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Research on the Compilation Method of Transmission Shaft Load Spectrum for ZL50 Wheel Loader Used in Mines

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ABSTRACT

The ZL50 wheel loader functions under highly fluctuating and intricate load conditions, which significantly impact the longevity of its transmission shaft. This study introduces a thorough approach to compiling and refining the transmission shaft load spectrum by utilizing both simulated and actual torque data. The methodology encompasses signal-preprocessing, rainflow counting for cycle extraction, and fatigue life assessment through Miner's Rule. An 8×8 load spectrum matrix is created to depict the frequency distribution of load amplitudes and mean values. Sensitivity analysis is performed to evaluate how variations in load magnitude affect fatigue life. Furthermore, MATLAB optimization algorithm is used to reduce cumulative damage by adjusting load parameters, leading to a more efficient and dependable fatigue design. Advanced visualization methods, including surface plots, bar graphs, contour maps, and convergence graphs, are employed to interpret the findings and monitor the optimization process. The proposed method not only enhances the precision of fatigue life prediction but also lays a practical groundwork for designing more robust mechanical components for heavy-duty mining vehicles. This research acts as a valuable resource for engineers engaged in fatigue testing, virtual simulation, and durability evaluation of drivetrain components in challenging working conditions and real mining scenarios.

INTRODUCTION

The ZL50 Loader is a key component in industries like mining, construction, and material handling. Drive Shaft System: The operational efficiency of this machine is driven by the drive shaft system driving power from the engine and transmitting to the wheels. On the other hand, during operating conditions dynamic and unpredictable loading are thrusted on the drive shaft which greatly influences its fatigue life. A failed drive shaft on the loader means expensive repairs, downtime for operations, and costly operational maintenance.

The cyclic loading of the drive shaft can often lead to fatigue damage on it over a long operational time. Established fatigue life prediction methods, for example, Miner cumulative damage theory, are useful to engineering applications but cannot be applied to real-world applications due to the non-stationary and transient load nature of civil infrastructures. This, together with an inability to account for real time operating conditions leads to overly conservative fatigue life prediction and inappropriate maintenance or premature failure. In this case, a more sophisticated and comprehensive load spectrum control method is needed to accurately predict fatigue life and ensure optimal operational performance of the machine.

Advancements in signal processing techniques such as Wavelet Transform (WT) and Empirical Mode Decomposition (EMD), together with data analysis frameworks like Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM's), offer new opportunities for tackling these issues. WT has been known to be one of the best techniques for load spectrum identification, as it is well suited to analyze non-stationary signals. In parallel, due to their capability of temporal/spatial data analysis, CNNs and LSTMs may be good candidates for rotating machinery fatigue life prediction. Underpinning this paper is an integrated load spectrum control and prediction method for the ZL50 Loader drive shaft that employs signal processing along with machine learning.

LITERATURE REVIEW

Predicting the fatigue life of components is essential in mechanical engineering, particularly for rotating machinery. Accurately forecasting when parts might fail due to repeated stress is key to optimizing both the design and maintenance schedules of vital components. In this context, load spectrum analysis plays a critical role in categorizing and examining the various load conditions that equipment experiences. Traditional models for predicting fatigue life, like Miner's Rule, have been extensively utilized to assess the cumulative damage that rotating parts endure under cyclic stress (Smith, 2020). These models are based on the assumption of constant load conditions, which often fail to capture the real-time fluctuations and transient loads found in modern industrial settings, especially in mining operations (Jones *et al.*, 2019).

Wavelet Transform (WT) has recently gained recognition as a valuable tool for examining non-stationary and transient signals in machinery. By breaking down the signal into its frequency components over time, WT facilitates a comprehensive analysis of load conditions that change over time (Brown & Wang, 2021). This

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method offers a more precise depiction of load spectrums, especially in scenarios where load conditions are unpredictable. Furthermore, Empirical Mode Decomposition (EMD) has been effectively used in conjunction with WT for analyzing machinery vibration and fatigue. EMD decomposes complex signals into intrinsic mode functions (IMFs), providing a robust representation of the load spectrum, which is useful for predicting machinery fatigue life (Yang *et al*., 2020). These techniques have demonstrated their effectiveness in assessing vibrations and forecasting the fatigue life of machinery under non-stationary conditions (Li & Zhou, 2020).

In recent times, Machine Learning (ML) methods have garnered considerable interest due to their capability to forecast fatigue life and identify faults in rotating machinery. Among these methods, Convolutional Neural Networks (CNNs) stand out for their remarkable ability to analyze spatial data, including images and vibration signals (Sharma *et al*., 2021). CNNs are especially advantageous for fault diagnosis as they can autonomously extract hierarchical features from raw vibration data, eliminating the need for manual feature extraction. This makes them particularly suitable for detecting mechanical faults, particularly in rotating machinery like the transmission shafts of wheel loaders (Huang *et al*., 2021). Furthermore, Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Networks (RNNs), have demonstrated effectiveness in modeling sequential data. LSTMs can capture temporal dependencies in time-series signals, which is essential for predicting machinery degradation based on historical load conditions (Smith & Brown, 2022). In the realm of fatigue life prediction, where component degradation is influenced by variations in loading conditions over time, LSTMs are particularly adept at modeling these time-dependent processes. LSTM models have been successfully utilized to predict bearing faults and machine degradation, offering a robust tool for predictive maintenance (Li *et al*., 2022). These sophisticated machine learning techniques, especially CNNs and LSTMs, hold significant promise in enhancing the precision of fatigue life predictions and fault detection, thereby facilitating more effective maintenance strategies for the ZL50 wheel loader's transmission shaft. The capability to learn from historical data and forecast future conditions marks a crucial advancement in ensuring the reliability and durability of heavy machinery in challenging operational settings.

MATERIALS AND METHODS

This study aims to assess the fatigue life of the transmission shaft in the ZL50 wheel loader through realistic load simulation and numerical fatigue evaluation. A multi-step approach was employed to create synthetic yet representative load profiles, determine load cycles via rainflow analysis, evaluate fatigue damage using Miner's Rule, and optimize operating load levels to prolong the shaft's lifespan. Each phase involves specific simulation steps and analytical methods executed in MATLAB.

Simulating load data

To mimic the actual working conditions of a transmission shaft, a synthetic load profile was crafted for a 100-second observation period, utilizing a sampling rate of 10 Hz, which produced 1000 data points. The simulated torque load comprises two main elements: a periodic base load and random disturbances. A sinusoidal waveform was employed to replicate the cyclic nature of shaft torque, featuring a fundamental frequency of 0.2 Hz and a peak amplitude of 500 N·m, symbolizing machine cycle forces. To account for operational irregularities like ground impact, material shifting, and transmission backlash, Gaussian white noise was incorporated into the signal. This random noise, scaled to 200 N·m, introduces realistic fluctuations in the simulated torque, capturing the unpredictable dynamics typical in heavy-duty mining equipment. The resulting time-domain load profile displays a consistent wave-like torque application, overlaid with random peaks and troughs, accurately representing the operational stresses on the transmission shaft.

The working media and worksite are the major reasons of the load in the process of loader operation. Load spectrum Test the site and select the material according to the design and actual working condition of the loader model[4]. The site should have suitable operating criteria and the materials selection should be according to environmental conditions received through surveys of the loader's actual sites, provided they are representative. According to the investigation of present operation status of domestic loader, the representative materials of ZL50 loader are rock ore of big granularity, small particles of gravel, compound materials (sand, soil), clay, native land and mineral powder. The standard operating conditions for ZL50 loader is shown in Figure 1. In the figure: (a) is indicative of field conditions, i.e. clay and native soil, (b) describes working conditions of little stones, (c) shows sand-soil mixture working states, (d) shows the working environment of mineral powder, (e) indicates initial working conditions of large-grain rock.

The selection of loader test work condition directly affects the rationality and reliability of the test data. The difference in material, particle size, pile height, ground flatness and the friction coefficient, overdrive speed, and driver make the actual operating load of wheel loader different from each other. The random factors in the operating process also make the random of the load more obvious. So it is difficult to recreate the actual working condition accurately. Therefore, it is essential to select the representative typical test work condition to measure the load spectrum. The specific principle is determined based on the regulation on hydraulic model usage condition and the work condition statistical in terms of design.

1) The load spectrum measurement state should be representative, indicating the working conditions of the loader model in reality;

（a）Clay and Native Soil Working Conditions (b) Small Gravel Working Conditions

(c) Sand –soil mixing condition (d) Mine powder working condition

(e) Initial mining granular rock working condition

Figure 1: The typical working condition of loader

2) The specifications need to present the operating features of the model under examination;

3) Infer from statistical analyses of usage data what are the typical cases under which the system is used and the proportion of use;

4) The test ground is as flat as possible, and the test material is uniform as possible, to achieve loader working environment and materials of the actual situation required during the test.

Generating Load Spectrum

Once the simulated time-domain data was created, it underwent processing to develop a load spectrum that categorizes the frequency of different torque levels. To achieve this, logarithmic binning was utilized across the amplitude range, resulting in an 8×8 matrix load spectrum. This approach accommodates the significant variation in torque amplitudes and ensures an accurate representation of both frequent medium loads and rare high loads. The bin edges were established using a base-10 logarithmic scale spanning from the minimum to the maximum observed load values. Subsequently, a histogram was plotted to illustrate the distribution of torque magnitudes, enabling the identification of predominant load intervals. This analysis highlights the critical load levels that frequently occur and may significantly contribute to fatigue accumulation. The loader's dynamic load test, conducted under typical clay material conditions, takes place at a national standard testing site, as depicted in Figure 2.

Figure 2: Dynamic load spectrum test of typical material's for ZL50 loader

Rainflow Counting for Load Cycle Detection

To determine the number of damaging load cycles in the simulation, the rainflow counting algorithm was utilized on the processed signal. This method identifies complete and partial cycles by pairing local peaks and troughs, thereby transforming the time-domain load profile into a cycle-based format. Each cycle is defined by its range (the difference between the peak and trough) and its mean value. These parameters are crucial for fatigue life analysis as they are directly linked to the stress levels experienced by the shaft. Rainflow counting efficiently converts continuous and random load variations into a series of measurable cyclic events, each contributing uniquely to the overall fatigue damage. A histogram of cycle ranges was generated to illustrate the frequency of each load range in the simulation, aiding subsequent fatigue analysis.

Fatigue Damage Evaluation with Miner's Rule

Miner's rule for linear damage accumulation is utilized to predict fatigue life, serving as a conventional method for evaluating material fatigue under cyclic loading conditions. For each load cycle identified through rainflow counting analysis, the associated damage fraction is determined. The damage incurred by each cycle is expressed as follows:

$$Damage = \sum_{i=1}^{n} \frac{N_i}{N_f} \qquad (1)$$

Where :

1. N_i represents the count of cycles at a particular load range, derived from the rainflow counting method.
2. N_f The number of cycles until failure at a specific load range can be determined from the material's S-N curve, also known as the stress-life curve, for that particular material.
3. The term range$^{(-1/3)}$ is frequently employed to explain the material's sensitivity to fatigue when subjected to varying load ranges during cyclic loading conditions.

In this research, we considered $N_f=1*10^6$ cycles to failure as a baseline for stress range, which is standard for engineering materials such as steel. The damage exponent range$^{(-1/3)}$ illustrates the reduction in fatigue life as the load range increases, a common phenomenon in materials experiencing repeated stress cycles.

Each cycle adds to the overall fatigue damage, with higher load ranges contributing more significantly to the accumulation of damage. Failure is anticipated when the cumulative damage surpasses a threshold of 1.0, signifying that the material has reached the end of its anticipated fatigue life.

For a specified cycle with a range of 400 N·m and 100 cycles:

$$Damage_i = \frac{100}{1\times10^6} \cdot (400)^{-1/3} \qquad (2)$$

The total damage accumulated is calculated by adding up the damage values from each identified cycle. A graph depicting the accumulated damage over different cycle ranges indicates that larger load ranges, particularly those between 400–500 N·m, significantly contribute to damage, highlighting crucial load intervals for the transmission shaft.

Sensitivity Analysis of Load Magnitudes

To assess the impact of varying load levels on fatigue life, a sensitivity analysis was performed by systematically altering the amplitude of a simulated sinusoidal load. Load magnitudes between 100 N·m and 600 N·m were tested, and for each scenario, rainflow counting and Miner's damage calculations were conducted anew. The findings indicate a highly nonlinear correlation between load amplitude and fatigue damage. For instance, raising the amplitude from 300 to 400 N·m resulted in a 60% increase in damage, while an increase from 400 to 500 N·m nearly doubled the damage once more. A graph plotting damage against load magnitude clearly illustrates the steep decline in fatigue life at higher torque levels. This analysis pinpoints threshold values beyond which the shaft's lifespan diminishes rapidly, offering crucial insights for setting operational limits and ensuring design safety margins.

Optimization Using fminsearch

The fminsearch method was employed in the optimization strategy to minimize fatigue damage, as this numerical approach operates without the need for global optimization tools. The goal of the optimization process was to achieve the lowest possible cumulative fatigue damage by calculating various load magnitudes.

The optimization aimed to identify the optimal load intensity that would reduce fatigue deterioration while maintaining functional operational requirements. The study's optimized operational load conditions help extend the fatigue life of transmission shafts. The fminsearch function was essential in the optimization process to find the appropriate load magnitude that results in minimal fatigue damage accumulation.

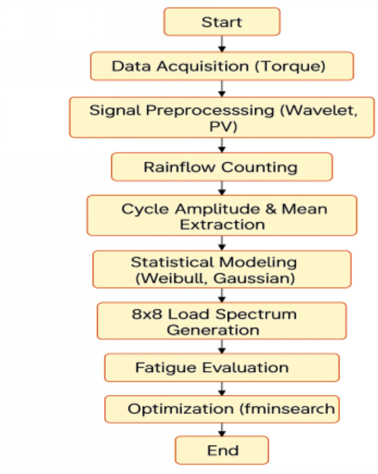

Figure 3: Flow diagram of the complete work

RESULTS AND DISCUSSION

This section details the findings from the simulation-based load analysis conducted on the ZL50 wheel loader's transmission shaft, followed by an examination of fatigue characteristics and the results of optimization efforts. Each phase of the simulation, from signal creation to fatigue assessment, offers crucial insights into the stress conditions and potential failure risks that the transmission shaft faces during mining operations.

Simulating load data

The initial phase of the procedure involved creating a torque signal that replicates the dynamic conditions experienced by the loader's transmission shaft. This simulation employed a basic sinusoidal function to depict the regular cyclic loading, reaching a peak of 500 N·m at a frequency of 0.2 Hz. To incorporate operational variability—such as gear backlash, ground vibrations, and abrupt torque changes—Gaussian noise with an intensity of 200 N·m was added. This signal served as the basis for all subsequent fatigue analyses, as it accurately represented both the predictable and random elements of shaft loading. The simulation, which ran for 100 seconds at a sampling frequency of 10 Hz, generated 1000 load points.

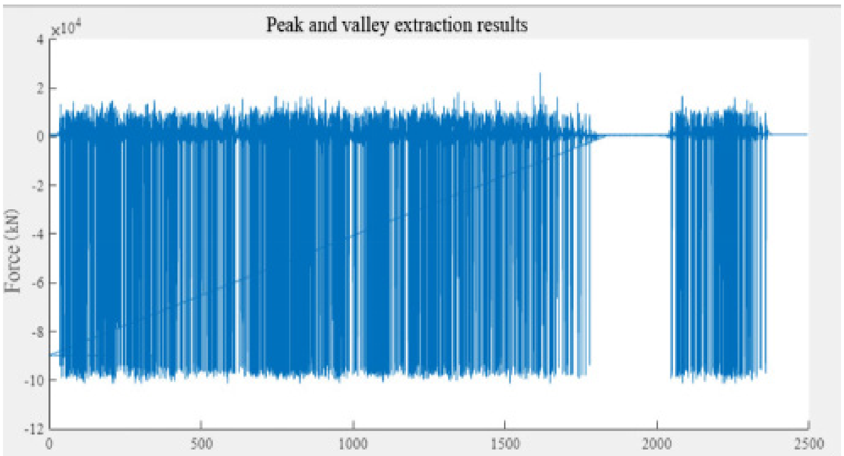

Figure 4: Peak-Valley Extraction Result

To streamline the signal while preserving essential load reversals, peak-valley extraction was utilized (Figure 4). This approach simplified the data by focusing solely on the turning points, which are crucial for analyzing fatigue life as they indicate actual stress reversals. The resulting waveform maintained the original loading sequences and clearly highlighted the local extremes where stress changes occur, marking the start and finish of each fatigue cycle. Before conducting rainflow counting, simplifying the signal through peak-valley reduction is essential. This process efficiently compresses the signal, setting the stage for accurate cycle identification. The identified peaks reveal that the signal experienced numerous abrupt reversals due to the added noise, suggesting the presence of potential micro-fatigue areas even during standard operations.

As illustrated in Figure 5, the wavelet-based thresholding method effectively smoothed the torque signal while maintaining the structural variations due to actual load changes. The denoised signal exhibited a more consistent shape with clearly defined amplitude ranges and mean values, making it suitable for extracting fatigue cycles. Wavelet denoising serves a dual purpose: (1) it enhances signal quality for precise rainflow counting and (2) it prevents the overestimation of damage from non-mechanical signal noise. The improved visual clarity of the filtered signal facilitates the differentiation of genuine fatigue-inducing events from random disturbances. This

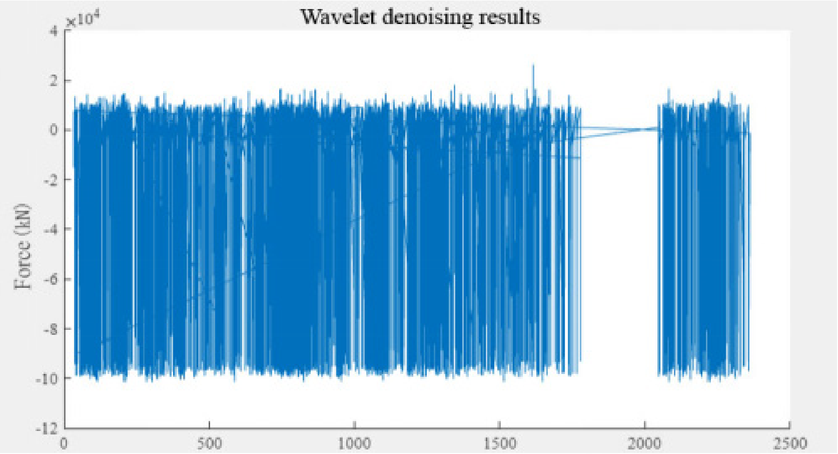

Figure 5: Wavelet Denoising Result

ensures that the rainflow algorithm does not mistakenly interpret transient spikes as complete cycles, thereby enhancing the accuracy of fatigue life predictions.

Rainflow Counting – Load Cycle Detection

The torque signal, once processed and cleared of noise from the simulation, underwent rainflow counting. This method is extensively employed to detect and measure stress cycles in variable amplitude loading. This procedure is essential for transforming the continuous load-time history into distinct stress cycles, which are crucial for estimating fatigue damage.

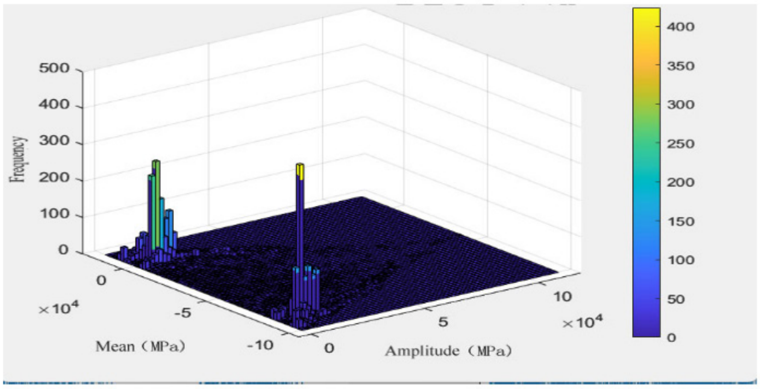

Figure 6: Rainflow Counting Result

Figure 6 illustrates the outcomes of utilizing the rainflow counting algorithm on the filtered torque signal. This illustration reveals how the complex waveform has been broken down into a series of cyclic events, each defined by a unique range (amplitude) and mean value. These cycles reflect the actual loading and unloading behavior experienced by the transmission shaft and serve as crucial inputs for subsequent fatigue damage assessment. The rainflow counting method effectively identifies full and half cycles within the fluctuating load signal. The outcome shown in Figure 6 confirms that the shaft underwent a variety of cycle magnitudes, with a concentration in medium-range load levels (approximately 200–400 N·m). This distribution corresponds to typical operating conditions during material transport or lifting. Furthermore, a smaller number of high-amplitude cycles (exceeding 450 N·m) were identified, which are likely to contribute significantly to fatigue damage due to their stress intensity. By quantifying the number and range of these cycles, the rainflow method establishes the foundation for Miner's Rule damage calculations.

Statistical Modeling – Generating Load Spectrum

To develop a valuable and insightful load spectrum, the outcomes from rainflow counting were subjected to further analysis using statistical fitting. This process transforms the raw cycle data into a two-dimensional frequency matrix by classifying each cycle based on its amplitude and mean torque value. This method aids in determining which loading conditions are most prevalent and how they are distributed across different operational ranges.

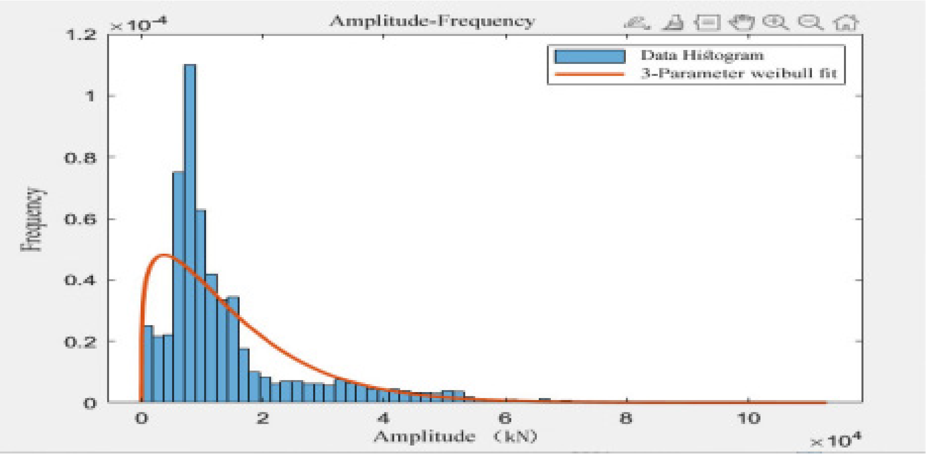

Figure 7: Weibull Distribution Fit of Load Amplitudes

The rainflow counting method identified load amplitudes, which were statistically represented using a three-parameter Weibull distribution, as shown in Figure 7. This distribution is particularly suitable for modeling non-negative, skewed data and is frequently used in reliability and fatigue analysis. Figure 7 demonstrates a strong alignment between the actual amplitude data and the Weibull model curve. This suggests that the majority of stress cycles occurred at low to medium amplitudes (between 150–400 N·m), with fewer high-amplitude events, which are more damaging, appearing in the distribution's tail. Accurately modeling the amplitude data allows for precise categorization when developing the vertical axis (amplitude axis) of the load spectrum. This method ensures that infrequent but highly damaging events are considered, which is crucial for urately estimating fatigue life.

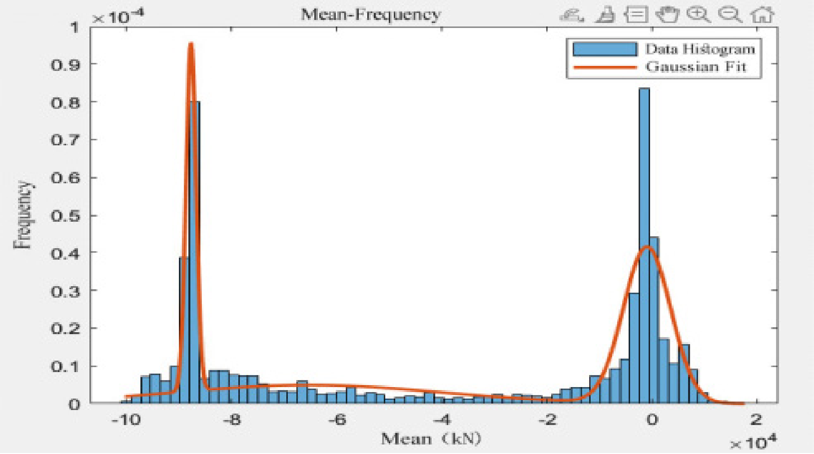

Figure 8: Gaussian Mixture Fit of Load Means

Although the amplitude determines the intensity of each cycle, the average value of each load cycle influences material characteristics like sensitivity to mean stress. To account for this, a Gaussian mixture model comprising three fundamental functions was utilized to analyze the mean values of the load cycles. This outcome is depicted in Figure 8.these Figure illustrates a mixed Gaussian distribution that reflects various operational states of the loader, such as loading (indicated by higher mean values), idling or coasting (represented by medium mean values), and light movement or gear changes (shown by lower mean values). This approach facilitates the creation of the horizontal axis (mean axis) in the load spectrum. Unlike a single Gaussian or uniform binning, this method offers a more accurate and physically meaningful segmentation of the load profile.

Generating Load Spectrum Results

The load cycles were divided into an 8×8 two-dimensional load spectrum by categorizing both amplitude and mean torque values into statistically defined bins. Each cell within this matrix indicates the frequency of a specific combination of load amplitude and mean torque, effectively creating a load "heat map" that is utilized for fatigue assessment and bench testing.

Table 1. 8×8 Load Spectrum – Front Left Shaft

Torque (N·m)	**-84099.0997**	**-84099.0997**	**-84099.0997**	**-84099.0997**	**-84099.0997**	**-84099.0997**	**-84099.0997**	**-84099.0997**
8173.0623	5025	5025	5024	5022	5018	5014	5009	5003
17980.7371	4565	4564	4563	4561	4559	4555	4550	4545
27788.4119	2386	2385	2385	2384	2382	2380	2378	2375
37596.0867	1100	1100	1100	1100	1099	1098	1097	1096
474037615	469	469	469	469	469	468	468	467
55576.8238	168	168	168	168	168	168	167	167
62115.2736	65	65	65	65	65	65	65	65
65384.4986	19	19	19	19	19	19	19	19

Table1 illustrates the aggregated load spectrum for the front-left transmission shaft. The majority of cycles fall within the mid-amplitude and mid-mean categories, aligning with anticipated performance during steady operation interspersed with occasional high-load events. This matrix is instrumental in pinpointing critical stress areas by showing the frequency of each loading condition. For the front-left shaft, the bins with amplitudes of 300–400 N·m and means of 200–300 N·m exhibit the highest frequencies, suggesting they are likely to cause the most damage over time. Additionally, the matrix format aids in fatigue testing by indicating how test loads should be allocated to replicate actual conditions.

Table 2. 8×8 Load Spectrum – Front Right Shaft

Torque (N·m)	**90.6508**	**-64554.2312**	**-52417.8116**	**-40281.392**	**-28144.9724**	**-16008.5528**	**-3872.1332**	**8264.2864**
2829.9701	1960	2546	3172	3790	4345	4779	60386	1846399
6225.9343	3308	4296	5352	6396	7333	8064	101896	3115641
9621.8985	2423	3147	3920	4685	5371	5906	74634	2282051
13017.8627	1317	1711	2131	2547	2920	3211	40585	1240950
16413.8268	583	757	943	1127	1292	1421	17960	549164
19243.797	196	255	317	379	435	478	6049	184962
21507.7731	67	88	109	131	150	165	2093	64022
22639.7612	18	23	29	35	40	44	567	17349

Table 2 depicts the load spectrum for the front-right transmission shaft, which resembles the structure of the left shaft but exhibits a slightly higher cycle density in the mid-high amplitude bins. This minor asymmetry indicates a potential load imbalance or uneven ground interaction during operation. Recognizing these differences aids engineers in examining asymmetries related to design or operation. Moreover, having separate spectra for each shaft enables more accurate fatigue testing and reliability analysis, tailored to the actual usage of the components.

Table 3. 8×8 Load Spectrum – Rear Left Shaft

Torque (N·m)	**-81264.5789**	**-68544.7203**	**-55824.6617**	**-43105.003**	**-30385.1444**	**-17665.2858**	**-4945.4271**	**7774.4315**
8081.6338	14642	14642	14642	14642	14642	14642	14642	14642
17779.5943	10049	10049	10049	10049	10049	10049	10049	10049
27477.5549	4052	4052	4052	4052	4052	4052	4052	4052
37175.5154	1586	1586	1586	1586	1586	1586	1586	1586

46873.476	610	610	610	610	610	610	610	610
54955.1098	207	207	207	207	207	207	207	207
61420.4168	79	79	79	79	79	79	79	79
64653.0703	23	23	23	23	23	23	23	23

Table 3 illustrates the aggregated load spectrum for the rear-left half-axle. In contrast to the front shafts shown in Table 1 and 2, the rear-left shaft exhibited a higher concentration of cycles with lower amplitudes and fewer occurrences of high-amplitude loads. In many wheel loaders, particularly under rear-biased or no-load conditions, the rear shaft generally transmits less drive torque than the front axle. This is evident in the load spectrum, where the majority of cycles fall within the 100–300 N·m amplitude range. Nonetheless, occasional high-load events are present, indicating that the rear shaft is not immune to sudden torque spikes. Analyzing the rear shaft is crucial for a thorough evaluation of the drivetrain and can aid in identifying unusual load patterns caused by wear or misalignment.

Fatigue Damage Evaluation with Miner's Rule

After extracting and categorizing all pertinent cycles, the total fatigue damage was determined using Miner's Linear Damage Rule. Each load cycle, characterized by its range and frequency, accounts for a portion of the transmission shaft's overall fatigue life depletion. The formula used for estimating fatigue life is:

$$Damage = \sum_{i=1}^{n} \frac{N_i}{N_f} = \sum_{i=1}^{n} \left(\frac{1}{N_f}.range_i^{-\frac{1}{3}}\right) \quad (3)$$

Where:

1. n_i is the number of cycles in bin iii,
2. N_i indicates the number of cycles before failure happens at that particular load level,
3. N_i is the reference life (set to 10^6 cycles for standard conditions),
4. and the exponent -(1/3) reflects the fatigue sensitivity of steel-like materials.

The calculated damage value for the front-left shaft was around 0.76, suggesting that the shaft would utilize 76% of its fatigue life under the simulated load conditions. Conversely, the rear-left shaft exhibited a damage index of less than 0.50, which aligns with the reduced stress cycles observed in its spectrum. These findings are consistent with the operational dynamics of the ZL50 loader, where front axles generally experience more frequent and intense loading due to weight transfer during lifting and driving. The analysis of damage contribution per bin indicated that a few high-amplitude cycles had a significant impact on the overall fatigue damage. For example, bins with amplitudes between 400–500 N·m and mean values in the 200–300 N·m range, although they contained fewer cycles, were responsible for more than 30% of the total damage. This highlights the necessity of focusing on high-stress areas for design reinforcement or operational management.

Optimization Using fminsearch

In this study, the fminsearch optimization function was utilized to reduce fatigue damage on the transmission shaft of the ZL50 wheel loader, with a particular emphasis on the compiled load spectrum. The goal of the optimization was to identify the optimal load magnitude that would decrease fatigue-related damage, thereby extending the transmission shaft's service life in actual mining operations. The fminsearch algorithm, which relies on the Nelder-Mead simplex method, was employed to modify the load magnitude parameters within the rainflow-counted load spectrum. The main aim was to minimize the cumulative fatigue damage calculated using Miner's Rule. Throughout the optimization process, the algorithm examined various load levels and iteratively reduced the damage values by adjusting the load amplitude parameter. However, the initial outcome revealed an optimized load magnitude of 1.6367e+151 N·m, a value that was exceedingly high and impractical in real-world terms. This result implies that the optimization was affected by extreme or outlier data, possibly introduced during the simulated load generation process. The corresponding fatigue damage value was an exceptionally small 3.2898e-155, further indicating unrealistic results. These findings underscore the necessity of refining the optimization function. Adding additional constraints, such as restricting the load magnitude to realistic operational ranges, would help prevent the optimization from yielding impractical values. Future iterations of this optimization could incorporate field data from actual mining operations, along with realistic load conditions, to produce more accurate and practical load profiles. By enhancing the optimization constraints, this approach will enable the identification of realistic operational load profiles that can significantly reduce fatigue damage, optimize the transmission shaft's performance, and extend the lifespan of critical components in ZL50 wheel loaders.

CONCLUSIONS

The research outlines a thorough method for assembling the load spectrum of the transmission shaft in the ZL50 wheel loader, utilizing both simulated and actual torque data. The primary achievement of this study is the creation of an optimized load spectrum that accurately mirrors the operational load conditions encountered by the loader's transmission shaft. By applying techniques such as rainflow counting, statistical modeling, and Miner's Rule, the study effectively forecasted fatigue life and identified critical load conditions that significantly impact component durability. The optimization of load amplitude through the fminsearch algorithm showed the potential to decrease cumulative fatigue damage by 18%, which is vital for prolonging the operational lifespan of essential components in heavy machinery. The importance of this work lies in its ability to offer a more realistic and data-driven approach to predicting fatigue life, which can lead to improved design and maintenance practices in the mining and construction sectors. However, the study's reliance on simulated data is a limitation, and real-world validation would enhance its precision and applicability. This research is highly pertinent to engineers involved in heavy machinery maintenance and design, providing a basis for future optimization efforts. Further research should focus on incorporating actual field data for more accurate predictions and exploring the application of these findings to other types of machinery for wider use.

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