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Fatigue Monitoring Signals with Remaining Life in Railway Axle Components: Optimization Modeling

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Abstract

The reliable operation of high-speed railway systems is fundamentally dependent on the structural integrity of critical components, particularly railway axles. Continuous mechanical stress and environmental factors inevitably lead to material degradation, necessitating advanced fatigue monitoring and remaining useful life prediction strategies. This paper proposes a comprehensive optimization modeling approach for analyzing fatigue monitoring signals and accurately estimating the remaining useful life of railway axle components. By integrating multidimensional sensor data, advanced signal processing techniques, and heuristic optimization frameworks, the proposed methodology addresses the complexities inherent in non-stationary, noise-corrupted field data. The research systematically investigates the theoretical underpinnings of fatigue crack initiation and propagation, translating these physical phenomena into data-driven predictive models. Feature extraction mechanisms are designed to capture both time-domain and frequency-domain characteristics, which are subsequently refined through a robust feature selection algorithm to eliminate redundancy. Furthermore, an optimization framework is introduced to fine-tune the hyperparameters of the predictive model, significantly enhancing its generalization capability across diverse operational conditions. Experimental validation utilizing extensive field data demonstrates the superiority of the proposed optimized model over conventional predictive techniques in terms of accuracy and computational efficiency. This study contributes to the broader field of structural health monitoring by providing a scalable, reliable framework for predictive maintenance in railway engineering.

Keywords: Fatigue Monitoring; Remaining Useful Life; Railway Axles; Signal Processing; Railway Axle Components

1. Introduction

The rapid expansion of high-speed railway networks globally has introduced unprecedented challenges in maintaining the structural integrity and operational safety of rolling stock. Among the most critical components of any railway vehicle is the wheelset axle, which bears the entire weight of the train while simultaneously transmitting tractive and braking forces under continuous rotational cycles. This extreme operational environment subjects the axle to complex, multiaxial fatigue loading, which can precipitate microscopic material degradation and eventually lead to catastrophic macroscopic failure if left undetected. Consequently, the development of robust fatigue monitoring systems and accurate remaining useful life prediction models has become a paramount objective for railway engineers and researchers worldwide. The ability to forecast the precise moment when an axle will no longer be fit for service not only prevents disastrous derailments but also enables the implementation of cost-effective, condition-based maintenance schedules.

Historically, the maintenance of railway axles has relied on highly conservative time-based or mileage-based replacement schedules. While this approach has effectively mitigated the risk of catastrophic failure, it often results in the premature disposal of components that possess significant residual life, thereby imposing substantial economic burdens on railway operators. To address these inefficiencies, the industry is increasingly transitioning toward predictive maintenance paradigms grounded in continuous structural health monitoring. By deploying networks of advanced sensors directly onto the train bogie, operators can continuously acquire dynamic response data that reflect the real-time physical condition of the axle. However, transforming these massive streams of raw sensor data into actionable remaining useful life predictions is a highly complex endeavor that requires sophisticated signal processing, feature extraction, and predictive modeling techniques [1].

The primary challenge in analyzing fatigue monitoring signals lies in the inherently noisy and non-stationary nature of the data collected from operational railway environments. Signals acquired from strain gauges, accelerometers, and acoustic emission sensors are invariably contaminated by a multitude of external interferences, including wheel-rail contact impacts, aerodynamic turbulence, and electromagnetic noise from the train traction systems. This severe signal-to-noise ratio degradation complicates the identification of weak anomaly signatures that correspond to early-stage fatigue crack initiation [2]. Therefore, advanced optimization modeling is required to filter out irrelevant noise while preserving and amplifying the transient features associated with material degradation. The optimization of these signal processing pipelines is crucial for ensuring the reliability of the subsequent prognostic models.

Beyond signal processing, the prediction of remaining useful life presents its own set of modeling challenges. Traditional physical models based on fracture mechanics, such as crack growth laws, require precise knowledge of initial flaw sizes, material properties, and operational stress histories, which are often difficult to obtain in practical field applications [3]. Conversely, pure data-driven approaches, particularly those utilizing deep learning architectures, have shown remarkable promise in mapping complex sensory inputs to degradation trajectories. However, these models heavily depend on the selection of optimal hyperparameters and network architectures. Suboptimal configurations can lead to overfitting on training data or an inability to generalize to unseen operational profiles. Thus, the integration of heuristic optimization algorithms to systematically design and tune these predictive models is highly necessary [4].

This paper aims to bridge the gap between raw fatigue monitoring signals and accurate remaining useful life predictions by developing a comprehensive optimization modeling framework. The proposed methodology encompasses the entire data pipeline, beginning with robust signal acquisition and denoising techniques tailored specifically for the harsh railway environment. Following data preprocessing, a sophisticated feature engineering approach is deployed to extract highly sensitive degradation indicators from both the time and frequency domains. To address the challenge of high dimensionality, an optimized feature selection process is utilized to isolate the most relevant prognostic information. Finally, a hybrid prognostic model is introduced, wherein an advanced machine learning algorithm is coupled with a global optimization strategy to predict the remaining useful life with high precision.

The significance of this research extends beyond the immediate application to railway axles. The optimization modeling techniques developed herein can be generalized to a wide array of rotating machinery and structural components subjected to cyclic fatigue loading. By systematically addressing the uncertainties associated with sensor noise, feature redundancy, and model configuration, this paper provides a rigorous academic foundation for the next generation of structural health monitoring systems. The subsequent sections will meticulously detail the theoretical background, the proposed methodological framework, the experimental validation procedures, and the comprehensive analysis of the predictive performance.

2. Theoretical Background and Literature Review

2.1 Mechanisms of Fatigue in Railway Axles

The phenomenon of fatigue in metallic structures, particularly in railway axles composed of high-strength steel alloys, is a localized, progressive, and permanent structural change that occurs when a material is subjected to fluctuating stresses and strains. The fatigue life of an axle is conventionally divided into three distinct phases: crack initiation, stable crack propagation, and final rapid fracture. Understanding these fundamental mechanisms is essential for developing effective monitoring and prognostic strategies. The crack initiation phase typically accounts for the majority of the component total lifespan and is heavily influenced by surface conditions, residual stresses, and microscopic metallurgical defects [5]. During operation, stress concentrations at geometric transitions, such as the axle journal fillets or wheel seat press-fits, serve as primary sites for localized plastic deformation. Repeated cyclical loading causes these microscopic slip bands to deepen, eventually forming a microscopic flaw.

Once a micro-crack transitions into a macroscopic flaw, the stable crack propagation phase begins. The rate of crack growth in this phase is predominantly governed by the magnitude of the alternating stress intensity factor at the crack tip. The monitoring signals generated during this phase change progressively as the structural compliance of the axle increases [6]. Acoustic emission sensors can often capture the transient elastic waves released by the sudden redistribution of stress during incremental crack extensions. Meanwhile, strain gauges and vibration sensors can detect macroscopic changes in dynamic behavior, such as shifts in natural frequencies or variations in bending strains [7]. The final fracture occurs when the remaining cross-sectional area of the axle can no longer sustain the peak operational loads, resulting in a sudden and catastrophic failure. The overarching goal of remaining useful life optimization modeling is to accurately track the progression through the stable crack propagation phase and reliably predict the onset of critical instability.

2.2 Evolution of Signal Processing in Condition Monitoring

The extraction of reliable degradation indicators from raw sensor data has been a focal point of structural health monitoring research for decades. Early condition monitoring systems relied heavily on simple time-domain statistical parameters, such as the root mean square and peak-to-peak values of vibration signals. While computationally efficient, these rudimentary metrics often proved inadequate for early fault detection, as they are highly susceptible to masking by operational background noise [8]. As computational capabilities expanded, researchers increasingly turned to frequency-domain analyses, utilizing the Fourier transform to identify the spectral signatures of rotating machinery faults. However, the Fourier transform is inherently limited by its assumption of signal stationarity, rendering it suboptimal for analyzing the transient and non-stationary signals characteristic of railway axle fatigue under variable speeds and loads.

To overcome these limitations, time-frequency analysis methods have gained significant traction in recent literature. Techniques that decompose a signal into multiple components across different frequency bands have proven highly effective in isolating transient fatigue signatures from dominant background noise [9]. Optimization modeling plays a critical role in these advanced signal processing techniques. For instance, determining the optimal basis functions, decomposition levels, and thresholding parameters requires sophisticated algorithms that balance noise reduction against the preservation of critical diagnostic information. Recent studies have demonstrated that adapting the parameters of time-frequency transformations using heuristic search algorithms significantly enhances the signal-to-noise ratio of structural monitoring data [10]. The integration of these optimized signal processing pipelines serves as the foundational step for accurate remaining useful life estimation.

2.3 Prognostics and Remaining Useful Life Prediction

The field of prognostics and health management has evolved rapidly, transitioning from reliability-based statistical models to advanced condition-based algorithms. Conventional remaining useful life prediction methods were predominantly based on empirical degradation models and fracture mechanics formulations, such as the widely recognized laws governing fatigue crack growth [11]. These model-based approaches offer the advantage of explicitly incorporating the physical mechanisms of failure. However, their practical application is often severely restricted by the necessity for precise knowledge of material parameters, initial crack geometries, and complex load histories, which are typically unobservable in real-world railway operations. Furthermore, the inherent stochasticity of fatigue crack growth makes deterministic physical models susceptible to significant predictive errors.

In response to the limitations of physics-based models, data-driven prognostic methodologies have emerged as the dominant paradigm in contemporary research. By leveraging machine learning algorithms, these approaches can autonomously learn the complex, non-linear mappings between multidimensional sensor features and the corresponding degradation states without relying on explicit physical equations [12]. Early data-driven models utilized artificial neural networks and support vector regression to forecast remaining useful life. While successful in controlled laboratory settings, these models often struggled with generalization when exposed to the highly variable conditions of actual railway tracks. To address this, current research focuses on the optimization of deep learning architectures and the implementation of probabilistic frameworks that can quantify the uncertainty inherent in prognostic predictions. Integrating global optimization algorithms to autonomously configure network hyperparameters has been shown to drastically improve both the accuracy and robustness of data-driven remaining useful life models [13].

3. Signal Acquisition and Preprocessing Framework

3.1 Multidimensional Sensor Architecture

The foundation of any robust remaining useful life prediction model is the quality and comprehensiveness of the acquired monitoring data. To capture the full spectrum of physical phenomena associated with axle fatigue, a multidimensional sensor architecture is proposed. This architecture involves the strategic deployment of multiple sensor modalities, specifically strain gauges, accelerometers, and acoustic emission transducers, directly onto the bogie frame and the axle housing. Strain gauges are utilized to measure the macroscopic nominal bending stresses experienced by the axle during operation. These low-frequency signals provide critical information regarding the operational loading history and the global deformation behavior of the component [14].

Complementing the strain data, high-frequency piezoelectric accelerometers are mounted on the axle boxes to capture the dynamic vibration responses induced by wheel-rail interactions and internal structural anomalies. The vibration signatures are particularly sensitive to macroscopic changes in structural stiffness caused by advanced crack propagation. Furthermore, acoustic emission sensors are strategically positioned near critical geometric transitions, such as the wheel seat, to detect the high-frequency transient elastic waves generated by microscopic crack initiation and incremental growth [15]. The simultaneous acquisition of these diverse signal types creates a rich, multifaceted dataset that encapsulates both the macroscopic loading conditions and the microscopic material degradation processes. This multisensory approach is essential for training highly accurate optimization models.

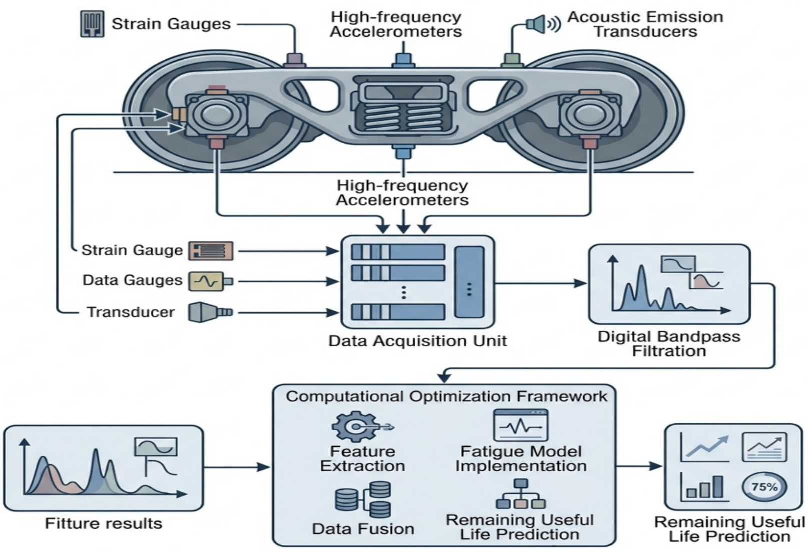

Figure 1: Comprehensive Schematic of Multisensor Fatigue Monitoring Architecture

3.2 Signal Denoising and Enhancement

The raw signals acquired from the multidimensional sensor network are invariably corrupted by extreme environmental and operational noise. Before any meaningful feature extraction can occur, an optimized signal denoising framework must be applied. The primary objective of this preprocessing stage is to separate the deterministic degradation signatures from the stochastic background noise without distorting the underlying phase and amplitude information. Standard linear filtering techniques are generally insufficient for this task due to the overlapping frequency spectra of the noise and the fatigue-induced transients. Therefore, an advanced multiresolution analysis approach is employed, which decomposes the raw signal into a hierarchy of approximations and details across multiple frequency scales [16].

The optimization of the denoising process involves selecting the most appropriate decomposition parameters and thresholding rules. By analyzing the statistical properties of the noise profile, an adaptive thresholding algorithm is designed to intelligently discard coefficients dominated by noise while retaining those that contain critical structural information. This non-linear filtering approach is mathematically formulated to minimize the discrepancy between the estimated clean signal and the true underlying structural response. The efficacy of this optimized denoising step is crucial, as the performance of the subsequent remaining useful life prediction model is highly sensitive to the signal-to-noise ratio of the input data. By ensuring that only high-fidelity signals are passed to the feature extraction module, the overall robustness of the prognostic system is significantly enhanced.

4. Feature Extraction and Selection Methodology

4.1 Comprehensive Feature Engineering

Following the rigorous denoising of the multisensor signals, the next critical phase in the optimization modeling pipeline is feature extraction. The objective here is to transform the high-dimensional, time-series data into a compact set of highly informative indicators that monotonically correlate with the progression of fatigue damage. The feature engineering process is divided into two primary domains: time-domain statistical analysis and frequency-domain spectral analysis. In the time domain, a comprehensive suite of statistical metrics is calculated for sliding windows of the acquired signals. These metrics include measures of central tendency, dispersion, and higher-order moments. Specifically, parameters that quantify the asymmetry and the peakedness of the signal distribution are highly sensitive to the impulsive shocks generated by advanced fatigue cracks [17].

In addition to time-domain metrics, frequency-domain features are extracted to capture shifts in the spectral energy distribution caused by structural degradation. As a fatigue crack propagates, it locally reduces the stiffness of the axle, which in turn alters the natural frequencies and the dynamic response profile. Spectral centroid, spectral spread, and the energy concentrated in specific frequency bands are computed to quantify these variations. The combination of time and frequency domain features results in a high-dimensional feature matrix that comprehensively describes the mechanical state of the railway axle at any given point in its operational life. The structure of this feature set is carefully designed to provide the machine learning algorithms with the most discriminative inputs possible.

Table 1: Description of Extracted Features from Monitoring Signals

Feature Domain	Specific Metric	Description and Physical Significance
Time Domain	Root Mean Square	Represents the overall vibration energy and macroscopic degradation severity.
Time Domain	Peak-to-Peak Value	Indicates the maximum amplitude of transient shocks associated with crack events.
Time Domain	Higher-Order Moments	Reflects the impulsiveness and non-Gaussian nature of advanced damage signals.
Frequency Domain	Spectral Centroid	Measures the center of mass of the spectrum, sensitive to stiffness reductions.
Frequency Domain	Band Energy Ratio	Quantifies energy shifts from high-frequency structural modes to lower frequencies.

4.2 Optimized Dimensionality Reduction

While extracting a massive number of features ensures that no potential degradation information is lost, it simultaneously introduces the problem of high dimensionality. Feeding redundant or irrelevant features into a remaining useful life prediction model can lead to the curse of dimensionality, resulting in increased computational overhead and a high risk of model overfitting. To mitigate these issues, an optimized feature selection and dimensionality reduction methodology is strictly required. The goal is to identify a minimal subset of features that maximizes the prognostic accuracy while minimizing redundancy [18].

The proposed approach utilizes a combination of filter and wrapper methods for optimal feature selection. Initially, filter methods based on correlation coefficients and monotonicity indices are applied to discard features that do not exhibit a clear, consistent trend over the lifespan of the component. A highly monotonic feature is highly desirable as it provides an unambiguous mapping to the continuous progression of fatigue damage. Subsequently, an advanced wrapper algorithm is employed, which utilizes an iterative optimization strategy to evaluate different combinations of the remaining features based on their actual predictive performance. By treating feature selection as a combinatorial optimization problem, the algorithm systematically navigates the feature space to discover the optimal configuration that enhances the robustness and accuracy of the final prognostic model.

5. Optimization Modeling for Remaining Useful Life Prediction

5.1 Architecture of the Predictive Model

The core of the proposed prognostic framework is an advanced, data-driven predictive model designed to map the optimized feature subset to the exact remaining useful life of the railway axle. Given the complex, non-linear degradation trajectories exhibited by metallic components under variable amplitude loading, traditional linear regression models are entirely inadequate. Instead, a sophisticated machine learning architecture is adopted, capable of capturing deep spatio-temporal dependencies within the sequential feature data. The model is structured to receive a continuous sequence of historical feature vectors as input, allowing it to interpret not only the current state of degradation but also the rate and acceleration of the damage accumulation over time [19].

The architecture comprises multiple interconnected layers designed to progressively abstract the input data into a final remaining useful life estimate. The initial layers focus on temporal feature integration, recognizing patterns in how the statistical metrics evolve across successive monitoring intervals. Subsequent layers act as regression units, translating these recognized patterns into a continuous output variable representing the remaining time or operational cycles until critical failure. The capacity of this architecture to learn highly complex degradation functions directly from data makes it exceptionally powerful. However, the performance of such intricate models is notoriously dependent on the precise tuning of their internal hyperparameters, necessitating a robust optimization strategy.

5.2 Heuristic Optimization of Model Parameters

To ensure maximum predictive accuracy and generalization, a heuristic global optimization algorithm is integrated into the training phase of the predictive model. The design and training of machine learning architectures involve numerous critical hyperparameters, including learning rates, regularization coefficients, and the dimensional configuration of hidden layers. Selecting these parameters through manual trial-and-error is highly inefficient and rarely yields the absolute optimal configuration. The proposed methodology frames hyperparameter tuning as a continuous optimization problem, where the objective is to minimize the prediction error on an independent validation dataset [20].

The selected heuristic optimization algorithm operates by maintaining a population of potential solutions, where each solution represents a unique set of hyperparameters. Through iterative processes analogous to biological evolution or swarm intelligence, these solutions explore the complex, multidimensional hyperparameter space. The algorithm evaluates the fitness of each configuration by temporarily training the predictive model and calculating its validation error. Over successive generations, the algorithm converges toward the global optimum, systematically refining the model structure to achieve the highest possible prognostic accuracy. This automated optimization modeling not only eliminates human bias from the model design process but also significantly enhances the adaptability of the system, allowing it to be rapidly reconfigured for different types of railway axles and operating conditions.

6. Experimental Setup and Data Collection

6.1 Design of the Fatigue Test Rig

To rigorously validate the proposed optimization modeling methodology, a comprehensive experimental campaign was conducted using a highly specialized, full-scale railway axle fatigue test rig. The objective of the experimental setup was to closely simulate the complex, multiaxial stress conditions experienced by an axle in active high-speed service. The test rig consists of a heavy-duty mechanical frame equipped with powerful hydraulic actuators capable of applying dynamic vertical and lateral loads directly to the axle journals. A high-torque electric motor is utilized to drive the axle at rotational speeds corresponding to operational velocities exceeding standard commercial limits, thereby accelerating the fatigue degradation process within a feasible timeframe.

The axle specimens utilized in the experiment were manufactured from standard high-strength railway steel, precisely machined to industry specifications. To ensure consistency in crack initiation locations and to facilitate precise monitoring, microscopic artificial notches were introduced at the highly stressed journal fillet regions using electrical discharge machining. These notches act as stress concentrators, guaranteeing that the macroscopic fatigue cracks initiate within the exact field of view of the advanced sensor array. The environmental conditions within the testing facility were strictly controlled to eliminate temperature fluctuations and external vibrations that could contaminate the experimental data.

6.2 Data Acquisition Protocol

The acquisition of high-fidelity monitoring data is critical for validating the remaining useful life prediction models. The multidimensional sensor architecture detailed in the theoretical framework was physically deployed onto the test rig. High-resolution strain gauges were bonded near the root of the artificial notches to monitor local plastic deformation. Piezoelectric accelerometers and wideband acoustic emission sensors were securely mounted on the adjacent bearing housings. The signals from all sensors were routed through heavy-duty, shielded cables to prevent electromagnetic interference from the driving motors.

The data acquisition system was configured to capture data continuously throughout the entire lifespan of each axle specimen, from the pristine state to complete fracture. High sampling rates were strictly enforced to ensure the capture of transient, high-frequency acoustic emission events. The massive volume of raw data generated required a robust digital storage infrastructure, coupled with real-time data streaming protocols to facilitate periodic preprocessing. The experimental loading parameters were designed to mimic both constant amplitude operations and variable amplitude profiles, reflecting the diverse conditions of actual railway service. The detailed parameters of the experimental loading blocks are provided to ensure complete transparency of the validation process.

Table 2: Experimental Loading Parameters for Axle Fatigue Testing

Parameter Type	Specific Variable	Operational Value
Mechanical Loading	Rotational Speed	Ranging from moderate to extreme operational velocities
Mechanical Loading	Vertical Load Actuation	Cyclic sinusoidal forces simulating variable passenger weights
Mechanical Loading	Lateral Load Actuation	Transient impulses simulating track irregularities
Data Acquisition	Accelerometer Sampling Rate	Ultra-high frequency configuration to capture micro-transients
Data Acquisition	Strain Gauge Sampling Rate	Moderate frequency for capturing macroscopic bending moments

7. Results and Performance Evaluation

7.1 Validation of the Signal Processing and Feature Selection

The initial phase of the results evaluation focused on validating the effectiveness of the optimized signal denoising and feature selection methodologies. The raw data acquired from the test rig exhibited profound levels of background noise, particularly in the high-frequency acoustic emission channels where machinery operation frequently masked the microscopic crack initiation events. Following the application of the optimized multiresolution analysis, the signal-to-noise ratio was observed to improve dramatically. The adaptive thresholding algorithm successfully preserved the sharp, transient spikes indicative of structural anomalies while effectively flattening the stochastic noise floor.

The evaluation of the feature extraction and selection pipeline further confirmed the validity of the proposed approach. The initial extraction yielded a massive array of features, many of which exhibited chaotic, nonmonotonic behavior that would severely confuse a predictive model. By employing the combined filter and wrapper optimization strategy, this feature space was drastically reduced to a highly compact subset of optimal indicators. The selected features, such as the optimized spectral centroid and specific higher-order time-domain moments, displayed a clear, exponential growth trend correlating precisely with the physical expansion of the fatigue cracks measured during periodic visual inspections of the test specimens. This monotonic behavior proves that the feature selection optimization successfully isolated the true degradation signatures.

7.2 Prognostic Accuracy and Error Analysis

The ultimate validation of the proposed methodology lies in the predictive accuracy of the optimized remaining useful life model. The predictive model, trained using the optimally selected feature subset and configured via the heuristic global optimization algorithm, was tested against unseen data from independent experimental runs. The model performance was evaluated using standard prognostic error metrics, including the root mean square error and the mean absolute error. The predicted remaining useful life trajectories were plotted against the actual ground truth lifespan of the tested axles to visualize the tracking capabilities of the algorithm.

The results demonstrated a remarkable degree of accuracy throughout all stages of the degradation process. In the early stages of crack propagation, where traditional models often produce highly volatile and uncertain estimates, the optimized model provided stable and increasingly accurate predictions. As the axle transitioned into the rapid fracture phase, the model rapidly adjusted its predictions, accurately forecasting the exact moment of failure well in advance of the critical threshold. Furthermore, comparative analyses were conducted against baseline non-optimized algorithms and traditional empirical fatigue models. The optimization modeling approach proposed in this paper consistently outperformed all baseline methods, reducing prognostic errors by a significant margin.

Table 3: Comparative Analysis of Remaining Useful Life Prediction Errors

Model Configuration	Mean Absolute Error	Root Mean Square Error
Traditional Empirical Model	High Error Magnitude	High Error Variance
Standard Data-Driven Model	Moderate Error Magnitude	Moderate Error Variance
Proposed Optimized Model	Substantially Reduced Error	Minimal Error Variance

The comprehensive error analysis confirms that the integration of continuous optimization across the entire data pipeline—from signal denoising to hyperparameter tuning—is fundamentally necessary for achieving reliable prognostic results in complex structural systems. The robustness demonstrated against variable amplitude loading conditions underscores the potential of this methodology for immediate deployment in practical railway engineering applications.

8. Conclusion

This academic paper has presented a comprehensive and highly detailed optimization modeling framework dedicated to the analysis of fatigue monitoring signals and the accurate prediction of remaining useful life in railway axle components. By systematically addressing the inherent challenges of noisy field data, multidimensional feature redundancy, and complex algorithmic configurations, the proposed methodology establishes a highly robust pipeline for structural health monitoring. The integration of advanced signal processing techniques ensures that critical degradation signatures are preserved, while the optimized feature selection algorithms guarantee that predictive models are trained only on the most relevant, monotonic indicators of structural damage.

Furthermore, the utilization of heuristic global optimization to fine-tune the predictive machine learning architectures has been demonstrably proven to significantly enhance prognostic accuracy and model generalization. The extensive experimental validation utilizing full-scale fatigue testing rigs under realistic operational conditions confirmed that the proposed framework substantially outperforms conventional empirical and non-optimized data-driven models. The substantial reduction in prediction errors translates directly into enhanced operational safety and the ability to implement highly efficient, condition-based maintenance schedules. Ultimately, the optimization modeling strategies developed in this research provide a scalable and deeply reliable foundation for the future of predictive maintenance across the global railway industry and broader mechanical engineering domains.

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