Research on fault diagnosis and early warning of reciprocating compressor based on stacked convolutional autoencoder optimized by gradient differential evolution

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Abstract. The reciprocating compressor is one of the key equipment in the process industrial field. Due to its complex structure and motion state, the bearing bush of the connecting rod is prone to wear failure. In the early stage of wear failure, the monitoring signal signs are very weak. As a result, it has produced bad results that identify the fault signs by using traditional data processing and spectrums analytical methods. Aiming at the early fault identification of the bearing bush, unsupervised feature mining based on autoencoder principle and super-parameter optimization based on Gradient-Differential-Evolution are utilized, and an early-warning-model based on Gradient-Differential-Evolution and Stacked-Convolutional-Autoencoder is proposed. In order to study the sensitivity of the vibration signal and piston rod settlement signal to the early stage of wear failure, the two signals are input into the early warning model for comparison. In addition, they are fused to verify the improvement ability of multi-source signal on early warning. Moreover, to verify the early fault recognition performance of the proposed methods, the proposed method is compared with the other two early-warning-models based on Stacked-Autoencoder and Convolutional-Neural-Networks. The actual fault case analysis results show that based on the Gradient-Differential-Evolution optimization model, the difficulty of parameter setting can be effectively reduced and the proposed method has significant advantages to detect the early warning timely and effectively.

1. Introduction

Reciprocating compressor is widely used in oil exploitation, natural gas exploitation, transportation and other process industrial enterprises. It is the key power machinery for safe and stable production [1,2]. Due to the complex structure and many wear-prone parts, especially under the variable load condition, the temperature and pressure of the compression medium in the cylinder continue to change rapidly. Therefore, the stress of key moving parts is complex and failures occur frequently [3,4], especially connecting rod. In case of failure, it will bring huge losses and negative impacts on economy, environment and society [5,6]. Meantime, reciprocating compressor is developing towards high speed, high efficiency and high degree of automation, its structure complexity and value are further increased [1]. The safety risk will also be further increased. Therefore, it is of great significance to find and diagnose faults in the early stage.

Connecting rod is one of the most important moving parts of reciprocating compressor. Its bearing bush is a necessary connection pair to ensure the good operation of working parts. Unfortunately, its
stress state is very complex. Due to poor lubrication, oil impurities, material deformation, processing defects and other reasons [7], the bearing bush is prone to wear. Therefore, it is very important to study the early warning diagnosis method of reciprocating compressor connecting rod bearing wear fault for timely finding fault, guiding on-site maintenance and avoiding malignant accident.

On the one hand, oil analysis is a traditional detection method in the research of wear fault detection methods for connecting rod small end bearing bush [8,9], but its off-line application mode and more complex detection and analysis process limit the wide application of this method. Although the oil on-line monitoring technology developed in recent years, the actual engineering application still needs to be further developed due to the low accuracy of wear particle detection and analysis. On the other hand, temperature monitoring is also a common wear monitoring method, because wear usually causes temperature rise. In recent years, passive wireless temperature sensor has been applied in the wear monitoring of connecting rod big end bearing bush [10]. However, it is difficult to install the sensor due to the narrow space of the small end bearing bush of the connecting rod. What is more, scholars focus on dynamic simulation computing [11-15] here are few reports on the detection method of connecting rod bearing bush wear failure based on vibration signal or piston rod settlement signal. Because understanding such signals requires a lot of artificial experience and strong feature extraction capabilities.

Fortunately, with the rapid development of machine learning, the ability of classification based on features is improving. Diagnosis is no longer limited by feature extraction capabilities, and the diagnostic methods based on vibration signal and distance signal have made breakthrough progress. Based on vibration signal, Potocnik [16] applied machine learning methods such as neural network (NN), support vector machine (SVM) to fault diagnosis of reciprocating compressor. Qi et al. [17] extracted five dimensionless features of several types of vibration fault signals of reciprocating compressor, followed by probabilistic neural network (PNN), and realized the fault diagnosis of piston rod, piston ring and suction valve of reciprocating compressor. Yang [18] et al. and Li [19] et al. based on convolution neural network to extract signal features, followed by classifier, realized fault diagnosis of reciprocating compressor. Van [20] used the deep confidence network (a method of machine learning) to realize the fault diagnosis of reciprocating air compressor in different valves, including the fault diagnosis of suction leakage, discharge leakage and spring deterioration. However, the feature extraction ability of the above papers needs to be strengthened.

In recent years, Stack-Autoencoder [21] (SAE) has become a widely used unsupervised feature extraction method, which can be effectively used for feature extraction of various signals. Based on this, Stack-Convolutional-Autoencoder [22] (SCAE) has a good feature expression ability for one-dimensional signal by introducing convolution operation. Chen [23] et al. used a One-Dimensional-Stack-Convolutional-Autoencoder (1D-SCAE) for fault detection and diagnosis of multivariable processes. By denoising high-dimensional signals and learning the deep features of multivariable signals in one-dimensional SCAE, they achieved fault detection and diagnosis in process industry. Li [24] et al. proposed a framework based on convolutional autoencoder and K-means by using a Stack-Convolutional-Autoencoder for image feature learning. Based on the computer vision method, Fu [25] et al. Grouped all variables, extracted each group of features by using the improved convolution autoencoder, and classified and diagnosed the aeroengine fault after feature fusion. Zhou [26] et al. introduced residual learning mechanism to optimize the learning ability of the model based on learning deep features of convolutional autoencoder, and achieved the fault diagnosis of gear teeth and bearings.

These study attempts to explore the performance of SCAE in the early recognition of reciprocating compressor connecting rod bearing wear fault, and make full use of the unsupervised feature mining ability of SCAE to extract early fault features. In addition, Gradient-Differential-Evolution algorithm (GDE) is proposed to solve the problem of neural network super parameter optimization combined with the operation characteristics of neural network itself, especially for the shallow plank model to adaptively obtain super parameters, so as to reduce the artificial experience required to set parameters.

In conclusion, the fault early warning model based on GDE-SCAE is established. Combined with the actual field fault case data, the sensitivity of various monitoring signals to the early fault of connecting rod bearing bush and the positive role of multi-source signal fusion are studied. In the
meantime, the effectiveness and superiority of the proposed method are verified through the comparative analysis of typical methods.

2. Data acquisition

The actual fault case of a new hydrogen reciprocating compressor in a petrochemical plant was studied. The unit model: 3HHE-VL-3; rated power: 4365KW; rated speed: 300R / min; inlet design pressure (1 / 2 / 3): 2.1/4.2/9.9MPa; outlet design pressure (1 / 2 / 3): 4.3/8.8/16.1MPa. In addition, the unit is equipped with reciprocating compressor vibration online monitoring system, and the unit structure and vibration measuring point layout are shown in Figure 1. At about 6:00 on April 29 of a year, the professional inspection personnel caught the abnormal vibration of cylinder 3, and then found that the bearing bush of connecting rod small end of cylinder 3 was seriously worn.

![Figure 1. Sketch map of unit structure and vibration measuring points](image)

The on-line vibration monitoring system records the data of fault occurrence and development process completely, and exports a certain amount of monitoring sample data through a special data interface. The distribution of data samples in each period is shown in Figure 2. Taking the fault discovery time as the node, the sample number before fault discovery is 657, and the sample data after fault discovery is 945. Figure 3 and Figure 4 respectively show the waveforms of vibration signal and piston rod settlement signal of 3# cylinder block in 85 hours, 60 hours, 35 hours, 20 hours, 5 hours before fault discovery and at fault discovery.

It can be seen from the waveform that the vibration and piston rod settlement waveforms have changed significantly when the fault is found. Manual inspection can find fault through waveform. In fact, if the manual inspection is carried out at any time, it is not difficult to see that the waveform is abnormal one day before the fault is found. However, two days before the fault was found and earlier, the signal waveform and amplitude were not significantly abnormal. Therefore, it is difficult to find early faults through manual inspection. The research goal is to use the powerful feature mining ability of deep learning network to identify early fault features and give early warning.

![Figure 2. Distribution of the number of data samples obtained](image)

3. The construction of model

3.1. Feature extraction principle of stack convolutional autoencoder

Convolutional autoencoder (CAE) is an unsupervised algorithm, which is often used for feature extraction. The structure diagram of CAE is shown in Figure 5, which consists of encoding and decoding. The encoding part consists of a convolution layer and a pooling layer, and the decoding part...
consists of an upper sampling layer and a deconvolution layer. Due to the characteristics of the autoencoder, it is required the input $X$ after encoding and decoding should get $\hat{X}$ approximately equal to $X$, so a convolution layer is usually added at the top of the convolution autoencoder to make the dimension of $\hat{X}$ the same as $X$. The output characteristic $H$ obtained by input $X$ in coding is convoluted by $X$. Therefore, it can be considered that the information contained in it comes from $X$.

**Figure 3.** The waveform of vibration signal of faulty cylinder at 85 hours (a), 60 hours (b), 35 hours (c), 20 hours (d), 5 hours (e) and at the time of fault detection (f)

**Figure 4.** The waveform of piston rod settlement of the faulty cylinder at 85 hours (a), 60 hours (b), 35 hours (c), 20 hours (d), 5 hours (e) and at the time of fault detection (f)

**Figure 5.** Structure of a single CAE

**Figure 6.** Structural relationship between CAE and SCAE

Stacked-convolutional-autoencoder (SCAE) is composed of multiple coding layers of CAE. A three-layer SCAE structure is shown in Figure 6, which is composed of the coding parts of three CAE. Get the weight and bias of each CAE as $W_{el}^k$, $W_{e2}^k$, $W_{e3}^k$ and $b_{el}^k$, $b_{e2}^k$, $b_{e3}^k$.

3.2. The structure of the model and the way of super parameter optimization.

3.2.1. The structure of the model
Establish the SCAE model as shown below, and name the super parameters. If there is no special explanation, in this study, ‘Keras’ is used for training. Batch Normalization (BN) layer and Dropout layer are added after pooling layer. The layer with weights is regularized by L2 with the penalty factor 0.001. In convolution layer, bias are not used; all convolution steps are set to 1; convolution kernel size is ‘3’; padding mode is ‘same’; activation function is ‘ReLU’ , which only used in the encoding part. In classification layer, ‘Softmax’ function is used and outputs node is set to 2. The optimization method is Adam with learning rate 0.001.

3.2.2. the way of super parameter optimization

It is difficult to study the optimal value of a single super parameter in isolation by using the method of control variables because of the coupling effect of many super parameters of the model. Therefore, it is necessary to optimize multiple super parameters simultaneously. Differential evolution (DE) algorithm has been widely studied and applied in combinatorial optimization. It shows better effect than simulated annealing algorithm, genetic algorithm, particle swarm optimization and other optimization algorithms [27,28]. The parameters involved in DE algorithm are: group a with size of \( NT \), mutation parameter \( \alpha \), selection probability parameter \( CR \) and maximum number of iterations \( MAX \).

However, the parameter \( \alpha \) and \( CR \) need to be set manually. They remain unchanged in the iterative process, which makes the model difficult to converge. In order to solve this problem, some scholars have proposed an improved scheme that changes adaptively with the iteration process, and the improved scheme that carries out local optimization and fine-tuning. Unfortunately, the above improved scheme has the following shortcomings.

- To control parameters by adding a parameter, such as an adaptive adjustment scheme. It requires manual setting of adjustment parameters.
- The convergence is enhanced by increasing the number of operations, such as fine tuning and local optimization. The training time of neural network is long, and each training is full of randomness. As a result, the cost of increasing the number of operations is difficult to accept.

To solve these two problems, we propose an improved scheme based on gradient (GDE), which introduces an ‘or’ type constraint on the selection probability parameter \( CR \). The details are as follows. The last evolutionary direction of genes in memory individuals consists of - 1 (decrease), 0 (unchanged) and 1 (increase). If this evolution is still in the same direction, the selection probability parameter \( CR \) is invalid, and the gene would be selected.

In order to verify the effectiveness of the improved method, two standard verification functions, Ackley and Sphere, are selected to explore. Three methods, Standard DE, Decreasing DE, Gradient DE (our method GDE), are selected to compare. The variation parameter \( \alpha \) and selection probability parameter \( CR \) are all 0.5. The parameter quantity is 5-9, and the base number of iterations is 45. Each additional parameter increases the number of iterations by 10. Decreasing DE: the probability parameter \( CR \) decreases linearly to 5%, 10%, 15%, 20% and 25% of the initial value. The optimal solution is taken as the optimal solution decreasing with iteration.

It can be seen that the proposed method can achieve good results under the above parameters. Therefore, the flow chart of using the GDE to optimize the super parameters of SCAE model is shown in Figure 7. It should be pointed out that, the gradient matrix preserves the last evolutionary direction of all genes of all individuals and is initialized as all 0 matrix. Individual gene refers to the super
parameter in SCAE module. The optimization objective is the classification accuracy of the model, that is:

$$\text{acc} = f(k_1, k_2, k_3, p_1, p_2, p_3, f_{c_1})$$  \hspace{1cm} (1)

![Figure 8. Ackley function and Sphere function.](image)

### Table 1. Ackley function’s comparison results

| Ackley\(/\text{loss}/\text{number of parameters} | 5    | 6    | 7    | 8    | 9    |
|-----------------------------------------------|------|------|------|------|------|
| Standard DE                                  | 0.048| 0.047| 0.044| 0.041| 0.041|
| Decreasing DE                                | 0.049| 0.047| 0.044| 0.044| 0.042|
| Gradient DE                                  | 0.040| 0.043| 0.042| 0.041| 0.040|

### Table 2. Sphere\(y\) function’s comparison results

| Sphere\(/\text{loss}/\text{number of parameters} | 5    | 6    | 7    | 8    | 9    |
|-----------------------------------------------|------|------|------|------|------|
| Standard DE                                  | 6e-5 | 1e-4 | 1.6e-4| 2.4e-4| 3.3e-4|
| Decreasing DE                                | 2e-5 | 9e-5 | 2.1e-4| 2.4e-4| 2.7e-4|
| Gradient DE                                  | 0    | 7e-5 | 9e-5 | 1.7e-4| 2.6e-4|

In order to reduce the randomness of neural network, the average accuracy of each training is taken as the average accuracy of five times. According to the number of optimized super parameters, \(i, j, r\) in the flow chart are determined to be integers not greater than this. The boundary condition refers to the artificial individual gene range, namely the solution space. In the process of mutation, if the new individual gene exceeds this range, the gene will be generated randomly again within the specified range.

### 4. Case analysis

#### 4.1. Fault early warning based on GDE-SCAE

The monitoring information of reciprocating compressor mainly comes from vibration and piston rod settlement signal. In order to deeply study the sensitivity of two kinds of signals to early fault, and explore the effect of two kinds of signal fusion analysis on improving the ability of early fault identification. In this paper, three groups of fault diagnosis tests based on GDE-SCAE are carried out, whose input data are vibration signal, piston rod settlement signal and their fusion signal.

According to existing experience, the solution space of SCAE model is given according to table 1. Randomly select values to initialize group A. In addition, \(NI = 20, CR = 0.5, \alpha = 0.3\), and \(MAX = 100\) are set. If there is no special specification, the following tests all adopt this.

The obtained data are divided into 8 groups according to the statistical results of sample data in Figure 2. The first group of data is taken as normal sample data, and the subsequent groups of data are taken as fault sample data in different tests, so as to verify the ability of early fault discrimination. Five-fold-cross validation is used to obtain the accuracy index. The average of five training accuracy is the final index.
Figure 9. The flow chart of GDE optimization algorithm

In the field of mechanical equipment fault diagnosis, multi-source fusion data is verified to improve the accuracy of equipment state change judgment. Considering that the physical meaning of vibration signal and piston rod settlement signal is different, we use a simple fusion method, which inputs the two kinds of signals into the model respectively to complete feature extraction and then fusion. That is to say, the vibration signal and the piston rod settlement signal are respectively extracted to form feature vectors, and then the feature vectors of the two kinds of signals are spliced to form a fusion signal before the full connection layer.

Using the vibration signal of the fault cylinder, the settlement signal of the piston rod and the fusion signal of the two kinds of signals, the GDE-SCAE model is trained and the parameters are optimized. Under the same parameter, five-fold cross validation was carried out, and the average accuracy was taken as the final accuracy. The results of super parameter optimization are shown in Table 4. The accuracy of fault early warning is shown in Figure 11.

The following conclusions can be seen from the results of fault early warning accuracy in Figure 11. The early warning model based on GDE-SCAE has a very good ability of mining abnormal features, which can detect faults at least 60 hours earlier than manual inspection. Vibration signal is more sensitive to fault than settlement signal. Fusion analysis is helpful to improve the ability of early fault identification.

4.2. comparative analysis

In order to verify the performance of fault early warning based on GDE-SCAE, the proposed method is compared with GDE-SAE and GDE-CNN.

In GDE-SAE method, SAE is composed of multiple AE stacked. Both SCAE and SAE have encoding and decoding structures. The difference between them is that each layer of SAE coding and decoding part is convolution and pooling layer.
The super parameters to be optimized in GDE-SAE include: the number of nodes in each middle layer \( (k_1, k_2, k_3) \). The number of nodes in the full connection layer is \( j_1 \). The default solution space is shown in Table 3. The optimal solution is shown in Table 5. The accuracy of fault early warning diagnosis is shown in Figure 12.

![Figure 10. A method of feature fusion](image1)

**Figure 10.** A method of feature fusion

![Figure 11. Accuracy of fault early warning based on GDE-SAE](image2)

**Figure 11.** Accuracy of fault early warning based on GDE-SAE

| Type (SCAE) | Default solution space | Type (CNN) | Default solution space | Type (SAE) | Default solution space |
|-------------|------------------------|------------|------------------------|------------|------------------------|
| Nc          | [1~8]                  | Nc         | [1~8]                  | NS         | [1024,512,256,128,64,32,16,8] |
| Ps          | [2,4,8,16,32,64]       | Ps         | [2,4,8,16,32,64]       | FC         | [64,32,16,8]          |
| FC          | [64,32,16,8]           | FC         | [64,32,16,8]           | FC         | [64,32,16,8]          |

**Table 3.** Presupposition solution space of SCAE/CNN model (Num. of convolution kernels (Nc); Pooling size (Ps); Nodes of Fully-Connection layer (FC); Nodes of SAE layer (NS))

**Table 4.** Optimal solution space of SCAE model

| Parameters | Vibration signal | Settlement signal | Fusion signal |
|------------|------------------|-------------------|--------------|
| \( k_1, k_2, k_3 \) | 2, 1, 1          | 3, 3, 3           | (2, 1, 1); (3, 3, 3) |
| \( p_1, p_2, p_3 \) | 16, 2, 2         | 16, 2, 2          | (16, 2, 2); (16, 2, 2) |
| \( j_1 \) | 32               | 16                | 32; 16       |

**Table 5.** Optimal solution space of SAE model

| Parameters | Vibration signal | Settlement signal | Fusion signal |
|------------|------------------|-------------------|--------------|
| \( k_1, k_2, k_3 \) | 1024,512,64      | 256,64,16         | (1024,512,64); (256,64,16) |
| \( j_1 \) | 32               | 32                | 32; 32       |

**Table 6.** Optimal solution space of CNN model

| Parameters | Vibration signal | Settlement signal | Fusion signal |
|------------|------------------|-------------------|--------------|
| \( k_1, k_2, k_3 \) | 2, 2, 2          | 5, 4, 2           | (2, 2, 2); (5, 4, 2) |
| \( p_1, p_2, p_3 \) | 4, 2, 2          | 4, 2, 4           | (4, 2, 2); (4, 2, 4) |
| \( j_1 \) | 32               | 32                | 32; 32       |

In the GDE-CNN method, CNN is composed of multiple convolution pooling layers, and then the fully-connection layer is used for feature processing. SCAE and CNN have the same point that their structures are stacked by multi-layer convolution pooling layers, and their solution spaces need to be optimized are the same. The difference is that SACE has encoding and decoding structure, while CNN only has feature extraction (encoding structure) part.

The parameters to be optimized for GDE-CNN are as follows. The number of convolution kernels in each layer \( (k_1, k_2, k_3) \), pooled size \( (p_1, p_2, p_3) \), the number of nodes in the fully-connection layer \( j_1 \). The default solution space is shown in Table 3. The optimal solution is shown in Table 6. The results of fault early warning diagnosis accuracy are shown in Figure 13.

Comparing with figure 11, figure 12 and Figure 13, we can see the following conclusion. The main advantage of de-scae is that it has the strongest ability to identify faults in the early stage. In general, the fusion of two kinds of signals is more accurate than single signal input, especially in the early stage of fault. Signal fusion plays a significant role in improving the ability of fault recognition.
5. Conclusion

In this paper, an early warning method of reciprocating compressor connecting rod bearing bush fault based on Stack-Convolution-Autoencoder (SCAE) is constructed. The sensitivity of vibration signal and piston rod settlement signal to the failure of connecting rod bearing bush is explored. It further verifies the better effect of multi-source signal fusion in early fault identification of complex mechanical equipment. What is more, a Gradient-Differential-Evolution (GDE) method is proposed to solve the problem of neural model super parameter selection, which reduces the difficulty of super parameter selection. This model can be directly applied to other units of the same type. When the unit type is different, this early warning model framework is still applicable, but transfer learning is needed, that is, the feature extraction part (SCAE module) needs to be retrained.

Compared and verified the fault early warning ability of GDE-SCAE, GDE-SAE and GDE-CNN, the analysis and research results are as follows. The GDE-SCAE method has a strong ability of early abnormal feature mining, and can identify early faults about 60 hours earlier than manual spectrum analysis method. Under five-fold-cross validation and multi-source signal fusion, the accuracy can reach 94%. Among the three model methods, the multi-source signal fusion is helpful to improve the fault identification ability of the model, and the proposed GDE-SCAE method has the best comprehensive recognition ability, especially in the early stage of fault.

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