MEST Journal
DOI 10.12709/mest.13.13.02.16

Review article
MEST Journal
MESTE WORLD

MULTIAXIAL HIGH-CYCLE FATIGUE IN MODERN ENGINEERING: PERSPECTIVES AND CONTRIBUTIONS

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JEL Category: **C5, C6, D24, L23, O3**

Abstract

The process of modeling quality indicators from mechanical and simulation tests aiming to establish the fulfillment of specific technical requirements is linked to resource efficiency. Imposing such a modern approach in the design process increases the efficiency of the used materials' expected capacity. The proposed design enhances material strength while reducing structural weight, leading to lower fuel consumption and a corresponding decrease in greenhouse gas emissions. Its successful implementation relies on continuous research to identify innovative solutions and advanced computational approaches that expand existing knowledge and best practices. This paper presents a comprehensive review of multiaxial and multicycle fatigue, a critical factor in the design of essential components exposed to complex loading conditions. The purpose is to review and examine the current state of this type of testing, modeling approaches, experimental techniques, and current real-world applications in the fields of aerospace and automotive design. The aim is to draw the attention of engineers, researchers, and industry professionals working with high-performance materials and structures that study complex stresses.

Keywords: *High-cyclic fatigue, Resource efficiency, Neural modeling, Machine learning, Fatigue modeling.*

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1 INTRODUCTION

The aim of this paper is to focus on the design of components under complex loading conditions (multiple forces from different directions simultaneously), and multi-axial and high cyclic fatigue from the automotive and aviation sectors.

The defined task imposes several requirements on the design of components, as preventing safety-critical fatigue failures is critical for accident avoidance.

Weight optimization is crucial in the design process, as it directly influences material selection in the automotive sector. Fuel costs and environmental concerns play a key role in determining the choice of materials in automotive design. This interdisciplinary challenge integrates mechanical engineering, materials science, and computer modeling to address three main aspects: fatigue failure prevention, simulation-based optimization, and sustainable lightning.

Reducing aircraft masses decreases energy consumption during flights. Every eliminated kilogram of mass results in 106 kg of jet fuel savings per year and reduces greenhouse gas emissions in aviation proportionally. This relationship is a driving innovation, such as the development of carbon fiber-reinforced polymers in plane wings, thereby achieving a 15-20% weight reduction compared to aluminum (Pryanshu, 2023).

Modern components, such as aircraft landing gears and automotive axles, are subject to bending and torsional loads, requiring accurate models to predict fatigue life. Traditional approaches, such as Miner's rule and critical plane methods, remain fundamental; however, they have limitations in addressing variable amplitudes and complex stress conditions (Bin, Jianhui, & Xiuli, 2014). Recent advances include computational models that incorporate additional hardening effects and synergistic interactions between mechanical and control systems. For example, validated real-time simulation frameworks allow designers to test servomotor configurations under dynamic loads while maintaining numerical stability (Pineau, Gailletaud, & Lindley, 1996).

Galvorn carbon nanotubes replace copper cables (2-3% of the aircraft mass), offering significant weight reduction and a negative carbon footprint from manufacturing (-2.3 kg CO_2 e/kg). Another impact of Galvorn carbon nanotubes is that aluminum production emits 16.7 kg CO_2 e/kg; in contrast, advanced composites and Galvorn reduce this to ≤5 kg CO_2 e/kg. Reducing material waste by 30-50% through additive manufacturing in components such as turbine blades also decreases emissions. Making everything lighter offsets higher SAF (sustainable aviation fuel) costs by reducing fuel consumption per flight (DexMat, 2023).

The integration of mechatronic system modeling allows simultaneous optimization of structural, electrical, and control parameters. An example of waterjet cutting machines is demonstrated where a 69% weight reduction is achieved by optimizing the topology with improved manufacturing accuracy. This approach reduces development resources by 40-60% compared to sequential design methods while enabling multidisciplinary design exploration (Priarone, Catalano, & Settineri, 2023).

On the other hand, the manufacturing processes and the new materials (composites, additive manufacturing) mentioned above require knowledge of the existing methodologies to determine how the fatigue models will be updated. The high testing costs make accurate modeling particularly valuable in reducing development time and expenses. These results align with a simulation and optimization framework, integrated into the entire product life cycle, ensuring balanced performance, safety, and environmental goals. Current research is focused on hybrid optimization algorithms and machine learning to address these challenges while maintaining real-time simulation capabilities.

2 MATERIAL FATIGUE: THEORIES, MODELS & APPROACHES BY LOAD & CYCLES

2.1 Characteristics and Features of Low- and High-Cycle Fatigue

Low-cycle fatigue (LCF) occurs under elevated stress conditions, often exceeding the material yield strength, resulting in significant plastic deformation during each cycle. This permanent deformation is a defining characteristic of this fatigue mechanism. As a result, LCF typically leads to failure within a relatively small number of cycles, usually fewer than 10^4. That is due to the higher stress amplitudes and the resulting plastic strains. The LCF is analyzed using *E-N* (or *ε-N*), which includes both elastic and plastic strain components to predict fatigue behavior. The Coffin-Manson relationship is commonly used to describe the behavior of materials under low-cycle fatigue (LCF) conditions, leading to microstructural changes such as crack propagation, mechanical work hardening, and strain concentration.

High-cycle fatigue (HCF) operates at stress levels much lower than the yield strength, involving predominantly elastic deformation. Materials subjected to HCF do not experience permanent changes in shape before failure. HCF is key in achieving a greater number of cycles to failure, often exceeding 10^5 cycles. Lower stress levels require more cycles to initiate and propagate cracks. HCF uses the "stress-life" (S-N) method, which focuses on the relationship between applied stress and the number of cycles to failure (refer to Table 1). This method emphasizes elastic behavior and uses S-N curves (Wehler curves). Failure in HCF results from the gradual propagation of microscopic cracks over time, without significant changes in the overall material structure. It is often initiated by surface imperfections or inclusions (Kim & Hwang, 2019).

Table. 1. Fatigue: Low vs. High Cycle

Aspect	Low-Cycle Fatigue (LCF)	High-Cycle Fatigue (HCF)
Stress Levels	High (near/above yield strength)	Low (below yield strength)
Deformation	Plastic deformation	Elastic deformation
Cycle Count	< 10^4cycles	> 10^5 cycles
Analysis Method	Strain–Life (E – N)	Stress–Life (S – N)
Material Behavior	Microstructural changes (plasticity)	Microscopic crack growth
Applications	Severe stress environments	Vibrations/rotating machinery

2.2 Approaches to High-Cycle Fatigue

The object of our study is high-cycle fatigue (HCF) under multiaxial loading. In the case where the modeling process is considered, based on experimental observations accompanied by theoretical justification, several key approaches are available. The main point is to predict the formation of macrocracks under the influence of cyclic stresses in the elastic regime. The equivalent stress criterion of Sines and Crossland, most used for HCF, integrates the shear stress amplitude with the hydrostatic stress.

Equation on Sines:

$$\sqrt{\frac{1}{3}[(\sigma_{1a}-\sigma_{2a})^2+(\sigma_{2a}-\sigma_{3a})^2+(\sigma_{1a}-\sigma_{3a})^2]} \leq$$
$$\leq A-\alpha\left(\sigma_{xm}+\sigma_{ym}+\sigma_{zm}\right)$$

Crossland's criterion includes the maximum hydrostatic stress.

Balthazar and Malcher review various theories for predicting, emphasizing the importance of invariant stress measurement methods (Balthazar & Malcher, 2007).

In a study by Li and de Freitas (2002), a rapid procedure for assessing HCF under multiaxial random loading using Crossland's criterion for fatigue damage assessment is presented. Evidence supports the unified mechanics' theory for predicting HCF lifetime, which integrates principles of materials physics to model dislocation, damage accumulation, and macrocrack initiation.

Sandberg's dissertation (2015) examines the application of experiments, computational methods, and modeling in HCF design, emphasizing the importance of accurate material parameters and a fine FE mesh for reliable predictions. A comparative study validates the equivalent stress approach in the Crossland and Sines criteria, showing their effectiveness in predicting multiaxial fatigue limits (Tchoupou & Fosting, 2015).

The critical plane method identifies the plane with the greatest stress (usually a combination of normal and shear stress) and estimates durability. Models based on strains with predominantly elastic behavior, along with energy models that estimate dissipated energy per cycle as an indicator of resistance loss and failure, are applied in the analysis. (Wei, et al., 2019).

Hassan Alkarawi's research applied the critical plane method, considering various fatigue damage models, including the Fatemi-Socie and Bannantine-Socie approaches (Alkarawi, 2018). Energy-based models play a crucial role in assessing fatigue life. The statistical distribution of strain and fatigue life in the LCF-HCF range is analyzed in a paper by Coffin-Manson and Morrow, providing insight into the energy dissipation per cycle. (Tridello & Paolino, 2023).

To further clarify this point, experimental evidence shows that in non-linear failure accumulation, identical cyclic loads can result in different failure rates depending on the load history. An example of this is that a pre-stressed condition can reduce the number of cycles. It has been found that in the nonlinear accumulation of fatigue damage in aircraft engine alloys under multi-axial loading, the interaction between low-cycle fatigue (LCF) and high-cycle fatigue (HCF) cycles increases fatigue damage. (Suman, 2013).

A modified nonlinear fatigue damage accumulation model accounting for load interaction effects highlights the importance of nonlinear damage accumulation in fatigue life prediction. (Lv, Huang, Zhu, Gao, & Zuo, 2014)

Considering the influence of the average stress, at the same amplitude, on the stress with a positive average value, a faster accumulation of failures is achieved. The study of the pre-stress state on high-cycle fatigue (HCF) behavior and fatigue crack propagation in steel with a complex phase composition demonstrates how material fatigue resistance is significantly affected. (Kim, Song, Sung, & Kim, 2021) A pre-applied stress state can reduce the number of cycles, as demonstrated in a study on the stress recovery behavior of a shape memory Fe-Mn-Si alloy under HCF loading. This has been observed under failure conditions due to relaxation induced by phase transformation during cyclic loading (Ghafoori, Hosseini, Leinenbach, Michelis, & Motayalli, 2017) Multi-component loads, for variable amplitudes and phases, use combinations of Rainflow in identifying cycles, such as Miner's rule for accumulated failure: $D=\sum_{i=1}^{k}\frac{n_i}{N_i}$, where n_i is the number of cycles at a given stress level, and N_i is the life at that level (Sun, Wen, Li, Cao, & Fei, 2025).

Developments in computation approaches have produced advanced models for analysis and exploration, such as a combination of critical planes and energy criteria, for example, the Liu-Mahadevan model, which integrates normal, shear, and hydrostatic components:

$$\left(\frac{\sigma_{a,c}}{f_{-1}}\right)^2+\left(\frac{\tau_{a,c}}{f_{-1}}\right)^2+\beta\left(\frac{\sigma_{H,a,c}}{f_{-1}}\right)^2=1$$

where β is a material constant.

A limitation of this modeling approach lies in the material inhomogeneities, which influence crack initiation and are challenging to describe using macroscopic models. Therefore, the development of universal models remains an active area of research, especially for complex scenarios such as out-of-phase loads and random amplitudes. The Liu-Mahadevan model, on top of a unified multiaxial fatigue damage model, integrates components of normal, shear, and hydrostatic stresses, providing a comprehensive approach to fatigue life prediction (Liu & Mahadevan, 2005)

This case has been validated using experimental results for isotropic and anisotropic materials, demonstrating its general applicability. The microstructure of the material significantly influences the high-cycle fatigue (HCF) behavior through several key mechanisms, like grain size. Smaller grains (fine grain structure) improve toughness due to the Hall-Petch effect, where grain boundaries act as crack propagation barriers. For example, alloys with controlled grain size show higher fatigue resistance. A study of the high-cycle fatigue behavior of β-annealed Ti-6Al-4V alloy shows that smaller primary α-grains improve the resistance to HCF due to the increased yield strength (Jeong, Kwon, Goto, & Kim, 2017). Investigation of the very high cycle fatigue (VHCF) behavior of Ti-6Al-4V alloy highlights the role of microstructure in crack initiation and fatigue behavior (Yuan, Zhao, Yue, Gu, & Zhang, 2024)

The Hall-Petch effect is extensively documented in materials science. The grain boundaries act as pinch points that impede the propagation of dislocations, thereby increasing the yield strength. Studies on titanium alloys have shown that fine-grained lamellar microstructures exhibit better resistance to fatigue crack initiation and propagation compared to coarser-grained structures. Anisotropic materials with preferential grain orientation can form critical planes with increased stress, which accelerates cracking. Fatigue strength may improve in solid phases containing carbides or intermetallic compounds. There are exceptions, such as sulfide inclusions (MnS) in steels, which promote crack initiation under cyclic loading and act as stress concentrators. The non-uniform distribution of alloying elements (e.g., Mn, C) also leads to local changes in mechanical properties which influence failure propagation. This applies to pores and microcracks, leading to the gradual formation and growth of larger cracks over time. Thermal or mechanical processing generates residual stresses in the microstructure that can accelerate or retard the accumulation of damage depending on their load orientation. The review of the effect of sulfide inclusions on the mechanical properties and failures of steel components is reviewed by Maciejewski (2015). The presence of sulfide inclusions in steel highlights their influence on the fatigue limit and crack propagation rate (Bigelow & Flemings, 1975)

Recrystallization alters the grain structure and phase distribution, and hardened steel with a martensitic structure exhibits a higher fatigue limit compared to pearlitic structures, which are typically formed after rolling. Martensite in steel significantly increases the yield strength and hence the fatigue limit of the material. Studies have shown that the ultrafine-grained ferritic-martensitic structure has a substantially higher fatigue limit than the coarse-grained ones. (Nikitina, Islamgaliev, Ganeev, & Frik, 2023). It has been observed that under cyclic loading, the ferrite-perlite structures accumulate defects more rapidly due to the uneven distribution of cementitious lamellae. Treatments aimed at producing bainitic structures reduce this effect due to the finer microstructure.

Mean stress plays a significant role in high-cycle fatigue (HCF), influencing the endurance limit and failure accumulation rate. This refers to mechanical stress, not electrical stress, and is defined as the mean value of the cyclic load. Its effects become evident through the following mechanisms.

For a uniform stress amplitude, a positive mean stress (e.g., tensile) reduces the material's durability. This is accounted for in classical fatigue models.

- *Goodman curve:*

$$\sigma_a = \sigma_{-1}(1 - \frac{\sigma_m}{\sigma_{UTS}})^2$$

where: σ_a - is the allowable stress amplitude, σ_{-1}- is the endurance limit of a symmetrical cycle, σm is the mean stress, σ_{UTS} - is the tensile strength

Goodman dependence is a widely used method in fatigue analysis to account for the impact of mean strain on fatigue life. It is often represented graphically in a Goodman diagram, which plots mean strain versus alternating strain. The Goodman diagram helps engineers assess the safe cyclic loading of a part by ensuring that the combination of mean and alternating stresses remains below the failure curve. Positive mean stress typically reduces fatigue life because it increases the effective peak stress experienced by the material, bringing it closer to the critical failure threshold. Understanding the relationship between mean stress and fatigue life is crucial for designing components that endure cyclic loading conditions.

- *The Gerber curve in fatigue analysis:*

$$\sigma_a = (1 - \frac{\sigma_m}{\sigma_{UTS}})$$

The Gerber curve is often used in fatigue assessment to account for the impact of mean strain on fatigue life. It is especially well-suited for materials exposed to cyclic loading. The comparison between Goodman and Gerber correction methods highlights the effectiveness of the Gerber curve for dealing with different mean stress scenarios, thus accounting for the nonlinear relationship between the mean stress and the alternating stress. The Gerber curve integrates both tensile strength and mean stress, offering a comprehensive approach to fatigue analysis. This makes it suitable for a wide range of materials and applications. The mean stress, however, can induce local residual stress in the material that alters the resistance to crack initiation. For example, under positive mean stress, dislocations move more easily, accelerating the formation of microcracks.

The influence of residual stress on crack initiation and propagation has been considered in detail in various studies, highlighting how positive mean stress can accelerate microcrack formation (Nakada, Norimitsu, Tanaka, Tsuchiyama, & Takaki, 2015)

In alloys with a heterogeneous phase structure (e.g., pearlitic steels), the average stress influences the stress distribution between ferrite and cementite, thereby modifying local ductility.

The Sines criterion is used in fatigue analysis to predict the lifetime of materials under multiaxial loading. It combines the shear stress amplitude τa with the hydrostatic stress σ_H, which includes the mean stress. The criterion is expressed as follows:

$$\tau_a + \alpha\sigma_H \leq \beta$$

where α and β are material constants.

A comprehensive review of defect accumulation models for multiaxial fatigue testing, including all criteria considered to date, is also made (Meggiolaro, Pinho de Castro, & Miranda, 2009).

For a combination of normal and shear voltages, the average voltage is included in the equivalent voltage criteria. For example, in the heat treatment industry, controlling the mean stress by thermal processes (e.g., backwash) can improve durability by relaxing residual stress. In HCF calculations, engineers use mean stress correction factors to avoid conservative predictions.

The average stress is influenced by the microstructure of the materials. At positive mean stress, dislocations move more easily in the grains, which accelerates the formation of microcracks. The average stress can affect the orientation of the grains, which changes the local mechanical properties and fatigue resistance. In alloys with a heterogeneous microstructure, the mean stress can affect the distribution of stress between different phases, which changes the local ductility and resistance to crack initiation.

The presence of hard inclusions (e.g., carbides) in alloys can be affected by the average stress, increasing the probability of crack formation around them. It can induce residual stresses in the material that alter the microstructure and affect fatigue behavior.

In some materials, mean stress can lead to microstructural changes, such as the formation of martensitic structures in some alloys, which changes the mechanical properties.

3 ANNEXES AND CONTRIBUTIONS OF THE RESEARCH REVIEW

Since the study must have a focus, the task we have set ourselves in this review is to determine the relevance of fatigue damage prediction and optimization for the automotive and aviation industries in the current research encountered:

In both industries, complex loading conditions depend on components exposed to multi-axial loads, necessitating advanced fatigue prediction models. For example, research on fatigue life prediction in automotive applications highlights the importance of considering real-world loading scenarios that involve complex stress distributions and multi-axial forces (Agrawal, et al., 2023)

Studies of additively manufactured lattice structures in aerospace applications highlight the need for accurate fatigue failure models to ensure structural integrity under high-cycle fatigue regimes. (Colucia & De Pasquale, 2023).

It has already been noted that weight reduction is a priority in both sectors, requiring a precise understanding of fatigue behavior to avoid over-design. A study of steel-polymer plates for automotive fuel cells showed how topology optimization and material selection can reduce weight while maintaining structural performance (Anand, Mielke, Heidrich, & Xiangfan, 2024) To reduce the section while ensuring the same design stress, it is necessary to implement materials with relatively higher strength. (Tontchev, Zumbilev, Yankov, & Zumbilev, 2021). This problem requires a multi-criteria method of solving, the governing parameters being either the alloying elements (such as quantity and type) or processing parameters, and the quality indicator is the technologically innovative effect. The introduction of new materials, such as composites and additive manufacturing, necessitates the updating of fatigue models.

Studies of the fatigue behavior of CFRP materials reveal challenges under inconsistent loading conditions, highlighting the need for tailored predictive tools (De Giorgi, Nobile, & Palano, 2022) This involves subjecting CFRP specimens to cyclic loading to determine their fatigue life and damage progression. Testing may be performed under tensile, compressive, or flexural conditions. In these methods, temperature changes are used to detect fatigue failures and evaluate the stiffness reduction of CFRP materials. Delamination testing aims to measure the rate of delamination growth under cyclic loading. The fatigue limit for CFRP materials typically falls in the range of 50-70 % of their tensile strength, and the critical number of cycles averages about 3 million cycles.

The high costs associated with experimental testing make modeling extremely important for reducing development time and costs. The aerospace industry uses digital mock-ups and simulation tools to optimize design processes and reduce costs, highlighting the value of predictive modeling (Dassault Systemes, 2025).

3.1 Inputs in Mathematical Modeling of High-Cycle Fatigue Using Regression Models

Mathematical modeling approaches for high cyclic fatigue (HCF) using regression models is an area in materials science and engineering that combines experimental data with mathematical approaches to predict component lifetimes. Modeling HCF is difficult because failure occurs at stress levels well below static failure thresholds, and microstructural features play a dominant role in crack initiation. There is significant statistical scatter in fatigue life data, and environmental factors can dramatically alter fatigue behavior. Regression models are used to establish mathematical relationships between input variables (stress amplitude, mean stress, frequency, temperature, etc.) and output variables (cycles to failure, probability of failure). These models can range from simple curve-fitting approaches to complex machine-learning algorithms. A detailed discussion of regression modeling techniques and their applications is presented below.

These models primarily use stress amplitude as the predictor variable and cycles to failure as the outcome. When multiple factors affecting fatigue life are considered, this approach may include different factors but may oversimplify nonlinear relationships in fatigue. In this case, it is modeled with nonlinear regression models, of which the more sophisticated include Gaussian process regression or neural networks.

New materials, such as composites and additive manufacturing (AM), are changing fatigue prediction models in the automotive and aerospace industries by introducing new challenges and requiring advanced computational approaches. Composite materials (e.g., carbon fiber-reinforced polymers) exhibit anisotropic properties, requiring fatigue models to account for directional dependencies. Enhanced series-parallel (ESP) constitutive models simulate composites by treating the fibers and matrix as parallel materials in the alignment direction and serial in the transverse directions, enabling accurate predictions of stresses and strains under multiaxial stress. Cumulative fatigue damage indices update component properties (e.g. stiffness degradation) layer by layer to predict residual strength in laminated structures (Salomon, Rastellini, Oller, & Onate, 2005).

Surface and defect parameters are integrated into the S-N curve models to constrain fatigue behavior. For AM 316L stainless steel, these parameters adjust the predictions based on the laser settings and subsequent machining (e.g. heat treatment) (Serjouei & Afazov, 2022)

3.2 Regression Models for HCF

Regression models aim to predict cycles to failure based on input variables such as stress amplitude, mean stress, temperature, and defect geometry.

A. Stress-Life (S-N) Curve Modeling

This classic approach fits experimental data to equations like:

1. *Basquin's equation*: $\sigma_a = \sigma_f'(2N)^b$, where σ_a is stress amplitude and N, cycles to failure.
2. *Power law relationships:* $log(N) = A - B \cdot log(\sigma)$.
3. *Stromeyer's equation:* $S = S_0 + (S_1 - S_0)e^{-\alpha N}$.

These models primarily focus on stress amplitudes as the predictor variable and are widely used for metals and alloys.

B. Multiple Linear Regression

This method incorporates multiple factors affecting fatigue life:

$$log(N) = \beta_0 + \beta_1(\sigma_a) + \beta_2(\sigma_m) + \beta_3(freq) + \beta_4(temp)$$

While simple, it may oversimplify non-linear relationships inherent in fatigue phenomena.

These models focus primarily on stress amplitude as a predictor variable and are widely used for metals and alloys (Zhou, et al., 2022).

Advanced nonlinear approaches include methods such as Gaussian regression, which effectively captures complex interactions between variables. In composite materials, moisture absorption can degrade matrix properties and reduce interfacial bonding, affecting life predictions. Regression models must account for time-dependent environmental degradation. Symbolic regression combining domain knowledge with machine learning for interpretation and accuracy (e.g., defect geometry effects in AlSi10Mg alloys) (Yu, et al., 2023). Symbolic regression has been applied to predict HCF life in Laser Powder Bed Fusion (L-PBF) AlSi10Mg alloys. By integrating defect geometries (size, location, morphology), these models outperform traditional empirical approaches in accuracy and generalization. Neural networks encompass highly nonlinear behaviors, but in some cases may lack physical interpretation. Nonetheless, techniques such as polynomial regression or machine learning models (e.g. neural networks) address the complex relationships between input variables and fatigue life outcomes (Meeker, et al., 2024) Bayesian regression, (Bayesian methods) incorporate prior knowledge and update predictions based on new data, effectively managing fatigue life variability caused by inconsistencies in materials or environmental factors (Gibson, Roger, & Cross, 2023).

Material fatigue inherently involves scatter, best described by random effects models that account for variability in individual batches or test conditions by including both fixed effects (e.g., stress amplitude) and random effects (e.g., batch-to-batch variation). (Dong-Yoon & Yu, 2014). Probabilistic methods related to the Weibull distribution modeling the failure probability under cyclic loading belong to this group of methods (Karolczuk, Skibicki, & Pejkowski, 2022). Bayesian regression accounts for uncertainty in forecasts and random effects models incorporating variability in different batches or material types (Gu, Lian, Lv, & Bao, 2022).

In deriving reliable and adequate models in HCF for DM, it is necessary to ensure that a sufficient experimental qualitative sample supports model development. To verify the accuracy of predictions, validation should be performed using separate datasets. Uncertainty can be quantified by incorporating statistical variance into the forecasts using probabilistic methods. It should also be assessed whether the models are consistent with physical mechanisms or are purely empirical. The latter aligns with the application's scope, which is evaluated based on the model's limitations regarding material types, stress ranges, and impact environments.

By combining experimental knowledge with advanced regression techniques, reliable predictions can be achieved while effectively managing data variability. This approach integrates statistical and computational methods to account for inherent uncertainties, scatter, and nonlinear relationships. All of this is critical for safety-critical industries such as automotive and aerospace. This computational approach is resorted to for a well-defined problem with a small data sample. When the observations are in a larger volume, the use of machine learning algorithms is resorted to which have their advantages over traditional regression models for HCF. The regression techniques are summarized in Table 2.

Table 2. Summary of Regression Techniques

Methods	**Advantages**	**Limitations**
Stress-Life (S-N Curve)	Simple, widely used	Limited to a single-variable analysis
Multiple Linear Regression	Incorporates multiple factors	Oversimplifies non-linear effects
Symbolic Regression	Balances of accuracy and interpretability	Requires domain-specific knowledge
Probabilistic Models	Accounts for scatter	Computationally intensive

3.3 Machine Learning vs. Regression for HCF: Advantages

The main advantage of machine learning (ML) algorithms over traditional regression models for predicting high cyclic fatigue (HCF), consists in sampling data with many variables and improving prediction accuracy. The data variables can be elements of the material compositions in their compositions or parameters of the modes by which each sampled material was produced.

ML algorithms, such as neural networks and gradient boosting, are excellent at modeling nonlinear interactions between variables (e.g., voltage amplitude, temperature, frequency) that traditional regression models often simplify. This makes ML particularly useful for fatigue life prediction of materials with complex behavior, such as composites or alloys produced by additives (Singal, et al., 2013).

It has been shown that in engineering applications ML can identify subtle patterns in fatigue data that traditional models may miss, leading to more reliable predictions. (Koprinkova-Hristova & Tonchev, 2011). (Koprinkova-Hristova & Tonchev, 2012).

3.3.1 High Dimensional Data Processing

Traditional regression models struggle to process large datasets with multiple predictors or features. ML algorithms can efficiently process high-dimensional data by applying feature selection techniques (e.g., random forests or Lasso regression) to identify the most relevant variables. One application outside the technique domain of the method is referred to in the next work (Chowdhury, et al., 2023).

In contrast to deterministic regression models, machine learning techniques often yield probabilistic results, enabling the quantification of uncertainty. This is particularly valuable for HCF modeling, where the variability of fatigue life data is significant due to the heterogeneity of material and environmental factors (Singal, et al., 2013)

ML algorithms can integrate diverse datasets, such as experimental fatigue data, along with microstructural information or environmental conditions, resulting in a multidimensional analytical framework. This adaptability allows the creation of more comprehensive models than traditional approaches. ML automates the model training and optimization process, reducing the manual intervention required in conventional regression analysis. In addition, ML models are scalable and can be updated efficiently as new data become available ML algorithms provide advanced feature importance analysis, and information about the relative importance of input features (e.g., voltage amplitude versus average voltage). All of this helps researchers understand which factors have the greatest influence on fatigue behavior (Desai, Wang, Vaduganathan, Evers, & Schneeweiss, 2020).

While ML offers these advantages, it also has limitations, including the need for large data samples to enable effective learning. It may lack physical interpretation compared to regression models based on fatigue mechanisms. Computational intensity compared to simpler regression techniques. However, using strengths, ML algorithms are increasingly being adopted for advanced HCF modeling where traditional methods fail to address complexity and variability. Machine learning algorithms now allow real-time adjustments to fatigue testing parameters, reducing cycle times by up to 50% while improving fault detection accuracy. For example, high-performance systems combined with artificial intelligence analysis offer simultaneous evaluation of lightweight materials such as composites under different stress conditions. Specialized neural networks predict fatigue life for advanced composites and aluminum alloys, addressing challenges in automotive design. These models incorporate data from Digital Image Correlation (DIC) and Acoustic Emission (AE) sensors to map crack propagation. (Avevor, Adeniyi, Eneejo, & Selasi, 2024)

Physically Informed Neural Networks (PINNs) simulate multiaxial loading scenarios, reducing dependence on physical prototypes. This approach has reduced development costs by 30% in automotive component validation (Schneller, et al., 2022)

3.3.2 Contributions to Aerospace Engineering Related to Material Fatigue

The optimization of additive manufacturing for AI-driven models has refined the microstructural properties of Ti-6Al-4V alloys used in aerospace components, resulting in a 20-30% improvement in fatigue crack resistance. Grain orientation and cooling rate are optimized through machine learning. It is critical for turbine blades and airframe parts. In terms of design, artificial intelligence-driven bio-printed geometries reduce component weight by 15% while maintaining yield strength, facilitating the development of lightweight structures for space exploration applications (Awd & Walther, 2025).

A neural network trained on 250,000 finite element samples predicted fatigue failure in rocket fuel chambers with an average error of 6.8%, achieving results in 0.1 ms. It is 3,000 times faster than traditional finite element methods. Early NASA prototypes use neural networks to estimate fatigue damage in reusable rocket engines during operation, enabling adaptive load management.

Physically Informed Neural Networks (PINNs) determined embedding defect characteristics (size, position, morphology) into loss functions improves predictions for additively manufactured

Ti-6Al-4V alloys. PINNs reduce errors by 20-30% in high-cycle modes compared to purely data-driven models, A characteristic feature of PINNs is that they generalize better with limited experimental data, which is critical for expensive testing of aerospace composites. Fiber Bragg gratings (FBGs) and vibration sensors feed live data into neural models, enabling adaptive updates to in-flight fatigue lifetime estimates (Li, Sun, Tian, Huang, & Zhao, 2024). Machine learning models (e.g., AutoGluon) have been shown to extract fatigue curves incorporating defect statistics improving the reliability of selective laser-melted (SLM) titanium parts. Physically informed neural networks (PINNs) account for AM-induced defects (e.g., porosity, nonmelted particles) in Ti-6Al-4V and TA15 alloys, reducing prediction errors by 20-30% compared to traditional methods. Defect characteristics such as size and morphology are incorporated into the loss functions for physically consistent results (Liu, Gao, Zhu, He, & Xu, 2025), (Wang, Zhu, Luo, Niu, & He, 2023)

ANNs trained on a single composite (e.g., IM7/977) accurately predict fatigue life for new materials (e.g., T800/5245), reducing experimental costs (Mathur, Gope, & Sharma, 2007). Radial Basis Function Neural Networks (RBF-NN) predict fatigue crack growth in aircraft-grade aluminum alloys (e.g., 2024-T3, 7075-T6) with high accuracy, enabling proactive maintenance (Younis, Kamal, Younis, & Younis, 2021)

Machine learning plays a transformative role in optimizing material properties for high-cycle fatigue resistance, particularly in advanced manufacturing and critical engineering applications. It involves machine learning models analyzing huge datasets from ultrasonic fatigue tests and microstructural imaging to identify and refine grain orientation, phase uniformity, and defect distribution. Improved resistance to fatigue crack initiation and propagation is being monitored, with studies reporting a 20-30% improvement in fatigue life for critical components such as turbine blades and housings. ML algorithms play a crucial role in optimizing additive manufacturing parameters—such as temperature gradients and cooling rates—that influence microstructure evolution. This enables the production of titanium and aluminum alloys with customized fatigue-resistant properties, reducing design iteration cycles by over 50% and accelerating the development of safer and more durable components.

By accurately predicting fatigue thresholds and performance based on process parameters and microstructural characteristics, ML models significantly reduce the need for extensive physical testing. This is particularly valuable for additively manufactured materials where traditional evaluation methods are time-consuming and expensive. Deep learning and genetic algorithms facilitate the reverse engineering of complex, bio-inspired geometries for metamaterials. These ML-driven designs achieve up to 15% weight reduction while maintaining or improving yield strength and fatigue resistance, which is critical for aerospace and automotive applications (Awd, Saeed, Muenstermann, Faes, & Walther, 2024).

Table 3. A summary of the role of machine learning in determining material fatigue

Role	Impact
Microstructural optimization	Increases fatigue crack resistance by 20-30%
Optimization of process parameters	Reduces cycles of, controlling design by >50% and adjusts fatigue properties at high cycles
Predictive modeling	Minimizes costly physical testing and accelerates process development
Material design/ geometry	Enables lightweight, high-strength designs with up to 15% weight savings
Physics-based modeling	Improves the accuracy and reliability of predictions
Real-time monitoring	Improves manufacturing precision and consistency

Physical machine learning frameworks combine experimental data with first-principles models (e.g., fracture mechanics, cyclic plasticity) to provide robust, physically consistent predictions. This approach improves model explainability and reliability, bridging the gap between empirical and theoretical understanding. ML techniques enable real-time process monitoring and anomaly detection during manufacturing, ensuring consistent quality, reducing material waste, and improving structural integrity. Based on the study performed, summarized results are given in Table 3.

4 CONCLUSIONS

Despite the progress of AI models, there are difficulties in extrapolating beyond the ranges of training data. Positive experiences have been gained in the use of hybrid approaches combining physics models and transfer learning. Here, we highlight the contributions of AI and digitalization to fatigue testing in the aerospace industry. Neural networks enable ultra-fast and precise failure predictions for critical components. In the automotive sector, AI helps optimize design by reducing structural weight. Future research needs to address data shortage. While PINNs provide physically consistent results, explaining ANN decisions remains crucial for certification. Neural models transform aerospace fatigue analysis from reactive inspections to predictive, simulation-driven workflows – essential for extending component life in next-generation spacecraft and hypersonic vehicles. Machine learning enables the integration of intelligent, adaptive data processing systems into the design and testing stages, providing improved fatigue resistance, reliability, and efficiency in high-performance engineering sectors.

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Acknowledgments

This paper was prepared by two participants within the framework of the FABER Project CA23109 (“Fatigue Benchmark Repository”), under the COST Program (European Cooperation in Science and Technology).

Received for publication: 25.05.2025
Revision received: 15.06.2025
Accepted for publication: 08.07.2025.

How to cite this article?

Style – **APA** *Sixth Edition:*

Tonchev, N., & Kirova, A. (2025, 07 15). Multiaxial High-Cycle Fatigue in Modern Engineering: Perspectives and Contributions. (Z. Cekerevac, Ed.) *MEST Journal, 13*(2), 205-219. doi:10.12709/mest.13.13.02.16

Style – **Chicago** *Sixteenth Edition:*

Tonchev, Nikolay, and Antoaneta Kirova. "Multiaxial High-Cycle Fatigue in Modern Engineering: Perspectives and Contributions." Edited by Zoran Cekerevac. *MEST Journal* (MESTE) 13, no. 2 (07 2025): 205-219.

Style – **GOST** *Name Sort:*

Tonchev Nikolay and Kirova Antoaneta Multiaxial High-Cycle Fatigue in Modern Engineering: Perspectives and Contributions [Journal] // MEST Journal / ed. Cekerevac Zoran. - Belgrade – Toronto: MESTE, 07 15, 2025. - 2 : Vol. 13. - pp. 205-219.

Style – **Harvard** *Anglia:*

Tonchev, N. & Kirova, A., 2025. Multiaxial High-Cycle Fatigue in Modern Engineering: Perspectives and Contributions. *MEST Journal*, 15 07, 13(2), pp. 205-219.

Style – **ISO 690** *Numerical Reference:*

Multiaxial High-Cycle Fatigue in Modern Engineering: Perspectives and Contributions. **Tonchev, Nikolay and Kirova, Antoaneta.** [ed.] Zoran Cekerevac. 2, Belgrade – Toronto: MESTE, 07 15, 2025, MEST Journal, Vol. 13, pp. 205-219..