A Survey on Uniaxial and Multiaxial Fatigue Analysis: Life Prediction and Computational Approaches

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Abstract

Fatigue analysis, a cornerstone of materials science and engineering, is crucial for predicting material behavior under cyclic loading. This survey explores the multifaceted aspects of fatigue analysis, focusing on uniaxial and multiaxial fatigue, life prediction models, and the role of computational approaches. The integration of advanced techniques, such as neural networks and machine learning, has significantly enhanced predictive accuracy and efficiency. Uniaxial fatigue analysis benefits from innovative methodologies like the Stress Energy Density criterion and Adaptive Cycle Jump scheme, which improve computational efficiency. Multiaxial fatigue analysis addresses complexities in stress-strain interactions, with critical plane approaches offering robust frameworks for life prediction. Life prediction models have evolved from traditional stress-based methods to sophisticated probabilistic and machine learning models, incorporating uncertainty quantification to improve reliability. Computational mechanics, particularly finite element methods, play a pivotal role in simulating material behavior, while data augmentation techniques enhance model training. Physics-informed neural networks further refine predictions by embedding physical laws into computational models. Case studies demonstrate the application of these techniques in diverse fields, from additive manufacturing to dental restorations. Future research should focus on optimizing neural network architectures and exploring long-term loading effects. Overall, the integration of computational methods and neural networks promises significant advancements in fatigue analysis, ensuring the durability and safety of engineering materials and structures.

1 Introduction

1.1 Overview of Fatigue Analysis

Fatigue analysis is vital in engineering and materials science, focusing on evaluating material behavior under cyclic loading. This analysis is crucial for assessing the mechanical performance and durability of components, such as prosthetic screws in dental restorations, where understanding fatigue behavior ensures implant reliability [1]. The process involves investigating crack initiation and propagation due to repeated stress cycles, which can lead to material failure.

In additive manufacturing, particularly laser powder bed fusion (L-PBF), fatigue analysis is increasingly significant, enabling the creation of metal parts with complex geometries that exhibit unique mechanical properties. A thorough understanding of their fatigue behavior is essential for safe applications in critical industries [2]. The variability in monotonic and cyclic behavior of components, such as Hastelloy-X, is influenced by complex thermal cycles during fabrication, underscoring the importance of fatigue analysis in predicting material life under operational conditions [3].

Fractography provides insights into the relationship between fracture surface topography and fracture mechanisms, enhancing the predictive capabilities of fatigue models and contributing to the development of more durable materials [4]. Thus, fatigue analysis serves as a foundational tool in

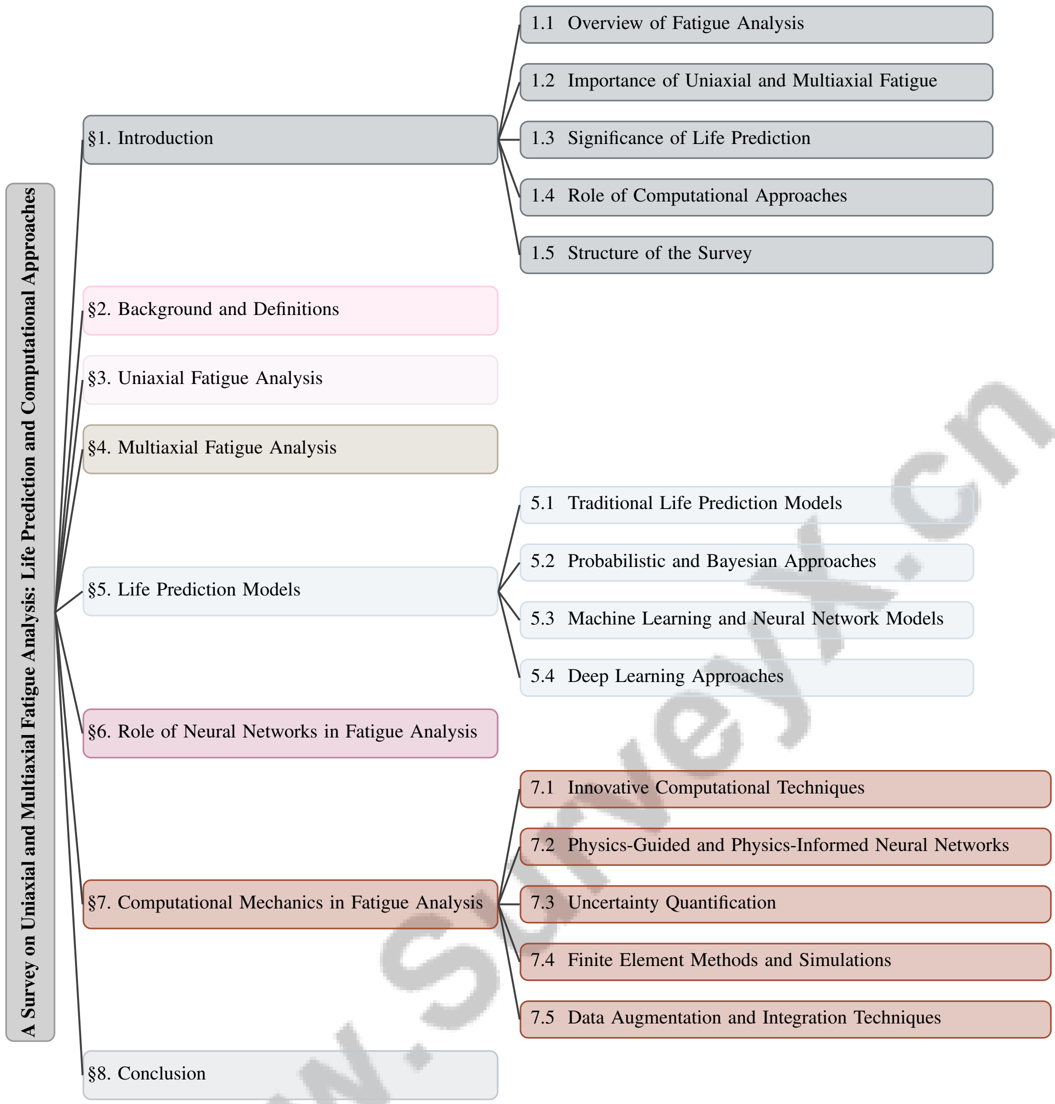

Figure 1: chapter structure

engineering and materials science, guiding the design and manufacturing of components to meet safety and performance standards.

1.2 Importance of Uniaxial and Multiaxial Fatigue

Understanding both uniaxial and multiaxial fatigue is essential for comprehending material behavior under various loading conditions. Engineering components, such as those in aero engines and railway axles, often experience complex multiaxial stress states, presenting challenges for accurate fatigue life prediction [5]. The heterogeneous microstructure of materials fabricated through selective laser melting (SLM) significantly impacts fatigue life, necessitating a detailed examination of both fatigue types to enhance predictive accuracy [3].

The degradation of residual strength and fatigue life due to low-velocity impact damage in plain-weave composite laminates further emphasizes the need to understand fatigue behavior under varied conditions [6]. Additionally, the fatigue behavior of A356-T6 alloys under multiaxial loading conditions highlights the limitations of traditional benchmarks focused primarily on uniaxial loading, necessitating a broader scope in fatigue studies [7].

Casting defects, such as spongeous shrinkages and pores, significantly degrade mechanical properties by promoting crack initiation and propagation, critical in both fatigue analyses [8]. Understanding these factors is crucial for predicting fatigue life under complex loading paths, as existing models often inadequately address these complexities [9].

In L-PBF components, predicting fatigue life is complicated by varying surface roughness, affecting fatigue behavior under different loading conditions [2]. Similarly, the fatigue behavior of prosthetic screws is influenced by implant geometry, further illustrating the need for comprehensive fatigue studies to address potential risks in key structural components [1, 10].

1.3 Significance of Life Prediction

Accurate life prediction in fatigue analysis is crucial for ensuring the safety and reliability of materials and structures under cyclic loading. This ability is particularly critical in aerospace applications, where microstructure-sensitive fatigue life prediction models are vital for maintaining material integrity [3]. Mean stress effects further underscore the necessity of reliable life prediction models, as they significantly influence fatigue performance and structural safety [11].

Traditional methods, such as the Palmgren-Miner rule, often fail to account for the non-linear nature of damage accumulation and overload effects on fatigue life, highlighting the need for more sophisticated approaches to predict strain life under variable amplitude loading [12]. The fatigue-driven residual strength model demonstrates the capability to accurately predict the fatigue life of post-impact composite laminates, emphasizing the importance of precise life prediction for material and structural reliability [6].

Integrating Basquin's and Weibull's laws through an analytical model enhances fatigue life prediction accuracy [13]. Accurate Remaining Useful Life (RUL) prediction is paramount for reliable operations, particularly in jet engine maintenance, where precise life predictions are vital for operational safety [14]. Advancements in life prediction methodologies are thus essential for addressing the complexities of fatigue behavior, ensuring material durability and safety across diverse applications.

1.4 Role of Computational Approaches

Computational approaches are indispensable for enhancing the accuracy and efficiency of fatigue analysis, providing advanced methods to simulate and predict material behavior under cyclic loading. The integration of machine learning techniques, especially neural networks, has transformed the modeling of inelastic material behavior, enabling more precise and automated fatigue analysis [15]. Data-driven models offer significant advantages in accurately predicting material behavior, thereby improving fatigue analysis efficiency [16].

Recent advancements in Physics-Informed Neural Networks (PINNs) have further improved computational fatigue analysis by incorporating full-field deformation and loading history as boundary conditions, allowing effective parameter identification even with noisy data [17]. Additionally, the shift from traditional cycle-based damage accumulation models to time-derivative approaches has significantly enhanced the accuracy and efficiency of fatigue analysis [18].

Utilizing extreme value statistics to establish a relationship between surface roughness and fatigue life exemplifies how computational methods refine predictive capabilities [2]. The application of machine learning techniques, such as Long Short-Term Memory (LSTM) networks, in predicting RUL underscores the potential of data-driven approaches to model complex relationships in time-series sensor data [14].

Moreover, the survey by [19] highlights emerging methods for uncertainty quantification in machine learning, particularly in neural networks, crucial for engineering design and health prognostics. This focus on uncertainty quantification ensures that computational models enhance predictive accuracy and provide reliable assessments of material performance under varied conditions. Integrating computational mechanics and neural networks thus plays a pivotal role in advancing fatigue analysis, offering innovative solutions to complex engineering challenges.

1.5 Structure of the Survey

The survey is systematically organized to provide a comprehensive understanding of fatigue analysis, focusing on uniaxial and multiaxial fatigue, life prediction, and computational approaches. The introduction emphasizes the importance of fatigue analysis in material durability, the significance of life prediction, and the role of computational methods. Following the introduction, the background and definitions section provides foundational knowledge, defining key concepts such as uniaxial fatigue, multiaxial fatigue, life prediction, and computational mechanics, which are crucial for understanding subsequent discussions.

The survey explores uniaxial fatigue analysis, methodologies, challenges, and the role of computational mechanics in simulating uniaxial fatigue behavior. This is followed by a discussion on multiaxial fatigue analysis, examining the complexities involved and the impact of loading history on fatigue life prediction. The life prediction models section reviews various models, including traditional, probabilistic, and machine learning approaches, highlighting their integration to enhance prediction accuracy.

Next, the role of neural networks in fatigue analysis is explored, showcasing how computational models improve life prediction through case studies and applications. The survey conducts an in-depth exploration of computational mechanics in fatigue analysis, highlighting cutting-edge techniques such as the strain-energy-density (SED) based fatigue criterion, adaptive acceleration schemes for phase-field computations, and statistical learning frameworks for predicting fatigue crack growth. It emphasizes the benefits of these innovative tools, such as improved accuracy and efficiency in life prediction and damage assessment, while addressing their limitations, including challenges related to load sequence effects and the computational intensity of high-cycle fatigue simulations [20, 10, 21, 22]. The conclusion summarizes key findings, highlighting the importance of integrating computational approaches and neural networks in advancing fatigue analysis and suggesting future research directions for potential advancements in the field.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Fundamental Concepts in Fatigue Analysis

Fatigue analysis is critical in materials science and engineering, focusing on material degradation under cyclic loading. Predicting fatigue life, which estimates the number of cycles a material can endure before failure, is influenced by microstructural characteristics, environmental conditions, and complex stress-strain behaviors under varying loading histories [3]. Traditional constitutive models, such as crystal plasticity, often inadequately capture this complex, path-dependent behavior, necessitating advanced modeling techniques [23].

A key aspect of fatigue analysis is distinguishing between uniaxial and multiaxial loading conditions. Uniaxial fatigue involves stress in a single direction, while multiaxial fatigue encompasses stresses in multiple directions, complicating life predictions due to diverse loading paths and material responses [5]. The impact of mean stress on fatigue life predictions under variable amplitude loading conditions is also significant [11].

The integration of computational methods, such as machine learning and neural networks, has enhanced predictive accuracy in fatigue analysis. Physics-Informed Neural Networks (PINNs) incorporate physical laws in their training, aiding in the identification of constitutive parameters in complex materials [24]. These models are crucial for quantifying predictive uncertainty, a vital factor for informed decision-making in engineering design and health prognostics [19].

Predicting fatigue crack growth and life-to-failure in structural components, such as gas turbines, is essential for ensuring safety and reliability. Accurate prediction of crack initiation and growth, especially under complex stress gradients, is imperative [25]. Mechanistic life prediction methodologies, which integrate statistical analysis of thermal barrier coating (TBC) morphology and non-destructive stress measurements, provide a robust framework for understanding fatigue behavior [26].

The scale effect in thin welded joints subjected to fatigue loading is significant, as current design rules often overlook the full range of thickness effects on fatigue strength [27]. In composite materials, pre-fatigue low-velocity impact (LVI) behavior is critical, particularly in applications like helicopter tail structures where complex loading conditions prevail [28].

The concept of Remaining Useful Life (RUL), defined as the time remaining before system or component failure, is vital for maintenance strategies [14]. Fundamental concepts in fatigue analysis encompass a wide array of factors, from microstructural influences and loading conditions to advanced computational methods, collectively enhancing the understanding of material behavior under cyclic loading and informing predictions of fatigue life, thereby ensuring the durability and safety of engineering structures [10].

2.2 Challenges in Fatigue Analysis

Fatigue analysis faces numerous challenges that hinder the accuracy and reliability of fatigue life predictions due to the inherent complexities of material behavior and loading conditions. A significant obstacle is the inadequacy of existing benchmarks to address multiaxial loading scenarios, which substantially affect fatigue life and introduce uncertainties that traditional models struggle to accommodate [7]. This challenge is amplified in critical applications, such as nuclear reactors, where accurate creep rupture life predictions are impeded by limited experimental data and existing methods' inability to account for uncertainty [29].

Complexities in damage mechanisms and the need for computational efficiency complicate the accurate prediction of impact damage tolerance and fatigue life in full-scale composite structures [28]. Moreover, traditional Remaining Useful Life (RUL) prediction methods, which rely heavily on physical models and statistical approaches, often struggle with generalization and require extensive historical data [14].

Traditional finite element method (FEM) approaches present significant challenges due to their high computational costs, particularly for large-scale problems, limiting their applicability in real-time analysis. This issue is critical in phase-field fatigue computations within the high-cycle fatigue (HCF) regime, where resolving small length scales and loading histories for millions of cycles is impractical. Accurately predicting fatigue life under variable amplitude loading conditions, especially in the presence of mean stresses, remains a significant challenge, as existing models often inadequately utilize constant amplitude strain-life data for accurate lifetime predictions [11].

The nonlinear degradation of residual strength and the substantial effects of load sequences on fatigue damage accumulation are often inadequately captured by current models, leading to inaccuracies in fatigue analysis [6]. Additionally, microstructural characterization poses a major challenge, as effective prediction models rely on detailed microstructural information, which is frequently difficult to obtain [3]. These challenges underscore the necessity for more sophisticated approaches and models capable of addressing the complexities of fatigue analysis, ensuring accurate predictions and reliable assessments of material performance under varied conditions.

In the realm of uniaxial fatigue analysis, a comprehensive understanding of the methodologies and innovations is crucial for enhancing fatigue life prediction. Figure 2 illustrates the hierarchical structure of these analysis methodologies, categorizing the main approaches into analytical and experimental methods, refinement techniques, computational methodologies, and modeling techniques. This categorization not only clarifies the landscape of uniaxial fatigue analysis but also highlights the significant contributions of each approach towards improving the accuracy and efficiency of fatigue life predictions. By examining this structured framework, researchers can better identify which methodologies align with their specific analytical needs and objectives, ultimately leading to more informed decision-making in fatigue analysis.

3 Uniaxial Fatigue Analysis

3.1 Methodologies for Uniaxial Fatigue Life Prediction

Method Name	Analytical Techniques	Experimental Models	Prediction Refinement
AR-BW[13]	Slope Factor	Notched Specimens	Strain-energy-density
PDM[28]	Basquin's Law	Progressive Damage Model	Prediction Refinement
EBNM[8]	Weibull Parameters	Progressive Damage Model	Machine Learning

Table 1: Summary of methodologies used in uniaxial fatigue life prediction, detailing the analytical techniques, experimental models, and prediction refinement strategies. The table includes methods such as AR-BW, PDM, and EBNM, highlighting their unique approaches and contributions to improving fatigue life estimations.

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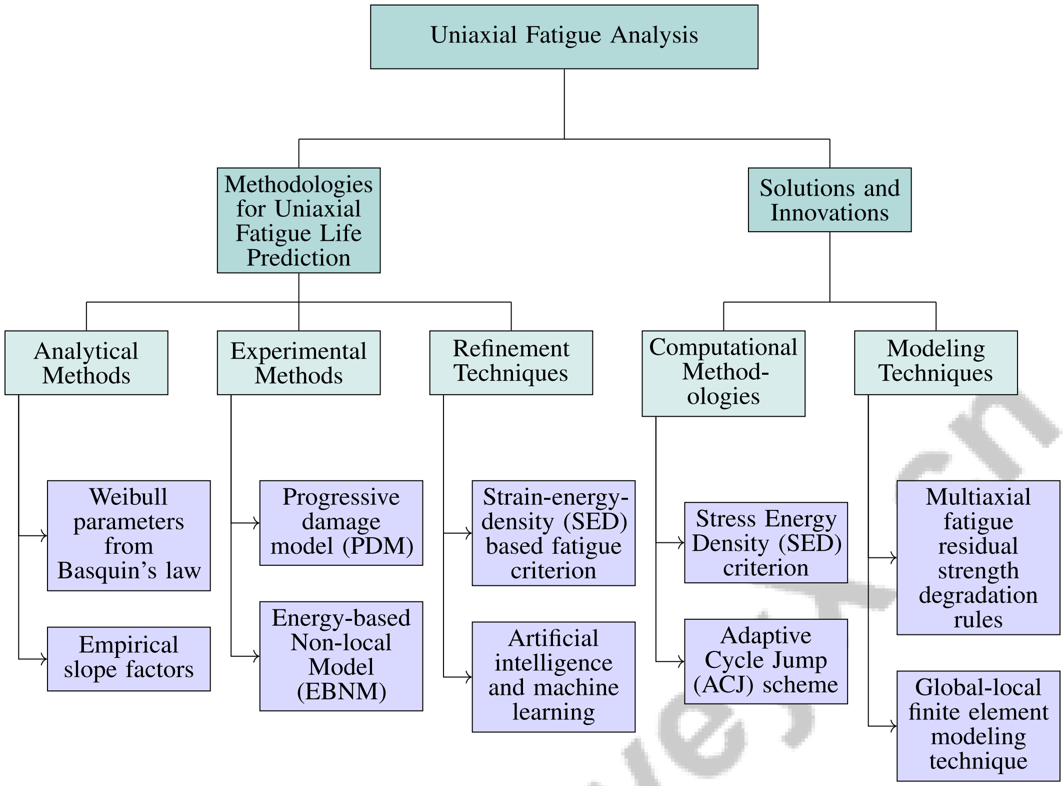

Figure 2: This figure illustrates the hierarchical structure of uniaxial fatigue analysis methodologies and innovations. It categorizes the main approaches into analytical and experimental methods, refinement techniques, computational methodologies, and modeling techniques, highlighting their contributions to improving fatigue life prediction accuracy and efficiency.

Uniaxial fatigue life prediction involves integrating experimental and analytical methodologies to address the complexities of material behavior under cyclic loading. Analytical methods, such as those deriving Weibull parameters from Basquin’s law, enhance predictions by incorporating empirical slope factors, thereby improving the accuracy of fatigue life estimations [13]. This underscores the importance of empirical adjustments in theoretical models.

Experimentally, the development of a progressive damage model (PDM) and a full-process analysis algorithm is crucial for understanding composite structures’ damage behaviors, especially in helicopter applications [28]. Additionally, the Energy-based Non-local Model (EBNM) provides insights into fatigue life by analyzing energy distribution around defects, focusing on stressed volumes and critical hotspots [8]. This model enhances predictive accuracy by evaluating energy dynamics near material defects.

These methodologies collectively advance uniaxial fatigue life prediction by merging analytical techniques with empirical data and experimental validation. Ongoing research aims to refine methods such as the strain-energy-density (SED) based fatigue criterion, which incorporates mean stress and plasticity effects, crucial for addressing fatigue behavior complexities in engineering materials. This refinement is vital for improving prediction reliability, especially in additive manufacturing, where traditional finite element methods face computational challenges. Leveraging artificial intelligence and machine learning can significantly accelerate low cycle fatigue life predictions, enhancing the accuracy and efficiency of material performance assessments [20, 30].

As illustrated in Figure 3, the methodologies for predicting uniaxial fatigue life are categorized into analytical methods, experimental models, and refinement techniques. The first example, a graph, illustrates stress versus the number of cycles for various materials, facilitating visual comparisons of endurance limits. The second schematic highlights mechanical behavior under uniaxial stress, emphasizing the importance of understanding material-specific responses for accurate life predictions and engineering applications [31, 5]. Together, these methodologies underscore the interplay between theoretical analysis and practical experimentation, ultimately aiming to enhance prediction reliability and efficiency in fatigue life assessments. Table 1 provides a comprehensive overview of the methodologies employed for uniaxial fatigue life prediction, integrating analytical techniques, experimental models, and prediction refinement strategies to enhance the accuracy and reliability of material performance assessments.

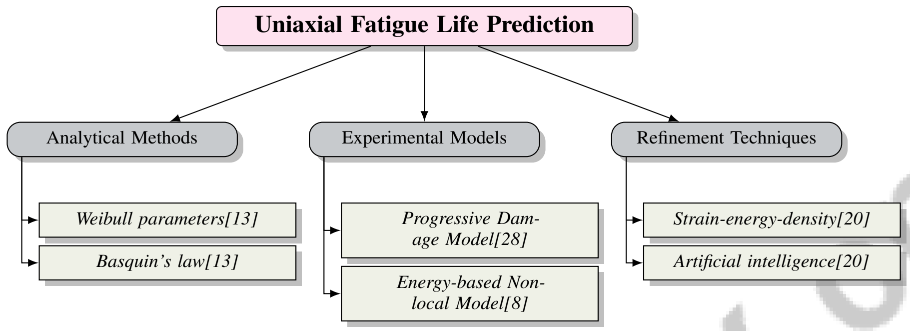

Figure 3: This figure illustrates the methodologies for uniaxial fatigue life prediction, categorizing them into analytical methods, experimental models, and refinement techniques. The analytical methods focus on deriving Weibull parameters from Basquin's law for improved prediction accuracy. Experimental models include the Progressive Damage Model and Energy-based Non-local Model, which enhance understanding of damage behaviors. Refinement techniques, such as strain-energy-density and artificial intelligence, aim to improve prediction reliability and efficiency.

3.2 Solutions and Innovations

Recent advancements in uniaxial fatigue analysis focus on enhancing computational methodologies for improved predictive accuracy and efficiency. The Stress Energy Density (SED) criterion, incorporating a Walker-like expression for mean stress effects and plastic SED components, offers a comprehensive predictive capability beyond traditional models [20]. This refinement addresses limitations of existing models, improving fatigue life evaluation under uniaxial conditions.

In computational mechanics, the Adaptive Cycle Jump (ACJ) scheme represents a significant advancement, particularly in high-cycle fatigue regimes. It achieves remarkable computational efficiency, offering speedups of up to four orders of magnitude while maintaining high accuracy with errors below 3% [22]. This innovation efficiently manages large-scale simulations without sacrificing accuracy.

Moreover, integrating multiaxial fatigue residual strength degradation rules with a novel global-local finite element modeling technique enhances both accuracy and computational efficiency [28]. This approach diverges from traditional methods, providing a detailed analysis of fatigue damage processes, especially in composite structures under complex loading scenarios. These innovations ensure uniaxial fatigue analysis continues to evolve, offering robust and efficient tools for predicting the fatigue life of engineering materials.

4 Multiaxial Fatigue Analysis

Understanding stress and strain interactions is crucial in multiaxial fatigue analysis, which is complicated by diverse loading conditions. This section delves into these complexities, emphasizing the challenges in predicting fatigue life accurately, thereby enhancing the comprehension of material fatigue behavior.

4.1 Complexity of Multiaxial Stress and Strain States

Multiaxial stress and strain states introduce significant challenges in fatigue analysis due to the interactions between stress components and material responses under varied loading conditions. Accurately estimating fatigue strength and lifetime under multiaxial non-proportional loading is critical for component design [32]. Critical plane criteria have been employed to evaluate fatigue behavior in both ductile and brittle materials, serving as benchmarks for model validation [5]. These criteria enhance the understanding of orientation-dependent fatigue damage mechanisms, leading to precise fatigue life predictions.

Techniques such as micro-computed tomography (μ-CT) and digital image correlation (DIC) are instrumental in analyzing damage mechanisms in composite laminates, categorizing damage types and their evolution under different loading conditions [33]. This comprehensive approach improves the understanding of multiaxial stress and strain interactions. The nonlinear nature of damage accumulation under variable amplitude loading adds complexity to multiaxial fatigue analysis, necessitating methods to approximate damage accumulation to constant amplitude scenarios [12]. Load sequences and nonlinear residual strength degradation significantly influence fatigue damage, requiring sophisticated models for accurate capture [6]. The integration of digital reconstruction in automated High-Frequency Mechanical Impact (HFMI) treatment enhances fatigue life predictions compared to traditional methods [34].

The intricate nature of multiaxial stress and strain states in engineering components demands advanced analytical and computational methods for fatigue life assessment. Approaches such as critical plane criteria and deep learning models improve predictive accuracy by accommodating the complexities of diverse loading conditions and material behaviors. By integrating methodologies like the Fatemi-Socie and modified generalized strain energy criteria with multi-view deep learning techniques, engineers can enhance the durability and safety of structures under multifaceted stressors [5, 20, 9, 35, 21].

4.2 Non-Proportional Loading and Cyclic Hardening

Non-proportional loading and cyclic hardening present significant challenges in multiaxial fatigue analysis due to complex interactions between stress components and material responses to varying loading paths, complicating crack initiation modeling and fatigue lifetime predictions [32]. Cyclic hardening under non-proportional loading alters material microstructure, affecting dislocation structures and internal stresses. Understanding these changes is crucial for quantifying multiaxial fatigue damage parameters, where non-proportional hardening is expressed through equivalent and direct damage parameters. Research underscores the importance of hardening effects in predicting fatigue life, especially for materials subjected to complex loading histories, impacting stress distribution and damage accumulation [32, 12, 8].

As illustrated in Figure 4, the hierarchical structure of non-proportional loading and cyclic hardening highlights the challenges and effects associated with these phenomena, as well as the computational techniques and applications that improve fatigue life predictions. Advanced computational techniques like finite element modeling (FEM) and multiscale simulations are essential for addressing complexities of non-proportional loading and cyclic hardening. FEM facilitates detailed material behavior analysis under varying stress and strain conditions, while multiscale simulations account for different material responses at various scales. Models incorporating non-proportional additional hardening, such as equivalent and direct damage parameters, enhance fatigue life predictions across metallic materials. Machine learning techniques integrated into these frameworks can further improve predictive capabilities by leveraging historical strain data and adapting to nonlinear material responses under complex loading scenarios [32, 12, 23, 16].

Investigating non-proportional loading and cyclic hardening effects is crucial for enhancing the reliability and accuracy of multiaxial fatigue predictions, particularly for engineering components like aero engine parts and railway axles experiencing complex multiaxial stress and strain states. By refining multiaxial fatigue damage parameters, engineers can better assess fatigue lifetimes, ensuring component durability and safety across various applications. Models incorporating non-proportional additional hardening significantly enhance predictive accuracy, mitigating risks associated with fatigue failure in critical applications [35, 32, 12, 5].

4.3 Critical Plane Approach for Fatigue Life Prediction

The critical plane approach is an effective framework for predicting fatigue life and determining crack failure directions under multiaxial loading. This method identifies the material plane where fatigue damage is most likely to initiate, providing a more accurate fatigue life assessment compared

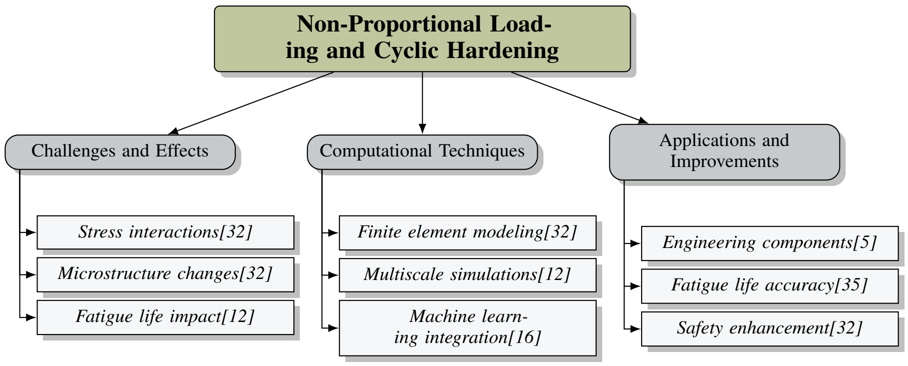

Figure 4: This figure illustrates the hierarchical structure of non-proportional loading and cyclic hardening, highlighting the challenges and effects, computational techniques, and applications and improvements in fatigue life prediction.

to traditional approaches. It accounts for the orientation-dependent nature of fatigue damage, crucial for understanding complex stress interactions in multiaxial loading scenarios [35].

Focusing on the critical plane allows detailed analysis of stress and strain states contributing to fatigue damage, enabling predictions of crack initiation and growth. This method is particularly advantageous under non-proportional loading, where maximum shear stress or strain amplitude direction may not align with principal stress directions. Discrepancies in fatigue life predictions and crack growth paths underscore the need for sophisticated analytical approaches incorporating material microstructures, variable amplitude loading effects, and multiaxial loading conditions. Leveraging advanced statistical learning frameworks, dimensionality reduction techniques, and multi-view deep learning models enhances fatigue life estimation accuracy and better accounts for uncertainties in real-world conditions [10, 9, 21, 13].

The critical plane approach is pivotal in assessing cyclic hardening and non-proportional loading impacts, facilitating detailed examination of microstructural responses to complex loading paths. It enables evaluation of various multiaxial fatigue criteria, such as the Fatemi-Socie and generalized strain energy models, providing robust life predictions for different materials under diverse loading conditions. By integrating insights from experimental data across multiple materials, this approach enhances fatigue life prediction accuracy, particularly for components facing intricate stress and strain states, such as those in aerospace and engineering applications [5, 32, 35, 25, 13]. Incorporating advanced computational techniques, such as finite element modeling, further enhances predictive accuracy of fatigue life assessments, ensuring reliability and safety of engineering components under diverse loading conditions.

The critical plane approach provides a comprehensive framework for multiaxial fatigue analysis, improving understanding of various fatigue damage mechanisms across different materials, including ductile and brittle types. By integrating advanced criteria such as the Fatemi-Socie, Wang-Brown, and modified generalized strain energy (MGSE) models, this methodology significantly enhances life prediction accuracy for engineering components under complex loading conditions, facilitating safer and more reliable designs in aerospace and structural engineering applications [35, 32, 5].

5 Life Prediction Models

5.1 Traditional Life Prediction Models

Traditional life prediction models underpin fatigue analysis, using stress-based and strain-based methodologies to estimate material fatigue life. Stress-based models, notably the S-N (stress-life) approach, are prominent in high-cycle fatigue scenarios with low stress amplitudes and high cycles to failure, employing regression analysis for extrapolating fatigue life across diverse designs [7]. However, they often fall short in addressing complex microstructural influences and environmental factors essential for accurate life predictions [3].

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Strain-based models are effective for low-cycle fatigue conditions involving significant plastic deformation, incorporating correction factors based on stress amplitude probability density functions to refine fatigue life estimation under variable loading [12]. Despite their sophistication, these models frequently struggle to generalize beyond training datasets and neglect physical constraints, underscoring the need for advanced methodologies [29].

The implicit gradient method advances fatigue behavior assessment in welded joints, particularly below traditional cut-off thicknesses, by addressing complex defect arrangements inadequately captured by traditional models [27, 8]. In multiaxial fatigue, models by Yu et al. simplify life prediction while maintaining accuracy across various loading conditions [35, 13]. Additionally, integrating fatigue damage criteria with global-local finite element modeling enhances fatigue life prediction reliability for composite structures under realistic loading [28].

Traditional models, including Miner's Rule and cumulative damage rule, provide a solid foundation for fatigue analysis but have limitations in accounting for complex variable amplitude loading (VAL) and load sequence effects. Recent advancements, such as multi-view deep learning approaches and machine learning models like support vector machines and artificial neural networks, exhibit improved predictive capabilities by integrating frequency-domain analysis and material characteristics. These innovative techniques enhance accuracy in predicting fatigue life under diverse loading conditions, addressing intricate interactions in modern engineering materials and paving the way for more reliable assessments [36, 21, 9].

5.2 Probabilistic and Bayesian Approaches

Probabilistic and Bayesian approaches effectively model uncertainty in fatigue life prediction, providing robust frameworks for quantifying and mitigating uncertainties in material behavior and loading conditions. Probabilistic methods, such as those using Schmid factors based on random grain orientations, enhance low-cycle fatigue (LCF) life predictability by accounting for microstructural variability [37]. This approach fosters a nuanced understanding of fatigue life influences, leading to more reliable predictions.

Bayesian methods, especially Bayesian maximum entropy sampling, optimize data collection strategies in fatigue testing, enhancing parameter estimation efficiency and improving material property characterization [31]. These methods are advantageous in scenarios with limited experimental data, allowing for the incorporation of prior knowledge and iterative prediction updates.

Integrating probabilistic and statistical techniques in design processes enables reliability assessment and uncertainty quantification in fatigue life predictions, crucial for robust engineering designs [38]. Probabilistic models that do not require additional material constants, as proposed by Yu et al., simplify life prediction while maintaining accuracy across various loading conditions [35]. Advanced techniques such as continuum damage mechanics, variance-based global sensitivity analysis, and machine learning models further enhance life prediction accuracy and design reliability. By employing probabilistic design methods, engineers can better manage incomplete and noisy data, improving model calibration and fatigue life reliability assessment, supporting informed decision-making in high-stakes applications [39, 38, 36, 19, 31].

5.3 Machine Learning and Neural Network Models

Machine learning (ML) and neural network models significantly enhance predictive accuracy and efficiency in fatigue analysis by leveraging data-driven insights to address fatigue behavior complexities. Artificial neural networks (ANNs), recognized as universal approximators, model complex relationships in high-dimensional data, improving life prediction reliability [40].

Innovative approaches like the Implant Screw Performance Study (ISPS) enhance neural network models' understanding of fatigue life in dental applications, demonstrating versatility across engineering contexts [1]. Convolutional neural networks (CNNs), particularly U-net architectures, aid in identifying fracture modes through semantic segmentation of scanning electron microscope images, improving fatigue damage characterization [4].

Machine learning techniques such as data augmentation via random rotations enhance recurrent neural networks (RNNs) training datasets, improving fatigue life prediction accuracy [41]. The Spatio-temporal Attention-based Hidden Physics-informed Neural Network (STA-HPINN) exemplifies

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integrating ML techniques to enhance fatigue life prediction by extracting degradation information from sensor data [24].

Long Short-Term Memory (LSTM) networks capture long-term dependencies in sequential data, outperforming traditional Multilayer Perceptron (MLP) models in predicting Remaining Useful Life (RUL) [14]. This highlights neural networks' potential to model complex relationships between material properties and loading conditions, improving fatigue life prediction reliability. Future developments may further enhance existing models by incorporating advanced ML techniques [8].

The integration of ML and neural network models in fatigue analysis enhances life prediction accuracy by combining data-driven methodologies with physics-informed insights and advanced uncertainty quantification techniques. This approach improves predictive accuracy for fatigue crack growth and life-to-failure estimations, contributing to engineering components' reliability and safety under variable amplitude loading conditions and material microstructural variations. High-fidelity simulations and ML algorithms facilitate real-time structural health monitoring and informed maintenance decision-making, reducing unexpected failure risks in critical applications [39, 10, 30, 19, 21].

5.4 Deep Learning Approaches

Deep learning approaches are integral to advancing fatigue analysis and life prediction, offering sophisticated methods to capture complex patterns in material behavior under cyclic loading. These techniques utilize neural networks to model intricate relationships among various factors influencing fatigue life, significantly enhancing predictive accuracy compared to traditional models. A study by Sun et al. demonstrates that deep learning models, particularly artificial neural networks (ANNs), outperform traditional frequency-domain models in predicting fatigue life, highlighting the potential of these approaches in refining life prediction methodologies [36].

The integration of multi-view neural networks, as proposed by Chen et al., exemplifies innovative deep learning applications in fatigue analysis. This method combines features from convolutional neural networks (CNNs), Long Short-Term Memory (LSTM) networks, and FNet to capture spatial, temporal, and frequency-domain characteristics, providing a comprehensive framework for fatigue life prediction [9]. Such multi-faceted approaches enable models to account for complex interactions between microstructural features, environmental conditions, and loading histories, which are critical for accurate life predictions.

Incorporating uncertainty quantification (UQ) in machine learning models is crucial for enhancing decision-making in high-stakes environments. Nemani et al. emphasize the importance of robust methods to quantify uncertainty, significantly impacting model interpretability and trustworthiness [19]. By integrating UQ techniques, deep learning models can provide more reliable assessments of fatigue life, ensuring the safety and durability of engineering components.

Future research directions, as suggested by Gloanec et al., should explore additional factors influencing fatigue life, indicating potential areas for deep learning approaches to further refine prediction models [42]. Continuous incorporation of new data and insights will allow deep learning models to evolve and address the complexities of fatigue behavior more effectively.

Deep learning approaches represent a transformative advancement in fatigue analysis and life prediction, significantly enhancing predictive capabilities through sophisticated neural network architectures and uncertainty quantification techniques. These methods tackle complex challenges, such as predicting fatigue life in additively manufactured materials influenced by unique factors like surface roughness. Traditional finite element methods for stress analysis often require extensive computational resources, taking over a day for a single prediction. In contrast, deep learning models can deliver low cycle fatigue life predictions in seconds. Furthermore, innovative multi-view networks that incorporate frequency-domain analysis enable precise predictions for various structural materials under multiaxial loading conditions, leveraging parallel processing of features from both loading paths and material properties. This approach has demonstrated robust performance across comprehensive datasets, showcasing its potential to significantly advance engineering fatigue research and applications [30, 9]. These developments promise to improve the reliability and safety of materials and structures across various engineering applications.

6 Role of Neural Networks in Fatigue Analysis

6.1 Neural Networks and Data-Driven Techniques

Neural networks have significantly enhanced fatigue analysis by improving predictive accuracy and efficiency, especially in contexts like additive manufacturing where traditional finite element methods are computationally intensive. Recent innovations, such as multi-view deep learning models integrating frequency-domain analysis, have advanced fatigue life prediction for various materials under complex loading scenarios. Machine learning models, including support vector machines and artificial neural networks, have surpassed conventional methods in predicting fatigue life under broad-spectrum random loads, highlighting their transformative impact on the reliability and speed of fatigue assessments [36, 30, 9, 10]. These models leverage extensive datasets to capture complex patterns in material behavior, effectively addressing the nonlinear and path-dependent nature of fatigue damage often overlooked by traditional approaches.

A key advancement is the time-derivative damage accumulation model, which offers a more accurate depiction of random loading effects on fatigue life by continuously monitoring damage over time, thus enhancing predictions under variable amplitude loading conditions [18]. Data-driven techniques using advanced machine learning algorithms like Gaussian process regression have been pivotal in uncovering complex trends in fatigue data, particularly for additive materials where surface roughness plays a crucial role. These techniques achieve remarkable predictive accuracy and speed, completing analyses in seconds compared to the extensive computational demands of conventional methods [36, 30]. This capability allows for the extraction of valuable insights from large datasets, facilitating the development of predictive models that consider the intricate interactions between material properties, environmental conditions, and loading histories.

Neural networks also enable uncertainty quantification, which is crucial for informed decision-making in engineering. By quantifying prediction uncertainties, engineers can enhance the reliability of fatigue life estimates, essential for ensuring material and structural safety. Advanced uncertainty quantification techniques, such as Bayesian neural networks and Gaussian process regression, address the complexities of material microstructures and variable amplitude loading conditions, enabling sound risk assessments and informed decisions that improve structural health monitoring and maintenance management [10, 21, 31, 19].

The application of neural networks and data-driven techniques in fatigue analysis marks a significant advancement, providing powerful tools for modeling complex fatigue behavior and enhancing the accuracy and reliability of life predictions. Recent methodologies, such as a novel strain-energy-density (SED) based fatigue criterion that incorporates mean stress and plasticity effects, along with innovative machine learning approaches for predicting fatigue life in additive materials, significantly improve our capacity to address the complexities of fatigue in modern engineering applications. These advancements contribute to the design of safer and more durable materials and structures, ultimately mitigating the risk of failure in critical engineering components [30, 10, 20, 9, 21].

6.2 Case Studies and Applications

Neural networks have been instrumental in fatigue analysis, offering innovative solutions to complex engineering challenges. A notable case study involves predicting the fatigue life of A356-T6 alloys under multiaxial loading conditions, where neural networks have effectively modeled fatigue behavior, addressing the limitations of traditional uniaxial-focused benchmarks [7].

In additive manufacturing, neural networks have been applied to predict the fatigue life of components fabricated via laser powder bed fusion (L-PBF), considering factors like surface roughness and microstructural heterogeneity to enhance predictive accuracy for these complex geometries [2]. This is particularly beneficial in industries that require lightweight and durable components.

Neural networks are also used to predict the fatigue behavior of prosthetic screws in dental restorations. By incorporating geometric factors and material properties into neural network models, researchers have improved fatigue life predictions, ensuring the longevity and reliability of dental implants [1]. This exemplifies the versatility of neural networks across diverse engineering applications.

Convolutional neural networks (CNNs) have been employed in quantitative fractography to analyze fracture mechanisms of materials under cyclic loading. By examining fracture surface images, CNNs classify different fracture modes, providing valuable insights for fatigue analysis and enhancing the understanding of material failure mechanisms [4].

These case studies underscore the transformative impact of neural networks in fatigue analysis. By leveraging advanced capabilities to analyze intricate patterns within material behavior, researchers and engineers can significantly enhance the accuracy and reliability of fatigue life predictions. This is particularly crucial for additive materials, where traditional methods struggle with computational demands and complexities such as surface roughness effects. For instance, a novel multi-view deep learning model integrating frequency-domain analysis has been developed to predict fatigue life under multiaxial loading conditions, utilizing a comprehensive database of 557 samples across various materials. Moreover, innovative statistical learning frameworks have been introduced to predict fatigue crack growth by leveraging digital libraries and neural network architectures, enabling real-time monitoring and maintenance decision-making. Ultimately, these advancements contribute to the design of safer and more durable materials and structures, addressing critical challenges in engineering applications [30, 9, 10].

7 Computational Mechanics in Fatigue Analysis

The exploration of fatigue within computational mechanics offers significant opportunities for innovation, necessitating the development of methodologies that enhance predictive capabilities. This section delves into the innovative computational techniques that have emerged as critical tools in fatigue analysis, streamlining modeling processes and significantly improving the accuracy and reliability of fatigue life predictions.

7.1 Innovative Computational Techniques

Innovative computational techniques have significantly advanced fatigue analysis by improving prediction precision and efficiency in modeling material behavior under cyclic loading. The integration of Proper Orthogonal Decomposition (POD) with feedforward neural networks exemplifies this advancement by reducing model complexity and enhancing training performance [16]. Additionally, embedding artificial neural networks (ANNs) into finite element analysis has improved accuracy in crystal plasticity simulations, offering deeper insights into microstructural responses [23]. Techniques such as crystal plasticity and Fast Fourier Transform (FFT) homogenization further refine microstructural modeling, leading to more accurate fatigue life predictions [3].

The Adaptive Cycle Jump (ACJ) method provides a flexible framework for phase-field fatigue computations, enhancing computational efficiency without sacrificing accuracy [22]. The Mean Stress Effect Correction Method (MSECM) streamlines fatigue life predictions by eliminating complex iterative calculations [11]. In multiaxial fatigue analysis, methods considering shear and normal strain effects on the critical plane offer nuanced insights into fatigue mechanisms, crucial for accurate predictions under complex loading conditions [35]. Furthermore, models integrating low-velocity impact damage and variable stress conditions exemplify the innovative use of computational techniques in capturing fatigue damage progression [6].

The application of Long Short-Term Memory (LSTM) networks for processing time-series sensor data illustrates the use of advanced computational techniques in predicting the remaining useful life of components, such as jet engines [14]. These methodologies signify a transformative advancement in fatigue analysis, offering sophisticated modeling capabilities for complex fatigue behavior across various structural materials and loading conditions. For instance, a novel multi-view deep learning model enhances fatigue life predictions under multiaxial loading paths by integrating frequency-domain analysis and advanced neural network architectures [30, 10, 9, 36, 21]. These advancements promise continued enhancement of fatigue analysis methodologies, contributing to the design of safer and more durable materials and structures.

7.2 Physics-Guided and Physics-Informed Neural Networks

The incorporation of physics-guided and physics-informed neural networks (PgNNs and PiNNs) into computational fatigue analysis represents a significant advancement, enhancing predictive accuracy and efficiency. These networks integrate physical laws and domain knowledge into their architectures, improving the modeling of complex material behaviors under cyclic loading. Faroughi et al. categorize research into four neural network types: PgNNs, PiNNs, Physics-encoded Neural Networks (PeNNs), and Neural Operators (NOs) [43].

PgNNs utilize domain-specific knowledge during training, enhancing generalization beyond the training dataset for more reliable fatigue life predictions. PiNNs incorporate governing differential equations into loss functions, ensuring consistency with physical laws and addressing challenges posed by sparse data [17, 15, 23, 24]. This integration is particularly beneficial in scenarios with sparse or noisy data, improving model robustness.

PeNNs further embed physical principles, while NOs facilitate direct mapping between complex function spaces, advancing machine learning in scientific computing across various fields [43, 17, 15, 40]. These techniques offer new avenues for addressing complexities in fatigue analysis, capturing intricate interactions between microstructural features, environmental conditions, and loading histories.

The integration of PgNNs and PiNNs in computational fatigue analysis provides a powerful toolset for improving the accuracy and reliability of life predictions. By embedding domain-specific knowledge and fundamental physical principles, researchers can enhance the interpretability of predictions, crucial for designing safer and more durable engineering materials and structures. This advancement facilitates effective modeling of complex multiscale and multiphysics phenomena, significantly improving computational efficiency and prediction accuracy [30, 43, 17, 29].

7.3 Uncertainty Quantification

Uncertainty quantification (UQ) in computational fatigue analysis is crucial for enhancing the reliability of predictive models. Integrating uncertainty estimation frameworks, as outlined by Li et al., provides insights into confidence levels associated with fatigue life predictions [40]. These frameworks enable risk identification and model reliability assessment, essential in high-stakes applications like the nuclear sector.

Chen et al. highlight that robust prediction methodologies improve predictive accuracy and reliability while offering quantifiable measures of uncertainty, facilitating informed engineering decisions [29]. Advanced UQ techniques utilize probabilistic models and Bayesian approaches to incorporate prior knowledge and dynamically update predictions as new data emerges. Methods like Gaussian process regression and Bayesian neural networks systematically assess uncertainties in data and models, enhancing decision-making in critical fields such as healthcare and engineering design [29, 10, 31, 19]. This dynamic approach ensures predictive models remain adaptable to evolving conditions.

Integrating UQ methods in computational fatigue analysis provides a comprehensive framework for evaluating material performance under cyclic loading. By systematically addressing uncertainties, these advanced methodologies enhance the reliability of engineering materials and structures. They employ a statistical learning framework that integrates high-fidelity simulations and neural networks to accurately forecast fatigue crack growth and life-to-failure under variable amplitude loading conditions, facilitating real-time structural health monitoring and improving maintenance decision-making [10, 21].

7.4 Finite Element Methods and Simulations

Finite Element Methods (FEM) and simulations are pivotal in fatigue analysis, providing detailed insights into the stress-strain behavior of materials under cyclic loading. FEM is integral to developing predictive models that account for complex interactions among material properties, environmental conditions, and loading histories. In gas turbine components, FEM is employed within probabilistic models to obtain stress and strain fields, facilitating comprehensive evaluations of life-cycle fatigue risks [25].

The Epidemiological Crack Percolation Model (ECPM) exemplifies the integration of finite element simulations with machine learning to predict stress changes and crack growth dynamics in grain networks [39]. Similarly, the Integrated Digital Reconstruction Framework (IDRF) emphasizes computational methods in fatigue analysis, enhancing the accuracy of life predictions by incorporating geometric and material details [34]. In welded joints, FEM derives effective stress values that consider geometry and loading conditions, capturing complex interactions between stress concentrations and joint geometry [27].

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Image-based finite element models simulate the effects of casting defects on fatigue life, enhancing predictive accuracy by incorporating microstructural information [8]. Moreover, developing a numerical database of local thermal barrier coating (TBC) stresses through FEM is integral to mechanistic life prediction methodologies, providing valuable insights into coated materials' fatigue behavior [26]. FEM and simulations enhance predictive accuracy by incorporating advanced criteria, such as strain-energy-density models that account for mean stress sensitivity and plasticity effects, ultimately leading to more reliable predictions of structural durability and performance [20, 21].

7.5 Data Augmentation and Integration Techniques

Data augmentation and integration techniques are essential for enhancing computational fatigue analysis, particularly in machine learning contexts. These techniques address challenges posed by limited datasets, enabling robust predictive models that accurately capture fatigue behavior dynamics. Data augmentation generates synthetic data from existing datasets, improving machine learning models' generalization capabilities through methods like random rotations, scaling, and noise addition [41].

Integration techniques combine data from multiple sources to provide comprehensive insights into fatigue behavior, particularly beneficial when synthesizing experimental measurements and simulation results. The integration of multiscale data, encompassing microstructural characteristics and macroscopic loading conditions, facilitates advanced predictive models that effectively capture complex interactions affecting fatigue life. A novel multi-view deep learning model exemplifies this approach, leveraging frequency-domain analysis to predict fatigue life across diverse structural materials and loading paths [30, 9].

Incorporating data-driven insights into physics-based models enhances predictive accuracy. By combining machine learning techniques with traditional finite element methods, researchers create hybrid models that effectively utilize both approaches' strengths. These models demonstrate superior accuracy in predicting fatigue life, particularly in complex scenarios involving multiaxial loading paths and variable material properties, leading to informed engineering decisions and improved structural health monitoring [30, 10, 9, 16, 36]. By enhancing training datasets and synthesizing information from diverse sources, these techniques contribute to the development of more accurate and reliable predictive models, ultimately improving the safety and durability of engineering materials and structures.

8 Conclusion

The application of advanced computational methods and neural networks has significantly enhanced the precision and efficiency of fatigue analysis, particularly for predicting uniaxial and multiaxial fatigue life. These approaches have refined material property predictions and present promising research opportunities, particularly in integrating microstructural features into predictive models. Research on multiaxial loading, especially in A356-T6 alloys, underscores their vital impact on fatigue behavior, offering critical insights for future applications.

Progress in developing multiaxial fatigue criteria has improved prediction accuracy, highlighting the need for universally applicable criteria that reduce reliance on material constants. Machine learning techniques, such as data augmentation, have minimized data requirements for training deep-learning models, thereby improving predictive accuracy in materials science. Implementing innovative computational methods has achieved substantial computational savings, effectively simulating complex loading histories. Moreover, convolutional neural networks have demonstrated high classification accuracy for fracture modes in ceramic materials.

Physics-Informed Neural Networks (PINNs) have effectively identified constitutive parameters for complex materials, showing robustness against noisy data. Advances in machine learning-based models have significantly enhanced the understanding of hyperelastic and plastic behaviors. Additionally, integrating diverse data types has improved the life prediction of thermal barrier coating systems.

Future research should focus on exploring alternative neural network architectures to enhance computational efficiency and examining sparsification techniques to reduce computational demands. Investigating the long-term effects of repeated loading on damage evolution and the influence of environmental factors on fatigue behavior remains crucial. The proposed meta-learning approach has shown superior performance in predicting creep rupture life, effectively addressing challenges related to limited data and uncertainty. Furthermore, optimizing scanning procedures within integrated frameworks can enhance fatigue life predictions through finite element modeling.

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References

[1] Mikel Armentia, Mikel Abasolo, Ibai Coria, and Nicolas Saintier. Effect of the geometry of butt-joint implant-supported restorations on the fatigue life of prosthetic screws, 2024.

[2] Ritam Pal, Brandon Kemerling, Daniel Ryan, Sudhakar Bollapragada, and Amrita Basak. Surface roughness-informed fatigue life prediction of l-pbf hastelloy x at elevated temperature, 2024.

[3] Chandrashekhar M. Pilgar, Ana Fernandez, and Javier Segurado. Microstructure sensitive fatigue life prediction model for slm fabricated hastelloy-x, 2022.

[4] Stylianos Tsopanidis, Raúl Herrero Moreno, and Shmuel Osovski. Toward quantitative fractography using convolutional neural networks, 2019.

[5] Shun-Peng Zhu, Zheng-Yong Yu, José Correia, Abílio De Jesus, and Filippo Berto. Evaluation and comparison of critical plane criteria for multiaxial fatigue analysis of ductile and brittle materials. *International Journal of Fatigue*, 112:279–288, 2018.

[6] Zheng-Qiang Cheng, Wei Tan, and Jun-Jiang Xiong. Progressive damage modelling and fatigue life prediction of plain-weave composite laminates with low-velocity impact damage, 2021.

[7] M. J. Roy, Y. Nadot, D. M. Maijer, and G. Benoit. Multiaxial fatigue behaviour of a356-t6, 2014.

[8] Arjun Kalkur Matpadi Raghavendra, Vincent Maurel, Lionel Marcin, and Henry Proudhon. Fatigue life prediction at mesoscopic scale of samples containing casting defects: A novel energy based non-local model, 2024.

[9] Shuonan Chen, Xuhong Zhou, and Yongtao Bai. A frequency-domain enhanced multi-view network for metal fatigue life prediction, 2024.

[10] Yingjie Zhao, Yong Liu, and Zhiping Xu. Predicting fatigue crack growth via path slicing and re-weighting, 2023.

[11] Pietro D'Antuono and Michele Ciavarella. Mean stress effect on gaßner curves interpreted as shifted wöhler curves, 2019.

[12] S. P. Beckman and P. J. Huffman. A non-linear damage accumulation fatigue model for predicting strain life at variable amplitude loadings based on constant amplitude fatigue data, 2012.

[13] Pietro D'Antuono. An analytical relation between weibull's and basquin's laws for smooth and notched specimens and application to constant amplitude fatigue, 2019.

[14] Anees Peringal, Mohammed Basheer Mohiuddin, and Ahmed Hassan. Remaining useful life prediction for aircraft engines using lstm, 2024.

[15] Max Rosenkranz, Karl A. Kalina, Jörg Brummund, and Markus Kästner. A comparative study on different neural network architectures to model inelasticity, 2023.

[16] Dengpeng Huang, Jan Niklas Fuhg, Christian Weißenfels, and Peter Wriggers. A machine learning based plasticity model using proper orthogonal decomposition, 2020.

[17] Siyuan Song and Hanxun Jin. Identifying constitutive parameters for complex hyperelastic materials using physics-informed neural networks, 2024.

[18] Shih-Chuan Tien, Haoyang Wei, Jie Chen, and Yongming Liu. Energy-based time derivative damage accumulation model under uniaxial and multiaxial random loadings, 2021.

[19] Venkat Nemani, Luca Biggio, Xun Huan, Zhen Hu, Olga Fink, Anh Tran, Yan Wang, Xiaoge Zhang, and Chao Hu. Uncertainty quantification in machine learning for engineering design and health prognostics: A tutorial, 2023.

[20] Journal paper: International jou.

[21] He-Wen-Xuan Li and David Chelidze. Fatigue life estimation of structures under statistically and spectrally similar variable amplitude loading, 2021.

[22] Jonas Heinzmann, Pietro Carrara, Marreddy Ambati, Amir Mohammad Mirzaei, and Laura De Lorenzis. An adaptive acceleration scheme for phase-field fatigue computations, 2024.

[23] Yuqing He, Yousef Heider, and Bernd Markert. Embedding an ann-based crystal plasticity model into the finite element framework using an abaqus user-material subroutine, 2024.

[24] Feilong Jiang, Xiaonan Hou, and Min Xia. Spatio-temporal attention-based hidden physics-informed neural network for remaining useful life prediction, 2024.

[25] Lucas Mäde, Sebastian Schmitz, Georg Rollmann, Hanno Gottschalk, and Tilmann Beck. Probabilistic lcf risk evaluation of a turbine vane by combined size effect and notch support modeling, 2017.

[26] Esteban Busso, L. Wright, H. E. Evans, L. N. McCartney, S. R. J Saunders, S. Osgerby, and J. Nunn. A physics-based life prediction methodology for thermal barrier coating systems, 2007.

[27] Paolo Livieri and Roberto Tovo. Analysis of the thickness effect in thin steel welded structures under uniaxial fatigue loading. *International Journal of Fatigue*, 101:363–370, 2017.

[28] Zheng-Qiang Cheng, Wei Tan, and Jun-Jiang Xiong. Modelling pre-fatigue, low-velocity impact and fatigue behaviours of composite helicopter tail structures under multipoint coordinated loading spectrum, 2022.

[29] Yu Chen, Edoardo Patelli, Zhen Yang, and Adolphus Lye. Towards robust prediction of material properties for nuclear reactor design under scarce data – a study in creep rupture property, 2024.

[30] Timothy Hanlon, Johan Reimann, Monica A. Soare, Anjali Singhal, James Grande, Marc Edgar, Kareem S. Aggour, and Joseph Vinciquerra. Artificial intelligence enabled material behavior prediction, 2019.

[31] Christopher M Magazzeni, Rory Rose, Chris Gearhart, Jicheng Gong, and Angus J Wilkinson. Bayesian optimised collection strategies for fatigue strength testing, 2022.

[32] Peng Luo, Weixing Yao, Luca Susmel, Yingyu Wang, and Xiaoxiao Ma. A survey on multiaxial fatigue damage parameters under non-proportional loadings. *Fatigue & Fracture of Engineering Materials & Structures*, 40(9):1323–1342, 2017.

[33] Yao Qiao and Marco Salviato. Micro-computed tomography analysis of damage in notched composite laminates under multi-axial fatigue, 2019.

[34] Anders Faarbæk Mikkelstrup and Morten Kristiansen. Integrated digital reconstruction of welded components: Supporting improved fatigue life prediction, 2023.

[35] Zheng-Yong Yu, Shun-Peng Zhu, Qiang Liu, and Yunhan Liu. Multiaxial fatigue damage parameter and life prediction without any additional material constants. *Materials*, 10(8):923, 2017.

[36] Hong Sun, Yuanying Qiu, Jing Li, Jin Bai, and Ming Peng. Novel models for fatigue life prediction under wideband random loads based on machine learning, 2023.

[37] H. Gottschalk, S. Schmitz, T. Seibel, G. Rollmann, R. Krause, and T. Beck. Probabilistic schmid factors and scatter of lcf life, 2014.

[38] Danial Faghihi, Subhasis Sarkar, Mehdi Naderi, Lloyd Hackel, and Nagaraja Iyyer. A probabilistic design method for fatigue life of metallic component, 2017.

[39] M. Harder, P. Lion, L. Mäde, T. Beck, and H. Gottschalk. Probabilistic modeling of lcf failure times using an epidemiological crack percolation model, 2022.

[40] Qing-Jie Li, Mahmut Nedim Cinbiz, Yin Zhang, Qi He, Geoffrey Beausoleil II au2, and Ju Li. Robust deep learning framework for constitutive-relation modeling, 2023.

[41] Hon Lam Cheung, Petter Uvdal, and Mohsen Mirkhalaf. Augmentation of scarce data – a new approach for deep-learning modeling of composites, 2023.

[42] Anne-Lise Gloanec, Thomas Milani, and Gilbert Henaff. Impact of microstructure, temperature and strain ratio on energy-based low- cycle fatigue life prediction models for tial alloys, 2012.

[43] Salah A Faroughi, Nikhil Pawar, Celio Fernandes, Maziar Raissi, Subasish Das, Nima K. Kalantari, and Seyed Kourosh Mahjour. Physics-guided, physics-informed, and physics-encoded neural networks in scientific computing, 2023.

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