Research on the Tightness Diagnosis and Network Security Risk Protection of Slot Wedge Tightness for Generator Wall-Climbing Robot Based on Multi-Scale Frequency Band Energy Entropy and CNN-LSTM

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Abstract:

During its operation, the generator stator is prone to vibration as a result of the joint effect of powerful centrifugal force and significant electromagnetic stress. This phenomenon may potentially give rise to significant incidents when the slot wedge is found to be loose. For an extended period, the detection of a loose slot wedge in a generator has necessitated the removal of the end cover and extraction of the rotor, followed by tapping and inspection by a designated professional. This particular process has been noted to demand a substantial quantity of human and material resources, thereby leading to a rise in operational expenditures. The present study showcases the creation of a space-efficient inspection robot, engineered to access the air gap of a sizable generator stator without the necessity of rotor pumping. The robot is furnished with a percussive head, allowing for the assessment of slot wedge looseness. Additionally, this study puts forward a technique for extracting the characteristics of slot wedge tightness using multi-scale frequency band energy entropy, which proficiently dissects the energy dispersion of the sound signal. Subsequently, a CNN-LSTM algorithm is employed to identify the faults of the extracted features. It is contrasted with a CNN and LSTM algorithms under identical experimental circumstances. The outcomes signify that the method proposed in this study exhibits greater precision.

Keywords: slot wedge tightness, electric power robots, fault detection, multi-scale frequency band energy entropy, CNN-LSTM, network security risk protection

INTRODUCTION

The swift progression of the social economy has led to a remarkable upsurge in the demand for electricity. In 2023, China's social electricity consumption reached 922.41 billion kilowatt-hours, representing a year-on-year growth of 6.7%. Additionally, the national installed capacity of generators reached 2.92 billion kilowatts, indicating a year-on-year expansion of 13.9%. The generator constitutes the central apparatus of the power plant, and its secure and stable operation holds crucial significance for the economic gains of the enterprise, as well as for the well-being of the general public [1]. Generators in operation will inevitably be subjected to high magnetic stresses in the power grid, transient shocks with potential destructive force, and high mechanical torque and centrifugal force from the turbine rotor [2]. These factors will result in the vibration of the generator's rotor-stator, which may lead to the loosening of the stator groove wedge. This, in turn, may cause stator bar vibration, destroying the bar's main insulation [3]. In particular, the generator rotor stator is susceptible to adverse effects when operating in non-ideal conditions. These elements, in combination, can substantially affect the dependability and steadiness of the generator, injecting a great deal of unpredictability into its functioning.

To guarantee the reliable operation of generators, it is essential to conduct regular overhauls of the stator slot wedge tightness for large generator sets [4]. The conventional overhaul method frequently necessitates the removal of the rotor, a process that is not only time-consuming and risky [5], but may also result in further damage to the unit. Concurrently, the conventional manual tapping approach is dependent on the expertise and subjective interpretation of the operator, which can lead to prolonged detection periods and potential inconsistencies in the results [6]. Consequently, the development and implementation of non-tapping rotor slot wedge tightness detection technology can facilitate the completion of essential overhaul tasks without disassembling the unit, thereby markedly enhancing both the efficiency and safety of the overhaul process.

In recent years, the rapid development of big data has led to a significant increase in the use of deep learning in studying electrical equipment faults [7,8]. This is particularly evident in the field of slot wedge faults, where scholars from both domestic and foreign institutions have conducted extensive research into the detection of robotic slot wedge looseness. The wall-climbing robot developed in the literature [9] represents a significant advancement in this field. An integrated shaker and sound acquisition module enables the fast Fourier transform of the sound signal and the acceleration signals into the frequency domain, thus distinguishing between a loose and a tight slot wedge. However, the robot device is exposed, which introduces the risk of introducing foreign objects. Kittipong Ekkachai [10] and other researchers designed a retractable slot wedge looseness detection device. The device was integrated into the robot, with the accelerometer acquiring vibration signals and the average amplitude being extracted to determine whether the slot wedge was loose. However, the method could only compare the relative magnitude of the current value and the vibration amplitude of the loosest and tightest wedges to ascertain whether the wedge was loose.

The objective of this study is to develop a wall-climbing robot utilizing a multi-scale frequency band energy entropy and CNN-LSTM algorithm to address the requirements for slot wedge tightness detection in the absence of rotor pumping. The excitation signal from the slot wedge is extracted using a multi-scale frequency band energy entropy method, with a CNN-LSTM algorithm employed to enhance the precision of slot wedge tightness assessment. This is integrated with the devised wall-climbing robot to facilitate rapid and effective detection of slot wedge tightness in large generators. The principal contributions of this study are as follows:

1) An excitation feature extraction method based on multi-scale frequency band energy entropy is proposed, which enhances the efficacy of the excitation signal features.

2) A novel type of wall-climbing robot is designed, and its efficacy is validated through experimentation.

THEORETICAL FOUNDATIONS AND TECHNICAL OVERVIEW

Slot Wedge Structure and Failure Principle

The slot wedge represents a crucial component of the turbine generator, serving to secure the stator winding and prevent displacement of the winding due to electromagnetic forces during generator operation [11]. Slot wedge structures vary across different generator designs, with this study focusing on a specific configuration comprising corrugated plates and pads for securing purposes [12]. This is illustrated in Figure l.

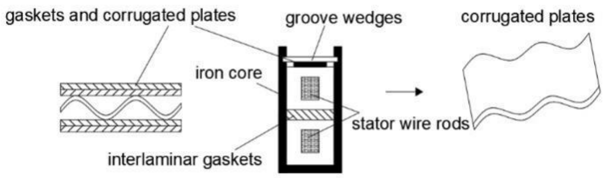


Figure 1. Structure of stator slot wedge

Each stator slot wedge is constructed from oblique wedge blocks, a series of cushion strips, and stator wire rods, which are stacked in sequence beneath the wedge. During generator operation, the stator slot wedge is maintained in a tight state by the force of corrugated boards and cushion bars. The overall structure of the stator slot wedge is illustrated in Figure 2.

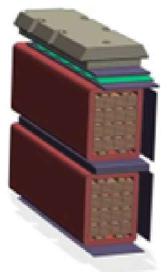


Figure 2. Overall structure of stator slot wedges

The causes of slot wedge loosening are more complex. From the perspective of the slot wedge design, this may be due to the specifications of the slot wedge size, shape, style, or material being unreasonable, as well as the geometric parameters of the corrugated plate design deviation and other conditions. These factors may then trigger the slot wedge loosening. During the operation of the generator set, several factors will affect the state of the slot wedge. During generator operation, the stator winding is subjected to an electromagnetic force. Should this force exceed the range of tolerance of the slot wedge, the likelihood of the slot wedge loosening is high. Furthermore, the generator will generate a considerable amount of heat during operation, resulting in thermal expansion and contraction of the stator core and slot wedge. If the coefficient of thermal expansion and contraction of the stator core and slot wedge is not aligned or the temperature change is significant, it can also lead to slot wedge loosening. Furthermore, the slot wedge is susceptible to mechanical vibration interference during unit operation. If the vibration amplitude is considerable or the vibration frequency approaches the intrinsic frequency of the slot wedge, triggering resonance, it may also result in slot wedge loosening [13].

Consequently, numerous factors have the potential to result in wedge loosening. The slot wedge is not only intimately associated with the performance and reliability of the generator set, but also exerts a pivotal influence on the safe operation and service life of the unit. Therefore, as a standard undertaking during generator overhaul, the enhancement program of slot wedge looseness detection is of considerable engineering significance.

Wall Climbing Robot Structural Design

This scheme has been developed for a pumped storage generator located in Hohhot. It includes a total of 171 sets of slot wedges, with a rotor guard ring having an outer diameter of 4584 mm and a stator core with an inner diameter of 4670 mm. Based on these dimensions, the design of the robot in this study specifies external measurements of 347.5 mm in length, 249.55 mm in width, and 33 mm in height. Furthermore, the robot has a radius of 4.21°. The schematic diagram illustrating the structural parameters of the robot body is shown in Figure 3, while Figure 4 displays the dimensional diagram of the corresponding generator.

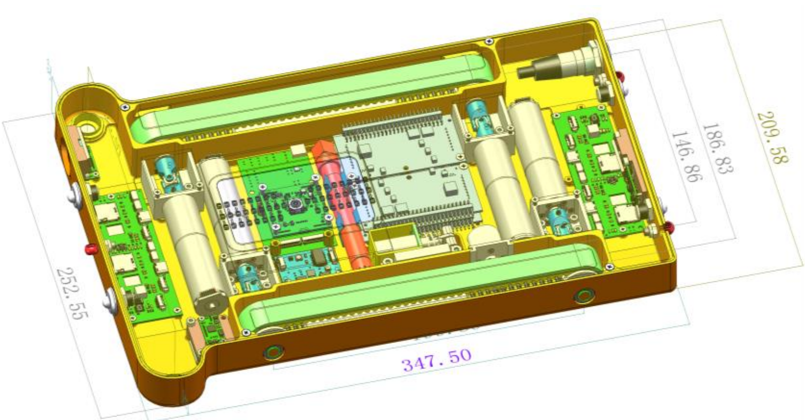


Figure 3. Robot structure parameters

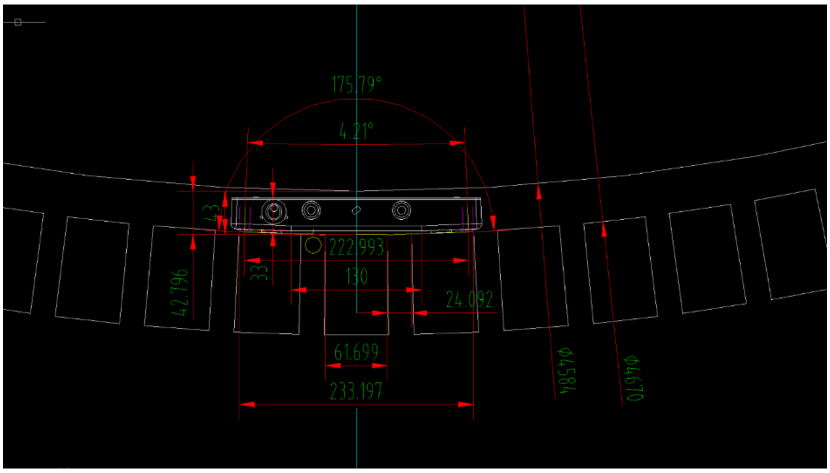


Figure 4. Comparison chart of robot and generator size

Principles of CNN-LSTM

Since the proposal of AlexNet [14] by Alex Krizhevsky in 2012, which won the ImageNet Image Classification Challenge, the Convolutional Neural Network has attracted significant interest from scholars.

In contrast to the earlier fully connected neural network, CNN no longer necessitates that each neuron in the input layer establish a complete connection with the neuron in the subsequent layer. Instead, it employs a method of sensory field and weight sharing to locally compute the neighboring inputs, which markedly reduces the number of references. This is illustrated in Figure 5. As illustrated in the figure, fully connected neural networks establish connections between all input data and the subsequent layer of neurons to generate the output. In contrast, the subsequent layer of neurons in convolutional neural networks accepts data exclusively within their receptive fields, thereby eliminating irrelevant data and reducing the network parameters [15].

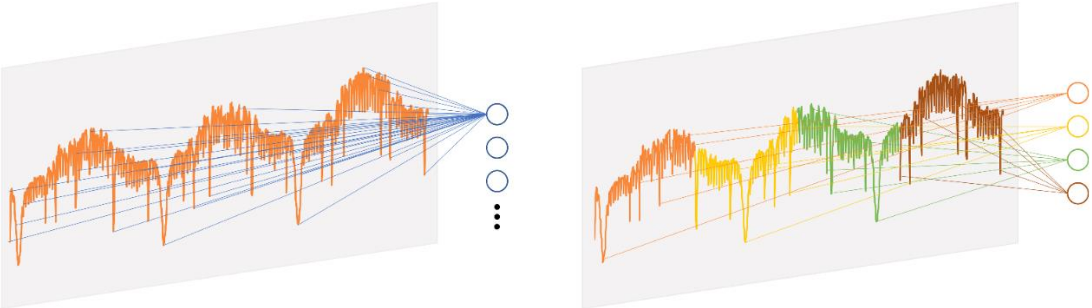


Figure 5. Parameter comparison chart of fully connected network and CNN

In a traditional CNN model, the input signal passes through each convolutional layer and pooling layer in turn, finally obtaining the output through the fully connected layer. During this process, there is no signal transmission between the same layers. Consequently, the final output is solely contingent upon the input, irrespective of the sequence in which the input signal is presented. Additionally, the neurons themselves lack the capacity to store information, thereby rendering the entire network incapable of memory retention. This type of network is unable to construct the relationship between input signals at different times when processing information with contextual relationships. Consequently, it is unsuitable for time series analysis, such as slotted wedge vibration.

In contrast to conventional fully connected networks, each node in an RNN considers not only the input at the current moment but also the output from the previous moment. The structure of a typical RNN network after unfolding at time point t is illustrated in Figure 6. However, during the learning process, the longer a node is from the current time step, the less evident its feedback information, which is susceptible to the issue of long-distance information loss.

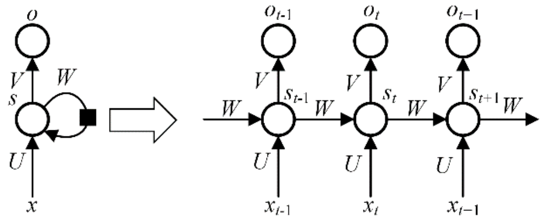


Figure 6. Network structure of RNN

To address the limitations of traditional RNN networks in processing information over extended periods during backpropagation, Hochreiter and Schmidhuber proposed a novel network architecture, termed long short-term memory (LSTM) [16]. LSTM incorporates specialized units and gating mechanisms, facilitating the continuous flow of errors in the network enables it to learn and store information over longer time intervals. The LSTM network replaces neurons with storage units, which are mainly composed of three gating units. The storage unit receives the cellular state and hidden state of the previous moment and outputs the cellular state and hidden state of the current moment. The structure of the storage unit is illustrated in Figure 7.

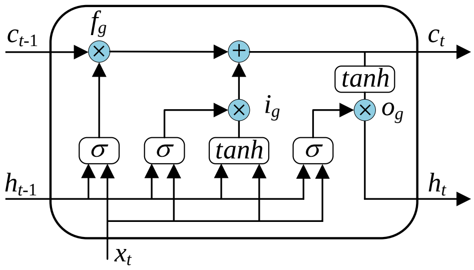


Figure 7. LSTM memory cell

c_t and h_t are the variables of interest. f_g, i_g and o_g are the gates that regulate the flow of information through the network. The sigmoid function (s) is used to determine the output of the gates.

Figure 7 illustrates the forward propagation process of an LSTM network.

$$
\begin{aligned}
f_t &= \sigma(W_f x_t + R_f h_{t-1} + b_f) \\
i_t &= \sigma(W_i x_t + R_i h_{t-1} + b_i) \\
g_t &= \tanh(W_g x_t + R_g h_{t-1} + b_g) \\
o_t &= \sigma(W_o x_t + R_o h_{t-1} + b_o) \\
c_t &= c_{t-1} \text{ e } f_t + i_t \text{ e } g_t \\
h_t &= o_t \text{ e } \tanh(c_t)
\end{aligned} \tag{1}
$$

f_t, i_t and o_t represent the outputs of the forget gate, input gate, and output gate. g_t denotes the candidate information, which is employed to augment the information stored in the storage cell. Finally, the Hadamard product, represented by e , is the multiplication of the corresponding elements of a matrix.

The CNN-LSTM [17] network is a hybrid model that combines the strengths of two distinct approaches: one that identifies local feature relationships within data and another that extracts temporal features from sequential data across different time series. This integration endows the model with the capacity to analyze complex data sets [18]. The CNN-LSTM network comprises four primary layers: the input layer, convolution and pooling layer, the LSTM layer, and the output layer. The structural configuration of these layers is illustrated in Figure 8.

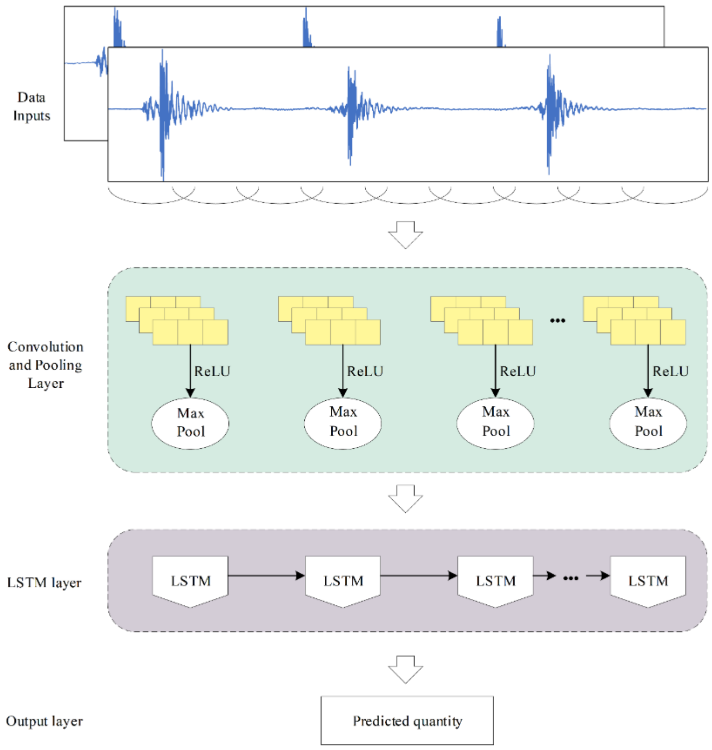


Figure 8. Network structure of CNN-LSTM

THEORETICAL FOUNDATIONS AND TECHNICAL OVERVIEW

The slot wedge tightness diagnostic system involved in this paper takes the multi-scale frequency band energy entropy of the sound signal as the fault feature parameter, and classifies and identifies the constructed fault feature matrix by the CNN-LSTM algorithm, so as to diagnose the state of the stator slot wedge for subsequent processing. Figure 9 shows the flow chart of the slot wedge tightness diagnosis system based on multi-scale frequency band energy entropy and CNN-LSTM.

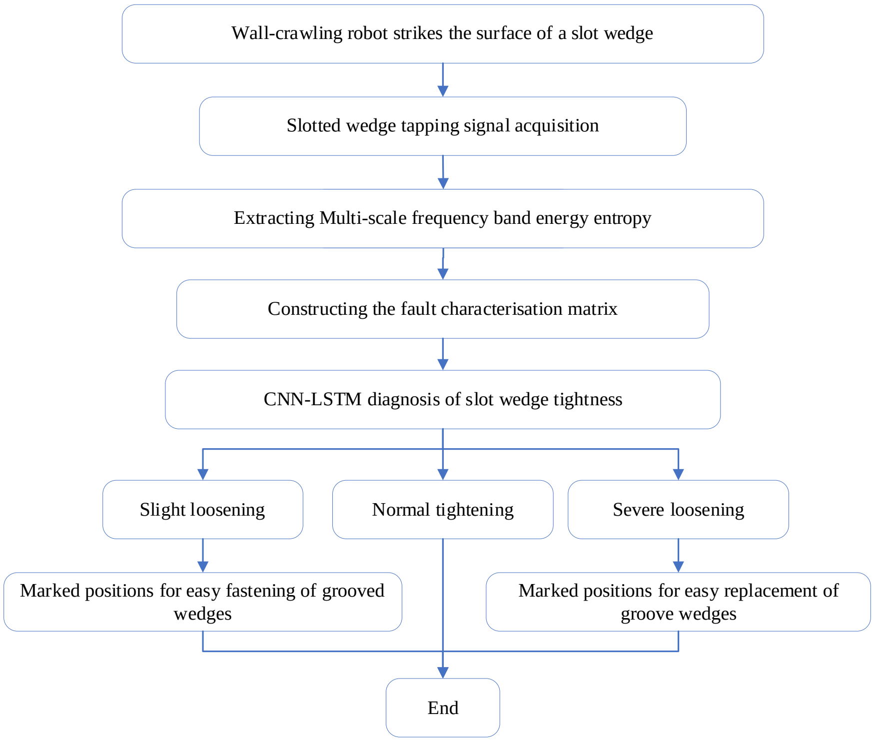


Figure 9. Flow chart of slot wedge tightness diagnostic system

The Robot is used to inspect as follows:

1) The wall-crawling robot travels to the top of the slot wedge, controls the shaker to strike the surface of the stator slot wedge to generate sound signals, and collects the sound signals;

2) The acquired slotted wedge knock signals are pre-processed to remove the noise. Then, the multi-scale frequency band energy entropy of the signal is extracted as the fault characteristics of the slotted wedge;

3) Construct the CNN-LSTM structure, train and optimise the CNN-LSTM algorithm diagnosis model. The model identifies and diagnoses the extracted and constructed slot wedge fault features, and outputs the diagnosis results;

4) According to the diagnostic results of the algorithm, mark the location of the groove wedge to facilitate the subsequent repair and replacement process.

FAULT FEATURE EXTRACTION AND VALIDITY ANALYSIS

Fault Feature Extraction Process

Energy entropy is a typical fault characterisation parameter that quantifies the randomness and uncertainty of the energy distribution in a signal. Its application in the field of fault diagnosis is extensive and crucial [19]. In this paper, we innovatively propose the multiscale frequency band energy entropy as a fault characteristic of slot wedge tightness, which describes the energy distribution characteristics of the signal at different scales. By combining the multiscale analysis and entropy theory, the energy distribution characteristics and complexity of the slot wedge knocking sound signal are characterised from different frequency bands and scales. Figure 10 shows the schematic diagram of the multi-scale frequency band energy entropy.

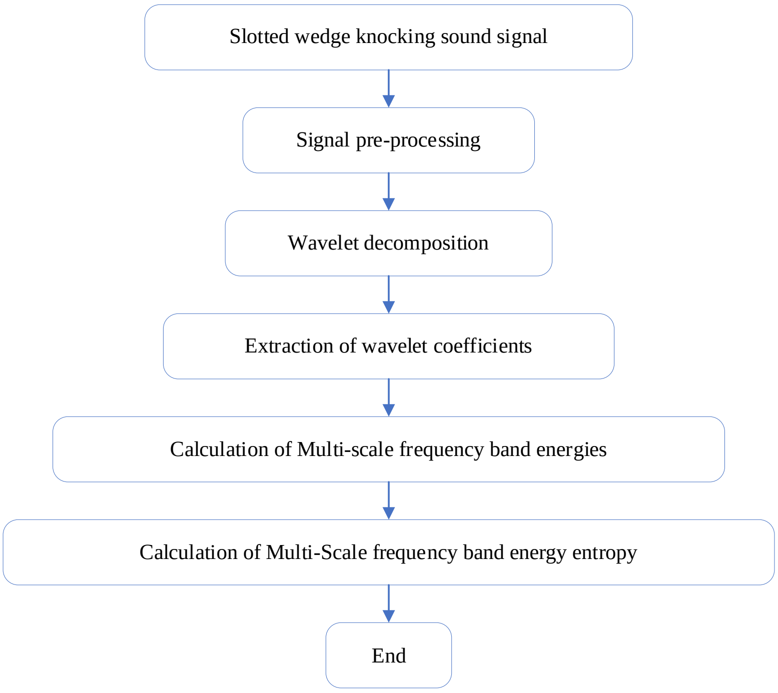


Figure 10. Schematic diagram of multi-scale band frequency energy entropy

The exact flow of the algorithm is as follows:

1) Signal pre-processing: normalisation of the original percussive sound signal. And remove the trend term in the original data by sliding average method;

2) Wavelet decomposition [20]: The appropriate wavelet bases and number of decomposition layers must be selected, after which the signal must be decomposed using the selected wavelets. The resulting wavelet coefficient matrix must then be established.

$$C = wavedec(f, N, wavelet, level) \tag{2}$$

In this context, C represents the coefficient matrix of the wavelet decomposition, f denotes the original signal, N indicates the length of the signal, *wavelet* specifies the name of the wavelet basis, and *level* denotes the number of decomposition layers.

3) Extraction of Wavelet Coefficients: The approximation coefficients and detail coefficients for each scale are extracted from the coefficient matrix of the wavelet decomposition.

$$\begin{aligned} D_i &= \det coef(C, L, i) \\ A_i &= appcoef(C, L, wavelet, i) \end{aligned} \tag{3}$$

In this context, D_i represents the detail coefficient of layer i, A_i signifies the approximation coefficient of layer i, and L denotes the vector of wavelet decompositions.

4) Multi-scale band energy calculations: the calculation of energy coefficients at each scale.

$$E_i = \sum_{j=1}^{N} |D_i(j)|^2 + |A_i(j)|^2 \tag{4}$$

In this context, the value of E_i represents the energy of layer i.

5) A multi-scale band energy entropy calculation is performed whereby the energy on each scale is normalised. This is then used as the basis for calculating the multi-scale band energy entropy.

$$P_i = \frac{E_i}{\sum_{i=1}^{N} E_i} \qquad H = -\sum_{i=1}^{N} P_i \log_2(P_i) \tag{5}$$

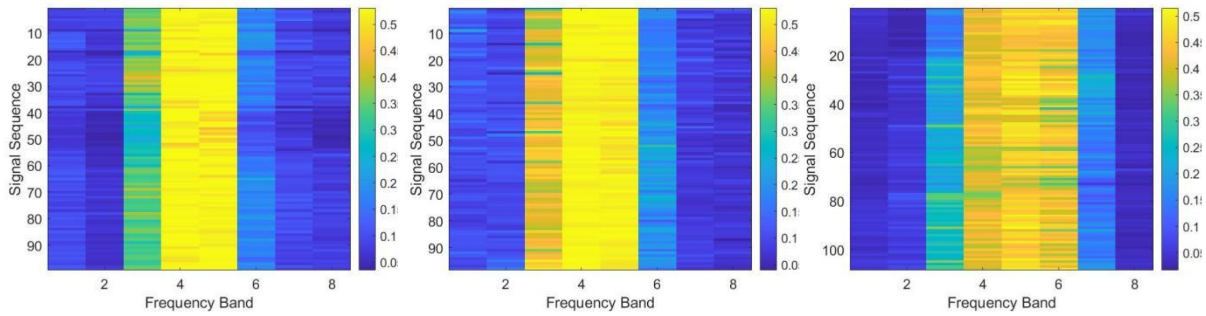
In this context, the value of *H* represents the multiscale band energy entropy.

Validity Analysis of Multi-Scale Frequency Band Energy Entropy

The dataset presented in this paper was obtained through the use of a grooved wedge looseness test rig, manufactured by the Harbin Electric Machinery Factory. As illustrated in Figure 11, the site where data was gathered for the slot wedge loosening experiment is shown. The test bench is equipped with a hydraulic valve that enables the adjustment of pressure, thereby facilitating the simulation of loosening and tightening of the grooved wedge.

Figure 11. Data collection

The acquired slotted wedge knocking sound signals should be processed through the aforementioned process. The multi-scale frequency band energy entropy of the slotted wedge knocking sound signals should be extracted in accordance with the different states. Subsequently, the multi-scale frequency band energy entropy thermograms of the slotted wedge knocking signals in different loosening and tightening states are generated and presented in Figure 12.



(a)Normal tightening (b)Slight loosening (c)Severe loosening

Figure 12. Multi-scale frequency band energy entropy thermograms of slot wedge tapping acoustic signals with different tightness states

As shown in Figure 12, the individual thermograms are analysed separately, and it is observed that the energy entropy values of the slotted wedge percussion signals in the same scale frequency band generally show consistency, which suggests that the percussion signals of the same kind of state slotted wedge have similar energy entropy characteristics in the same frequency band. Further analysis of the overall comparison of the three thermograms reveals that there are significant differences in the energy entropy values of the percussion signals of different states of slotted wedges in the same frequency band. The results show that the multi-scale frequency band energy entropy has significant validity and reliability as a fault characteristic for the diagnosis of stator wedge looseness, so it can be preliminarily determined that the multi-scale frequency band energy entropy is a kind of characteristic parameter suitable for wedge looseness condition monitoring and fault diagnosis.

SLOT WEDGE TIGHTNESS DIAGNOSIS

The constructed multi-scale band energy entropy matrix is assigned a label. Subsequently, the test set and the training set are separated, with the training set comprising 260 data sets and the test set consisting of 45 data sets. The data are randomly disrupted during the division process to ensure that the model maintains a high degree of generalisation. The accuracy plot and loss function plot of the training iteration process of the CNN-LSTM model are presented in Figure 13. Figure 14 illustrates the confusion matrix and prediction result graph of the training set obtained following diagnosis by the CNN-LSTM algorithm.

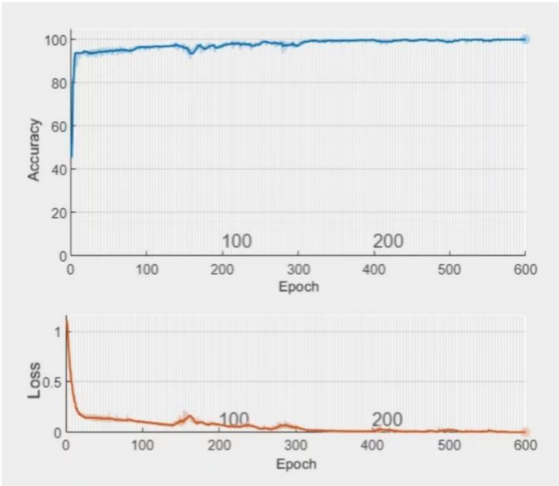
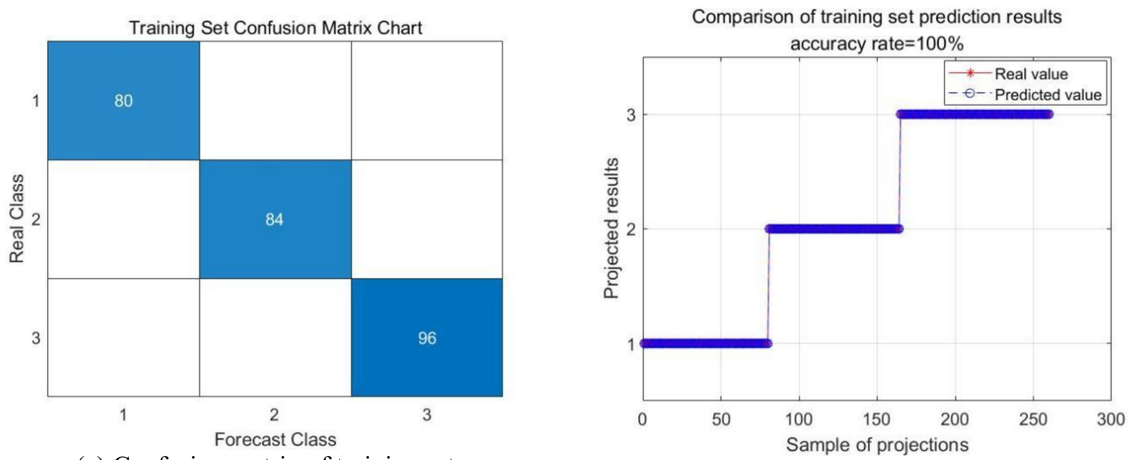


Figure 13. Model accuracy and loss function graph

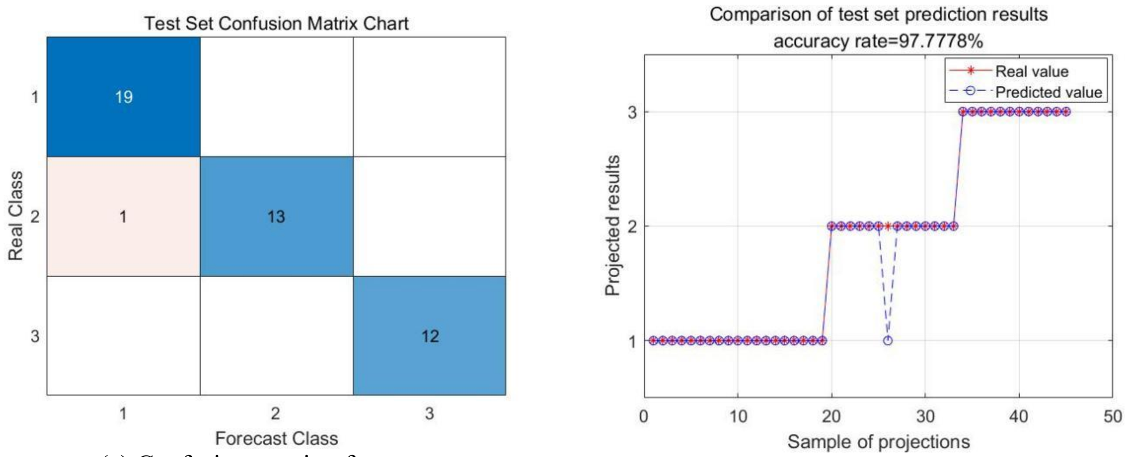


(a) Confusion matrix of training set

(b) Prediction result of training set

Figure 14. Confusion matrix and prediction result diagram of training set

As illustrated in Figure 14, the model training results demonstrate that the diagnostic accuracy of the training set is up to 100%. The trained model is employed for the diagnosis and identification of the test set, with the results presented below.



(a) Confusion matrix of test set

(b) Prediction result of test set

Figure 15. Confusion matrix and prediction result diagram of test set

As illustrated in Figure 15, the mark '1' denotes the typical tightening wedge signal, the mark '2' signifies a slight loosening wedge signal, and the mark '3' represents a severe loosening wedge signal. The results demonstrate that the diagnostic accuracy of slot wedge tightness in the test set, based on multi-scale frequency band energy entropy and CNN-LSTM, is 97.78%.

This is to emphasise that there is a more effective diagnostic performance based on multi-scale band energy entropy and CNN-LSTM. In this section, the experimental data are subjected to diagnosis and classification by models such as CNN and LSTM, respectively. The final diagnostic results are then compared in terms of accuracy, as illustrated in Figure 16.

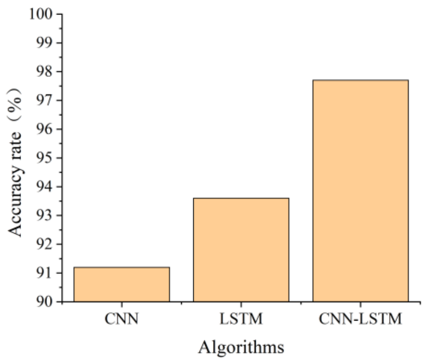


Figure 16. Diagnostic accuracy of different models

RESULTS

This paper proposes a multi-scale frequency band energy entropy and CNN-LSTM diagnosis method for slot wedge looseness in wall-climbing robots. The stator slot wedge is the object of study, with the knocking sound signal used as the detection signal. Multi-scale frequency band energy entropy is extracted as the feature parameter of the slot wedge looseness, and a CNN-LSTM is used to diagnose and recognize the constructed fault feature matrix, thus enabling efficient and accurate diagnosis and determination of the state of the stator slot wedge. The following conclusions are drawn from this paper:

1) The multi-scale frequency band energy entropy was proposed as a novel fault characteristic parameter for the diagnosis of stator slot wedge loosening. This parameter expresses the energy distribution characteristics of the slot wedge knocking sound signal from different scale frequency bands and was analyzed for its effectiveness as a fault characteristic parameter for the slot wedge loosening state through the use of visualization and comparison.

2) The diagnosis and identification of the slot wedge loosening state of the stator is conducted using the CNN-LSTM in this paper. The results demonstrate that the diagnostic accuracy of utilizing the energy entropy of multi-

scale frequency bands as the characteristic parameter for slot wedge loosening faults can reach 97.78%. Furthermore, the results are characterized by high accuracy and high stability.

3) The CNN, LSTM, and CNN-LSTM methods of this paper are employed to diagnose and identify the slot wedge loosening and tightening state. The diagnostic results are then compared and analyzed, and it is found that, in comparison with the CNN-LSTM algorithm, the diagnostic accuracy of the other algorithms can reach more than 90%. Of these, the CNN accuracy is relatively the highest. In comparison, the slot wedge loosening faults can be diagnosed and identified by using the multiscale frequency band energy entropy. In contrast, the slot wedge tightness diagnosis method based on multiscale frequency band energy entropy and CNN-LSTM is superior, providing a novel and efficient method for the practical application of generator stator slot wedge tightness diagnosis in engineering.

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