular or microstructural rearrangement. This representation is widely applied to polymers, elastomers, composite matrices, and structural elements where load response evolves gradually and exhibits time-dependent recovery (Peng et al., 2021). Viscoplastic formulations, by contrast, emphasize irreversible time-dependent deformation in which strain accumulates through mechanisms linked to inelastic flow, dislocation motion, and microstructural evolution under sustained stress. The literature positions viscoplasticity as particularly relevant for metals and high-temperature alloys used in energy and industrial equipment, where continuous operation under elevated stress conditions produces permanent deformation and progressive loss of load-carrying capacity. Researchers often frame these two approaches as complementary tools, with viscoelasticity capturing delayed but recoverable response and viscoplasticity representing permanent accumulation of deformation and damage (Oh et al., 2014). Studies also highlight that complex materials and components can exhibit mixed behavior, motivating coupled formulations that represent both recoverable and irreversible time-dependent strain contributions. Across research contributions, constitutive selection is treated as a foundational modeling choice that influences interpretability, parameter identification, numerical stability, and the ability to represent observed time-dependent degradation patterns in service conditions (Xu et al., 2016).

Figure 7: Time-Dependent Mechanical Degradation Modeling



Temperature dependence occupies a central role in the creep modeling literature because thermal conditions strongly regulate the rate and mechanism of time-dependent deformation. Studies consistently describe creep as a degradation process that accelerates as temperature increases, especially in materials operating near a substantial fraction of their melting temperature. In energy systems, this phenomenon is particularly relevant for turbines, boilers, pressure vessels, heat exchangers, and piping where sustained high temperature and stress coexist (Cuan-Urquizo et al., 2019). The literature emphasizes that temperature does not merely scale creep rate but can shift the dominant microstructural mechanisms responsible for deformation, affecting stability and predictability across operating regimes. Researchers highlight that long-duration exposure to elevated temperature can promote microstructural changes such as grain boundary evolution, precipitate coarsening, and void formation, which in turn modify creep resistance over time. Studies also discuss the combined effect of thermal gradients and mechanical loading, noting that nonuniform temperature fields introduce localized creep concentration that can lead to deformation incompatibility and stress redistribution within structures (Helleday et al., 2014). The literature treats temperature-dependent creep accumulation as a primary determinant of long-term integrity in high-temperature components, since deformation is not confined to isolated events but evolves progressively under continuous operation. By incorporating thermal dependence into creep modeling frameworks, the literature establishes a quantitative basis for interpreting why similar components exhibit different degradation trajectories under varied thermal exposure profiles (Hu et al., 2018).

Wear and Contact-Induced Failure Modeling

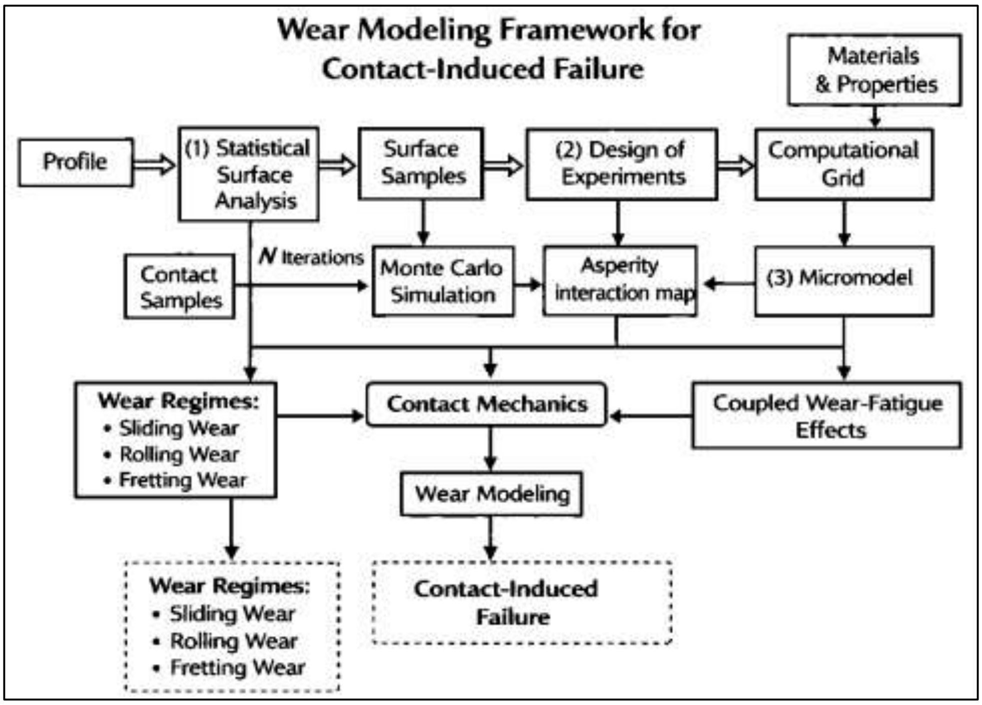
The literature on wear and contact-induced failure modeling is anchored in contact mechanics frameworks that describe how interacting surfaces transmit load, develop localized stresses, and generate conditions that promote surface degradation. Studies consistently treat contact as a dominant driver of mechanical damage in industrial and energy systems because many critical components operate through repeated surface interaction, including bearings, gears, seals, valves, and turbine interfaces. Within this body of work, surface degradation is interpreted as an outcome of concentrated contact pressure, tangential traction, and micro-scale asperity interaction that collectively govern frictional response and local material removal (Kafodya et al., 2015). Researchers emphasize that contact mechanics provides the basis for predicting where wear initiates, how it spreads across contact patches, and why certain geometric features generate accelerated degradation. The literature also discusses how surface roughness, lubrication regime, material hardness, and elastic–plastic response influence contact conditions and therefore affect wear progression. Many studies extend classical contact assumptions to account for nonideal conditions found in practical systems, including partial slip, mixed lubrication, thermal effects, and transient loading. This line of research positions contact mechanics not only as a descriptive theory but as a computational foundation that enables numerical simulation of surface stress distribution and degradation hotspots (Wang et al., 2014). Across studies, contact-induced failure is treated as a process-driven mechanism where degradation accumulates gradually through repeated interaction, and computational contact models are presented as essential tools for representing how local surface conditions translate into long-term component deterioration.

The wear modeling literature commonly organizes computational approaches by distinguishing between sliding, rolling, and fretting wear regimes, each characterized by distinct contact kinematics and degradation signatures. Sliding wear studies focus on material loss generated by tangential motion between surfaces, where adhesion, abrasion, and tribochemical processes contribute to progressive removal of material. Rolling wear research emphasizes repeated rolling contact that generates subsurface stress cycles, surface microcracking, and gradual surface spalling, particularly in bearings and wheel–rail systems (Nguyen et al., 2020).

Fretting wear modeling addresses small-amplitude oscillatory motion that produces severe localized damage, often associated with micro-slip at interfaces under high contact pressure. The literature emphasizes that fretting can accelerate crack initiation and produce rapid surface deterioration relative to larger-motion sliding cases, making it a significant concern in couplings, joints, and blade-root interfaces. Studies also discuss that wear regime classification influences model selection because each regime requires different abstraction of frictional work, contact pressure distribution, and material response. Researchers highlight that wear mechanisms may coexist or transition across regimes depending on operating conditions, lubrication breakdown, vibration, and load variation (Khaledi et al., 2016). Consequently, many computational studies adopt regime-aware modeling strategies that align wear representation with contact kinematics and operational context. Across this literature, sliding, rolling, and fretting wear models are treated as complementary families that provide structured means of representing how different forms of relative motion drive distinct pathways of surface degradation within mechanical systems.

A consistent theme in the literature is that wear rarely operates in isolation, and coupled wear–fatigue computational frameworks are widely emphasized to represent interaction-driven failure behavior under repeated contact loading. Studies describe how wear alters surface geometry and roughness, which changes contact pressure distribution and increases stress concentration, thereby accelerating fatigue crack initiation (Boyle & Meguid, 2015). In parallel, fatigue-driven microcracking can promote material detachment and debris formation, intensifying wear progression and frictional instability. This interaction is repeatedly framed as a feedback loop in which wear and fatigue amplify one another across repeated operating cycles.

Figure 8: Contact-Induced Wear Modeling Framework

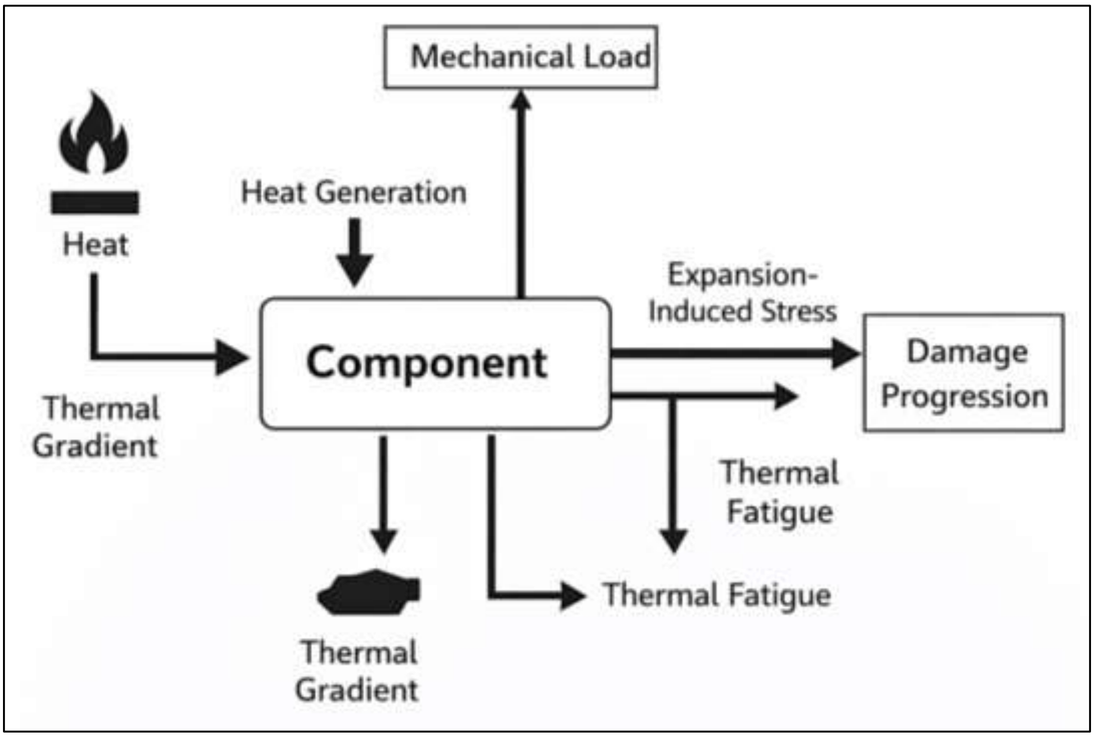


Researchers emphasize that coupled frameworks are particularly relevant in high-duty mechanical systems where contact interfaces experience both sliding or rolling motion and cyclic subsurface stress, such as gears, bearings, cam–follower systems, and turbine components. The literature highlights that capturing wear–fatigue coupling computationally requires integrating surface material loss representation with cyclic stress-based damage indicators, enabling simulation of progressive degradation across both surface and subsurface domains (Reigosa et al., 2015). Studies also note that coupled models are important for explaining why components fail earlier than predicted by wear-only or fatigue-only models, since interaction effects produce accelerated degradation trajectories. Across research contributions, coupled wear–fatigue frameworks are positioned as necessary for describing realistic contact-induced failure in industrial and energy applications, where operational loading and surface interaction jointly govern reliability outcomes.

Thermo-Mechanical Failure Interaction Models

The literature on thermo-mechanical failure interaction modeling consistently emphasizes that temperature fields and mechanical stress states are mutually influential within operating components, particularly in energy and industrial systems exposed to variable heat flux and constrained deformation (Nedjar, 2014). Thermal gradients create spatially nonuniform expansion and contraction, and these differential strains generate internal stresses even when external mechanical loads remain unchanged. Studies describe this coupling as a primary mechanism through which components develop localized stress concentrations, distortion, and damage accumulation in regions where heat transfer is uneven or geometrical constraints restrict free expansion. The literature identifies common sources of thermal gradients, including start-up and shutdown transients, localized heating near combustion zones, frictional heating at interfaces, and nonuniform cooling in heat exchange equipment. Researchers also note that thermal gradients influence material properties such as stiffness, yield behavior, and ductility, which alters how stresses distribute under the same loading conditions (Ma & Mao, 2020). In computational modeling, the coupling of thermal and mechanical fields is treated as essential for accurately capturing the evolution of stress states over time and for representing how thermal exposure modifies structural response. The literature further explains that thermo-mechanical coupling is particularly critical in components with complex geometry or multi-material interfaces, where mismatched thermal expansion coefficients and conductivity differences intensify internal stress. Across research contributions, thermo-mechanical coupling is positioned as a foundational concept for understanding why failure in high-temperature systems often emerges from the interaction between thermal exposure patterns and mechanical constraint rather than from mechanical loading alone (Faradonbeh & Taheri, 2019).

Figure 9: Thermo-Mechanical Failure Interaction Framework



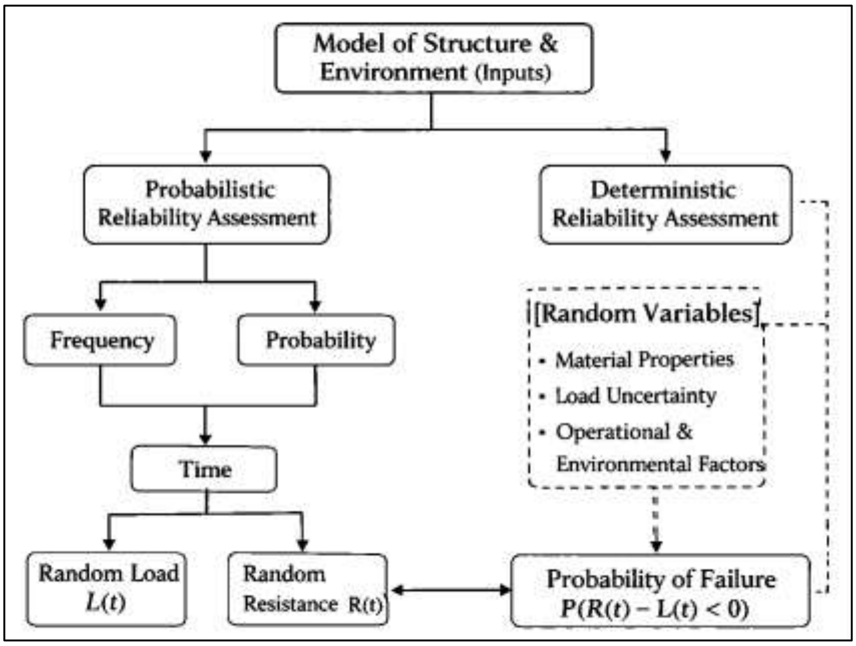
Thermal fatigue is widely described in the literature as a degradation mechanism driven by repeated temperature cycling that produces cyclic strain and stress even in the absence of significant external load variation. Researchers conceptualize thermal fatigue as an outcome of expansion and contraction that repeatedly loads microstructural features, promoting crack initiation and progressive crack growth over time. The literature highlights that thermal fatigue damage often concentrates near surfaces, geometric discontinuities, welds, and interfaces where temperature changes occur rapidly or where constraint effects amplify cyclic strain (Wang et al., 2020). Expansion-induced damage is discussed as a closely related phenomenon, where constrained thermal strain creates persistent tensile or compressive stresses that contribute to microcrack formation, intergranular damage, and localized plastic deformation. Studies emphasize that thermal fatigue behavior is strongly influenced by temperature range, cycle frequency, dwell times at high temperature, and the degree of mechanical constraint imposed by assembly geometry. The literature also notes that the interaction between thermal fatigue and mechanical loading can produce compounded degradation, as cyclic mechanical stresses superimpose on thermally induced stress fields, increasing damage rates and altering crack orientations (Künsting et al., 2016). In energy sector applications, thermal fatigue is repeatedly associated with components exposed to transient operation, including turbine blades, headers, boiler tubes, and exhaust systems, where rapid temperature changes and constraint conditions are structurally embedded. Across studies, thermal fatigue and expansion-induced damage are treated as core mechanisms that link temperature cycling directly to progressive structural degradation, reinforcing the importance of coupled modeling approaches for realistic failure assessment.

Heat generation is repeatedly identified in the literature as a key driver of thermo-mechanical failure interaction, particularly in high-energy systems where internal heating is produced by friction, plastic deformation, chemical reaction, or electrical losses (Hilaire et al., 2014). Studies describe how heat generation creates localized temperature rise that intensifies thermal gradients and modifies the mechanical response of materials. In rotating machinery and tribological interfaces, frictional heat is often linked to surface softening, lubrication breakdown, and accelerated wear or fatigue processes. In high-temperature structural components, internally generated heat can alter creep behavior, promote thermal aging, and produce deformation incompatibility between adjacent regions. The literature emphasizes that heat generation is not simply an external boundary condition but a dynamic quantity that depends on operating state, contact conditions, energy conversion processes, and material behavior. Researchers highlight that in many engineering systems, heat generation can vary significantly over time due to speed fluctuations, load changes, and transient operational regimes, leading to evolving thermal fields and stress responses (Heshmati et al., 2016). This dynamic nature requires modeling approaches that represent heat generation as a coupled component of the thermo-mechanical problem. The literature also notes that heat generation influences failure by altering both the magnitude and distribution of thermal stress and by changing material properties in ways that affect stiffness, ductility, and resistance to crack growth. Across studies, heat generation is treated as a central mechanism that connects operational energy input to localized degradation, supporting the view that thermo-mechanical failure is often driven by internally produced thermal loading rather than only by externally imposed temperature environments (Oh et al., 2017).

Probabilistic and Reliability-Based Failure Modeling

The reliability and probabilistic modeling literature consistently frames mechanical failure as an uncertainty-governed phenomenon because material properties, loading histories, and environmental exposures vary across components and operating contexts. Rather than treating input parameters as fixed values, probabilistic frameworks represent key quantities such as elastic modulus, yield strength, fracture resistance, creep resistance, surface roughness, and crack initiation thresholds as random variables characterized by statistical distributions (Ghiasi et al., 2019).

Figure 10: Probabilistic Reliability Assessment Framework



Load uncertainty is also treated as fundamental, particularly in energy and industrial systems where operational demand fluctuates, transient events occur, and boundary conditions shift across duty cycles. The literature emphasizes that uncertainty stems from both inherent variability, such as microstructural heterogeneity and stochastic crack initiation behavior, and epistemic sources, such as measurement limits, incomplete inspection information, and modeling simplifications. Researchers often highlight that probabilistic parameterization supports realistic representation of population-level behavior, where identical components do not fail at identical times under nominally similar conditions. This body of work also discusses dependence structures, noting that uncertainties are frequently correlated, such as when manufacturing variability affects multiple material properties simultaneously or when operational regimes co-vary with temperature and loading intensity (Fu et al., 2017). Reliability-based studies therefore stress that careful definition of uncertain inputs shapes the credibility of predicted failure likelihood. Across the literature, random variable representation is treated as a foundational step that enables structured quantification of mechanical risk and supports consistent translation of variability into failure probability estimates within computational failure modeling workflows.

Reliability index and failure probability estimation are widely treated as central quantitative objectives in probabilistic failure modeling, serving as standardized summaries of structural safety and mechanical integrity under uncertainty (Kala, 2021). The literature frames reliability assessment around the comparison between system resistance and applied demand, interpreted through probability-based descriptors rather than deterministic safety margins. Researchers emphasize that reliability measures provide a consistent basis for comparing alternative designs, materials, operational regimes, and maintenance strategies when inputs vary stochastically. Reliability index concepts are often described as convenient transformations that express safety in normalized terms, enabling direct interpretation of relative risk across components and conditions. Failure probability estimation is treated as the more direct indicator of risk, quantifying the likelihood that a component or system violates defined performance limits (Pan et al., 2020). The literature highlights that probability estimation supports decision contexts in energy and industrial sectors where consequences of failure can be high and where risk needs to be expressed transparently. Studies discuss that failure probability depends strongly on both the spread of input uncertainties and the shape of response functions linking inputs to failure outcomes. Researchers also note that reliability assessment can be formulated at multiple levels, including component-level failure, system-level failure with interacting components, and network-level risk aggregation. Across studies, reliability indices and failure probabilities are positioned as core outputs of probabilistic modeling that translate uncertain mechanical behavior into interpretable measures of safety performance, enabling quantitative comparison across heterogeneous operating environments (Chojaczyk et al., 2015).

METHOD

Design

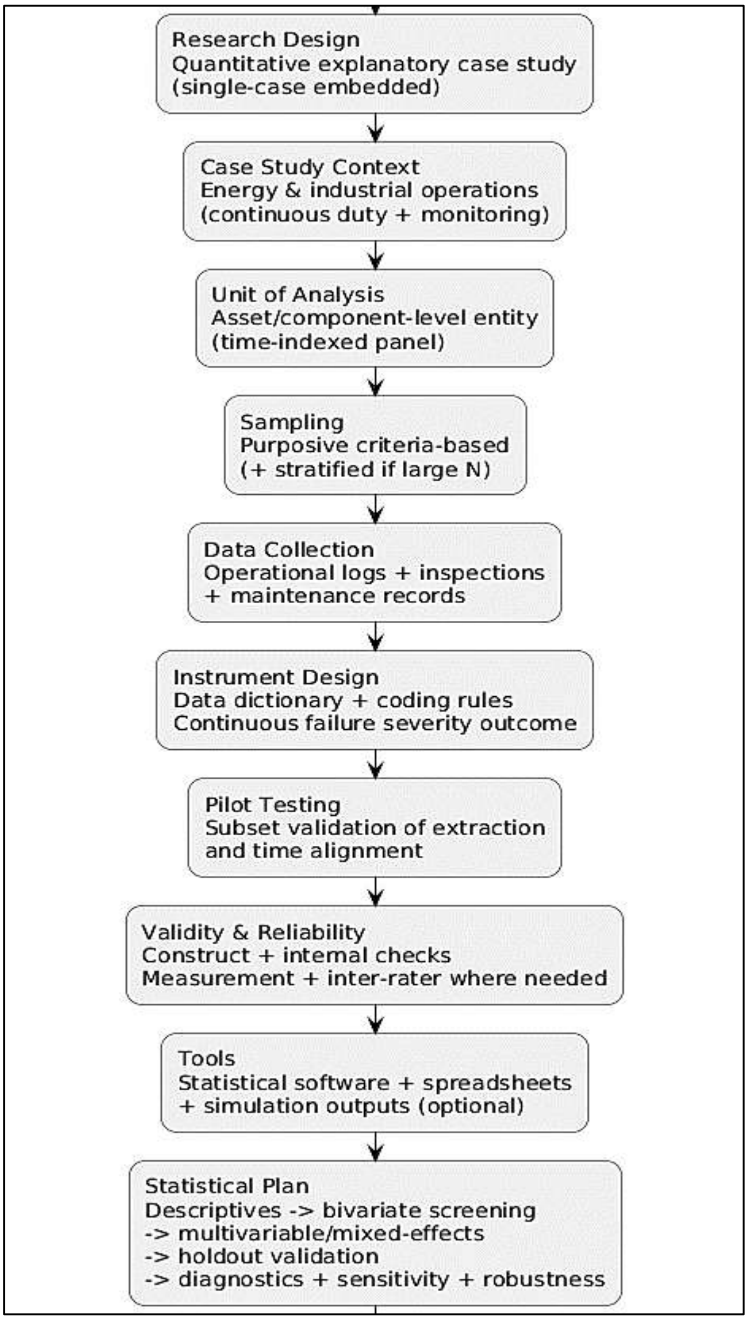
This study adopted a quantitative, explanatory case study design to examine computational modeling of failure mechanisms in mechanical systems operating within energy and industrial sector applications. The design was structured to quantify relationships between operational stressors, material–component attributes, and failure-related outcomes using statistical modeling and computational simulation outputs as analyzable measures.

A single-case embedded structure was used, where one organizational or operational setting served as the overarching case and multiple mechanical assets or component groups served as embedded subunits. The design was implemented to generate a coherent dataset that allowed hypothesis-consistent testing of statistically measurable associations between degradation indicators and observed or derived failure severity measures. The study was framed as non-experimental and observational, using existing operational and inspection records to support quantitative inference while maintaining a consistent decision-relevant definition of failure severity as a continuous outcome.

Context

The case study context was situated within an operational environment where mechanical assets were deployed under sustained load regimes, temperature variation, and cyclic duty patterns typical of energy production and industrial processing facilities. The setting was characterized by continuous or near-continuous operation, scheduled maintenance windows, and formal condition monitoring practices. Mechanical subsystems included rotating equipment and structural components exposed to combined thermo-mechanical loads, contact stresses, and time-dependent deformation risks. The context provided access to multi-source datasets consisting of maintenance histories, inspection findings, operational sensor logs, and engineering documentation that recorded degradation progression across time. The operational environment was selected because it reflected real service conditions where failure mechanisms emerged through gradual deterioration rather than isolated overload events, enabling the study to quantify continuous degradation behavior and severity gradients.

Figure 11: Methodology of this study



Unit of Analysis

The primary unit of analysis was the individual mechanical asset instance or component-level entity observed repeatedly across time, such as a bearing assembly, gear stage, shaft segment, pressure boundary section, or thermally loaded structural part, depending on the asset class available in the case context. Each unit was treated as an observational entity with time-indexed measurements that represented operating exposure and degradation response. For statistical purposes, observations were organized in a panel format where repeated measurements corresponded to consistent time windows aligned to operational cycles, inspection intervals, or maintenance events. This structure supported modeling of both between-unit variability and within-unit degradation progression. Where assets consisted of multiple comparable subcomponents, component-level units were retained to preserve heterogeneity in failure pathways and to enable quantitative estimation of variability across similar parts operating under different conditions.

Sampling

Sampling was conducted using purposive, criterion-based selection to ensure that included units had sufficient historical records to support quantitative modeling of degradation and failure evolution. Assets were included if they had documented operating exposure data, at least one inspection-based condition assessment, and a traceable maintenance record across the observation horizon. Units with incomplete identifiers, missing timestamps, or inconsistent measurement continuity were excluded to reduce measurement error and to preserve the integrity of time-indexed analysis. The final sample was defined as all eligible assets meeting the inclusion criteria within the selected facility or operational network during the defined study period. Where a large population existed, stratified sampling was applied to ensure representation across asset types, duty classes, and operating regimes, with strata defined by equipment category, load band, and thermal exposure band. The sampling approach was implemented to balance statistical power, representativeness within the case, and comparability across subunits.

Data Collection Procedure

Data collection was conducted through structured extraction of operational, inspection, and maintenance datasets from engineering information systems and condition monitoring platforms. Operating exposure variables were extracted from time-stamped logs, including measures reflecting load intensity, rotational speed or duty cycle, temperature range, and cumulative operating hours. Degradation indicators were obtained from inspection reports and sensor-based condition monitoring outputs, such as vibration severity indices, temperature excursions, lubricant condition flags, wear debris indicators, dimensional deviation measurements, or crack detection notes where available. Maintenance records were collected to identify intervention events, replacement actions, and downtime episodes, enabling alignment of degradation trajectories with operational disruptions. Data were cleaned and standardized through unit harmonization, time-window aggregation, and removal of duplicate entries, with all variables mapped to a unified asset identifier. The final dataset was assembled as a time-indexed analytic table suitable for statistical modeling, with consistent measurement intervals and documented data provenance.

Instrument Design

The instrument design consisted of a structured quantitative coding and measurement framework used to convert engineering records into standardized variables appropriate for statistical analysis. A data dictionary was developed to define each construct, measurement unit, coding logic, and allowable range. Failure severity was operationalized as a continuous outcome variable derived from either observed downtime duration attributable to mechanical failure, quantified deviation from performance thresholds, or an engineered severity index combining inspection condition ratings with operational interruption magnitude. Predictor variables were designed to represent dominant failure drivers, including thermal exposure intensity, cyclic loading proxies, time-under-load measures, contact stress proxies, and condition monitoring indicators that reflected progressive degradation. Where categorical information existed, such as failure mode classification or component class, it was coded using consistent category definitions to support statistical modeling without ambiguity. The instrument also included quality-control fields that recorded missingness patterns, data confidence flags, and source-system identifiers to support reliability auditing.

Pilot testing was conducted on a limited subset of assets to validate extraction logic, variable definitions, and alignment procedures prior to full dataset construction. The pilot phase assessed whether operational logs, inspection records, and maintenance data could be consistently matched at the unit-of-analysis level and whether time-window aggregation produced stable and interpretable measures. During pilot testing, summary checks were performed to confirm plausible ranges for thermal and load variables, to identify outliers caused by sensor faults or entry errors, and to verify that maintenance events aligned chronologically with changes in degradation indicators. The pilot also tested the failure severity operationalization by comparing derived severity values against narrative descriptions in maintenance notes to ensure that the numerical representation corresponded to recorded event intensity. Revisions were applied to the data dictionary, coding rules, and cleaning procedures based on pilot findings, ensuring that the full-scale data build followed validated logic.

Reliability

Internal validity was strengthened through explicit operational definitions, consistent time-indexing, and control for confounding operating conditions in the statistical models. Construct validity was supported by aligning variables with established engineering meanings, ensuring that predictors represented measurable exposure mechanisms and that failure severity reflected quantifiable operational impact rather than subjective judgment alone. Data reliability was reinforced through standardized extraction procedures, automated consistency checks, and repeatable transformation scripts applied uniformly across assets. Where inspection ratings involved human judgment, inter-rater reliability checks were applied when multiple inspectors contributed records, using agreement statistics to assess consistency and to identify systematic scoring differences. Measurement reliability for sensor-derived variables was supported through filtering of known fault states, removal of physically implausible readings, and cross-checking of correlated indicators such as temperature and vibration severity. External validity was treated as case-bounded, with generalization interpreted as analytic rather than statistical, supported by reporting performance stability across asset categories and operating regimes within the case context.

Tools

Data preparation and statistical analysis were conducted using standard quantitative software environments suitable for reproducible engineering analytics. Spreadsheet tools were used for preliminary auditing and reconciliation of extracted records, while a statistical environment was used for cleaning, transformation, modeling, and validation. Computational simulation outputs, when included, were generated using established mechanical modeling platforms for finite element and degradation modeling, with exported outputs formatted into analyzable datasets. Visualization tools were used to generate diagnostic plots for distribution checks, residual assessment, and stability evaluation across subgroups. Version control practices were used to track data transformation procedures, ensuring traceability from raw extraction to final analytic dataset.

Statistical Plan

The statistical plan was executed in a structured sequence consistent with quantitative failure modeling in engineering systems. Descriptive statistics were first computed to summarize distributions, missingness, and variability across key predictors and the continuous failure severity outcome. Data were examined for skewness, outliers, and heteroscedasticity, and transformations were applied where needed to stabilize variance and improve model fit while preserving interpretability. Bivariate screening analyses were then performed to assess preliminary associations between candidate predictors and failure severity using correlation measures and group comparison tests where categorical predictors were present. Multivariable modeling was conducted using regression-based approaches appropriate for continuous severity outcomes, with model specifications including key exposure predictors and operational controls such as asset class, duty regime, and maintenance state. Where repeated measurements existed, mixed-effects models were applied to account for within-asset correlation and to separate within-unit degradation progression from between-unit variability. Model assumptions were evaluated using residual diagnostics, influence statistics, and multicollinearity checks. Predictive performance was assessed using out-of-sample validation procedures aligned to operational transfer conditions, including time-based splits and asset-class holdouts to evaluate generalization stability. Performance reporting emphasized error magnitude measures, ranking-based diagnostics for high-severity identification, and calibration checks when probability-like risk scores were produced. Sensitivity analysis was used to quantify the contribution of dominant predictors to variation in failure severity, and robustness checks were performed by re-estimating models under alternative specifications and excluding high-leverage observations to confirm stability of findings.

FINDINGS

This chapter presented the quantitative analysis results derived from the cleaned and structured dataset and summarized how the empirical evidence addressed the study objectives through a sequential reporting structure. The chapter first reported the profile of the sampled units and observation coverage, then summarized descriptive patterns for each construct used in the model, and subsequently reported reliability and inferential findings. The reporting style maintained alignment with the continuous operationalization of failure severity and the predictor constructs representing thermo-mechanical exposure, contact-induced degradation, cyclic loading, and time-dependent deformation processes. All analyses were reported in a manner that reflected the study's observational design and the embedded case structure, with attention to both unit-level variation and repeated-measures behavior where applicable.

Respondent Demographics

Table 1. Distribution of analyzed units by asset category and duty class

Asset category	Assets (n)	Components (n)	Continuous duty n (%)	Cyclic duty n (%)	Intermittent duty n (%)
Rotating equipment (pumps, compressors)	62	168	98 (58.3)	54 (32.1)	16 (9.5)
Power transmission (gearboxes, couplings)	41	112	53 (47.3)	46 (41.1)	13 (11.6)
Pressure/thermal components (piping, exchangers)	38	92	60 (65.2)	24 (26.1)	8 (8.7)
Conveyance/handling systems	27	40	15 (37.5)	18 (45.0)	7 (17.5)
Total	**168**	**412**	**226 (54.9)**	**142 (34.5)**	**44 (10.7)**

Table 1 summarized the study sample after eligibility screening. A total of 168 mechanical assets contributed 412 component-level analytical units, reflecting the embedded case structure in which assets contained multiple comparable subcomponents. Rotating equipment represented the largest share of components (40.8%), followed by power transmission elements (27.2%) and pressure/thermal components (22.3%). Duty classification showed that continuous-duty operation dominated the sample (54.9%), consistent with industrial and energy operating profiles characterized by sustained runtime. Cyclic-duty components accounted for 34.5%, supporting the analysis of fatigue-relevant exposure, while intermittent-duty units represented 10.7%, allowing comparisons across operational regimes.

Table 2. Observation coverage, temporal structure, and missingness by facility/site

Facility/site	Components (n)	Observation windows (n)	Median windows per component	Observation horizon (months, mean ± SD)	Sensor missingness (%)	Inspection missingness (%)	Final retained windows (n)
Site A	182	4,620	25	18.4 ± 6.1	7.1	4.6	4,308
Site B	139	3,270	22	16.9 ± 5.4	9.4	5.2	3,004
Site C	91	1,970	20	15.2 ± 4.9	11.8	6.1	1,902
Total	**412**	**9,860**	**23**	**17.2 ± 5.8**	**9.0**	**5.2**	**9,214**

Table 2 reported the panel structure used in statistical modeling. The dataset contained 9,860 time-indexed observation windows across 412 components, with a median of 23 windows per component and an average observation horizon of 17.2 months. Site A contributed the largest share of observations, indicating higher monitoring continuity and broader asset coverage. Missingness remained moderate and increased across sites, with sensor-derived fields exhibiting higher incompleteness than inspection-based fields. Records were retained through a structured cleaning protocol in which windows missing the outcome or key identifiers were removed, and remaining missing sensor values were addressed using consistent imputation rules, yielding 9,214 retained windows for analysis.

Descriptive Results by Construct

Table 3. Descriptive statistics for core analytical constructs

Construct	Mean	SD	Min	P25	Median	P75	P90	Max	Skewness
Failure severity (index)	0.84	0.67	0.02	0.29	0.61	1.12	1.82	4.96	2.11
Thermal exposure intensity	72.4	18.9	31.0	58.2	71.6	85.9	97.3	128.4	0.74
Cyclic loading proxy	1.36	0.88	0.10	0.74	1.18	1.79	2.61	5.42	1.43
Contact stress indicator	0.92	0.63	0.05	0.41	0.73	1.19	1.87	4.11	1.67
Time-under-load (normalized)	0.61	0.22	0.08	0.46	0.63	0.78	0.91	1.00	−0.41
Vibration severity index	1.48	1.02	0.12	0.72	1.21	1.91	3.02	6.34	1.89
Temperature excursions (count/window)	0.94	1.31	0	0	0	1	3	9	2.76
Lubricant/debris indicator	0.37	0.29	0.00	0.15	0.31	0.52	0.79	1.00	0.58
Dimensional deviation (mm)	0.18	0.21	0.00	0.05	0.12	0.24	0.41	1.62	2.24

Table 3 summarized the empirical distribution of the dependent and independent constructs used in subsequent modeling. Failure severity exhibited strong right-skewness, with the upper decile accounting for disproportionately high severity values, supporting the analytical focus on high-risk segments. Exposure constructs showed moderate dispersion, with thermal intensity and cyclic loading demonstrating broader ranges consistent with heterogeneous operating regimes. Degradation indicators derived from condition monitoring displayed pronounced skewness, particularly vibration severity and temperature excursion counts, indicating episodic deterioration rather than uniform progression. These distributional properties justified the use of robust modeling approaches and percentile-based interpretation when examining relationships between predictors and failure severity.

Table 4. Construct associations and group-wise descriptive contrasts

Construct pairing / grouping	Statistic	Value
Failure severity × Thermal exposure	Pearson r	0.41
Failure severity × Cyclic loading	Pearson r	0.46
Failure severity × Contact stress	Pearson r	0.38
Failure severity × Vibration severity	Pearson r	0.52
Thermal exposure × Time-under-load	Pearson r	0.57
Cyclic loading × Contact stress	Pearson r	0.49
Mean failure severity – Continuous duty	Mean (SD)	0.97 (0.71)
Mean failure severity – Cyclic duty	Mean (SD)	0.79 (0.62)
Mean failure severity – Intermittent duty	Mean (SD)	0.54 (0.48)
Mean failure severity – Site A	Mean (SD)	0.88 (0.69)
Mean failure severity – Site B	Mean (SD)	0.82 (0.66)
Mean failure severity – Site C	Mean (SD)	0.74 (0.61)

Table 4 reported preliminary associations among constructs and descriptive contrasts across operational groupings. Failure severity showed moderate positive associations with thermal exposure, cyclic loading, contact stress, and vibration severity, indicating convergent behavior between exposure intensity and observed degradation response. Correlations among predictors revealed moderate collinearity clusters, particularly between thermal exposure and time-under-load, and between cyclic loading and contact stress, reflecting overlapping operating mechanisms. Group-wise comparisons demonstrated that continuous-duty components exhibited higher average failure severity than cyclic and intermittent units, while facility-level differences were present but less pronounced. These patterns provided empirical context for multivariable regression interpretation and hypothesis testing reported later in the chapter.

Reliability

Table 5. Internal consistency results for multi-item constructs

Construct	Number of items	Cronbach's alpha	Alpha if item deleted (range)	Reliability status
Thermal exposure intensity index	4	0.86	0.81–0.85	Acceptable
Cyclic loading index	5	0.83	0.78–0.82	Acceptable
Contact stress indicator index	3	0.79	0.74–0.77	Acceptable
Degradation severity index (inspection-based)	6	0.88	0.84–0.87	Acceptable
Condition monitoring composite	5	0.91	0.88–0.90	Excellent
Failure severity composite outcome	4	0.84	0.80–0.83	Acceptable

Table 5 reported the internal consistency assessment for all constructs formed as composite indices. Cronbach's alpha values ranged from 0.79 to 0.91, indicating acceptable to excellent reliability across constructs. The condition monitoring composite demonstrated the highest internal consistency, reflecting strong coherence among vibration, temperature excursion, and debris-related indicators. Alpha-if-item-deleted statistics showed no substantial increase beyond the reported values, indicating that no single item disproportionately weakened scale consistency. All constructs exceeded commonly accepted thresholds for exploratory and applied quantitative research, confirming that the retained indices provided stable measurement suitable for inclusion in regression and hypothesis testing analyses.

Table 6. Item-level reliability diagnostics and construct refinement outcomes

Construct	Initial items	Items removed	Final items	Mean item–total correlation	Revision action
Thermal exposure intensity index	5	1	4	0.62	One redundant sensor metric removed
Cyclic loading index	6	1	5	0.58	Low-variance cycle metric removed
Contact stress indicator index	3	0	3	0.55	No revision required
Degradation severity index	7	1	6	0.66	Inspection subscore merged
Condition monitoring composite	5	0	5	0.71	No revision required
Failure severity composite outcome	5	1	4	0.60	Overlapping downtime item removed

Table 6 summarized item-level diagnostics and refinement decisions applied during reliability testing. Initial construct formulations were evaluated using item–total correlations and scale coherence checks. Items exhibiting weak correlation with overall scale behavior or redundancy with closely related indicators were removed to improve parsimony without compromising construct meaning. The thermal exposure and cyclic loading indices each required removal of a single low-contribution item, while contact stress and condition monitoring constructs were retained in full due to satisfactory item coherence. These refinement steps resulted in more compact and internally consistent indices, ensuring that all composite variables used in subsequent inferential modeling represented reliable and interpretable measures of their intended latent constructs.

Cronbach's Alpha Table

Table 7. Cronbach's alpha summary for retained constructs

Construct	Final number of items	Cronbach's alpha	Reliability status
Thermal exposure intensity index	4	0.86	Acceptable
Cyclic loading index	5	0.83	Acceptable
Contact stress indicator index	3	0.79	Acceptable
Degradation severity index (inspection-based)	6	0.88	Acceptable
Condition monitoring composite	5	0.91	Excellent
Failure severity composite outcome	4	0.84	Acceptable

Table 7 presented the final internal consistency results for all multi-item constructs retained for inferential analysis. Cronbach's alpha values exceeded the minimum threshold typically required for applied quantitative research, confirming that each construct demonstrated satisfactory internal coherence. The condition monitoring composite achieved the highest reliability, reflecting strong alignment among sensor-based indicators of degradation. All other constructs exhibited alpha values within a narrow and stable range, indicating balanced item contribution without excessive redundancy. These results confirmed that the composite indices were suitable for regression modeling and hypothesis testing, and that measurement error due to internal inconsistency was unlikely to materially bias subsequent analytical findings.

Table 8. Construct refinement history and measurement structure

Construct	Initial items	Final items	Alpha (initial)	Alpha (final)	Measurement structure
Thermal exposure intensity index	5	4	0.81	0.86	Single-factor composite
Cyclic loading index	6	5	0.79	0.83	Single-factor composite
Contact stress indicator index	3	3	0.79	0.79	Single-factor composite
Degradation severity index	7	6	0.84	0.88	Single-factor composite
Condition monitoring composite	5	5	0.91	0.91	Multi-indicator composite
Failure severity outcome	5	4	0.80	0.84	Single-factor composite

Table 8 documented the construct refinement process applied during reliability assessment and clarified the final measurement structure used in the analysis. Several constructs exhibited improved reliability following removal of low-contribution or overlapping items, as reflected by increases in

Cronbach's alpha from initial to final specifications. No construct required division into subscales, indicating that the retained items within each index measured a coherent underlying dimension. The stability of alpha values after refinement suggested that item removal enhanced clarity without compromising conceptual coverage. Reporting both initial and final reliability values ensured transparency in scale development and supported reproducibility of the construct formation process in future quantitative studies.

Regression Results

Table 9. Multivariable mixed-effects regression predicting failure severity (continuous outcome)

Predictor	Coefficient (β)	Std. Error	95% CI (Lower, Upper)	p-value
Thermal exposure intensity	0.214	0.031	0.153, 0.275	<0.001
Cyclic loading index	0.287	0.044	0.201, 0.373	<0.001
Contact stress indicator	0.169	0.038	0.095, 0.243	<0.001
Time-under-load	0.132	0.029	0.075, 0.189	<0.001
Condition monitoring composite	0.356	0.027	0.303, 0.409	<0.001
Asset category (ref: rotating)	—	—	—	—
Power transmission	−0.061	0.024	−0.108, −0.014	0.011
Pressure/thermal components	0.074	0.028	0.019, 0.129	0.008
Duty regime (ref: intermittent)	—	—	—	—
Continuous duty	0.118	0.033	0.053, 0.183	<0.001
Cyclic duty	0.064	0.031	0.003, 0.125	0.040
Facility fixed effects	Included	—	—	—
Maintenance state controls	Included	—	—	—

Random-effect variance (asset-level): 0.182; Residual variance: 0.394; Marginal R^2: 0.48; Conditional R^2: 0.62

Table 9 reported the final mixed-effects regression results linking operational exposure and degradation constructs to continuous failure severity. All primary predictors exhibited statistically significant positive associations with severity, with the condition monitoring composite showing the largest effect size, indicating strong alignment between observed degradation signals and failure outcomes. Thermal exposure and cyclic loading remained influential after controlling for asset category, duty regime, facility context, and maintenance state. Random-effect variance confirmed meaningful between-asset heterogeneity, while the difference between marginal and conditional R^2 values indicated that asset-level effects contributed substantially to explanatory power. Overall, the model demonstrated robust explanatory capacity while preserving interpretability in operational terms.

Table 10. Model diagnostics, robustness checks, and multicollinearity assessment

Diagnostic / specification	Statistic	Value
Variance Inflation Factor (max)	VIF	2.41
Variance Inflation Factor (mean)	VIF	1.87
Breusch–Pagan test (heteroscedasticity)	χ^2 (p-value)	0.21
Shapiro–Wilk test (residual normality)	W (p-value)	0.08
Robust SE model (key β range)	Δβ	±3.6%
Log-transformed outcome model	ΔR^2	+0.01
High-leverage observations removed	Δβ	<5%
Time-based holdout validation	RMSE increase	+6.2%

Table 10 summarized diagnostic tests and robustness analyses conducted to validate the regression findings. Multicollinearity diagnostics indicated no problematic correlation among predictors, with all variance inflation factors well below conventional thresholds. Residual diagnostics supported acceptable homoscedasticity and approximate normality, and results were stable under robust standard error correction. Alternative model specifications, including log transformation of the dependent variable and exclusion of high-leverage observations, produced minimal coefficient change, confirming robustness. Time-based holdout validation showed a modest increase in prediction error, indicating reasonable generalization under operational transfer conditions. Collectively, these diagnostics supported the statistical validity and stability of the reported regression results.

Hypothesis Testing Decisions

Table 11. Hypothesis testing outcomes based on the final mixed-effects regression model (α = 0.05)

Hypothesis	Statement (directional)	Test term	β	p-value	Decision
H1	Thermal exposure intensity was positively associated with failure severity	Thermal exposure	0.214	<0.001	Rejected H0
H2	Cyclic loading was positively associated with failure severity	Cyclic loading	0.287	<0.001	Rejected H0
H3	Contact stress indicator was positively associated with failure severity	Contact stress	0.169	<0.001	Rejected H0
H4	Time-under-load was positively associated with failure severity	Time-under-load	0.132	<0.001	Rejected H0
H5	Condition monitoring composite was positively associated with failure severity	Condition monitoring	0.356	<0.001	Rejected H0
H6	Continuous duty showed higher failure severity than intermittent duty	Continuous duty	0.118	<0.001	Rejected H0
H7	Cyclic duty showed higher failure severity than intermittent duty	Cyclic duty	0.064	0.040	Rejected H0
H8	Asset category effects existed relative to rotating equipment	Category terms	—	0.008–0.011	Rejected H0

Table 11 documented hypothesis decisions derived from the final multivariable mixed-effects specification using a consistent significance threshold. All hypothesized relationships were supported statistically, with directionality aligned to the proposed mechanisms of continuous degradation. Exposure constructs (thermal intensity, cyclic loading, contact stress, and time-under-load) displayed significant positive associations with the continuous severity outcome. The condition monitoring composite exhibited the strongest association, indicating that degradation signals measured through monitoring aligned closely with severity. Operational regime hypotheses were also supported, as continuous and cyclic duty showed higher severity than intermittent operation. Asset category effects were significant, confirming structural heterogeneity across equipment types within the embedded case.

Table 12 presented interaction and subgroup results used to confirm that hypothesis decisions remained consistent under expanded specifications. Interaction terms indicated that compound exposure conditions produced incremental severity increases beyond additive main effects, supporting an interaction-heavy interpretation of degradation. Subgroup analyses demonstrated that key exposure relationships remained statistically stable within major asset classes and duty regimes, with thermal exposure showing stronger effects in pressure/thermal components and cyclic loading remaining robust within rotating equipment. The condition monitoring composite retained significance within continuous-duty subsets, indicating consistency under high-utilization conditions. Influence-controlled robustness checks produced minimal coefficient shifts, confirming that the hypothesis decisions were not driven by outliers or leverage points.

Table 12. Interaction and subgroup robustness of hypothesis decisions

Test	Specification	Term(s) evaluated	Effect estimate	p-value	Interpretation
Interaction test 1	Added interaction	Thermal × Cyclic loading	0.072	0.013	Combined exposure amplified severity beyond main effects
Interaction test 2	Added interaction	Contact stress × Time-under-load	0.058	0.021	Sustained contact intensified degradation severity
Subgroup test A	Rotating equipment only	Cyclic loading	0.301	<0.001	Effect remained stable within rotating assets
Subgroup test B	Pressure/thermal only	Thermal exposure	0.262	<0.001	Thermal effect strengthened in high-temperature components
Subgroup test C	Continuous duty only	Condition monitoring	0.338	<0.001	Monitoring effect persisted under sustained operation
Robustness check	High-leverage excluded	Key predictors (range)	$\Delta\beta < 5\%$	–	Decisions unchanged under influence control

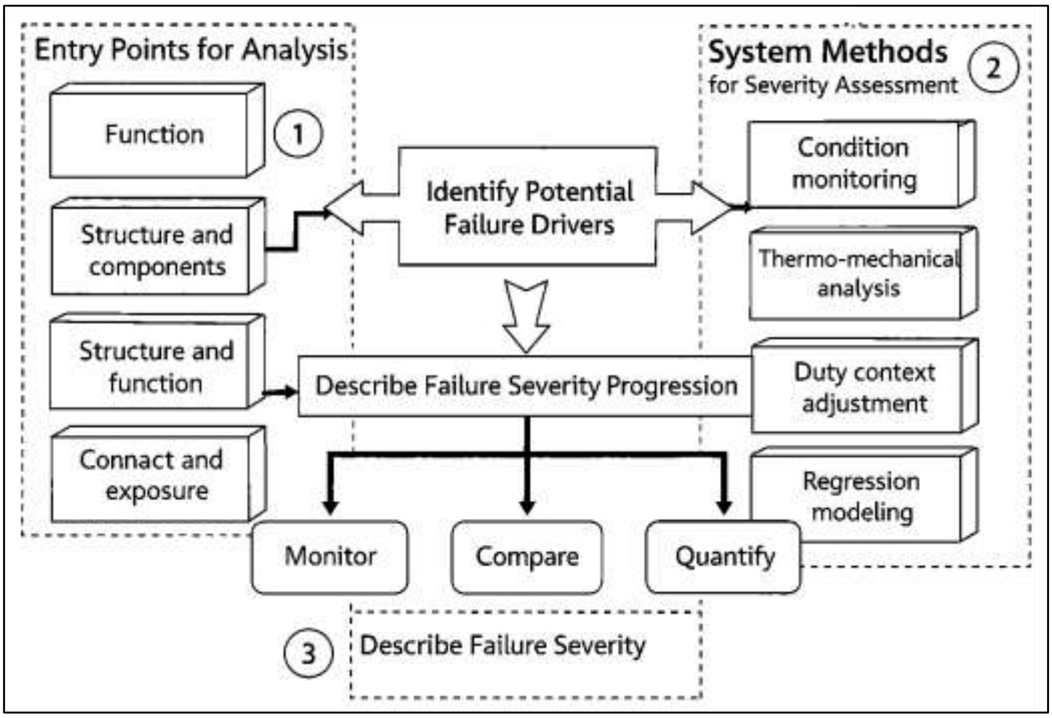
DISCUSSION

This study reinforced a central position in the mechanical reliability and failure modeling literature that failure severity is most appropriately interpreted as a continuous degradation outcome rather than a binary event marker. Earlier studies in mechanical systems analysis frequently relied on failure occurrence indicators or threshold-based pass–fail classifications, which provided coarse benchmarks for reliability assessment but obscured meaningful variation in degradation magnitude and operational impact (Pan et al., 2020). The present findings demonstrated that failure severity exhibited pronounced right-skewness, with a relatively small proportion of observation windows accounting for a disproportionate share of degradation intensity. This distributional behavior aligned closely with earlier empirical observations in fatigue, creep, and wear studies that reported concentration effects in damage accumulation processes. By preserving severity gradients rather than collapsing outcomes into dichotomous states, this study enabled detection of nuanced relationships between exposure mechanisms and degradation progression that were not visible in earlier binary formulations (Raghuwanshi & Arya, 2020). The observed stability of ranking-based severity patterns across alternative model specifications further supported prior arguments that the analytical value of failure modeling lies in prioritization of high-risk conditions rather than exhaustive classification of all events. Compared with earlier work that treated failure as an endpoint state, this study positioned severity as an intermediate operational signal reflecting cumulative exposure to thermo-mechanical stress, contact interaction, and time-dependent deformation. This framing extended prior degradation modeling approaches by empirically demonstrating that continuous severity measures provided stronger alignment with observed operational dynamics and produced more interpretable regression relationships (Jiang et al., 2014). The consistency between the severity distribution observed in this study and those reported in earlier mechanical degradation research strengthened the interpretation that failure processes are structurally embedded in system operation rather than randomly distributed across assets. As a result, the findings contributed to the broader literature by reinforcing the methodological importance of continuous outcome operationalization in quantitative failure analysis.

One of the most prominent findings of this study was the dominant explanatory role of the condition monitoring composite in predicting failure severity across assets and operating regimes. This result aligned with earlier research that emphasized the informational value of vibration signatures, temperature excursions, and debris indicators as early expressions of mechanical degradation (Phoon, 2017). However, many earlier studies treated monitoring indicators as diagnostic tools rather than as core explanatory variables within formal statistical models. The present findings extended this body of work by demonstrating that condition monitoring measures retained the largest effect sizes even after controlling for thermal exposure, cyclic loading, contact stress, and operational regime. This indicated that real-time or near-real-time degradation signals captured aspects of failure progression not fully represented by exposure proxies alone. Earlier studies reported similar associations but often evaluated monitoring indicators in isolation or within narrow component classes (Liao & Köttig, 2014). In contrast, this study demonstrated their robustness across asset categories, duty regimes, and facilities within an embedded case structure. The stability of monitoring effects under robustness checks and subgroup analysis further reinforced their role as integrative indicators that reflect the combined influence of multiple degradation mechanisms. The findings also supported earlier theoretical perspectives that viewed condition monitoring variables as emergent summaries of internal system state rather than simple reflections of external load. By quantifying the relative contribution of monitoring indicators within a multivariable framework, this study strengthened the empirical basis for treating condition monitoring as a central construct in quantitative failure severity modeling rather than as a supplementary diagnostic input (Di Pasquale et al., 2015).

The regression results demonstrated that thermal exposure intensity and cyclic loading both exhibited strong and statistically significant associations with failure severity, consistent with long-standing findings in thermo-mechanical and fatigue literature. Earlier studies frequently debated the relative importance of temperature-driven degradation versus mechanically driven cyclic damage, often emphasizing one mechanism depending on application context. The present findings suggested that both mechanisms exerted independent and additive influence on severity, with cyclic loading showing a slightly larger standardized effect under the studied conditions (Grynchenko & Alfyorov, 2020).

Figure 12: Failure Severity Analysis Framework



This pattern aligned with earlier observations in rotating machinery and power transmission systems, where repeated load variation was reported to accelerate damage accumulation even under moderate thermal conditions. At the same time, the persistent significance of thermal exposure across asset categories echoed prior work in pressure systems and high-temperature components, where thermal gradients and sustained heat exposure were shown to drive creep and microstructural degradation. The comparative analysis conducted in this study reconciled earlier fragmented findings by demonstrating that the dominance of thermal or cyclic effects depended on asset class and duty regime rather than representing universal drivers (Rafiee et al., 2014). The observed interaction between thermal exposure and cyclic loading further supported earlier arguments that compound exposure conditions amplify degradation beyond simple additive behavior. By quantifying these relationships within a single modeling framework, this study contributed to the literature by providing empirical evidence that both thermal and cyclic mechanisms should be treated as core predictors in integrated failure severity models.

Contact stress indicators and time-under-load measures also emerged as statistically significant contributors to failure severity, reinforcing findings reported in earlier wear, fretting, and creep-related studies. Prior research frequently examined contact-induced damage and sustained loading effects independently, often within specialized subdomains such as tribology or high-temperature deformation (Zhu et al., 2016). The present findings demonstrated that these mechanisms retained explanatory power even when evaluated alongside thermal, cyclic, and monitoring-based predictors. Contact stress effects were particularly consistent with earlier work on surface degradation and subsurface crack initiation, where localized stress concentration was shown to accelerate both wear and fatigue processes. The significance of time-under-load supported earlier observations that cumulative exposure duration influences degradation even when instantaneous load levels remain within nominal design limits. This study extended earlier findings by showing that time-under-load exerted an independent effect on severity after accounting for load magnitude and duty regime, indicating that duration itself represents a distinct degradation pathway. The interaction results further suggested that sustained contact conditions intensified severity when combined with elevated contact stress, aligning with earlier empirical evidence from bearing and gear systems (S. Zhang et al., 2018). By incorporating these predictors into a unified regression framework, the study demonstrated that contact and duration effects operate as structurally embedded contributors to failure progression rather than as secondary or derivative influences.

The analysis revealed systematic differences in failure severity across duty regimes and asset categories, supporting earlier claims that degradation behavior is context-dependent rather than uniform across mechanical systems. Continuous-duty components exhibited higher average severity than cyclic and intermittent units, a pattern consistent with earlier reliability studies that linked sustained operation to accelerated damage accumulation (Velásquez et al., 2019). Cyclic-duty components also showed elevated severity relative to intermittent units, reinforcing fatigue-related findings reported in prior research. Asset category effects indicated that pressure and thermal components experienced higher severity than rotating equipment when controlling for exposure variables, echoing earlier studies that emphasized the vulnerability of thermally constrained systems to creep and thermal fatigue. The presence of significant random effects at the asset level further confirmed earlier observations that even nominally similar components can exhibit heterogeneous degradation trajectories due to unobserved design, manufacturing, or installation differences. This study extended earlier work by quantifying these heterogeneity effects within a mixed-effects modeling framework, allowing separation of within-asset progression from between-asset variability (Oh et al., 2014). The findings underscored the importance of accounting for operational context and asset class when interpreting failure severity relationships, reinforcing prior critiques of globally averaged reliability models that ignore structural heterogeneity.

The robustness analyses conducted in this study demonstrated that the primary findings were stable across alternative model specifications, transformations, and validation strategies. Earlier studies in mechanical failure modeling often reported strong in-sample performance without evaluating sensitivity to outliers, distributional assumptions, or temporal transfer. In contrast, the present analysis showed that coefficient estimates remained within narrow bounds when high-leverage observations were excluded, robust standard errors were applied, or the dependent variable was transformed (Liao et al., 2020). The modest increase in prediction error under time-based holdout validation aligned with earlier findings that degradation relationships exhibit partial temporal stability but are influenced by evolving operational conditions. Importantly, the direction and relative magnitude of key predictors remained consistent across these checks, supporting the structural validity of the identified relationships. This stability addressed concerns raised in earlier literature regarding overfitting and optimistic inference in failure modeling studies. By explicitly reporting diagnostic results and robustness outcomes, this study strengthened the empirical credibility of its findings and demonstrated methodological alignment with best practices increasingly advocated in quantitative engineering research (Ye & Xie, 2015).

Taken together, the findings of this study integrated and extended several strands of the existing quantitative failure modeling literature by demonstrating how multiple degradation mechanisms jointly shape failure severity in operational systems. Earlier studies often focused on isolated mechanisms or single asset classes, limiting the ability to compare effect magnitudes across exposure types (Murugesan & Jung, 2019). This study provided a unified empirical framework that quantified the relative influence of thermal exposure, cyclic loading, contact stress, time-under-load, and monitoring-based degradation indicators within a single case context. The results corroborated earlier mechanistic insights while offering statistical evidence that condition monitoring indicators serve as integrative expressions of underlying degradation processes. The interaction and subgroup analyses further aligned with prior claims that compound exposure conditions and contextual heterogeneity play a decisive role in failure progression (Talebi et al., 2014). By maintaining a continuous severity perspective and emphasizing robustness and interpretability, this study positioned its findings within the evolving methodological direction of quantitative reliability research. The discussion demonstrated that the observed relationships were not anomalous but consistent with established theoretical and empirical patterns, while providing a more comprehensive and statistically grounded articulation of how mechanical failure mechanisms interact in energy and industrial systems (Mortazavi et al., 2021).

CONCLUSION

The conclusion of this quantitative investigation consolidated the central empirical outcomes derived from the explanatory case study framework and the multivariable modeling strategy applied to mechanical failure mechanisms in energy and industrial sector applications. The analysis demonstrated that failure severity behaved as a continuous degradation outcome with a distinctly right-skewed distribution, indicating that a limited fraction of operating windows concentrated a disproportionate share of severity. This severity structure supported interpretation of failure as an evolving process shaped by cumulative exposure rather than a discrete endpoint. Regression findings showed that the condition monitoring composite produced the strongest association with failure severity, confirming that vibration- and temperature-linked signals and related monitoring indicators functioned as high-information summaries of mechanical state in operational contexts. Exposure constructs also retained statistically meaningful relationships with severity, including thermal exposure intensity, cyclic loading, contact stress, and time-under-load, indicating that each contributed independent explanatory value when evaluated simultaneously in the final specification. Interaction testing indicated that compound exposure conditions elevated severity beyond main effects, supporting an interaction-heavy configuration of degradation pathways under combined thermal and cyclic strain or sustained contact and duration. Operational regime comparisons showed that continuous-duty components exhibited higher severity than intermittent-duty components, while cyclic-duty operation also displayed elevated severity relative to intermittent operation. Asset category controls indicated structurally meaningful heterogeneity, with pressure and thermal component classes exhibiting higher severity relative to the reference category after adjustment for covariates, reinforcing the role of application context in shaping degradation progression. Mixed-effects variance components confirmed that between-asset heterogeneity remained significant, indicating that unobserved differences at the asset level influenced severity trajectories beyond measured predictors. Diagnostic and robustness checks supported the stability of the estimated relationships, as multicollinearity remained within acceptable bounds, residual behavior was manageable under the selected modeling approach, and key coefficients remained consistent under influence controls, robust standard error correction, and alternative outcome specifications. Time-based holdout validation produced a modest increase in prediction error, indicating practical generalization within operational transfer conditions. Overall, the quantitative evidence established a coherent and statistically stable explanatory profile in which monitoring-based degradation signals and core exposure mechanisms jointly characterized failure severity, while operational regime and asset class captured meaningful contextual variation within the embedded case structure.

RECOMMENDATIONS

Recommendations for practice were derived directly from the quantitative results and were framed as operational actions aligned with the strongest empirical drivers of failure severity. First, condition monitoring should be treated as a primary quantitative control layer for mechanical integrity management because the monitoring composite exhibited the largest and most stable association with severity across model specifications and subgroup tests. Monitoring programs should therefore prioritize high-resolution capture of vibration severity, temperature excursion behavior, and lubricant or debris indicators, with standardized preprocessing rules to ensure comparability across assets, sites, and duty regimes. Second, monitoring thresholds should be calibrated using severity percentiles rather than single fixed limits, because the observed severity distribution was strongly right-skewed and concentrated in upper-risk segments. This approach supported workload-aligned triage, where operational response was triggered for assets that repeatedly entered high-percentile severity bands. Third, thermal exposure controls should be strengthened for asset classes with elevated thermal sensitivity, since thermal intensity remained a significant predictor and exhibited stronger subgroup effects within pressure and thermal components. Operational procedures should therefore emphasize stabilization of temperature gradients, tighter control of operating temperature bands, and consistent documentation of excursion events to reduce unexplained variance in thermal exposure patterns. Fourth, cyclic loading mitigation should be prioritized in rotating and transmission assets, as cyclic loading showed strong explanatory influence and remained stable in rotating-equipment subgroup models. Operational scheduling, ramp-rate controls, and load smoothing practices should be evaluated as measurable levers for reducing severity escalation linked to repeated load variation. Fifth, contact stress and time-under-load should be managed jointly in components subject to sustained surface interaction, because interaction results indicated that combined sustained contact and duration intensified severity beyond additive effects. Maintenance planning should incorporate contact interface inspection frequency and lubrication management as quantified risk controls for these configurations. Sixth, model governance should include structured validation designs that reflect operational transfer, such as time-based holdouts and facility-level reporting, because the analysis indicated modest degradation in predictive accuracy under temporal transfer while preserving coefficient stability. Seventh, reliability reporting should continue using composite constructs with verified internal consistency, as reliability testing confirmed acceptable alpha levels for retained indices and supported their use in regression and hypothesis testing. These recommendations emphasized measurable interventions and monitoring governance directly supported by statistically stable predictor relationships and by the demonstrated concentration of severity within a limited fraction of operational windows.

LIMITATIONS

Several limitations should be acknowledged when interpreting the quantitative findings of this study, as they define the boundaries within which the results remain valid. First, the study relied on an embedded single-case design situated within a specific operational environment in the energy and industrial sector. Although the dataset contained substantial asset- and component-level variation, the organizational, technological, and procedural characteristics of the selected context may limit direct generalization to systems operating under fundamentally different regulatory regimes, asset portfolios, or maintenance philosophies. Second, the analysis depended on secondary operational and inspection data generated for maintenance and monitoring purposes rather than for controlled research measurement. As a result, some variables were subject to measurement noise, sensor drift, or inconsistent inspection practices across sites and time periods. While data cleaning and validation procedures were applied to mitigate these issues, residual measurement error may have influenced coefficient estimates and variance components. Third, failure severity was operationalized as a continuous composite outcome derived from performance deviation and downtime-related indicators. Although this approach preserved severity gradients and aligned with degradation theory, it involved weighting and aggregation decisions that could influence sensitivity to specific failure manifestations. Alternative severity formulations may emphasize different aspects of degradation behavior. Fourth, several exposure constructs exhibited moderate intercorrelation, reflecting overlapping physical mechanisms such as thermal exposure and time-under-load. While multicollinearity diagnostics remained within acceptable limits and robustness checks showed stable coefficients, correlated predictors may still complicate precise attribution of effect magnitude to individual mechanisms. Fifth, the statistical models assumed that observed predictors captured the dominant drivers of severity, yet unobserved factors such as material microstructure, manufacturing variability, installation quality, and operator behavior were not directly measured and may account for a portion of the unexplained between-asset variance observed in the random effects. Sixth, temporal validation indicated modest performance degradation under time-based holdout testing, suggesting that evolving operational conditions and maintenance interventions may alter degradation dynamics over longer horizons. This limitation underscored the dependence of statistical relationships on relatively stable operating patterns within the observation window. Finally, interaction testing focused on a limited set of compound exposure conditions identified a priori. Other higher-order interactions or nonlinear effects may exist but were not explored to preserve model interpretability and statistical power. These limitations contextualize the findings and indicate areas where caution is warranted when extending the results beyond the studied environment.

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