Failure Warning of Harmonic Reducer Based on Power Prediction

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Abstract—Harmonic reducer is the core component of industrial robots. During its operation, the power signal is a key parameter that embodies the performance of the harmonic reducer. Therefore, accurate power prediction of the harmonic reducer has instructive significance for its failure warning and performance prediction. In this paper, a hybrid deep neural network (DCBNN) based on CNN and BiLSTM was proposed to process the condition monitoring data of the harmonic reducer and improve the prediction accuracy of power signal. First, the operating parameters were pre-processed and the data sets were divided. Then, the pre-processed data were input into DCBNN, and the spatial characteristics and bidirectional timing dependencies of the condition monitoring data are captured by CNN and BiLSTM. On this basis, the absolute value of the residual of the actual power and the predicted value is obtained according to the prediction result, and the residual curve is fitted by the distribution fitting method to obtain the alarm threshold of the harmonic reducer failure warning. Finally, 8 different data sets constructed using the experimental data of the harmonic reducer are used to verify the effectiveness and superiority of the proposed method. The test results on the complete data set show that the DCBNN model can complete effectively failure warning of the harmonic reducer.

1. Introduction
Harmonic reducer has significant advantages such as high transmission efficiency, high transmission accuracy, large single-machine transmission ratio, small size, and strong carrying capacity, and has been widely used in the field of industrial robots [1]. As one of the core components of industrial robots, the harmonic reducer plays the role of reducing the output speed and increasing the output torque. Its performance is directly related to the positioning accuracy and health status of the industrial robot [2]. The power signal of the harmonic reducer is one of the important parameters that reflect the operating state of the harmonic reducer. Under long-term load work, the performance of the harmonic reducer will be degraded. Therefore, accurate prediction of the power of the harmonic reducer has instructive significance for its failure warning and performance prediction. Then it can reduce the loss caused by sudden failure and improve the performance and useful life of industrial robots.

In recent years, with the continuous development of artificial intelligence technology and deep learning, the existing industrial equipment failure warning and performance prediction methods have gradually evolved from mathematical model methods[3] to artificial intelligence technology[4,5], such as support vectors Machine [6], random forest [7], decision tree [8] and other methods. However, these diagnosis methods have a single network structure, and the diagnostic accuracy of data with
characteristics of high latitude, nonlinearity, and time series needs to be improved. For the complex problems, deep learning has the advantages of self-learning, multi-dimensional features, prediction of non-linear change, spatiotemporal invariance, and parallel computing. Therefore, it has received extensive attention from scholars at home and abroad. Xia [9] proposes a fault diagnosis method based on convolutional neural network for the gearbox, using the fusion-CNN model to classify gear transmission faults, and the method has obtained higher classification accuracy than traditional methods. In order to predict the remaining useful life under different bearing failure behaviors, Cheng [10] proposed a transferable convolutional neural network to learn the domain invariant features of bearing failure, and verified the effectiveness of the model through the bearing failure data set. Long short-term memory (LSTM) is suitable for processing and predicting the sequence data, and is now widely used in natural language processing, text translation, time series prediction and other fields. Wang [11] proposed a day-ahead PV power forecasting model based on long-short-term memory recurrent network (LSTM-RNN) for solar energy with random fluctuation characteristics, which is effectively predicted photovoltaic power. Zhang [12] applied the LSTM to the remaining useful life prediction of lithium-ion batteries, and combined Monte Carlo simulation to generate the RUL prediction probability. Bi-directional long short-term memory (BiLSTM) is the combination of forward LSTM and backward LSTM. BiLSTM can extract features from front to back and back to front at the same time, and is widely used in voice recognition, machine translation, sentiment analysis and other fields with its good performance. Wang [13] proposed a deep BiLSTM network to process the C-MAPSS data set to predict the remaining useful life of the turbofan engine. But compared with CNN, this model lacks the extraction of spatial features.

At present, most of the researches on the failure warning and performance prediction of the harmonic reducer use theoretical formulas to calculate the performance degradation process of the harmonic reducer [14], but these theoretical formulas often rely on preset conditions, and equally the accuracy and practicality need to be improved. At the same time, most industrial robotic arms perform cyclic reciprocating actions, and the load distribution and parameter changes of each joint are nonlinear. How to effectively use the decline data of the harmonic reducer to complete accurate and reliable failure warning and performance prediction has become an urgent problem. Aiming at the problem of accuracy and practicability of the above-mentioned data-driven method and the insufficiency of related research work on harmonic reducer performance prediction, a hybrid deep neural network (DCBNN) based on CNN and BiLSTM is proposed, which uses the operating and state parameters of the harmonic reducer collected by the accelerated life experiment to accurately predict the driving power of the harmonic reducer. First, one branch of the model uses convolutional neural networks to extract the spatial features of the condition monitoring data, while another branch uses two layers of BiLSTM to effectively extract the temporal features. The combination of CNN and BiLSTM can effectively extract the depth spatiotemporal features of condition monitoring data and alleviate the problem of vanishing gradient, thereby improving the accuracy and stability of power prediction. Finally, the accelerated life experiment data set of the harmonic reducer is used to verify the effectiveness and accuracy of the proposed method for the failure warning of the harmonic reducer.

2. Materials and Methods

The power prediction method proposed in this paper mainly includes three stages. First, normalize the original harmonic reducer condition monitoring data, and divide the training set and test set. Second, establish a DCBNN hybrid prediction model to complete feature extraction and model training. Finally, use the trained model to predict the power signal.

2.1. The structure of DCBNN

In this work, we propose a hybrid deep learning model for power prediction based on CNN and BiLSTM, which can extract the spatiotemporal characteristics of monitoring data of the harmonic reducer better. The structure of the model is presented in Figure 1. It consists of two branches, one of which is composed of 3-layer convolution, 2-layer maximum pooling and 1-ayer flattening. It is
mainly used to filter the noise of input data and extract the spatial characteristics of monitoring data. The other branch consists of a stack of two BiLSTM layers. BiLSTM can avoid vanishing gradient and exploding gradient when training the model. Meanwhile, it can extract the temporal features which are difficult for CNN. After that, the outputs of the two branches are connected with concatenate layer, then through a 3-layer full connection layer network, and the result is finally obtained.

![Diagram of DCBNN](image)

**Fig.1 The structure diagram of DCBNN.**

The first convolution layer of the DCBNN uses a filter with a size of \((1 \times 5)\) and a maximum pooling operation with a pooling size of \((1 \times 2)\). The filter sizes used in the second and third layers of convolution are both \((1 \times 3)\), and the activation functions of those three layers all select the ReLU function. Meanwhile, the convolution layer adopts a zero-filling method in order to prevent errors of the input data. For adjusting the learning rate of the model better, the optimizer of the DCBNN chooses the Adam optimization algorithm. On the other hand, this paper adopts the regularization method of Early Stopping for the sake of preventing the hybrid model from over-fitting. Before the training of DCBNN, the original training data is divided into the training set and the validation set at a ratio of 9:1. Each epoch of training must first train the model on the training set, and then test on the validation set. When the error of the model on the validation set does not decrease for ten epochs, the training is terminated early, and the last set of training parameters are saved to the DCBNN.

2.2. **DCBNN training and testing process**

It should be noted before training that the physical meaning and dimensions of the monitoring data collected by the sensor are different. In order to offset the influence of different parameters and improve the prediction accuracy of the DCBNN, it is necessary to normalize the input data, that is, the value range of the 9-dimensional input parameters is specified to the interval of \([0, 1]\). In this work, we use the min-max standardization method. For a given input time series \(\{x_0, x_1, x_2, \ldots, x_{n-2}, x_{n-1}\}\), the normalized data sequence can be obtained by the following equation:

\[
\text{Normalized value} = \frac{x - \min(x)}{\max(x) - \min(x)}
\]
The sliding window method is used to divide the monitoring data of the harmonic reducer, then the training set and the test set are generated. Root Mean Squared Error (RMSE) is chosen as the loss function of the DCBNN:

\[
\text{loss}_{\text{RMSE}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{\text{pred}} - y_{\text{real}})^2}
\]

(2)

Where \(y_{\text{pred}}\) represents the prediction value of the DCBNN, and \(y_{\text{real}}\) represents the actual value of the power.

The training and testing process of the DCBNN are indicated in Figure 2. The input dimension of the DCBNN is 9, and the output dimension is 1. The optimization algorithm uses Adam optimization algorithm [15], the number of training epochs is set to 100, and the batch size is 64.

3. Validation

3.1. Experimental design

For the sake of monitoring and analyzing the operating parameters of the harmonic reducer, an accelerated life experiment platform of the harmonic reducer was built. The top view of the experimental device is shown in Figure 3. It is mainly composed of a variable frequency motor, an input torque-speed sensor, an accelerometer, an output torque-speed sensor, a magnetic powder brake, and a data acquisition system. The rated speed of the variable frequency motor is 2845 \(\text{r/min}\) and the rated power is 1.1 kW. The range of the input torque-speed sensor is 5 \(N\cdot m\), and the torque indication error is <0.2\%FS. The range of the output torque-speed sensor is 200 \(N\cdot m\), and the torque indication error is also <0.2\%FS. The output end uses a magnetic powder brake to provide the load. The maximum torque that can be provided is 200 \(N\cdot m\), the rated speed is 1000 \(\text{r/min}\), and the adopted cooling mode is water cooling. The harmonic reducer used in the experiment has a reduction ratio of 1:51, a rated torque of 32 \(N\cdot m\), and a maximum allowable torque of 121 \(N\cdot m\). This experiment uses the TR-3 acquisition instrument that is matched with the sensor, communicates with the upper computer using the RS485 protocol, and transmits the collected monitoring data.
3.2. Experimental scheme

In this work, we design and complete multiple sets of accelerated life experiments for obtaining the monitoring data of the whole life of the harmonic reducer. The triple load and quadruple load are set in the experiments respectively. After the harmonic reducer has been operated for a period of time, fatigue fracture will appear, which can be regarded as complete failure. At the same time, the experimental platform stops running. The experimental schemes and results are shown in Table 1.

| Group | Load  | Running time / h | Fracture region |
|-------|-------|------------------|-----------------|
| 1     | Triple| 21.3             | Flexspline      |
| 2     | Triple| 89               | Flexspline      |
| 3     | Triple| 69.3             | Flexspline      |
| 4     | Triple| 54.4             | Flexspline      |
| 5     | Quadruple| 5.7             | Flexspline      |
| 6     | Quadruple| 20              | Flexspline      |
| 7     | Quadruple| 9.8             | Flexspline      |
| 8     | Quadruple| 8.5             | Flexible bearing|

3.3. Performance of the DCBNN

To quantify and evaluate the performance of the model designed in this work, three universal methods including Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used. First, the equation (1) will be utilized to normalize the monitoring data set of 8 groups of experiments, then divide it into training set and testing set according to 7:3 and 8:2, and set the length of sliding window length to 20. Then input the preprocessed data into the DCBNN model. Before the training starts, the original training data will be divided into training set and validation set by 9:1. Whenever the DCBNN is trained on the training set, it will be verified on the validation set. When the error obtained in the verification set does not decrease for 10 epochs or reaches the preset number of epochs, the DCBNN will terminate the training. The preset number of epochs and batch size of the model are set to 100 and 64, respectively. Figure 4 indicates the changes of the losses on the training set and the validation set during the training process.

It can be seen from the figure that as the training of the DCBNN starts, the losses of the training set and the validation set drop rapidly and begin to gradually converge, and the hybrid model terminates the training after reaching the conditions of Early Stopping. The trained model will be saved and it will be called in the testing set. The prediction results of 8 different data sets are shown in Table 2. When the ratio of training set to test set is 8:2, the maximum, minimum, and average values of MSE are 0.002636, 0.000723 and 0.001499 respectively. The maximum, minimum and average values of MAE are 0.033021, 0.02105 and 0.027282. In the meanwhile, the maximum, minimum and average values of MAPE are 7.72%, 3.94% and 5.58%. In addition, when the ratio of the training set to the test set is 7:3, the maximum, minimum and average of MSE are 0.00169, 0.000604 and 0.001103, respectively. For MAE, the maximum, minimum and average are 0.029817, 0.018679 and 0.023557.
At the same time, the maximum, minimum and average of MAPE are 5.56%, 3.6% and 4.76%, respectively. In order to evince the power prediction results of the DCBNN more intuitively, the curves of predicted power and actual value in the two data sets are shown in Figure 5, which indicates that the results of power prediction are close to the real data. Therefore, the hybrid prediction model proposed in this work can achieve accurate prediction of the operating power of the harmonic reducer.

![Fig.4 The training and validation loss of DCBNN.](image1)

![Table 2 Performance evaluation of DCBNN on different data sets.](image2)

| Group | Ratio | Load  | MSE      | MAE      | MAPE   |
|-------|-------|-------|----------|----------|--------|
| 1     | 8:2   | Triple| 0.002636 | 0.033021 | 6.24%  |
| 2     | 8:2   | Triple| 0.001701 | 0.030902 | 7.72%  |
| 3     | 8:2   | Triple| 0.000935 | 0.024155 | 4.43%  |
| 4     | 8:2   | Triple| 0.000723 | 0.02105  | 3.94%  |
| 5     | 7:3   | Quadruple| 0.00169  | 0.029817 | 5.56%  |
| 6     | 7:3   | Quadruple| 0.000952 | 0.021739 | 4.44%  |
| 7     | 7:3   | Quadruple| 0.001166 | 0.023994 | 5.43%  |
| 8     | 7:3   | Quadruple| 0.000604 | 0.018679 | 3.6%   |

![Fig.5 Power prediction curves of DCBNN and actual curves on different datasets.](image3)

3.4. Comparisons with existing methods

In this part, the existing prediction methods were trained and tested on 8 datasets for verifying the performance of the DCBNN, and those trained models were evaluated using MSE, MAE and MAPE.
The comparison methods are used include: Support Vector Regression (SVR), Random Forest (RF), Deep Neural Networks (DNN), LSTM, and CNN. When building the SVR model, the kernel uses the radial basis function, the tolerance criterion is set to 0.002, the penalty coefficient C is set to 12, and the unpunished width $\varepsilon$ is set to 0.001. In RF, the number of decision trees is set to 3, the maximum number of features is set to 8, and the maximum depth of the tree is 8. We use the four-layer fully connected network in DNN which are connected in series. The activation function of the hidden layer is sigmoid activation function, and the number of neurons in the four layers is set to $\{256, 128, 64, 1\}$. The LSTM model consists of a two-layer LSTM and a three-layer fully connected network. The number of neurons in the fully connected layer is set to $\{64, 32, 1\}$. At the same time, the Dropout and the Early Stopping method are used for preventing the model from overfitting. Meanwhile, the CNN model is composed of three convolutional layers, three maximum pooling layers, and two fully connected networks in series. The convolutional layer and the pooling layer are used to extract features from the input monitoring data. Dropout and Early Stopping are also used to avoid overfitting. The evaluation results of several model are shown in Tables 3-5.

Table 3 The value of MSE of six methods.

| Group | DCBNN | SVR  | RF   | DNN  | LSTM | CNN  |
|-------|-------|------|------|------|------|------|
| 1     | 0.002636 | 0.013451 | 0.015915 | 0.014115 | 0.003775 | 0.004697 |
| 2     | 0.001701 | 0.012956 | 0.013876 | 0.013137 | 0.003956 | 0.006325 |
| 3     | 0.000935 | 0.005472 | 0.004364 | 0.004778 | 0.001399 | 0.002446 |
| 4     | 0.000723 | 0.024337 | 0.008955 | 0.01063 | 0.003656 | 0.002534 |
| 5     | 0.001769 | 0.007187 | 0.006523 | 0.007801 | 0.001857 | 0.003979 |
| 6     | 0.000952 | 0.008981 | 0.011164 | 0.007724 | 0.001862 | 0.002505 |
| 7     | 0.001166 | 0.00905 | 0.009119 | 0.00529 | 0.001466 | 0.002808 |
| 8     | 0.000604 | 0.014517 | 0.008295 | 0.009882 | 0.000924 | 0.001577 |

Table 4 The value of MAE of six methods.

| Group | DCBNN | SVR  | RF   | DNN  | LSTM | CNN  |
|-------|-------|------|------|------|------|------|
| 1     | 0.033021 | 0.09143 | 0.091886 | 0.08513 | 0.044056 | 0.052484 |
| 2     | 0.030902 | 0.089994 | 0.093333 | 0.09062 | 0.048441 | 0.062471 |
| 3     | 0.024155 | 0.060645 | 0.053664 | 0.056388 | 0.029749 | 0.039733 |
| 4     | 0.021049 | 0.100525 | 0.068046 | 0.078266 | 0.038607 | 0.037453 |
| 5     | 0.029817 | 0.0661 | 0.063716 | 0.069929 | 0.03163 | 0.049504 |
| 6     | 0.021739 | 0.068183 | 0.076648 | 0.066304 | 0.031638 | 0.037502 |
| 7     | 0.023994 | 0.068174 | 0.063923 | 0.052461 | 0.028631 | 0.039365 |
| 8     | 0.018679 | 0.093152 | 0.062932 | 0.076309 | 0.023835 | 0.028976 |

Table 5 The value of MAPE of six methods.

| Group | DCBNN | SVR  | RF   | DNN  | LSTM | CNN  |
|-------|-------|------|------|------|------|------|
| 1     | 6.24% | 17.97% | 16.7% | 15% | 8.32% | 10.27% |
| 2     | 7.72% | 18.23% | 19.03% | 17.92% | 9.9% | 12.7% |
| 3     | 4.44% | 11.62% | 10.15% | 10.74% | 5.46% | 7.3% |
| 4     | 3.94% | 25.46% | 12.19% | 15.65% | 9.64% | 7.32% |
| 5     | 5.56% | 12.1% | 11.72% | 12.45% | 5.82% | 9.35% |
| 6     | 4.44% | 13.72% | 14.79% | 14.49% | 6.6% | 7.74% |
| 7     | 5.43% | 14.5% | 13.28% | 12.16% | 6.34% | 9.4% |
| 8     | 3.6% | 17.49% | 10.27% | 13.97% | 3.97% | 5.92% |

It can be seen from Tables 3-5 that the values of MSE, MAE and MAPE of the proposed DCBNN model on 8 different datasets are all smaller than those of the other five comparison methods. The
average of MSE, MAE and MAPE of DCBNN in 8 datasets are 0.00130, 0.02542, 5.17%, respectively. The average of MSE, MAE and MAPE of SVR are 0.011994, 0.079775, 16.39%, respectively. For RF, the average values are 0.009776, 0.071769 and 13.52%. It is indicated that the MSE and MAE of DCBNN decreased by 89.15%, 68.14% and 86.70%, 64.58% compared with SVR and RF. And the prediction accuracy was improved by 11.22% and 8.35% compared with SVR and RF. It means that traditional machine learning methods cannot extract the desired features from high-dimensional time series data well.

Similarly, for the deep learning models, the average of MSE, MAE and MAPE in 8 datasets of DNN are 0.00917, 0.071926, and 14.05%, respectively. For LSTM, the average values are 0.002362, 0.034573, and 7.01%. In addition, the average of MSE, MAE, and MAPE of CNN are 0.003359, 0.043436, and 8.75%. Therefore, the average of MSE of DCBNN decreased by 85.81%, 44.92% and 61.27% respectively compared to DNN, LSTM, and CNN. The average of MAE dropped by 64.66%, 26.48% 41.48%. The prediction accuracy of DCBNN is 8.88%, 1.84%, 3.58% higher than that of DNN, LSTM, and CNN respectively. From those quantitative comparison results, it is apparent that the LSTM network is significantly better than DNN and CNN, and the performance of the DCBNN model is also better than DNN, CNN and LSTM. This is due to the optimization of the network structure of the DCBNN, that is, two branches separately extract the spatial and temporal features of the monitoring data, so the DCBNN has higher accuracy of power prediction.

To sum up, the model based on machine learning has a relatively simple structure, and it is difficult to extract the nonlinear characteristics and time series features of the monitoring data of the harmonic reducer, so the performance on 8 different datasets is poor. Although models based on deep learning can better extract the complex features of monitoring data, single model still has certain limitations. For example, the CNN model can effectively extract the spatial features of the dataset, but it is difficult to deal with the temporal features. LSTM is more sensitive to the time series data, but the utilization of the spatial features is very low. Therefore, the hybrid prediction model proposed in this work comprehensively analyzes the spatial and temporal characteristics of the monitoring data of the harmonic reducer, and achieves good general-purpose effects for different load conditions and failure modes.

3.5. Early failure warning of harmonic reducer

Through the hybrid prediction model established above, accurate power prediction can be performed on the monitoring datasets of the harmonic reducer, then the power prediction value can be obtained. Next, calculate the absolute value of the residual between the actual value of the power and the predicted value, denoted as $\varepsilon$. Using the distribution fitting method of the probability theory to fit the residual curve, it can be considered that it conforms to the logarithmic normal distribution, and the probability density distribution of $\varepsilon$ is as follows:

$$f(\varepsilon) = \frac{1}{\varepsilon \sqrt{2\pi} \sigma} \cdot e^{-\frac{(\ln(\varepsilon)-\mu)^2}{2\sigma^2}}$$

(3)

Where $\mu$ and $\sigma$ are the mean and standard deviation of the $\varepsilon$ distribution.

According to this distribution, the alarm threshold $Q$ of the early failure warning of the harmonic reducer can be obtained, and $Q$ conforms to the formula (4):

$$\int_0^Q f(ln(\varepsilon)) \cdot dln(\varepsilon) = 1 - \alpha$$

(4)

Where $\alpha$ represents the significance level of that distribution. In this work, we set $\alpha = 0.01$ for improving the accuracy of failure warning. That is, when $\varepsilon < Q$, the harmonic reducer is considered to be in normal operation. However, it is considered that the performance of the harmonic reducer is greatly degraded when $\varepsilon \geq Q$, and is about to fail. Therefore, it is necessary to stop the harmonic reducer in time and carry out maintenance and replacement.

Taking dataset 4 as an example, by fitting the distribution of the residual $\varepsilon$ of actual power value and the predicted value, the mean value of the $\varepsilon$ distribution is -6.5855 and the standard deviation is 0.7032. From this, it can be calculated that the harmonic reducer early failure warning threshold $Q = 0.007087$ corresponding to the dataset 4. Intercepting the data for a period of time before the failure of
the harmonic reducer to draw the failure warning diagram of the harmonic reducer as shown in Figure 6. It is simple to find that when the harmonic reducer is in a health state, the residual error \( \epsilon \) of the predicted value and the actual value of the power is always kept at a state less than \( Q \). When the performance of the harmonic reducer is degraded, that is, the harmonic reducer may malfunction or even fail, the residual \( \epsilon \) changes drastically and is soon greater than the alarm threshold \( Q \). At this time, it is considered that the harmonic reducer is about to fail and a warning is issued. In fact, the harmonic reducer failed after running for a period of time under quadruple load, so it can illustrate that the effectiveness and accuracy of the method proposed in this paper.

![Fig.6 The schematic diagram of failure warning on dataset 4.](image)

Similarly, applying the method to dataset 6, by fitting the distribution of residual \( \epsilon \) of the actual power value and the predicted value, the mean value of the \( \epsilon \) distribution is -6.427, the standard deviation is 0.5142. According to formula (13) and formula (14), the early failure warning threshold \( Q = 0.006079 \). Figure 7 indicates the failure warning of the harmonic reducer corresponding to dataset 6. When the harmonic reducer is in healthy operation state, the residual \( \epsilon \) is always kept less than \( Q \). When \( \epsilon \) reaches the alarm threshold \( Q \), the performance of the harmonic reducer is degraded, therefore the equipment needs to be stopped. It can be seen from the figure that after reaching the alarm threshold, the residual fluctuates greatly and drops below the threshold sometimes, but the subsequent residuals rise sharply, and it can still be considered that the harmonic reducer is about to fail.

![Fig.7 The schematic diagram of failure warning on dataset 6.](image)

### 4. Conclusion

In this paper, a hybrid deep neural network based on CNN and BiLSTM is proposed to predict the power of harmonic reducer. Among that, the CNN branch of the DCBNN is used to extract the spatial
characteristics of the monitoring data, and the BiLSTM branch is used to capture the bidirectional dependency of the time series data. For the sake of verifying the accuracy and reliability of the model, 8 different datasets were constructed. The highest prediction accuracy of this method is 96.4%, and the average prediction accuracy is 95.24%. At the same time, five existing methods are selected for comparative experiments. The analysis results indicate that compared to traditional machine learning and deep learning models such as SVR, RF, DNN, LSTM and CNN, the proposed method has better performance on 8 datasets. Finally, it is verified on the complete dataset, and the proposed method can accurately warn the failure of the harmonic reducer. In the future, the practical application of deep learning methods on harmonic reducers will be further studied, with a view to making breakthroughs in early failure warning and performance prediction.

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