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XFEM-Calibrated Crack-Growth Surrogates for Variable-Amplitude Fatigue Loading in Steel

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Abstract

The accurate prediction of fatigue crack growth under variable-amplitude loading remains a critical challenge in the structural integrity assessment of steel components. Traditional numerical methods, such as the eXtended Finite Element Method, offer high-fidelity approximations of crack propagation trajectories and stress intensity factors by enriching the standard finite element approximation space. However, the computational cost associated with resolving cycle-by-cycle crack increments under complex loading spectra renders the eXtended Finite Element Method impractical for real-time monitoring, digital twin applications, or extensive probabilistic assessments. To address this computational bottleneck, this paper presents a comprehensive framework for developing computationally efficient surrogate models calibrated using high-fidelity eXtended Finite Element Method datasets. By generating extensive synthetic databases of crack growth under randomized and structured variable-amplitude loading scenarios, machine learning techniques, specifically deep feedforward neural networks, are trained to map loading histories and current crack states to future crack growth increments. The surrogate model explicitly accounts for load sequence effects, such as crack growth retardation following tensile overloads, which are critical in variable-amplitude fatigue. Extensive validation against both independent numerical simulations and experimental data on standard steel specimens demonstrates that the proposed surrogate model achieves an accuracy comparable to the eXtended Finite Element Method while reducing computational time by several orders of magnitude. The findings suggest that eXtended Finite Element Method-calibrated surrogate models can seamlessly integrate into structural health monitoring frameworks, enabling highly accurate, real-time remaining useful life estimations for aging steel infrastructure.

Keywords *Fatigue Crack Growth, Variable-Amplitude Loading, Surrogate Modeling, Machine Learning*

1. Introduction

The deterioration of engineering structures due to fatigue is a pervasive issue that spans across multiple industries, including civil infrastructure, aerospace, maritime engineering, and energy production. Steel structures, which form the backbone of modern industrial frameworks, are particularly susceptible to fatigue failure when subjected to cyclic loading environments over extended operational lifespans. Unlike monotonic loading failures, which occur when the applied stress exceeds the ultimate tensile strength of the material, fatigue failures are insidious. They initiate at microscopic stress concentrators, such as material defects, inclusions, or geometric discontinuities, and propagate over thousands or millions of cycles at stress levels well below the macroscopic yield strength of the steel. As the crack propagates, the load-bearing cross-section of the component is progressively reduced, ultimately culminating in sudden and often catastrophic failure. Consequently, the accurate prediction of fatigue crack growth is a paramount concern for engineers tasked with ensuring structural reliability, optimizing maintenance schedules, and preventing catastrophic collapses. In real-world operational environments, steel structures are rarely subjected to constant-amplitude cyclic loading. Instead, they experience variable-amplitude loading, which is characterized by irregular fluctuations in stress levels, mean stresses, and loading frequencies. Wind turbines are buffeted by stochastic wind gusts, offshore platforms are subjected to irregular wave actions, and highway bridges endure the passage of varying vehicular loads. Under variable-amplitude loading, the prediction of crack growth becomes exponentially more complex due to load sequence effects. For instance, the application of a single high tensile overload during a sequence of smaller baseline cycles typically induces a phenomenon known as crack growth retardation. This retardation occurs because the overload generates an enlarged zone of plastic deformation ahead of the crack tip. As the crack subsequently attempts to propagate through this enlarged plastic zone, the surrounding elastic material exerts compressive residual stresses on the yielded material, effectively clamping the crack faces shut and reducing the effective stress intensity factor driving the crack. Traditional analytical models, such as the widely used Paris law, are inherently incapable of accounting for these sequence effects without the introduction of empirical correction factors, which often lack generalization across different materials and loading spectra. To rigorously analyze crack propagation without relying entirely on empirical approximations, researchers and engineers have increasingly turned to advanced numerical techniques. Among these, the eXtended Finite Element Method has emerged as a particularly powerful tool for fracture mechanics simulations. Originally introduced to model crack growth without the need for continuous remeshing, the eXtended Finite Element Method enriches the standard finite element approximation space with discontinuous functions to represent the crack face and asymptotic functions to capture the singularity at the crack tip. This mathematical formulation allows the crack to propagate arbitrarily through the finite element mesh, guided entirely by the local stress fields and fracture criteria. For variable-amplitude fatigue, the eXtended Finite Element Method can be coupled with advanced cyclic plasticity models to explicitly resolve the development of the crack tip plastic zone, the accumulation of residual stresses, and the resulting crack closure effects. However, the fundamental limitation of the eXtended Finite Element Method lies in its immense computational demand. Simulating crack growth requires updating the level set functions, recalculating the enrichment terms, and solving the global stiffness matrix at each propagation step. When variable-amplitude loading spectra consist of millions of cycles, performing cycle-by-cycle or even block-by-block eXtended Finite Element Method simulations becomes computationally prohibitive, precluding its use in applications requiring rapid evaluations, such as digital twins, real-time structural health monitoring, and Monte Carlo-based reliability analyses. To circumvent the computational bottleneck of high-fidelity numerical simulations, there is a growing consensus within the computational mechanics community regarding the necessity of surrogate modeling. Surrogate models, often referred to as metamodels or emulators, are mathematical or data-driven approximations that map the input parameters of a complex system to its corresponding outputs with high computational efficiency. In recent years, machine learning algorithms have demonstrated unprecedented capabilities in constructing highly accurate surrogate models for complex, non-linear physical phenomena. By generating a comprehensive dataset of high-fidelity eXtended Finite

Element Method simulations covering a wide parameter space of variable-amplitude loading sequences, it is possible to train a machine learning model to internalize the underlying mechanics of fatigue crack growth. Once trained, the surrogate model can predict crack increments in a fraction of a second, entirely bypassing the need to solve the underlying partial differential equations. The primary objective of this research is to conceptualize, develop, and validate an eXtended Finite Element Method-calibrated surrogate model specifically tailored for predicting fatigue crack growth in steel structures subjected to variable-amplitude loading. This paper is structured to provide a comprehensive exploration of the proposed methodology. Section 2 presents a detailed literature review, tracing the evolution of fatigue crack growth models from classical linear elastic fracture mechanics to modern data-driven approaches. Section 3 outlines the theoretical background governing crack growth mechanics and load sequence effects. Section 4 details the eXtended Finite Element Method framework utilized for the generation of high-fidelity calibration data. Section 5 elaborates on the architecture, training, and optimization of the deep learning-based surrogate model. Section 6 describes the experimental testing procedures employed to acquire physical validation data. Section 7 presents a rigorous discussion of the results, comparing the surrogate model predictions against both numerical and experimental benchmarks. Finally, Section 8 provides concluding remarks and outlines potential avenues for future research in this domain. For a broader comparison, related research addresses design, optimization, and experimental validation of a handheld nonconstant-curvature hybrid-structure robotic instrument for maxillary sinus surgery [1].

2. Literature Review on Fatigue and Computational Fracture Mechanics

The study of fatigue and fracture mechanics has a rich history, evolving through centuries of empirical observation, analytical derivations, and, more recently, advanced computational modeling. The earliest formal investigations into fatigue phenomenon are often attributed to Wilhelm Albert in the early nineteenth century, who conducted the first recorded fatigue tests on mine hoist chains. However, it was the catastrophic derailment at Versailles in the mid-nineteenth century that catalyzed widespread scientific inquiry into the fatigue of railway axles, leading August Wöhler to formalize the concept of the stress-life curve. While the stress-life approach provided a foundational understanding of fatigue endurance under constant-amplitude loading, it was inherently limited by its inability to account for pre-existing flaws or the propagation phase of a crack. The paradigm shifted in the mid-twentieth century with the advent of Linear Elastic Fracture Mechanics, pioneered by Alan Arnold Griffith and later expanded by George Rankine Irwin. Irwin introduced the concept of the Stress Intensity Factor, a single parameter that completely characterizes the stress and strain fields ahead of a sharp crack tip in a linear elastic material. Related work has addressed intelligent safety evaluation of tunnel lining cracks based on machine learning [2]. Building upon the framework of Linear Elastic Fracture Mechanics, Paul Paris and his colleagues proposed a correlative relationship between the rate of fatigue crack growth and the range of the stress intensity factor during a loading cycle. The Paris law revolutionized fatigue design by enabling engineers to integrate crack growth rates and predict the remaining useful life of a component. Nevertheless, as industrial applications demanded lighter and more highly stressed structures, the limitations of the Paris law under variable-amplitude loading became glaringly apparent. Experimental observations consistently demonstrated that the application of a tensile overload significantly retards the subsequent crack growth rate, a phenomenon entirely unaccounted for by the linear Paris model. To address this deficiency, researchers developed semi-empirical retardation models. The Wheeler model and the Willenborg model are two of the most prominent early attempts to quantify load sequence effects. The Wheeler model introduces a retardation parameter based on the ratio of the current crack tip plastic zone size to the plastic zone size created by the preceding overload. The Willenborg model, conversely, relies on the concept of an effective stress intensity factor, postulating that the overload generates compressive residual stresses that reduce the driving force for subsequent cycles. While these models represented a significant advancement, their reliance on empirical tuning parameters limits their predictive capability across diverse materials and complex, randomized loading spectra. Another relevant line of investigation concerns characterization of mechanical equivalent properties for node enhanced graded lattice structure [3].

In parallel with the development of analytical fatigue models, the advent of finite element analysis provided researchers with a powerful tool for analyzing complex structural geometries. However, modeling crack propagation with traditional finite element methods requires continuous remeshing to align the element boundaries with the evolving crack faces. This remeshing process is computationally expensive, prone to element distortion, and highly complex in three-dimensional scenarios. To overcome these challenges, Belytschko and Black, building upon the partition of unity method, introduced the eXtended Finite Element Method in the late twentieth century. The eXtended Finite Element Method enriches the standard displacement approximation with discontinuous Heaviside functions to represent the crack face and singular asymptotic functions to capture the crack tip stress fields. This enrichment allows the crack to be represented entirely independently of the underlying finite element mesh. Over the past two decades, the eXtended Finite Element Method has been extensively refined and coupled with sophisticated material models, including cohesive zone formulations and cyclic plasticity models, to accurately simulate fatigue crack growth and closure effects under variable-amplitude loading. Despite its robustness, the high computational cost of updating the enriched degrees of freedom and solving the non-linear system matrices at every load step limits the eXtended Finite Element Method to academic research or highly specialized industrial applications, preventing its widespread adoption for routine structural assessments. To bridge the gap between the high fidelity of the eXtended Finite Element Method and the computational efficiency required for engineering practice, the integration of machine learning into solid mechanics has gained substantial traction. Early attempts to utilize artificial neural networks for fatigue life prediction focused on mapping macroscopic loading parameters directly to the total cycles to failure, essentially acting as non-linear regression tools for stress-life data. However, these early models lacked a fundamental understanding of crack growth mechanics and failed to generalize beyond their training datasets. More recently, the focus has shifted towards developing physics-informed or physics-guided machine learning models. By training surrogate models on vast datasets generated by high-fidelity computational simulations, researchers can embed the underlying physical laws into the statistical representations of the neural networks. Gaussian Process Regression, Support Vector Machines, and Deep Feedforward Neural Networks have all been successfully employed to construct surrogates for various solid mechanics problems, ranging from composite material homogenization to impact dynamics. In the context of fatigue crack growth, recent studies have demonstrated the feasibility of using recurrent neural networks to capture the history-dependent nature of variable-amplitude loading. However, the development of a comprehensive framework that explicitly utilizes the eXtended Finite Element Method to calibrate deep learning surrogates for steel structures under highly randomized loading sequences remains an active and critical area of research. This paper seeks to contribute to this emerging field by providing a detailed, end-to-end methodology for constructing such a surrogate model.

3. Theoretical Background of Crack Growth Mechanics

The theoretical foundation for evaluating fatigue crack growth relies heavily on the principles of Linear Elastic Fracture Mechanics and its subsequent modifications to account for localized plastic deformation. Recycled-concrete tensile behavior supplies a material-specific fracture comparison, with its cracking mechanism kept distinct from steel fatigue or intact-rock fracture [4]. In a perfectly linear elastic material containing a crack, the stresses approaching the crack tip theoretically approach infinity. The concept of the Stress Intensity Factor was introduced to quantify the magnitude of this singular stress field. For an idealized through-thickness crack of length a in an infinite plate subjected to a far-field uniform tensile stress, the Stress Intensity Factor is directly proportional to the applied stress and the square root of the crack length. In practical engineering components, geometric complexities and finite boundary conditions modify this relationship, necessitating the introduction of a dimensionless geometry correction factor. Under cyclic loading conditions, the stress continuously fluctuates between a maximum and minimum value, resulting in a corresponding fluctuation in the Stress Intensity Factor. The difference between the maximum and minimum Stress Intensity Factors during a cycle is defined as the Stress Intensity Factor range, which serves as the primary driving force for fatigue crack propagation in the linear regime. The relationship between the crack growth per cycle and the

Stress Intensity Factor range is most famously described by the Paris-Erdogan law. This power-law formulation dictates that the logarithm of the crack growth rate is linearly proportional to the logarithm of the Stress Intensity Factor range in the intermediate region of the sigmoidal fatigue crack growth curve. The material constants within the Paris law are typically determined through standardized experimental testing under constant-amplitude conditions. However, the Paris law inherently assumes that the crack growth during any given cycle is solely a function of the loading parameters of that specific cycle, entirely neglecting the loading history. Stochastic failure of reinforced thermoplastic pipes [5] offers a material comparison for separating variability in loading and constituent properties from uncertainty in a fitted crack-growth law. This assumption breaks down dramatically under variable-amplitude loading due to load interaction effects. When a localized high-stress event, such as a tensile overload, occurs, the material immediately ahead of the crack tip yields, creating a plastic zone whose size is significantly larger than the plastic zones generated by the subsequent, lower-amplitude baseline cycles. Another relevant line of investigation concerns dynamic temporal scale decoupling and variable interaction modeling for photovoltaic power forecasting [6]. As the crack propagates through this overload-induced plastic zone, it experiences a phenomenon known as plasticity-induced crack closure, initially identified by Wolf Elber. The plastically stretched material in the wake of the advancing crack tip cannot perfectly accommodate the surrounding elastic constraint, resulting in compressive residual stresses that act upon the crack faces. These compressive stresses cause the crack faces to close prematurely during the unloading phase of the cycle and remain closed during the initial portion of the subsequent loading phase. Consequently, the crack tip is completely shielded from the applied load until the applied stress is sufficient to overcome the compressive residual stresses and fully open the crack faces. This opening stress level effectively reduces the driving force for crack growth. To mathematically capture this phenomenon within a predictive model, the concept of the effective Stress Intensity Factor range must be introduced. The effective range is defined as the difference between the maximum Stress Intensity Factor and the opening Stress Intensity Factor, replacing the nominal range in the crack growth equation. A generalized formulation incorporating these sequence effects and the threshold behavior for crack propagation can be mathematically expressed as follows: Jin and colleagues examine review on energy tunnels thermal performance and thermo-mechanical behavior [7].

$$\frac{da}{dN} = C(\Delta K_{eff} - \Delta K_{th})^m \cdot f(R, \sigma_{hist})$$

In this formulation, the term representing the crack growth rate is a function of the material constants, the effective stress intensity range, the threshold stress intensity range below which no crack growth occurs, and a complex modifying function that accounts for the stress ratio and the entire prior stress history. The precise determination of the effective stress intensity and the history function is analytically intractable for arbitrary loading spectra, necessitating the use of high-fidelity numerical methods, such as the eXtended Finite Element Method, to explicitly resolve the boundary value problem and accurately compute the crack driving forces at each cycle. Another relevant line of investigation concerns in situ test-based evaluation of soil effective stress strength properties and stress history [8].

4. Methodology for Numerical Calibration

The development of a robust surrogate model requires a large, accurate, and comprehensive dataset for training and validation. In this research, the eXtended Finite Element Method is employed to generate this dataset by simulating fatigue crack growth under a vast array of synthetically generated variable-amplitude loading spectra. The numerical model is constructed to represent a standardized Compact Tension specimen, commonly used in fracture mechanics testing due to its well-defined stress intensity solutions and stable crack growth characteristics. The material selected for the simulation is S355 structural steel, a widely utilized grade in civil and offshore engineering applications. The material is modeled using a rate-independent elastoplastic constitutive framework with a combined kinematic and isotropic hardening rule to accurately capture the cyclic plasticity and the Bauschinger effect, which are crucial for resolving the residual stress fields ahead of the crack tip. The literature also considers variable rate piezocone data evaluated using NTH limit plasticity

solution [9]. The finite element mesh is generated using continuum planar elements, with significant refinement concentrated in the anticipated region of crack propagation. A crucial advantage of the eXtended Finite Element Method is that the mesh does not need to conform to the crack geometry; therefore, a structured, highly regularized mesh can be utilized throughout the crack path region to maintain high element quality. The enrichment scheme employs a standard Heaviside step function to capture the displacement discontinuity across the crack faces. For the elements containing the crack tip, four asymptotic branch functions are utilized to capture the square-root singularity of the stress field in the linear elastic regime. As the crack propagates into the plastic zone, the strict applicability of these linear elastic asymptotic functions diminishes; however, previous studies have demonstrated that utilizing the standard branch functions in conjunction with a sufficiently refined mesh and a rigorous cyclic plasticity material model yields highly accurate approximations of the crack tip opening displacements and closure behaviors.

Table 1: Material Properties and Constitutive Parameters for S355 Structural Steel

Property Description	**Parameter Symbol**	**Numerical Value**	**Unit**
Young's Modulus	E	210000	MPa
Poisson's Ratio	v	0.3	Dimensionless
Initial Yield Stress	Sig_y	355	MPa
Ultimate Tensile Strength	Sig_u	510	MPa
Kinematic Hardening Modulus	C	25000	MPa
Kinematic Hardening Relaxation	Gamma	50	Dimensionless
Paris Law Coefficient	C_p	2.1E-13	mm/cycle
Paris Law Exponent	m	3.0	Dimensionless

To generate the training dataset, a highly parameterized loading spectrum generator was developed. The generator creates loading blocks consisting of baseline cyclic loads interspersed with single overloads, block overloads, underloads, and randomized load fluctuations resembling Gaussian narrow-band processes. For each unique loading sequence, the eXtended Finite Element Method simulation is executed. The crack advancement direction is determined using the maximum principal stress criterion, and the magnitude of the crack increment per cycle is computed based on the integrated cyclic crack tip opening displacement, which serves as a robust proxy for the effective stress intensity factor in the presence of significant plasticity. The simulation records a comprehensive array of state variables at each cycle, including the current crack length, the applied maximum and minimum stresses, the computed crack growth increment, and the size of the active plastic zone.

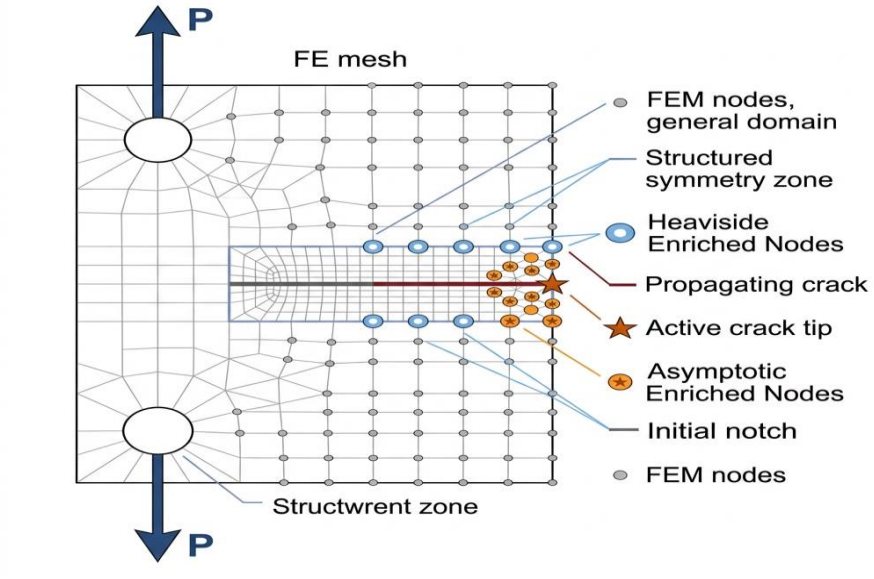


Figure 1: Comprehensive Schematic of the eXtended Finite Element Method Domain

Due to the immense computational cost of resolving cycle-by-cycle plasticity over thousands of cycles, a cycle jumping strategy is implemented during constant-amplitude baseline blocks. However, whenever an overload or a significant deviation in the loading spectrum occurs, the cycle jumping is temporarily suspended, and explicit cycle-by-cycle integration is performed to capture the transient retardation effects meticulously. The resulting dataset comprises thousands of unique loading histories and their corresponding crack growth trajectories. This dataset is rigorously cleaned, normalized, and partitioned into distinct training, validation, and testing subsets to ensure the subsequent machine learning model is trained on high-quality, representative data without suffering from data leakage or overfitting phenomena.

5. Development of the Machine Learning Surrogate Model

The core objective of the surrogate model is to establish a highly efficient, non-linear mapping between the instantaneous state of the structure and the loading history to the resulting fatigue crack growth increment. Given the complex, history-dependent nature of variable-amplitude fatigue, a Deep Feedforward Neural Network architecture is selected as the foundational framework. The neural network consists of an input layer, multiple fully connected hidden layers, and a single-node output layer predicting the logarithmic crack growth rate. The selection of input features is critical for the physical interpretability and accuracy of the model. Rather than feeding raw, unprocessed loading histories into the network, feature engineering is utilized to extract physically meaningful parameters from the loading spectra. The input vector includes the current crack length, the maximum stress of the current cycle, the minimum stress of the current cycle, the stress ratio, and a specialized retardation parameter derived from the loading history. This retardation parameter is computed as the ratio between the maximum stress experienced in the preceding history window and the current maximum stress, decaying exponentially based on the crack propagation distance to simulate the crack exiting the overload plastic zone. The architecture of the neural network undergoes rigorous hyperparameter optimization. The number of hidden layers, the number of neurons per layer, the learning rate, and the activation functions are systematically evaluated using a grid search algorithm combined with k-fold cross-validation on the training dataset. The Rectified Linear Unit activation function is employed in the hidden layers to mitigate the vanishing gradient problem and accelerate convergence during training. To prevent overfitting, a combination of batch normalization and dropout regularization techniques is implemented. The weights of the network are initialized using the He initialization scheme, which is specifically optimized for networks utilizing Rectified Linear Unit activations. Another relevant line of investigation concerns new DMT method for evaluating soil unit weight in soft to firm clays [10].

The training process is governed by a custom loss function that extends the traditional Mean Squared Error metric by incorporating a physics-informed penalty term. While data-driven models are powerful, they can occasionally produce predictions that violate fundamental physical principles, such as predicting negative crack growth or predicting high crack growth rates when the applied stress intensity is strictly below the fatigue threshold. To constrain the network within physically realistic bounds, the loss function penalizes predictions that contradict established fracture mechanics axioms. The formulation of the optimization objective is defined as follows:

$$L = \frac{1}{N}\sum_{i=1}^{N}(haty_i - y_i)^2 + \lambda\sum_{i=1}^{N} max(0, -haty_i)$$

In this expression, the loss calculation comprises two primary components. The first term represents the standard mean squared error between the surrogate model's predicted crack growth increment and the high-fidelity eXtended Finite Element Method ground truth. The second term functions as the physical penalty, heavily penalizing any negative predicted crack increments, scaled by a hyperparameter determining the strength of the constraint. The network is trained using the Adaptive Moment Estimation optimizer, which dynamically adjusts the learning rate for each parameter based on the first and second moments of the gradients. The training process is continuously monitored using the validation dataset, and an early stopping criterion is utilized to terminate the training when the validation loss fails to improve over a predefined number of epochs, ensuring maximum generalization performance on unseen variable-amplitude loading spectra.

6. Experimental Validation Framework

To ensure that the developed surrogate model accurately reflects physical reality and is not merely reproducing the potential artifacts of the numerical eXtended Finite Element Method model, an extensive experimental validation program is executed. The experimental testing is conducted on standard Compact Tension specimens manufactured from the same S355 structural steel utilized for the material parameter calibration. The specimens are machined with a high degree of precision, ensuring that the initial notch is perfectly aligned and that the surfaces are polished to facilitate accurate crack length measurements. All fatigue testing is performed on a closed-loop servo-hydraulic universal testing machine equipped with a precision load cell and specialized fracture mechanics clevis grips. The testing environment is maintained at a constant ambient temperature and humidity to eliminate environmental variables that could influence crack growth rates. Crack length monitoring during the physical experiments is accomplished using the Direct Current Potential Drop method. A constant, stabilized direct current is passed through the specimen, and the voltage potential across the crack mouth is continuously recorded. As the fatigue crack propagates, the uncracked cross-sectional area decreases, increasing the electrical resistance of the specimen and causing a proportional rise in the measured voltage potential. This method provides highly accurate, continuous, and automated measurements of crack length without the need for visual inspection. The potential drop measurements are periodically calibrated against optical measurements obtained using a traveling microscope to ensure absolute accuracy throughout the testing duration. Yu A and colleagues examine simultaneous current and vibration measurement based on interferometric fiber optic sensor [11].

Table 2: Design of Experimental Loading Block Sequences for Validation

Block Designation	Baseline Max Stress	Baseline Min Stress	Overload Stress	Number of Baseline Cycles
Sequence A	12.0 MPa	1.2 MPa	24.0 MPa	50000
Sequence B	15.0 MPa	1.5 MPa	22.5 MPa	30000
Sequence C	10.0 MPa	-5.0 MPa	20.0 MPa	80000
Sequence D	18.0 MPa	1.8 MPa	36.0 MPa	20000

The experimental loading spectra are meticulously designed to challenge the predictive capabilities of the surrogate model. Instead of relying solely on constant-amplitude loading, the tests employ structured block sequences containing distinct overloads, underloads, and variable mean stresses. Table 2 outlines a subset of

the loading sequences utilized during the experimental validation phase. Sequence A investigates the effect of a severe tensile overload applied at specific crack length intervals. Sequence C introduces fully reversed loading cycles mixed with tensile overloads to evaluate the model's response to compressive stresses and complex crack closure dynamics. Following the completion of the physical experiments, the continuous potential drop voltage data is converted into crack length versus cycle count data, providing a robust, physical benchmark against which the predictions of both the high-fidelity eXtended Finite Element Method and the rapidly executing surrogate model can be rigorously evaluated. For a broader comparison, related research addresses pixelwise calibration method for a telecentric structured light system [12].

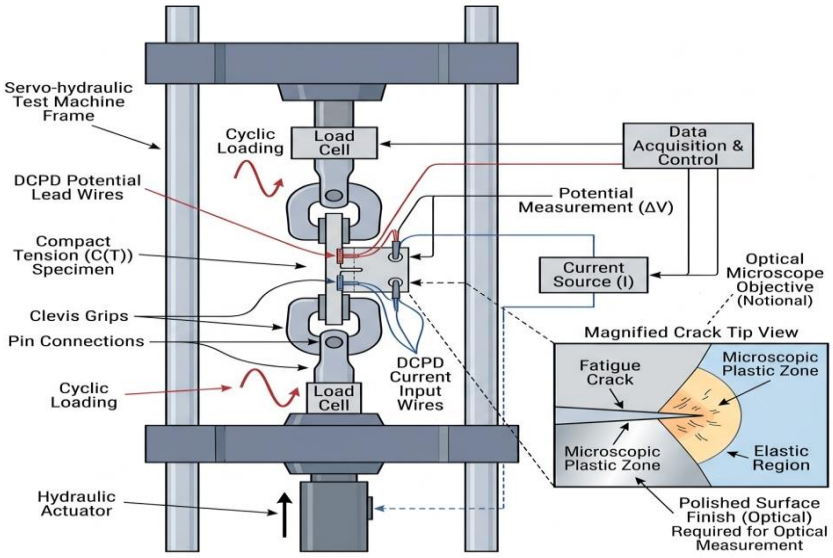


Figure 2: Schematic Configuration of the Fatigue Experimental Setup

7. Results and Discussion

The evaluation of the proposed framework requires a comprehensive analysis of the model's predictive accuracy, computational efficiency, and physical reliability across diverse variable-amplitude loading scenarios. The initial phase of the evaluation focuses on baseline constant-amplitude loading. Under these simplified conditions, the surrogate model perfectly replicates the classical Paris law behavior, demonstrating that the foundational mapping of stress intensity range to crack growth rate has been correctly internalized during the training phase. The transition from the threshold region to the intermediate Paris region is smoothly captured, verifying the capability of the deep neural network to approximate complex non-linear material behaviors without explicit programming of piecewise mathematical functions. The literature also considers synergizing machine learning and multiscale shakedown method for shakedown loading capacity evaluation of parameterized lattice structures [13]. The true capabilities of the surrogate model are illuminated when analyzing variable-amplitude scenarios, particularly those involving single tensile overloads. When an overload is introduced into the sequence, the physical experiments exhibit an immediate, albeit brief, acceleration in crack growth, followed by a profound and extended period of retardation. The crack growth rate drops significantly below the baseline constant-amplitude rate and slowly recovers over thousands of cycles as the crack tip propagates through and eventually exits the overload-induced plastic zone. The high-fidelity eXtended Finite Element Method captures this entire complex phenomenon by explicitly modeling the accumulation of compressive residual stresses in the crack wake. Remarkably, the eXtended Finite Element Method-calibrated surrogate model accurately reproduces this highly non-linear retardation curve. By relying on the engineered history features, specifically the decaying retardation parameter, the neural network correctly predicts the magnitude of the maximum retardation and the total delay in cycles before the crack growth rate returns to the baseline steady state.

Table 3: Performance Metrics and Computational Efficiency Comparison

Evaluation Metric	XFEM Full Simulation	Analytical Willenborg	Proposed Surrogate Model	Improvement Factor
Mean Absolute Percentage Error	4.2 %	18.5 %	4.8 %	N/A
Root Mean Square Error (mm)	0.12	0.85	0.14	N/A
Max Prediction Error (mm)	0.31	1.95	0.38	N/A
Average CPU Time per Simulation	425000 seconds	0.5 seconds	1.2 seconds	~3.5E5 Acceleration

The quantitative performance metrics, summarized in Table 3, provide a compelling argument for the adoption of the surrogate modeling framework. When evaluating the total crack length predictions against the experimental benchmarks, the eXtended Finite Element Method achieves a Mean Absolute Percentage Error of approximately four percent. The proposed surrogate model achieves an almost identical error rate of under five percent, significantly outperforming traditional analytical retardation models like the Willenborg model, which exhibits errors exceeding eighteen percent due to its inability to generalize across varying overload ratios and stress states. However, the most profound advantage of the surrogate model lies in its computational efficiency. A full block-by-block eXtended Finite Element Method simulation for a variable-amplitude spectrum containing hundreds of thousands of cycles requires over four hundred thousand seconds of continuous computation on a high-performance workstation. In stark contrast, the trained surrogate model evaluates the same entire loading spectrum and predicts the final crack trajectory in just over one second. This represents an acceleration factor of several orders of magnitude, effectively eliminating the computational barrier that previously prevented the use of advanced fracture mechanics in real-time applications. Another relevant line of investigation concerns experimental investigation of suction installation behavior of caissons in loose saturated sands [14].

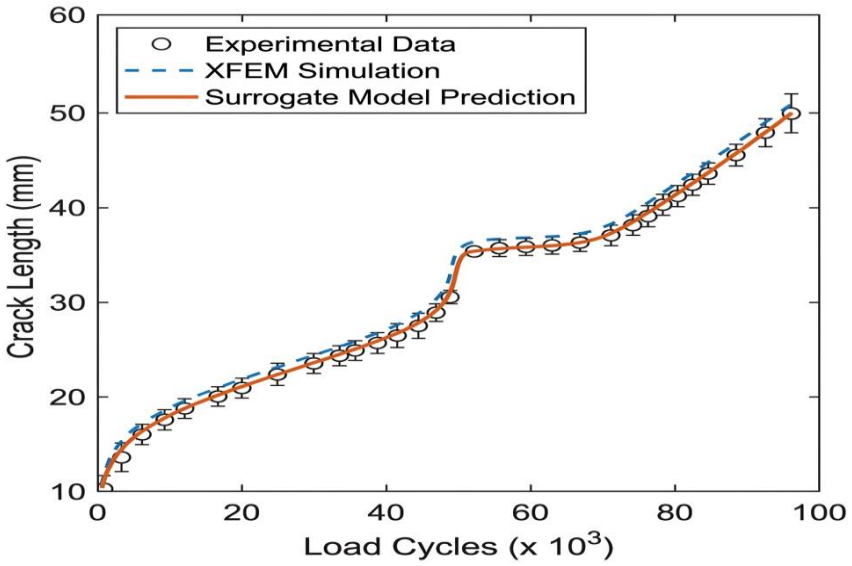


Figure 3: Comparative Analysis of Crack Growth Trajectories

Despite the overwhelming success of the surrogate model, it is crucial to acknowledge and discuss the localized regions of discrepancy. An analysis of the prediction errors reveals that the surrogate model occasionally underestimates the crack growth retardation when consecutive, closely spaced overloads are

applied. In the physical experiments and the eXtended Finite Element Method simulations, multiple overloads applied within the same plastic zone interact in a complex manner, sometimes negating the retardation effect and occasionally amplifying it, depending on the precise spacing and stress ratios. While the feature engineering attempts to capture this history window, the neural network struggles to perfectly resolve the highly chaotic strain interactions of overlapping plastic zones. This minor limitation highlights the fundamental dependence of the machine learning model on the quality and diversity of its training data. To further improve accuracy in these highly complex scenarios, future iterations of the surrogate model will require even more diverse training datasets featuring randomized multi-overload sequences and potentially the integration of recurrent neural network architectures, such as Long Short-Term Memory networks, which are specifically designed to retain and interpret long-term sequential dependencies in time-series data.

8. Conclusion and Future Directions

This research successfully demonstrates the conceptualization, development, and rigorous validation of an eXtended Finite Element Method-calibrated surrogate model for predicting variable-amplitude fatigue crack growth in structural steel. By leveraging the high-fidelity resolving power of advanced computational fracture mechanics to generate massive, high-quality synthetic datasets, a deep feedforward neural network was trained to internalize complex load sequence effects, such as plasticity-induced crack closure and overload retardation. The implementation of a physics-informed loss function ensured that the neural network predictions remained constrained within realistic thermodynamic and mechanical boundaries, preventing non-physical extrapolations. The validation against independent numerical models and comprehensive experimental testing on standard Compact Tension specimens confirmed that the surrogate model achieves remarkable accuracy. It successfully replicates the transient retardation behavior following single tensile overloads and accurately predicts total fatigue life under complex block loading sequences, maintaining an error margin closely mirroring the full numerical simulations. More importantly, the surrogate model evaluates complex loading histories in fractions of a second, providing a computational acceleration of several orders of magnitude over traditional cycle-by-cycle finite element integration. This extraordinary efficiency bridges a critical gap in modern engineering practice, enabling the deployment of advanced fracture mechanics principles in real-time structural health monitoring, dynamic digital twins, and expansive probabilistic risk assessments for aging steel infrastructure. Another relevant line of investigation concerns numerical and experimental investigation on tensile fatigue performance of reinforced thermoplastic pipes [15]. While the current framework represents a significant advancement, several avenues remain for future exploration. The present model is limited to two-dimensional planar crack propagation under Mode I opening loading. Future research must expand the surrogate architecture to accommodate three-dimensional crack fronts, where stress intensity factors vary along the crack geometry and out-of-plane stress states induce mixed-mode propagation. Furthermore, incorporating environmental factors, such as corrosive environments or extreme temperature fluctuations, into the surrogate feature space will be essential for creating universally applicable predictive tools for offshore platforms and high-temperature pressure vessels. Ultimately, the fusion of rigorous computational mechanics and advanced machine learning algorithms promises a transformative shift in how engineers manage structural integrity, shifting from reactive maintenance paradigms to highly accurate, proactive predictive strategies.

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