**LSTM-based Fault Severity Estimation in Rotating Machinery using Predictive Accuracy**

Abstract

Monitoring the health of rotating machinery plays a pivotal role in ensuring the reliability of industrial processes. Bearings, being significant sources of failure in such equipment, necessitate the implementation of effective fault diagnosis methods. While traditional diagnostic methods involve classifying signals based on different fault types and levels, it's important to note that fault occurrence is a continuous process rather than a discrete one. As a result, the adoption of continuous indicators that accurately reflect fault severity is imperative for timely and precise detection. This paper proposes a novel approach that leverages vibration signals and Long Short-Term Memory (LSTM) time series prediction for fault detection in rotating machinery. Through the extraction of pertinent features from vibration signals and the utilization of LSTM models for prediction, the severity of faults can be effectively quantified. The experimental results reveal a gradual reduction in prediction accuracy with increasing fault severity. By establishing appropriate thresholds, the method enables the early identification of incipient fault indications, facilitating timely machinery shutdown as a preventive measure. Moreover, this approach demonstrates robustness across various fault types, thus exhibiting its applicability as a comprehensive solution for mechanical system fault detection.

*Keywords*: fault severity estimation; LSTM; time series prediction; vibration signal; rotating machinery

**1. Introduction**

Monitoring the health condition of rotating machinery stands as a pivotal endeavor in ensuring the reliability of industrial processes. Among the components of rotating machinery, rolling element bearings emerge as particularly critical. Thus, effective diagnosis of bearing faults assumes a pivotal role in curtailing maintenance expenses with-in manufacturing systems.

Modern industries heavily rely on rotating machinery, which operate under harsh conditions for extended periods, rendering them susceptible to component failures that entail safety risks and economic losses. Consequently, the vigilance over the well-being of rotating machinery becomes indispensable. Notably, bearings, extensively deployed mechanical elements in rotating systems, stand out as significant sources of failures within such equipment. Bearing faults alone can constitute up to 44% of the total fault occurrences in certain devices [1]. Consequently, research in fault detection and diagnosis within rotating machinery predominantly revolves around bearing faults.

When it comes to fault diagnosis, a multitude of parameters can be monitored, such as vibrations, acoustic emissions, currents, flow, speed, pressure, temperature, lubricant conditions, strain, wear, and rotor-to-stator rubbing, among others. Among these parameters, vibration emerges as the widely acknowledged, extensively utilized, and highly effective condition monitoring technique in the realm of rotary machinery. As evidenced by Malla and Panigrahi's research in 2019 [2], vibration-based condition monitoring has demonstrated the ability to detect ap-proximately 90% of machine faults or failures.

Drawing from prior research, techniques for assessing fault severity can be broadly categorized into signal processing-based methods and learning-based methods [3]. Traditional signal processing techniques involve extracting features from signals obtained from various sources linked to fault severity estimation and bearing wear assessment. This is achieved through the analysis of specific frequencies or the computation of indicators that characterize the faults. Esteemed methods in this category encompass the Fourier transform, Hilbert transform [4], wavelet transform [5], empirical mode decomposition [6], and related methodologies.

Since its inception, deep learning has achieved remarkable feats across numerous domains and has found extensive applications in engine fault diagnosis. Deep learning methods for diagnosing faults in rotating machinery can be broadly classified into two categories.

The first category concentrates on detecting fault locations or types, with fault classification as the primary goal. This domain has yielded highly promising results. Noteworthy achievements include CNN-LSTM (Convolutional Neural Network-Long Short-Term Memory) achieving 99.6% accuracy [7], SDAE (Stacked Denoising Autoencoder) attaining 99.83% accuracy [8], and EDAE (Ensemble Deep Autoencoder) reaching 99.15% accuracy [9], among other notable outcomes.

The second category involves computing a degradation indicator that quantifies machinery health, facilitating the assessment of fault severity. Regression models are often employed for this purpose. Shen et al. [10], for instance, utilized an SVR (Support Vector Regression) model to quantitatively estimate fault sizes. Additionally, it's possible to treat varying levels of fault severity as distinct categories, leveraging classifiers to achieve the task. Lei et al. [11] employed WNN (Wavelet Neural Networks) as a severity classifier, with input features selected from the most sensitive Intrinsic Mode Function (IMF) obtained via Empirical Mode Decomposition (EMD). The selection criteria were grounded in the mean and standard deviation of kurtosis values for data samples of each IMF.

This study argues that in real operational contexts, the severity of mechanical faults inherently exhibits continuous variation, spanning from mild to severe. Categorizing faults based on predetermined severity levels becomes impractical when applied to real-world scenarios. However, a significant portion of existing research in this field predominantly employs artificial intelligence methods tailored to classification. Thus, this paper endeavors to introduce an artificial intelligence-driven approach for establishing a degradation indicator for rotating machinery faults, with a particular focus on engine vibration signals. This indicator embodies the universality and context-independence inherent in artificial intelligence, while also maintaining continuity, rendering it suitable for practical applications.

In real operational environments, mechanical faults inherently manifest as a continuous spectrum of severity, ranging from mild to severe. Attempting to categorize these faults into predefined severity levels becomes impractical when applied to real-world scenarios. Despite this, a significant portion of the existing research in this field primarily relies on artificial intelligence methods that are centered around fault classification. Consequently, the objective of this paper is to introduce an artificial intelligence-based approach for establishing a degradation indicator for faults in rotating machinery, with a specific focus on the utilization of engine vibration signals. This indicator combines the universality and robustness inherent in artificial intelligence with the crucial aspect of maintaining continuity, thereby rendering it highly suitable for practical applications.

To attain this goal, the study employs the extraction of time and frequency domain features from the original vibration signals. These features are subsequently utilized in conjunction with an LSTM network to predict sequences of the selected features. In instances involving fault-free signals, the predictions are anticipated to closely align with the actual observations. Conversely, when forecasts deviate inaccurately from the observed values, it indicates the presence of unidentified faults. The degree of this inaccuracy corresponds to the magnitude of the fault. The efficacy of this methodology has been verified across a range of datasets.

This paper follows the subsequent structure: Section 1 introduces the context and current research landscape pertaining to fault detection and estimation in rotating machinery. Section 2 elucidates fundamental concepts, encompassing time and frequency domain features, LSTM networks, and the Dynamic Time Warping algorithm. Within Section 3, we propose a novel fault detection approach. Section 4 offers an account of the experimental validation of the proposed method using simulated vibration signals, coupled with a comprehensive analysis of the outcomes. Finally, Section 5 draws conclusions grounded in the insights garnered from the study's findings.

**2. Theoretical fundamental**

This section offers insights into the theorems employed in the proposed diagnosis approach.

*2.1. Features extraction*

As bearing faults progress, the mechanical system undergoes an increase in vibration intensity, manifesting in the vibration signals. To avert machinery breakdown and ensure optimal production efficiency, the challenge lies in real-time monitoring of defect severity, enabling timely interventions guided by defect trends. Hence, it becomes imperative to extract sensitive features that precisely mirror the current health status of the bearing. This step holds a pivotal role in subsequent procedures.

As demonstrated in [10, 12], a comprehensive array of features was scrutinized for analysis, as detailed in Tables 1 and 2. Table 1 delineates the definitions of ten time-domain features, encompassing root mean square (RMS), square root of amplitude (SRA), kurtosis value (KV), skewness value (SV), peak-to-peak value (PPV), crest factor (CF), impulse factor (IF), margin factor (MF), shape factor (SF), and kurtosis factor (KF). Table 2 expounds on the definitions of three frequency-domain features: frequency center (FC), RMS frequency (RMSF), and root variance frequency (RVF).

Moreover, traditional statistical metrics such as mean, variance, maximum value, and minimum value were also integrated as features, outlined in Table 3.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 1** Time domain features | | | |
| Feature | Definition | Feature | Definition |
| RMS |  | CF |  |
| SRA |  | IF |  |
| KV |  | MF |  |
| SV |  | SF |  |
| PPV |  | KF |  |

|  |  |
| --- | --- |
| **Table 3** Statistical domain features | |
| Feature | Definition |
| Mean |  |
| Var |  |
| Std |  |
| Max |  |
| Min |  |

|  |  |
| --- | --- |
| **Table 2** Frequency domain features | |
| Feature | Definition |
| FC |  |
| RMSF |  |
| RVF |  |

*2.2. Dynamic time warping*

Dynamic Time Warping (DTW) [13] is a non-linear warping technique that employs dynamic programming to perform time warping and calculate distance measures. By establishing a matching path between data points within two correlated time series of arbitrary lengths, the algorithm assesses the similarity of these sequences. DTW excels at handling time misalignments between sequences and demonstrates notable fault tolerance and robustness. Hence, it has found application in the feature selection phase of rotating bearing fault detection. Experimental outcomes indicate that DTW can enhance the accuracy of fault diagnosis while minimizing the feature count, thereby enhancing the efficiency and efficacy of fault diagnosis [14].

Assuming that the corresponding lengths of the two time series and are and respectively. The core principle of DTW revolves around finding an optimal alignment path between and . DTW aims to discover an alignment path that minimizes the total distance between corresponding elements in and. To construct , we define a set of conditions: the path starts at the first elements of both sequences , ends at the last elements, and adheres to monotonically increasing indices, where and. The objective is to find the alignment path that satisfies these conditions while minimizing the accumulated cost along the path.

To compute the DTW distance between sequences 𝑋 and 𝑌, the algorithm employs a dynamic programming approach. It constructs a matrix with dimensions , initialized with infinity values. The elements represent the cumulatived cost up to the element in the alignment path. The computation involves pairwise comparison elements in the sequences and updating the matrix based on the following formula:



Upon the completion of the matrix, the DTW distance is calculated as , which signifies the optimal accumulated cost of the alignment path.

*2.3. Long Short-term Memory*

Recurrent Neural Networks (RNNs) have gained extensive popularity in the realm of sequence learning. As depicted in Fig. 1, at a given time , the recurrent hidden layer neurons receive input not just from the input layer at time but also from their own state at time, denoted as.

图示

描述已自动生成

Fig. 1 Architecture of RNN.

As a result, the output is a blend of the present and prior states, and this mechanism can be represented by Equation (1):



Where,

represents the input to the RNN at time ,   
 denotes the state of the hidden layer at time ,   
 represents the state of the neural network at,  
 is the bias of the hidden layer,   
 is the bias of the output layer,   
 denotes the weights between the hidden and input layer,   
 represents the weights of the hidden layer at and the hidden layer at .

Despite encountering the vanishing gradient problem during the training backpropagation phase, which can impede the performance of traditional RNNs, progress has been made to address this limitation and capture long-term dependencies within data features. An exemplar of such progress is the Long Short-Term Memory (LSTM) architecture introduced by Hochreiter and Schmidhuber in 1997 [15]. LSTM has demonstrated superior classification and regression capabilities on time series datasets, including voice and natural language processing datasets, in contrast to conventional RNNs. LSTM incorporates a memory cell that supersedes the role of hidden RNN units. This memory cell encompasses four gates: the forget gate (dictating the extent of information retention from the previous cell state), the input gate (determining whether to incorporate new information into the cell), the input modulation gate (regulating the volume of information to be written into the cell), and the output gate (managing the quantity of information to be extracted from the cell) [16]. LSTMs proficiently maintain error propagation during back-propagation across time and layers.

日程表

描述已自动生成

Fig. 2 LSTM memory cell.

Fig.2 depicts the typical LSTM cell, where (sigmoid) represents the gate activation function, and (tanh) denotes the input or output node activation. The LSTM model presented in Fig.2 is described by Equation (2).



Where,

and are the weights at time between the input and hidden layer,

and are the weights at time and between the hidden layers,

and are the biases of the gates,

is the value of the hidden layer at time ,

and are the output values of the forget gate, input modulation gate, input gate, output gate respectively,

and are the current state at time and respectively.

**3. Proposed method**

This paper introduces a fresh approach to quantifying the severity of faults: employing a time series prediction model to forecast the feature sequence extracted from normal signals. Signals that align with the predictions are regarded as normal, whereas deviations from the predictions signify the existence of faults, with greater deviations indicating more severe faults.

The delineation of the proposed method for recognizing bearing fault severity is illustrated in Fig.3.

图示

描述已自动生成

Fig. 3 Flowchart of proposed method.

Similar to other prevalent fault detection methods, the initial stage entails utilizing a sliding window to extract signal samples from the original signal. For each segment of the sample, features are derived to construct a new feature time series. It's imperative to recognize that the earlier mentioned feature calculation formula is exclusively applicable to one-dimensional signals, where each point within the time series is a scalar value rather than a vector. However, authentic signal acquisition involves multiple measurement points, resulting in high-dimensional time series data, where the data for each measurement point constitutes a signal channel. Hence, during actual processing, features should be individually extracted for every channel of the signal. Consequently, the ultimate feature time series will also be high-dimensional, with its dimension being the product of the number of channels in the original signal and the number of features.

Given the criticality of prediction accuracy for evaluating signal faults, the selected features should possess specific characteristics: the feature sequences derived from faulty signals and normal signals should exhibit minimal similarity. Guided by this principle, the DTW algorithm is employed to gauge the similarity between feature sequences. Features boasting high DTW scores are expected to be chosen and integrated into the subsequent stages.

For the unknown signal to undergo detection, its feature sequence is likewise extracted as input for the prediction model. The resulting prediction value is juxtaposed with the actual value, subsequently yielding an error score. In this paper, the chosen error metric is the Mean Absolute Error (MAE). This score is subsequently contrasted with a predetermined threshold. Should the score surpass this threshold, it signifies the existence of a fault within the unknown signal. The threshold can be established during the training phase. Assuming the error score derived from normal signals within the training dataset is. , and the error score for fault signals is , any value between and can be used as the threshold. To accomplish the objective of early fault detection, we suggest setting the threshold to a value closely to .

**4. Experiment validation**

This section introduces the dataset employed in experiments and validates the efficacy of the proposed method through experimental assessments.

*4.1. Data description*

For the evaluation, we utilized two datasets: the Beijing University of Chemical Technology Bearing Fault Excitation Data (BUCT-ED) and the Xi'an Jiaotong University Bearing Fault Dataset (XJTU-SY). The former originates from a multi-body contact transient dynamic model of a conventional gas turbine engine's high-pressure rotor-bearing support system. Meanwhile, the latter dataset was collected from a bearing accelerated life testbed.

4.1.1. Beijing University of Chemical Technology Bearing Fault Excitation Data (BUCT-ED)

This fault dataset is constructed using simulated fault excitation data from a gas turbine engine and the transmission characteristics of the thin-walled casing. This process involves reconstructing simulated fault characteristic data for measurement points on the casing. Subsequently, this data is integrated with health test data to generate the comprehensive dataset. Specifically, the dataset encompasses five distinct fault types: high/low rotor unbalance fault, high/low rotor support non-concentric fault, and high-pressure rotor front support bearing outer ring peeling fault. All of these fault types incorporate response data from three measuring points located on the fan casing, the intermediate casing, and the turbine rear casing. Within this dataset, two sets of typical operational condition data are provided for rotor unbalance faults, corresponding to low speed and high speed conditions. Furthermore, the dataset encompasses three variations of rotor unbalance faults.

At the same time, there are three types of rotor unbalance: 0.5g·m, 1g·m, and 2g·m. There are also two typical working condition data of low speed and high speed for rotor non-concentric fault. At the same time, there are three different degrees of rotor non-concentricity: deflection angle 1°-elevation 1mm, deflection angle 1.5°-elevation 1.5mm and deflection angle 2°-elevation 2mm. The working condition of bearing fault data is 100% working speed, which corresponds to the fault characteristic frequency of the outer ring of the bearing at this time of 1620Hz. At the same time, there are 0.5mm, 0.75mm and 1mm three types of defect widths in the outer ring of the bearing.

In the multi-body dynamics model of a typical gas turbine engine high-pressure rotor bearing support system, groove defects were intentionally introduced to the bearing's outer ring. This model comprehensively incorporates the contact, friction, and load-bearing characteristics of each bearing component. This approach facilitates the simulation of the intricate contact and collision dynamics between the ball and the raceway defect during the operational state of the rolling bearing. Consequently, an equivalent bearing fault excitation force with intricate nonlinear attributes is derived. In Figure 4, you can observe the representation of this equivalent bearing outer ring fault excitation force. The sampling rate employed for this data is 32768Hz. Moving on, Figure 5 presents a highly detailed three-dimensional solid finite element model of a typical gas turbine engine casing. This model captures the intricate geometrical and material properties of the casing. To further elucidate the system's behavior, a single excitation force is applied at the bearing support position within the model. This force is simulated using a shock pulse. By doing so, we can accurately compute the dynamic responses at measurement points across the fan casing, intermediate casing, and turbine rear casing.



(a) Time-domain diagram of equivalent bearing fault excitation force

图示

描述已自动生成

(b) Local enlarged diagram of equivalent bearing fault excitation force

Fig. 4 Equivalent bearing fault excitation force acting on casing structure.

图片包含 钟表, 电脑

描述已自动生成

Fig. 5 High-fidelity 3D solid finite element model of a typical gas turbine engine casing.

The time-domain vibration acceleration signal from the intermediate measuring point in the simulated bearing fault exhibits characteristics similar to the background noise commonly encountered in gas turbine measurements. Remarkably, this signal encompasses valuable bearing fault-related information.

As depicted in Figure 6, the bearing fault data is synthesized by incorporating simulated bearing fault features while also incorporating the measured background noise. This fusion results in a dataset that effectively encapsulates both the fault patterns and the typical noise profile observed in gas turbine operations.



Fig. 6 The acceleration signal of the measurement point of the bearing fault intermediary casing with the characteristics of measured background noise.

4.2.2. Xi'an Jiaotong University Bearing Fault Dataset (XJTU-SY)

The bearing dataset from XJTU-SY has been made public which could be download at http://biaowang.tech/xjtu-sy-bearing-datasets. And the outer race fault data was used to demonstrate the efficacy of the suggested method in this fault diagnosis[17].

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 4** LDK UER204 Bearing parameters | | | |
| Parameter | Value | Parameter | Value |
| Out race diameter(mm) | 29.30 | Ball diameter(mm) | 7.92 |
| Inner race diameter(mm) | 39.80 | Number of balls | 8 |
| Bearing median diameter(mm) | 34.55 | Contact angle(°) | 0 |
| Basic rated dynamic load(N) | 12820 | Basic rated static load(N) | 6.65 |

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 5** Bearing Accelerated Life Test Conditions | | | |
| Number | 1 | 2 | 3 |
| Rotational Speed | 2100 | 2250 | 2400 |
| Radial Force | 12 | 11 | 10 |

The dataset employed in this study utilized LDK UER204 rolling bearings as the test subjects. The relevant parameters of these bearings can be found in Table 4. To comprehensively evaluate their performance, experiments were structured around three distinct operational conditions, as outlined in Table 5. Across each operational condition, multiple sets of vibration signals were meticulously collected throughout the complete lifecycle of the bearings. Throughout the experiments, two PCB 352C33 unidirectional acceleration sensors were affixed to the test bearings using magnetic mounts, ensuring secure attachment in both horizontal and vertical orientations. A DT9837 portable dynamic signal acquisition system was employed to record the vibration signals. The sampling frequency was meticulously set to 25.6 kHz, accompanied by a 1-minute sampling interval. Each individual sampling session spanned a duration of 1.28 seconds. For a detailed interpretation of the dataset, please refer [18].

To obtain a complete time series, the data obtained from each sampling is concatenated, resulting in run-to-failure vibration signals. The first two signals are shown in Fig.7. The label Bearing 1\_2 means the data is the second test in work condition 1, and so on.

|  |  |
| --- | --- |
| 图表  描述已自动生成 | 图表  描述已自动生成 |
| Fig. 7 The run-to-failure signals for the first two experiments under test condition 1. | |

*4.2. Experiment set*

Using the BUCT-ED dataset as an example, let's illustrate the execution process of the method described in Section 3. The experiment was conducted using signals obtained at a rotational speed of 4647 (rpm). In addition to normal signals, the dataset also includes various rotor fault signals, such as high rotor support non-concentric (gybtx), low rotor support non-concentric (dybtx), high rotor unbalance (gybph), and low rotor unbalance (dybph). Each fault class has three fault degree. And for each fault type, the data collected from three measurement points are considered as three channels of that signal.

4.2.1. Sliding window set

Let the representation of the original signals under a specific operating condition be denoted as , where represents a vector of dimension (depending on the data, in this experiment, it is ). By employing a sliding window of length , the -th sample can be defined as . The accumulation of multiple such matrices constitutes the signal sample set. Within the program, individual samples are stored as matrices with rows and columns. The count of samples is established as , a quantity determined by subsequent experimental configurations.

The proximity between two successive samples is a significant factor to consider. This can be addressed through two strategies: complete non-overlapping and partial overlapping. Generally, deep learning architectures necessitate a substantial number of samples to attain notable performance levels. With this in mind, and aiming to gather a larger array of samples, the present experiment adopts a strategy of maximal overlap for adjacent samples. In essence, this entails configuring the sliding window's movement step as . Subsequent experiments will demonstrate that this setup notably contributes to the convergence of the prediction model.

4.2.2. Features extraction and selection

All features mentioned in Section 3 will be extracted from the raw signals. Each sample matrix resulted in a feature vector with a dimension of . These feature vectors were arranged in chronological order, forming a high-dimensional feature sequence. In the program, they were stored as a matrix with rows and columns, where each column represented a feature extracted from one channel of the original signal.

During the selection stage, the low rotor unbalance signal with a fault severity level of 2 was chosen as the fault data. Feature sequences were extracted separately from normal and fault signals. The DTW scores were calculated for each column of the feature sequences and arranged in descending order. A higher ranking indicated a greater difference in performance between the normal and fault signals for that feature, making it suitable for our method. It is an important note that these scores are only reference values, and the determination of actual features to be used should consider other factors such as the convergence of the prediction model.

In this experiment, the top 10 ranked features are shown in Table 6. The label *tun0\_SF* means feature SF extracted from the tunnel numbered 0. Since the feature(s) would be extracted in all 3 tunnels in later step, it shall perform well in all tunnels. Ultimately, the mean value *Mean* was selected as the feature used in the prediction model.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 6** DTW scores of different features | | | |
| feature | DTW score | feature | DTW score |
| tun2\_Mean | 14.93 | tun0\_CF | 9.79 |
| tun1\_Mean | 14.22 | tun0\_IF | 9.55 |
| tun0\_Mean | 12.25 | tun0\_Max | 9.19 |
| tun0\_SV | 11.56 | tun0\_Min | 8.80 |
| tun0\_SF | 10.63 | tun0\_PPV | 7.86 |

It is worth mentioning that although feature extraction and selection may not be necessary steps from a conceptual perspective, the experiments have shown that directly predicting from the raw signal does not lead to model convergence, nor using the entire 18 features. Therefore, this step of feature extraction and selection is an indispensable part of the algorithm.

4.2.3. Model establishment

Once again, features were extracted from the normal data, but this time only the selected feature *Mean* was extracted to obtain a new feature time series. Sliding windows were applied to the feature time series to generate a series of feature samples for training the LSTM prediction model. The LSTM model we designed aims to predict the next points’ values based on the previous points in the sequence. The training dataset should consist of at least samples. Therefore, the sliding window length on the feature time series is set as . Similarly, to collect more samples, the sliding window has a movement step of .

Now, each feature sample is a matrix of rows and columns. The first rows are considered as the network input, while the subsequent rows serve as the learning target for training the LSTM model. Table 7 are the model accuracy after training for different parameter combinations . In each test, the epoch was set 200 and the batch size 20. And the model accuracy was inflected through MAE.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 7** training result with | | | | | |
|  |  | MAE |  |  | MAE |
| 20 | 1 | 0.400 | 50 | 5 | 0.255 |
| 50 | 1 | 0.533 | 100 | 5 | 0.266 |
| 100 | 1 | 0.309 | 50 | 10 | 0.275 |
| 20 | 5 | 0.338 | 100 | 10 | 0.240 |

Based on this MAE results from each test, it was observed that longer values of and yield better results (lower MAE). However, it should be noted that as increases with larger and , more memory and time resources are required. Due to the limitation of the memory capacity of the personal laptop used for the experiment, the values of were chosen asfor validation in this experiment.

4.2.4. Model validation

To validate the accuracy of the model, multiple signals with different fault locations and severities were used as test data. After extracting the mean value as the feature, the trained LSTM model was used for prediction. The MAE between the predicted values and the true values was calculated. Since the prediction targets are high-dimensional time series, the model is a multi-output model. When calculating the prediction errors for each category, the MAE is calculated separately for each component of the output, and then the mean MAE is obtained for that category.

The prediction results for different signals are presented in Table 8.

|  |  |
| --- | --- |
| **Table 8** Prediction error of different classes | |
| Faults (degree) | mean MAE |
| normal | 0.244671 |
| dybph(0.5) | 0.250187 |
| dybph(1) | 0.266532 |
| dybph(2) | 0.320075 |
| gybph(0.5) | 0.252173 |
| gybph(1) | 0.280574 |
| gybph(2) | 0.380611 |
| dybtx(1) | 0.264082 |
| dybtx(1.5) | 0.291311 |
| dybtx(2) | 0.326696 |
| gybtx(1) | 0.265845 |
| gybtx(1.5) | 0.279169 |
| gybtx(2) | 0.294082 |

*4.3. Results and analysis*

From Table 8, it can be seen that for each type of fault, the MAE increases with the severity of the fault. This validates the correctness of our approach, indicating that as the fault severity increases, the prediction accuracy gradually decreases, and this decrease process is continuous.

It is also noteworthy that during training, only data related to the low rotor unbalance (dybph) fault type was used, while during testing, data from three other fault types were used: high rotor support non-concentric (gybtx), low rotor support non-concentric (dybtx), and high rotor unbalance (gybph). Despite this, the proposed method achieved excellent results, demonstrating the robustness of our approach. It shows that even with limited knowledge of fault data, the trained model can yield positive results on other fault data. This is one of the significant achievements of this research.

To further demonstrate the advantages of this method, the Xi'an Jiaotong University Bearing Fault Dataset (XJTU-SY) was also used to validate the effectiveness of the proposed approach.

In this experiment, data Bearing 1\_1, Bearing 1\_2, and Bearing 1\_3 under operating condition 1 were utilized, all of which exhibited faults in the outer race. Bearing 1\_1 was used for training, while them all were used for testing. Since the data is run-to-failure vibration signals of the bearings, it is not possible to accurately categorize them based on fault severity. However, one can consider that the machine is expected to be in a normal state at the beginning of its operation, while severe faults may occur towards the end. Therefore, we ignore the intermediate evolution details and simply divide the data into two sections: the initial portion as normal signals and the final portion as faulty signals. This strategy can fulfill the requirements for training.

Other parameters were set as follow: ,, , feature *Mean* and *RVF* were used in experiment. The MAE variation with time was plotted for testing on data sets Bearing 1\_1, Bearing 1\_2, and Bearing 1\_3. Refer to Fig.8 for the graphical representation.

|  |
| --- |
| 图表  描述已自动生成 |
| 图片包含 图表  描述已自动生成 |
| 1. MAEs of Bearing 1\_1 |
| 图表  描述已自动生成 |
| 图表  描述已自动生成 |
| 1. MAEs of Bearing 1\_2 |
| 图表  描述已自动生成 |
| 图片包含 图表  描述已自动生成 |
| 1. MAEs of Bearing 1\_3 |

Fig. 8 Prediction result of XJTU-SY.

As time progresses, the MAE generally increases, indicating a gradual worsening of the fault. It can also be observed that at certain points in time, the MAE increases to the threshold, which indicate the aggravation of faults. By setting an appropriate threshold, these points in time can be identified, enabling timely shutdown of the machinery before the fault becomes severe. In this experiment, by observing the MAE plot of Bearing 1\_1 and setting the threshold to , the first significant increase in MAE for Bearing 1\_2 and Bearing 1\_3 (in experiment they represented as unknown signals) can be captured. These captured points appear before the obvious rise in the amplitude of the original signal, indicating that our proposed method can detect faults in advance.

**5. Conclusions**

This paper presents a novel method for detecting faults based on engine vibration signals. The method involves extracting time and frequency domain features from normal signals to establish an LSTM time series prediction model. It utilizes the prediction accuracy as a continuous indicator for unknown signals to indicate the presence of faults. And the effectiveness of the method is validated through experiment.

The advantages of this method are as follows:

(1) Overcoming the limitations of traditional strategies that categorize fault severity in a discrete manner, this method utilizes a continuous indicator to indicate the severity of faults. As a result, it provides greater flexibility in setting threshold values to differentiate faults.

(2) During training, the method uses data from a single fault category, but the resulting model performs well on different types of fault data. It can accurately reflect the severity of faults, even for fault types that were not encountered during training, as indicated by the MAE.

(3) Only severe faults data were used in training (exactly in features selecting), however, by setting lower detection thresholds, the method can detect faults that are much milder than the training fault data. Since collecting fault data in real-world engineering environments can be challenging and typically only severe faults are reliably captured, this method is more suitable for practical production.

The limitations of this work include:

(1) Training deep learning model requires a large number of feature time series samples, and obtaining these feature samples necessitates slicing the original signals. Therefore, implementing this method requires a sufficient amount of original data, and it can consume significant memory resources during computation.

(2) The process of feature selection and threshold determination lacks standardized criteria and relies on the subjective decisions of researchers. There is a need for more universally applicable and robust methods for adaptive decision-making.

Acknowledgements

This work was supported by the National Science and Technology Major Project, China, under Grant J2019-I-0019-0018 and Grant J2019- I-0001-0001.

Weirui Zhang and Haihui Wang is with the School of Mathematical Sciences, Beihang University (BUAA), Beijing 100191, China (Corresponding author: Haihui Wang e-mail: whhmath@buaa.edu.cn).

**References**

[1] G. Georgoulas, T. Loutas, C. D. Stylios, and V. Kostopoulos, ‘Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition’, *Mech. Syst. Signal Process.*, vol. 41, no. 1–2, pp. 510–525, Dec. 2013, doi: 10.1016/j.ymssp.2013.02.020.

[2] C. Malla and I. Panigrahi, ‘Review of Condition Monitoring of Rolling Element Bearing Using

Vibration Analysis and Other Techniques’, *J. Vib. Eng. Technol.*, vol. 7, no. 4, pp. 407–414, Aug. 2019, doi: 10.1007/s42417-019-00119-y.

[3] M. Cerrada *et al.*, ‘A review on data-driven fault severity assessment in rolling bearings’, *Mech. Syst. Signal Process.*, vol. 99, pp. 169–196, Jan. 2018, doi: 10.1016/j.ymssp.2017.06.012.

[4] C. Bujoreanu, R. Monoranu, and N. D. Olaru, ‘Study on the Defects Size of Ball Bearings Elements Using Vibration Analysis’, *Appl. Mech. Mater.*, vol. 658, pp. 289–294, 2014, doi: 10.4028/www.scientific.net/AMM.658.289.

[5] M. Singh and R. Kumar, ‘Thrust bearing groove race defect measurement by wavelet decomposition of pre-processed vibration signal’, *Measurement*, vol. 46, no. 9, pp. 3508–3515, Nov. 2013, doi: 10.1016/j.measurement.2013.06.044.

[6] S. Zhao, L. Liang, G. Xu, J. Wang, and W. Zhang, ‘Quantitative diagnosis of a spall-like fault of a rolling element bearing by empirical mode decomposition and the approximate entropy method’, *Mech. Syst. Signal Process.*, vol. 40, no. 1, pp. 154–177, Oct. 2013, doi: 10.1016/j.ymssp.2013.04.006.

[7] ‘An Improved Bearing Fault Diagnosis Method using One-Dimensional CNN and LSTM’, *Stroj. Vestn. - J. Mech. Eng.*, Jun. 2018, doi: 10.5545/sv-jme.2018.5249.

[8] X. Guo, C. Shen, and L. Chen, ‘Deep Fault Recognizer: An Integrated Model to Denoise and Extract Features for Fault Diagnosis in Rotating Machinery’, *Appl. Sci.*, vol. 7, no. 1, p. 41, Dec. 2016, doi: 10.3390/app7010041.

[9] H. Shao, H. Jiang, Y. Lin, and X. Li, ‘A novel method for intelligent fault diagnosis of rolling bearings using ensemble deep auto-encoders’, *Mech. Syst. Signal Process.*, vol. 102, pp. 278–297, Mar. 2018, doi: 10.1016/j.ymssp.2017.09.026.

[10] C. Shen, F. Hu, F. Liu, A. Zhang, and F. Kong, ‘Quantitative recognition of rolling element bearing fault through an intelligent model based on support vector regression’, in *2013 Fourth International Conference on Intelligent Control and Information Processing (ICICIP)*, Beijing, China: IEEE, Jun. 2013, pp. 842–847. doi: 10.1109/ICICIP.2013.6568189.

[11] Y. Lei, Z. He, and Y. Zi, ‘EEMD method and WNN for fault diagnosis of locomotive roller bearings’, *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7334–7341, Jun. 2011, doi: 10.1016/j.eswa.2010.12.095.

[12] T. W. Rauber, F. De Assis Boldt, and F. M. Varejao, ‘Heterogeneous Feature Models and Feature Selection Applied to Bearing Fault Diagnosis’, *IEEE Trans. Ind. Electron.*, vol. 62, no. 1, pp. 637–646, Jan. 2015, doi: 10.1109/TIE.2014.2327589.

[13] E. Keogh and C. A. Ratanamahatana, ‘Exact indexing of dynamic time warping’, *Knowl. Inf. Syst.*, vol. 7, no. 3, pp. 358–386, Mar. 2005, doi: 10.1007/s10115-004-0154-9.

[14] G. Wang, T. Wang, J. Chen, and S. Zhao, ‘Bearing fault feature selection method based on dynamic time warped related searches’, *J. Vibroengineering*, vol. 25, no. 2, pp. 311–324, Mar. 2023, doi: 10.21595/jve.2022.22863.

[15] S. Hochreiter and J. Schmidhuber, ‘Long Short-Term Memory’, *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[16] R. Sabir, D. Rosato, S. Hartmann, and C. Guehmann, ‘LSTM Based Bearing Fault Diagnosis of Electrical Machines using Motor Current Signal’, in *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, Boca Raton, FL, USA: IEEE, Dec. 2019, pp. 613–618. doi: 10.1109/ICMLA.2019.00113.

[17] B. Wang, Y. Lei, N. Li, and N. Li, ‘A Hybrid Prognostics Approach for Estimating Remaining Useful Life of Rolling Element Bearings’, *IEEE Trans. Reliab.*, vol. 69, no. 1, pp. 401–412, Mar. 2020, doi: 10.1109/TR.2018.2882682.

[18] L. Yaguo, H. Tianyu, W. Biao, L. Naipeng, Y. Tao, and Y. Jun, ‘XJTU-SY Rolling Element Bearing Accelerated Life Test Datasets: A Tutorial’, *J. Mech. Eng.*, vol. 55, no. 16, p. 1, 2019, doi: 10.3901/JME.2019.16.001.