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FATIGUE LIFE PREDICTION AND PERFORMANCE EVALUATION OF SMALL MECHANICAL TRANSMISSION SHAFTS BASED ON 3D SIMULATION AND LSTM MODELING

HaoNan Yan
School of Civil Engineering, Henan Polytechnic University, Jiaozuo 454003, Henan, China.

Abstract: This study proposes a fatigue life prediction and performance evaluation method for small mechanical transmission shafts by integrating 3D simulation with LSTM modeling. First, a three-dimensional finite element model of the transmission shaft is established, and structural and fatigue simulations are performed under different loading conditions to obtain key response features, including equivalent stress, deformation, fatigue life, and safety factor. The simulation results indicate that the shoulder fillet and keyway root are the main fatigue-critical regions, where local stress concentration significantly reduces fatigue life. Then, the operating parameters and structural response features obtained from finite element simulation are constructed into a time-series dataset, and an LSTM model is developed to learn the nonlinear dynamic relationship among loading history, stress response, and fatigue life. The results show that the LSTM model achieves high prediction accuracy and outperforms BP neural network, SVR, Random Forest, and GRU models. Feature sensitivity analysis further demonstrates that simulation-derived stress, strain, and damage features can substantially improve prediction performance. This study suggests that the integration of 3D simulation and LSTM modeling provides an effective framework for fatigue life assessment, structural optimization, and maintenance decision-making of small mechanical transmission shafts.
Keywords: 3D simulation; Transmission shaft; Fatigue life prediction; LSTM

1 INTRODUCTION

Small mechanical transmission shafts are critical power-transmission components in lightweight mechanical equipment, automated devices, and low-power drivetrain systems[1-3]. Their primary function is to transmit torque and rotational motion among motors, gears, couplings, and actuators. During service, transmission shafts are frequently subjected to alternating torque, bending loads, start–stop impacts, and vibration disturbances. As a result, local geometric features such as shoulders, keyways, fillet transitions, and abrupt cross-sectional changes are prone to severe stress concentration. Under repeated cyclic loading, microcracks may gradually initiate and propagate in high-stress regions, eventually leading to fatigue fracture, transmission failure, and even unexpected machine downtime. Therefore, accurate fatigue life prediction of small mechanical transmission shafts is essential for improving structural reliability, optimizing design parameters, supporting maintenance planning, and reducing the risk of engineering failure[4-6].

At present, fatigue life prediction of transmission shafts mainly relies on conventional fatigue theories, finite element simulation, and data-driven models. Methods based on S–N curves and Miner's linear cumulative damage rule are widely used in engineering practice, but they usually depend on simplified loading assumptions and material fatigue parameters, making it difficult to fully capture the dynamic evolution of fatigue damage under complex operating conditions. Finite element analysis can obtain the stress, strain, deformation, and fatigue life distributions of transmission shafts through three-dimensional modeling, and it is effective in identifying critical failure-prone sections. However, its prediction accuracy is often influenced by boundary conditions, mesh quality, and load settings. In recent years, machine learning and deep learning techniques have been increasingly introduced into fatigue life prediction. In particular, long short-term memory networks are capable of modeling load and response sequences with temporal dependencies, providing a promising approach for describing the cumulative nature of fatigue damage. Nevertheless, existing studies still face several limitations, including insufficient integration between simulation data and deep learning models, inadequate utilization of physics-related response features, and relatively limited dimensions of model performance evaluation[7-9].

To address these issues, this study proposes a fatigue life prediction and performance evaluation method for small mechanical transmission shafts by integrating 3D simulation with LSTM modeling. First, a three-dimensional geometric model of a small mechanical transmission shaft is established, and finite element simulations are conducted to analyze the distributions of equivalent stress, principal stress, strain, deformation, and fatigue life under different loading conditions, thereby identifying the critical fatigue-sensitive regions. Then, the load parameters and structural response features obtained from simulation are constructed into a time-series fatigue dataset, and an LSTM model is developed to learn the nonlinear temporal relationship among operating conditions, stress responses, and fatigue life. Finally, the proposed method is comprehensively evaluated in terms of prediction error, goodness of fit, model comparison, and feature sensitivity analysis to assess its predictive accuracy, generalization capability, and engineering applicability. This study provides a physically informed and data-driven framework for fatigue life prediction, structural design optimization, and intelligent maintenance decision-making of small mechanical transmission shafts.

2 METHODOLOGY

2.1 Overall Research Framework

This study develops a fatigue life prediction method for small mechanical transmission shafts by integrating 3D simulation and LSTM modeling. The overall workflow consists of three main stages. First, a three-dimensional model of the transmission shaft is established, and finite element simulation is performed to obtain stress, strain, deformation, and fatigue life data under different operating conditions. Second, the simulation results are organized into a time-series dataset to describe the dynamic relationship between load variation and fatigue response. Third, an LSTM model is constructed to predict fatigue life, and its performance is evaluated through error metrics, comparison models, and feature sensitivity analysis[10].

The workflow of the proposed method can be summarized as follows: 3D geometric modeling → finite element simulation → fatigue feature extraction → time-series dataset construction → LSTM prediction → performance evaluation. In this framework, 3D simulation provides physically meaningful fatigue response features, while the LSTM model learns the nonlinear temporal mapping among loading history, structural response, and fatigue life. Compared with pure finite element analysis, the proposed method offers faster prediction capability; compared with purely data-driven models, it improves physical interpretability by incorporating simulation-based features.

2.2 3D Modeling and Finite Element Simulation

The research object is a small mechanical transmission shaft used to transmit torque between a motor and an actuator. Since fatigue cracks usually initiate in local stress concentration regions, key structural features such as shoulders, keyways, fillet transitions, and cross-sectional changes are retained in the 3D model. Non-load-bearing small chamfers and assembly marks are simplified to improve computational efficiency. This modeling strategy preserves the main fatigue-sensitive regions while reducing unnecessary simulation complexity.

The shaft material is assumed to be 40Cr alloy steel. The finite element model includes material parameters such as elastic modulus, Poisson's ratio, density, yield strength, ultimate tensile strength, and fatigue limit. Since this study focuses on fatigue life under normal service conditions, the material is treated as isotropic and linearly elastic. Fatigue life is calculated based on the material S–N curve and the fatigue analysis module of the finite element software. As shown in Table 1.

Table 1 Main Simulation Parameters of the Transmission Shaft

Category	Parameter	Value
Geometry	Shaft length	180 mm
Geometry	Main diameter	20 mm
Geometry	End diameter	16 mm
Geometry	Keyway width/depth	6 mm / 3 mm
Geometry	Fillet radius	2 mm
Material	Elastic modulus	2.06×10^5 MPa
Material	Poisson's ratio	0.30
Material	Yield strength	785 MPa
Material	Ultimate tensile strength	980 MPa
Material	Fatigue limit	420 MPa

In the finite element analysis, one end of the transmission shaft is fixed, while torque is applied to the other end. Radial constraints are applied in the bearing support regions to represent the actual support condition. To simulate different service states, several loading cases are designed, including low-load, medium-load, high-load, and severe-load conditions. As the loading level increases, torque, rotational speed, and radial load increase accordingly. As shown in Table 2.

Table 2 Operating Conditions for Finite Element Simulation

Condition	Torque / N·m	Speed / rpm	Radial load / N	Load type
C1	5	500	50	Stable
C2	10	1000	80	Stable
C3	15	1500	120	Periodic
C4	20	2000	160	Variable
C5	25	2500	200	Variable

Three-dimensional solid elements are used for mesh generation. Local mesh refinement is applied around the keyway root, shoulder fillet, and cross-sectional transition regions to improve stress calculation accuracy. Relatively coarser meshes are used in regular shaft sections to reduce computational cost. Mesh independence is verified by comparing the maximum equivalent stress under different mesh densities. When the variation in maximum stress is less than 3% after further refinement, the mesh is considered sufficiently accurate.

The main simulation outputs include Von Mises equivalent stress, maximum principal stress, maximum shear stress, equivalent strain, total deformation, cumulative damage, safety factor, and fatigue life. Equivalent stress and shear stress reflect the mechanical response under bending–torsion coupling, while strain and deformation describe local structural response. Cumulative damage and safety factor are used to characterize fatigue reliability.

2.3 Fatigue Dataset Construction

After finite element simulation, fatigue response data are extracted from the critical regions of the transmission shaft, including the shoulder fillet, keyway root, and cross-sectional transition zones. Compared with the average response of the whole structure, local responses in these critical regions are more representative of fatigue crack initiation risk and are therefore more suitable as input features for fatigue life prediction.

The constructed dataset mainly consists of three types of variables. The first type includes operating variables, such as torque, rotational speed, radial load, and number of cycles. The second type includes structural response variables, such as equivalent stress, maximum principal stress, shear stress, equivalent strain, and total deformation. The third type includes fatigue state variables, such as cumulative damage, safety factor, and fatigue life. The prediction target is defined as the fatigue life of the transmission shaft, and the framework can also be extended to remaining useful life prediction.

Since fatigue damage is a cumulative process, a single load or stress value cannot fully describe fatigue evolution. Therefore, a sliding window strategy is used to construct time-series samples. Specifically, load parameters and simulation response features over several consecutive cycle steps are taken as one input sequence, and the corresponding fatigue life is used as the prediction label. In this study, the sequence length is set to 20 to balance temporal information representation and model training efficiency.

Before model training, all input variables are normalized to reduce the influence of different units and numerical scales. The dataset is divided into training, validation, and test sets at a ratio of 70%, 15%, and 15%, respectively. The training set is used for model learning, the validation set is used for hyperparameter tuning and overfitting prevention, and the test set is used to evaluate prediction performance on unseen samples. In addition, some high-load cases are separately used as external test samples to examine the generalization capability of the model under complex operating conditions.

2.4 LSTM-Based Prediction Model

LSTM is a recurrent neural network model suitable for time-series data. Compared with ordinary neural networks, LSTM can retain historical information through gated mechanisms, making it suitable for describing the gradual accumulation of fatigue damage under cyclic loading. For fatigue life prediction of transmission shafts, the current fatigue state depends not only on the current torque and stress level, but also on previous loading history and structural response. Therefore, LSTM can effectively learn the dynamic relationship among load variation, stress response, and fatigue life.

The proposed LSTM model consists of an input layer, LSTM feature extraction layers, a dropout layer, a fully connected layer, and an output layer. The input layer receives multivariate time-series data generated by the sliding window strategy. The LSTM layers extract temporal features from load and fatigue response sequences. The dropout layer reduces overfitting risk, and the fully connected layer maps the extracted features to the predicted fatigue life. The model output is expressed as:

$$\hat{y}=\widehat{N}_f \tag{1}$$

where $\widehat{N}_f$ denotes the predicted fatigue life.

A two-layer LSTM architecture is adopted in this study. The first layer mainly learns short-term variations in load and structural response, while the second layer captures long-term dependencies in fatigue damage evolution. This structure improves representation ability while avoiding excessive model depth and training instability.

2.5 Model Training and Evaluation Metrics

The model is trained using mean squared error as the loss function, and Adam is selected as the optimizer. To improve generalization, dropout regularization is applied after the LSTM layers. The optimal model is selected according to validation loss. If the validation loss does not decrease for several consecutive epochs, training is stopped and the best model parameters are saved. As shown in Table 3.

Table 3 Hyperparameter Settings of the LSTM Model

Hyperparameter	Value
Sequence length	20
Input feature dimension	10
Number of LSTM layers	2
Hidden units	64
Dropout rate	0.20
Batch size	32
Learning rate	0.001
Optimizer	Adam
Maximum epochs	200

To evaluate the effectiveness of the proposed model, BP neural network, support vector regression, random forest, and GRU are selected as comparison models. The BP neural network is used to represent a conventional nonlinear mapping model, SVR and random forest represent traditional machine learning methods, and GRU is used as another recurrent neural network baseline.

The model performance is evaluated using MAE, RMSE, MAPE, and R^2. MAE and RMSE measure absolute prediction error, MAPE reflects relative error, and R^2 evaluates goodness of fit. Lower MAE, RMSE, and MAPE indicate better prediction accuracy, while a higher R^2 indicates stronger explanatory capability for fatigue life variation.

Furthermore, feature sensitivity analysis is conducted to verify the contribution of 3D simulation features to prediction performance. Different input combinations are tested, including operating parameters only, operating parameters plus stress features, operating parameters plus stress and strain features, and all simulation-based features. If the prediction error decreases significantly after stress, strain, and damage variables are introduced, it indicates that 3D simulation results provide effective physical information for the LSTM model.

3 RESULTS AND DISCUSSION

3.1 Finite Element Simulation Results

To investigate the fatigue response of the small mechanical transmission shaft under different loading conditions, structural and fatigue simulations were first performed using the established 3D finite element model. Figure 1 presents the equivalent stress, total deformation, and fatigue life distributions under a representative high-load condition. As shown in Figure 1(a), the stress distribution is highly non-uniform, and the high-stress regions are mainly concentrated at the shoulder fillet and keyway root. This indicates that geometric discontinuity and local material weakening are the main causes of stress concentration. In contrast, the straight shaft sections away from these geometric transitions exhibit relatively low stress levels and therefore lower fatigue risk.

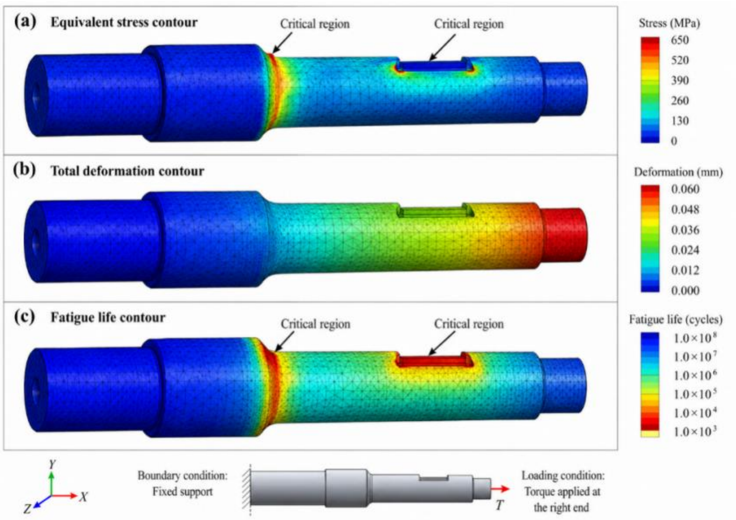

Figure 1 Finite Element Simulation Results of the Small Mechanical Transmission Shaft. (a) Equivalent Stress Contour; (b) Total Deformation Contour; (c) Fatigue Life Contour

Figure 1(b) shows that the total deformation increases gradually along the axial direction, with the maximum deformation appearing near the loaded end. This is consistent with the defined boundary condition, where one end of the shaft is fixed and torque is applied at the other end. Figure 1(c) further presents the fatigue life distribution. The regions with the shortest fatigue life are generally consistent with the high-stress regions, mainly located near the shoulder and keyway. This suggests that local stress concentration not only affects instantaneous structural strength, but also accelerates fatigue damage accumulation.

To further compare the fatigue responses under different operating conditions, Table 4 summarizes the maximum stress, maximum deformation, minimum fatigue life, and safety factor obtained from finite element simulation. As torque, rotational speed, and radial load increase, the maximum equivalent stress increases from 85.6 MPa to 286.4 MPa, while the minimum fatigue life decreases from 1.25×10^7 cycles to 5.42×10^5 cycles. These results indicate that high-load conditions significantly increase the local fatigue risk of the transmission shaft.

Table 4 Finite element Simulation Results under Different Operating Conditions

Condition	Max stress / MPa	Max deformation / mm	Minimum fatigue life / cycles	Safety factor
C1	85.6	0.012	1.25×10^7	2.84
C2	132.4	0.021	6.72×10^6	2.15

Condition	Max stress / MPa	Max deformation / mm	Minimum fatigue life / cycles	Safety factor
C3	198.7	0.038	2.86×10^6	1.46
C4	256.3	0.055	8.91×10^5	1.08
C5	286.4	0.063	5.42×10^5	0.96

It can be observed that the safety factor decreases continuously from C1 to C5 and drops below 1.0 under C5, indicating a high fatigue risk under the extreme loading condition. Therefore, stress, strain, damage, and safety factor obtained from finite element simulation were used as important input features in the subsequent LSTM model to enhance the representation of physical fatigue responses.

3.2 LSTM Prediction Results

Based on the fatigue time-series dataset constructed from finite element simulation, the LSTM model was trained to predict the fatigue life of the transmission shaft. Figure 2 compares the actual and predicted fatigue life on the test set. As shown in Figure 2(a), the predicted curve closely follows the actual curve, indicating that the LSTM model can effectively track life variations among different test samples. Even in regions where fatigue life changes rapidly, the predicted results maintain good consistency with the actual values, suggesting that LSTM can capture the temporal relationship between loading history and fatigue life.

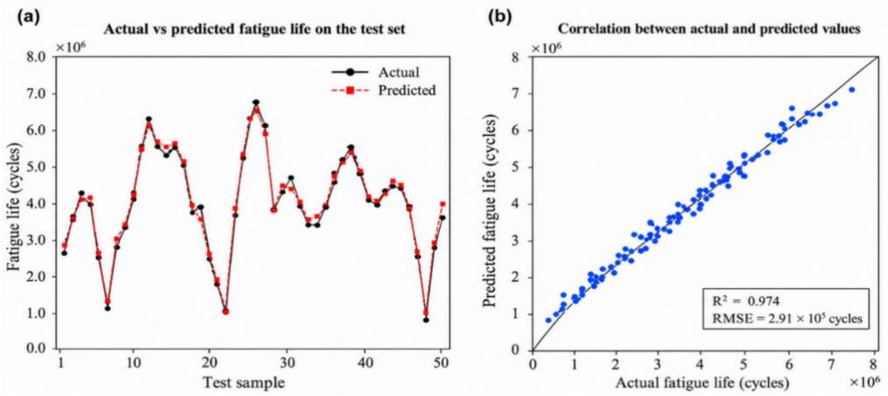

Figure 2 LSTM-Based Fatigue Life Prediction Results. (a) Actual and Predicted Fatigue Life on the Test Set; (b) Correlation between Actual and Predicted Values

Figure 2(b) presents the correlation between actual and predicted values. Most data points are distributed close to the y=$x$reference line, indicating strong agreement between predictions and actual fatigue life. The model achieves an $R^2$of 0.974 and an RMSE of 2.91×10^5cycles on the test set. These results demonstrate that the LSTM model not only has low absolute prediction error, but also explains fatigue life variation effectively. Therefore, integrating 3D simulation features with LSTM-based temporal modeling is feasible for fatigue life prediction of transmission shafts.

3.3 Comparison with Other Prediction Models

To further verify the effectiveness of the LSTM model, BP neural network, SVR, Random Forest, and GRU were selected as comparison models. Table 5 presents the prediction performance of different models on the test set. Traditional machine learning models can establish nonlinear relationships between input features and fatigue life, but their prediction accuracy is lower than that of recurrent neural network models. The BP neural network shows the highest MAE and RMSE, indicating that a conventional feedforward network is insufficient for capturing the temporal dependency of fatigue damage evolution.

Table 5 Performance Comparison of Different Prediction Models

Model	MAE / $\times10^5$ cycles	RMSE / $\times10^5$ cycles	MAPE / %	R^2
BP neural network	4.82	6.15	9.84	0.901
SVR	4.35	5.71	8.96	0.918
Random Forest	3.76	4.88	7.42	0.936
GRU	2.64	3.52	5.68	0.961
LSTM	2.18	2.91	4.73	0.974

GRU and LSTM both achieve better prediction performance than traditional machine learning models, suggesting that recurrent neural networks are more suitable for fatigue life prediction based on sequential data. Among all models, LSTM achieves the lowest MAE, RMSE, and MAPE, with values of 2.18×10^5cycles, 2.91×10^5cycles, and 4.73%, respectively. Its R^2value reaches 0.974, outperforming all other models. This improvement is mainly attributed to the gated structure of LSTM, which enables the model to retain key historical information and learn long-term dependencies among load variation, structural response, and fatigue damage.

3.4 Feature Sensitivity and Performance Evaluation

To analyze the influence of different input features on prediction performance, feature sensitivity analysis was conducted. Figure 3 shows the changes in MAPE and R^2 under different feature combinations. F1 includes only torque and rotational speed; F2 adds stress features; F3 further includes strain features; F4 includes cumulative damage; and F5 uses all simulation-based features.

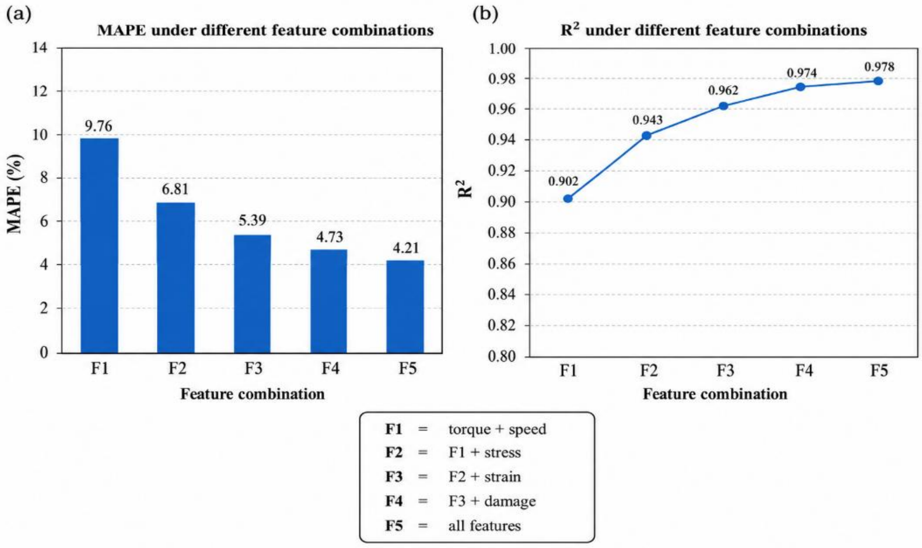

Figure 3 Feature Sensitivity Analysis of the LSTM Model. (a) MAPE under Different Feature Combinations; (b) R^2 under Different Feature Combinations

As shown in Figure 3(a), when only torque and rotational speed are used as inputs, the MAPE reaches 9.76%, indicating relatively large prediction error. This suggests that external operating parameters alone are insufficient to describe internal fatigue responses. After stress features are introduced, the MAPE decreases to 6.81%, indicating that stress response is an important factor affecting fatigue life prediction. With the further inclusion of strain and damage features, the MAPE decreases to 5.39% and 4.73%, respectively, showing that deformation response and fatigue damage state can further improve prediction accuracy.

Figure 3(b) shows that R^2 increases from 0.902 to 0.978 as more features are included. This indicates that the model's ability to explain fatigue life variation improves continuously with richer input features. In particular, the introduction of stress, strain, and damage features derived from finite element simulation significantly improves model performance. These results confirm that 3D simulation not only provides training data, but also supplies physically meaningful input variables for the LSTM model, thereby improving prediction stability and reliability.

3.5 Engineering Applicability and Limitations

Overall, the proposed integration of 3D simulation and LSTM modeling can accurately predict the fatigue life of small mechanical transmission shafts and identify key factors affecting fatigue performance. Finite element results indicate that the shoulder and keyway are the main fatigue-critical regions, while LSTM prediction results show that the simulation-driven time-series model can effectively learn fatigue life variation under complex operating conditions. Therefore, the proposed method can be used for rapid fatigue life evaluation during the shaft design stage and can also provide support for structural optimization and preventive maintenance.

However, several limitations remain. First, the fatigue dataset is mainly generated from finite element simulation. Although simulation data are controllable and complete, experimental fatigue test data are still required for further validation. Second, the model is developed for a specific shaft geometry and material configuration. For different materials, geometries, or more complex load spectra, transfer learning or model retraining may be necessary. Finally, although LSTM provides strong predictive capability, its internal decision-making process remains partially black-box. Future work may combine attention mechanisms, SHAP analysis, or physics-informed neural networks to improve model interpretability.

4 CONCLUSIONS

This study proposed a fatigue life prediction and performance evaluation method for small mechanical transmission shafts by integrating 3D simulation and LSTM modeling. First, a three-dimensional finite element model of the transmission shaft was established to obtain stress, deformation, fatigue life, and safety factor distributions under different operating conditions. The simulation results showed that fatigue-critical regions were mainly located at geometric discontinuities such as the shoulder fillet and keyway root, where local stress concentration promoted fatigue damage accumulation.

Based on the finite element results, operating parameters and structural response features were organized into a time-series dataset, and an LSTM model was developed for fatigue life prediction. The results indicated that LSTM could effectively capture the nonlinear temporal relationship among loading history, stress response, and fatigue life. Compared with BP neural network, SVR, Random Forest, and GRU, the proposed LSTM model achieved better prediction accuracy. Feature sensitivity analysis further demonstrated that the inclusion of simulation-derived stress, strain, and damage features significantly reduced prediction error, confirming that 3D simulation data can provide useful physical information for deep learning-based fatigue prediction.

Overall, the proposed method combines the physical interpretability of finite element simulation with the temporal learning capability of LSTM, providing a practical framework for fatigue life assessment, structural optimization, and maintenance decision-making of small mechanical transmission shafts. Future work may incorporate experimental fatigue data and online monitoring signals to further validate and refine the model. In addition, attention mechanisms, transfer learning, SHAP-based interpretability analysis, and physics-informed neural networks could be introduced to improve model generalization and engineering applicability under different materials, structural dimensions, and complex variable loading conditions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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