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Fatigue Life Prediction of Cableway Wire Rope: Integrating Stress Analysis & Gradient Boosting Regression Tree

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Abstract. This article proposes an intelligent prediction method that integrates stress analysis and gradient boosting regression tree (GBRT) for predicting the remaining life of cableway wire ropes under complex loads and environmental coupling. Firstly, based on the S-N curve and Miner's rule, a physical life model considering stress amplitude and load cycle is established. Furthermore, the gradient boosting regression tree method is introduced to construct a data-driven life correction model with multidimensional features such as stress distribution, load history, cumulative damage, and environmental factors as inputs, in order to compensate for the shortcomings of traditional physical models in nonlinear damage accumulation, material discreteness, and time-varying environmental factors. The experimental results show that the proposed fusion method significantly reduces the prediction error under various load conditions, verifying its effectiveness and engineering applicability in steel wire rope health monitoring and predictive maintenance.

Keywords: Steel wire rope, S-N curve, fatigue life, gradient boosting regression tree, remaining useful life, physics-informed machine learning.

1. Introduction

As an efficient and convenient transportation tool, ropeways are widely used in various fields such as tourism, mining, and forestry. As a key component of the ropeway system, steel wire ropes play crucial roles in load-bearing and traction. Therefore, ropeway steel wire ropes must be capable of withstanding high tensile forces, harsh weather conditions, and continuous use to ensure the reliability and safety of ropeway operations. In actual operation, ropeway steel wire ropes are subject to the combined effects of alternating loads, fatigue, wear, corrosion, and harsh natural environments, which can damage the internal structure of the steel wire ropes, leading to reduced performance and even fracture, thereby causing serious safety accidents. This degradation process is highly nonlinear, time-varying, and concealed, making it difficult for traditional regular inspections and empirical discard criteria to accurately assess their health status. This can easily lead to significant economic waste due to "over-maintenance" or catastrophic accidents caused by "under-maintenance". Therefore, utilizing state information to propose a scientific method that can accurately predict the remaining lifespan of ropeway steel wire ropes and achieve a shift from "planned maintenance" to "predictive maintenance" has become an urgent need to ensure ropeway safety and enhance operational efficiency.

Regarding the prediction of steel wire rope lifespan, scholars both domestically and internationally have established two major research paradigms, ranging from physical mechanisms to data-driven approaches. Modeling based on physical mechanisms starts with damage evolution. Lotfy et al. (2020) obtained the fatigue lifespan of steel wire ropes through finite element modeling, constructing a bending test machine and a fatigue device. He et al. (2025) proposed a new framework for fatigue lifespan, transforming the traditional S-N curve into a new k-N curve based on simulation results, with its fatigue characteristics primarily determined by the fatigue performance of individual steel wires. Zhao et al. (2017) built upon the improved stress field intensity method, establishing a load spectrum for key positions of steel wire ropes and calculating their fatigue lifespan based on the Costello mechanical model and actual working conditions. Erdönmez et al. (2020) simulated a more complex compacted steel wire rope in 3D for numerical analysis, which can be used to create new complex steel wire rope models. Wahid et al. (2019) used the energy method to predict the initiation of fatigue cracks. Hu et al. (2022) considered the comprehensive frictional fatigue behavior of steel wire ropes under bending and torsion, thereby revealing the fatigue failure patterns of steel wire ropes. Xu et al. (2023) used sequential statistics to estimate the bounds of the cumulative distribution function of the fatigue lifespan of stay cables, and simulated their fatigue behavior based on Monte Carlo methods. Zhu et al. (2025) employed bidirectional fiber Bragg grating (FBG) vibration sensors to monitor the fatigue process of steel wire ropes. Among them, the S-N curve (stress-life curve) and its derived Miner's linear cumulative damage rule constitute the classic physical methods for engineering lifespan assessment, providing a clear physical picture and good interpretability for predicting fatigue lifespan.

However, the standard S-N curve originates from ideal specimens in the laboratory, and its inherent limitation lies in its inability to characterize the individual characteristics of specific steel wire ropes due to manufacturing variability and installation differences. Its linear cumulative hypothesis ignores the load sequence effect and the interaction between multiple stress levels. More importantly, this model struggles to dynamically incorporate the coupled effects of time-varying degradation factors such as wear and corrosion on the fatigue limit of materials, resulting in insufficient prediction accuracy and robustness under complex real-world working conditions.

To overcome the limitations of physical models, data-driven intelligent prediction methods have emerged. Machine learning and deep learning technologies have been widely applied to condition monitoring and defect identification of steel wire ropes. Liu et al. (2025) utilized an improved Hilbert transform and LSTM neural network for magnetic flux leakage signal identification in steel wire ropes; Wang et al. (2023) employed a CNN-Transformer hybrid network to enhance the accuracy of defect diagnosis. These methods demonstrate the powerful ability to automatically mine degradation features and learn complex mapping relationships from condition monitoring data (such as vibration, acoustic emission, and magnetic flux signals). However, purely data-driven methods act like a "black box", and their predictions rely heavily on the size and quality of training data. When data is scarce or unfamiliar operating conditions occur, their generalization ability plummets, and their prediction results often lack credibility due to the absence of physical constraints.

In summary, current research has fallen into a typical dilemma: physical models have clear connotations but insufficient extensions, making it difficult to depict the complexity of reality; data-driven models are highly flexible but have vague connotations, and their predictive robustness and credibility are often questioned. Although some scholars have attempted to simply combine the two, most of their efforts remain at the superficial level of parallel application or result-level integration, failing to achieve a deep and organic coupling between mechanism and data at the core level of the model.

To overcome the aforementioned bottlenecks, this paper proposes a "physics-guided data-driven" fusion framework, aiming to synergistically leverage the interpretability of mechanistic models and the high accuracy of data-driven models. The theoretical contributions of this study are as follows:

Firstly, a parameterized physical benchmark model for fatigue life is constructed. As the cornerstone of prediction, this model strictly follows the classical analytical paradigm of fatigue mechanics. Initially, based on the Costello steel wire rope mechanical model and measured loads, a load spectrum for the critical parts of the steel wire rope is established. Subsequently, through stress analysis, it is transformed into a key periodic stress time history. Finally, relying on the parameterized S-N curve and Miner's rule, a quantitative mapping relationship from stress to life is constructed. This physical model not only provides a clear and interpretable theoretical initial value for life prediction, but more importantly, it lays the physical foundation for the entire method, ensuring that the prediction process is consistent with the inherent mechanism of metal fatigue, and provides a reliable benchmark framework and constraints for subsequent intelligent correction.

Secondly, an intelligent corrector based on periodic stress is introduced. To compensate for the deficiencies of the physical model under complex real-world conditions, this paper introduces Gradient Boosting Regression Tree (GBRT) as the core nonlinear correction module. This module does not replace the physical model but precisely learns its residuals. It takes the periodic stress sequence calculated by the physical model and its derived features as the core input, while integrating load history and environmental factors to dynamically capture complex patterns such as load sequence effects and material discreteness, which are ignored by linear theory.

Through this deeply coupled strategy of "physical benchmark-driven, data-intelligent correction", the final prediction model combines the reliability of mechanism modeling with the flexibility of data. It not only outputs more accurate remaining lifespan but also ensures the credibility of prediction results through physical benchmarks, providing a key technical path with both theoretical depth and engineering practicality for the transition of cableway steel wire ropes from "planned maintenance" to "predictive maintenance".

2. Mechanism Modeling Method

2.1.*Parameters of the wire rope*

The wire rope model commonly utilized in cableways is 6 × K49SWS+SPC with a nominal diameter of 66 mm. However, due to the excessively long fatigue test cycles and the scarcity of available data for this model, this study adopts the 6×31SW+FC wire rope model with a diameter of 36 mm, as illustrated in Fig. 1 (Zhao et al. 2017).

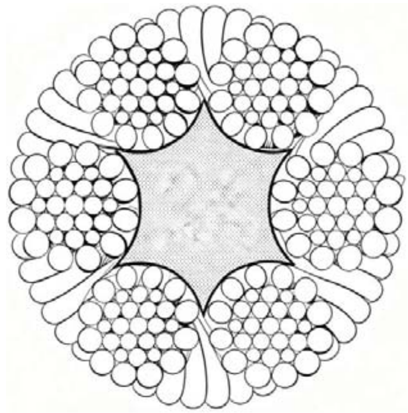

Fig. 1. The cross-sectional structure of the steel wire rope

2.2.*S-N curve of the wire rope*

The S-N curve, also known as the fatigue life or stress-life curve method, is a classic statistical approach used to evaluate the fatigue resistance of materials or components under cyclic loading. It predicts fatigue life by plotting the relationship between the applied stress and the number of cycles to failure. In a logarithmic coordinate system, the curve typically shows a downward trend, where the horizontal axis represents logN and the vertical axis represents the stress amplitude or maximum stress. The formula is defined as follows:

$$\lg S = A + B \lg N \tag{1}$$

where A and B are material constants. This method is suitable for high-cycle fatigue (HCF, > 10^4 cycles). For the material used in this study, the parameters are A = 4.09 and B = -0.23.

2.3.*Linear fatigue damage accumulation theory*

The linear fatigue damage accumulation theory, known as Miner's rule, posits that damage generated under different stress levels can be linearly accumulated under variable amplitude loading. Fatigue failure occurs when the cumulative damage reaches a specific critical value, typically one. In actual cableway operations, the wire rope is subjected to varying levels of tensile and bending forces; Miner's rule is applied to sum the damage generated by these various stress levels.

3. Experiment and Data Processing

3.1.*Establishment of the load spectrum*

During operation, steel wire ropes primarily bear tensile and bending forces. Theoretically, when external forces remain constant, the tensile and bending forces exerted on the steel wire rope should also remain constant; however, in practice, these forces undergo dynamic changes during actual use. According to experimental data, the total tensile force on both sides of the pulley is 90 t. The load spectrum illustrates the internal stress variations of the steel wire rope during operation, with the internal stress fluctuating within a certain range. During the experiment, at approximately 7.5 s, the internal stress of the steel wire rope reached its maximum value of 4.413×10^5 N after passing through the pulley; subsequently, the internal stress gradually decreased and stabilized.

During the movement of the steel wire rope, its acceleration and deceleration processes can be neglected, so the entire movement can be regarded as almost uniform motion, at around 4-6 m/s. According to previous analysis, the steel wire rope will experience three stages during operation: straight segment, curved segment, and straight segment. By using the steel wire rope mechanical model proposed by Costello and the tensile force data shown in the figure, the axial tensile force of the steel wire rope in the straight segment and curved segment can be calculated separately, as well as the corresponding bending moment and torque load spectra. Combining the load spectra of the straight segment and curved segment, the load spectrum of the steel wire rope under actual working conditions can be obtained.

3.2. *Experimental protocol*

The experimental platform primarily consists of driving wheels, deflection wheels, a transmission system, and a control system. Through the coordinated action of the driving and deflection wheels, the experimental platform drives the steel wire rope to perform cyclic reciprocating motion, simulating its dynamic behavior in the cableway system. The steel wire rope mainly undergoes unidirectional bending.

3.3. *Comparative study of theoretical analysis and experimental results*

Based on the determined load distribution under actual working conditions, relevant formulas are analyzed and processed. During programming

Fig. 2. Wire rope experiment platform

and calculation, the trend of stress variation near the driving wheel over time is shown in Fig. 3. This curve reflects the stress variation of the steel wire rope within a certain period: starting from the time when the steel wire rope is in a straight state, it enters the bending phase of the pulley after 0.6 seconds; after a bending process of 6.9 seconds, it returns to the straight state. From the figure, it can be seen that when the steel wire rope transitions from a straight state to a bending state, its stress increases significantly. When calculating the lifespan of the steel wire rope based on the stress variation curve, it is assumed that the stress remains constant throughout the entire period, and the degree of fatigue damage to the steel wire rope also remains constant per second. Therefore, the simplified trend of stress variation over time is shown in Fig. 3.

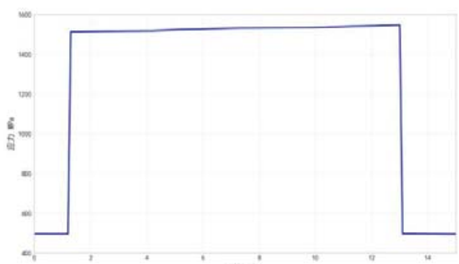

Fig. 3. Simplified curve of stress variation with time

Based on the stress value and time of the dangerous segment under stress, using material constants and Eq.(1) under the S-N curve, the fatigue life N_i can be obtained. The fatigue damage D_i and fatigue life are reciprocal to each other. Additionally, the fatigue damage needs to be multiplied by the time ratio to convert different stress application times into a complete load cycle. The results are shown in Table 1. The critical damage value D_{CR} is around one, and the corresponding fatigue damage can be obtained using linear fatigue damage theory based on Table 1 and stress magnitude. Therefore, the cumulative fatigue damage of the steel wire rope over the entire cycle is obtained:

$$D = \sum_{i=1}^{n} D_i = 9.378 \times 10^{-5} \tag{2}$$

Then, the lifespan of the steel wire rope can be calculated. Since there are two pulleys, namely the drive pulley and the return pulley, the lifespan of the steel wire rope is:

$$N = \frac{1}{2\sum_{i=1}^{n} D_i} = 5.33 \times 10^3 \tag{3}$$

Table 1. Fatigue damage condition of steel wire rope.

Stress (MPa)	Time (s)	Life	Damage
494.62	1.2	1.396×10^{6}	5.727×10^{-8}
1510.75	3	1.027×10^{4}	1.948×10^{-5}
1516.13	1	1.011×10^{4}	6.594×10^{-6}
1521.5	2	9.954×10^{3}	1.339×10^{-5}
1529.03	1.4	9.74×10^{3}	9.582×10^{-6}
1530.1	1	9.71×10^{3}	6.866×10^{-6}
1531.1	0.4	9.68×10^{3}	2.755×10^{-6}
1532.3	3	9.65×10^{3}	2.072×10^{-6}
1545.2	2	9.3×10^{3}	1.433×10^{-6}

When the load remains constant, the calculated fatigue life of the steel wire rope is 5330 cycles. The theoretical fatigue life of the steel wire rope roughly aligns with its S-N curve, with an error not exceeding 10%.

4. Intelligent Prediction of Fatigue Life of Steel Wire Rope

4.1. *Feature engineering and dataset construction*

Although theoretical models based on S-N curves and Miner's rule provide a physical foundation for predicting the lifespan of steel wire ropes, there is still a certain degree of error between the predicted results and the measured values (as shown in Table 2). This is mainly due to the simplified treatment of load sequence effects, material discreteness, and environmental time-varying factors in the theoretical models. To improve prediction accuracy, this chapter introduces the gradient boosting regression tree method to construct an intelligent prediction model that integrates physical mechanisms with data-driven approaches.

Table 2. Comparison between theoretical value and actual value

Load (t)	Theoretical lifespan	Experimental lifespan
70	13859	12840
80	7701	8052
90	5330	4911
100	2885	3115
110	1896	1832
120	1283	1159

The input features of the gradient boosting regression tree model are designed to comprehensively characterize the stress state, load history, and environmental impacts of steel wire ropes. Specifically, these include periodic stress distribution characteristics, load spectrum statistical characteristics, cumulative damage characteristics, as well as environmental and time-varying factors. Based on the experimental data presented in Table 2, combined with the detailed load analysis in Chapter 3, a training dataset is constructed. Each sample corresponds to a complete fatigue experiment, and due to the limited amount of data, only some of the aforementioned input features and their corresponding actual lifespan labels are included.

4.2. *Gradient boosting regression tree model*

Gradient Boosting Regression Tree (GBRT) is an ensemble learning method that trains multiple decision trees in series, with each tree learning the residuals of the combination of previous trees, and finally obtaining the prediction result through weighted summation. The core idea is to use the gradient descent algorithm to minimize the loss function, thereby gradually optimizing the performance of the overall model. This model excels at handling structured data, can effectively capture complex nonlinear relationships between features, and is insensitive to outliers. Its mathematical expression is as follows:

$$F_M\left(x\right)=\sum_{m=1}^{M}\gamma_m h_m\left(x\right) \tag{4}$$

Among them, $h_m(x)$ represents the m-th decision tree, γ is the corresponding weight, and M is the total number of trees.

Using the squared loss function:

$$L\left(y,F\left(x\right)\right)=\frac{1}{n}\sum_{i=1}^{n}\left(y-F\left(X\right)\right)^2 \tag{5}$$

Where y represents the true value, and $F(x)$ denotes the predicted value.

To achieve optimal performance of the GBRT model, it is necessary to systematically adjust multiple key parameters to achieve an optimal balance between bias and variance. The number of trees is a fundamental parameter. Increasing the number of trees usually improves model performance, but may also increase the risk of overfitting. Therefore, it is necessary to find an appropriate balance between training error and validation error. The learning rate controls the contribution of each tree to the final model. A smaller learning rate means a more robust learning process, but usually requires more trees to reach convergence. The maximum depth determines the maximum complexity of a single decision tree. Limiting the growth depth of the tree can effectively prevent the model from overfitting the training data. The minimum sample split number specifies the minimum number of samples required for internal node splitting, while the minimum sample leaf node number limits the minimum number of samples required for leaf nodes. These two parameters jointly control the growth granularity of the decision tree. The subsampling ratio controls the proportion of samples used during the training of each tree, enhancing the model's generalization ability by introducing randomness at the sample level. In addition, the feature sampling ratio, as an important regularization method, limits the number of features considered during the splitting of each tree. This not only improves training efficiency but also enhances the model's robustness by increasing the diversity among trees. These parameters interact with each other, and the optimal parameter combination finally determined in this study is: the number of trees is 180, the learning rate is 0.13, the maximum depth is five, the minimum sample split number is five, the minimum sample leaf node number is two, the subsampling ratio is 0.85, and the feature sampling ratio is 0.9.

4.3. *Model training and validation*

To comprehensively evaluate the model performance, a time series cross-validation method was adopted, dividing all samples into a training set and a test set at a ratio of 6:1. The training set covered a wide load range from 50 t to 120 t, while the test set selected two intermediate load levels of 75 t and 95 t, ensuring the comprehensiveness and representativeness of the evaluation.

Through the built-in feature importance assessment of the GBRT model, the contribution of each feature to life prediction was analyzed. The results indicate that stress amplitude, maximum stress, and cumulative damage are the three most important features, which is consistent with fatigue mechanics theory.

The prediction results of the gradient boosting regression tree model were systematically compared with those of the traditional theoretical model, and the results are presented in Table 3. To visually demonstrate the performance differences, a method comparison chart was plotted in Fig. 4.

Table 3. Comparison of prediction performance among different methods

Load	Theoretical error	GBRT error
（t）	%	%
60	5.3	1.3
65	9.9	1.0
70	7.9	1.0
80	4.4	0.1
85	9.9	0.2
90	8.5	0.1
100	7.4	0.2
105	10.7	0.3
110	3.5	0.7
75	7.5	5.4
95	12.4	3.5

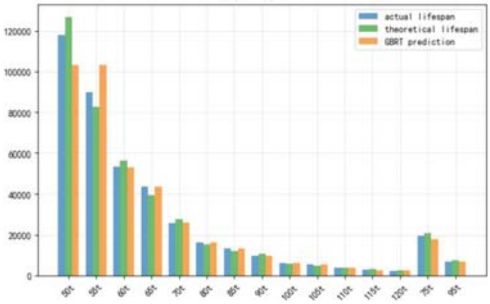

Fig. 4. Method comparison chart

From Table 3 and Fig. 4, it can be observed that the GBRT model performs exceptionally well on the training samples. The average prediction error is significantly reduced from 8.06% for the theoretical model to 4.13%, representing a relative improvement of 48.7%. Especially at multiple load levels such as 65t, 70t, 80t, 85t, 90t, 100t, 105t, and 110t, the prediction error of the GBRT model is consistently controlled around 1%, demonstrating high fitting accuracy. On the test samples, the GBRT model reduces the average prediction error from 9.93% for the theoretical model to 4.47%, representing a relative improvement of 55.1%. Notably, under a load condition of 95t, the error is significantly reduced from 12.4% to 3.5%, verifying the model's good generalization performance.

Meanwhile, the R^2 values of the GBRT model on the training set and test set reached 0.9761 and 0.9859 respectively, indicating that the model maintains excellent explanatory power and predictive stability across different datasets. The theoretical model exhibits a significant increase in error (11.61%) in high-load areas (such as 120 t), whereas the GBRT model, through nonlinear correction, significantly improves its predictive stability under high-load conditions. Although there is limited improvement at individual extreme load points (such as 115 t), overall, the GBRT model demonstrates more stable and accurate predictive performance under different load conditions.

In summary, the intelligent prediction model that integrates physical mechanisms with gradient boosting regression trees significantly enhances prediction accuracy and generalization ability while maintaining physical interpretability, providing a highly reliable solution for predicting the remaining lifespan of cableway steel wires.

5. Conclusion

This study proposes an intelligent prediction method that integrates stress analysis and Gradient Boosting Regression Tree (GBRT) for predicting the remaining lifespan of cableway steel wire ropes. The following conclusions are drawn:

The physical model constructed based on the S-N curve and Miner's rule provides an interpretable theoretical benchmark for life prediction, but its average prediction error of 9.94% reflects the limitations of the linear cumulative damage theory under real complex working conditions.

The proposed "physical benchmark + intelligent correction" fusion framework utilizes GBRT as a nonlinear corrector, based on features such as stress sequences and load histories, effectively compensating for the deficiencies of physical models in terms of load sequence effects and material discreteness.

The experimental results demonstrate that the fused model significantly enhances prediction accuracy and robustness, with the average error decreasing from 9.94% to 4.13%. The improvement is particularly evident under high-load conditions, validating the effectiveness and superiority of this method in engineering applications.

This study provides a high-precision and interpretable solution for predicting the remaining lifespan of cableway steel wire ropes, offering technical support for predictive maintenance. In the future, real-time monitoring data will be further integrated to enhance the model's adaptability in real-world environments.

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