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Fault Diagnosis of Air Compressor in Nuclear Power Plant Based on Vibration Observation Window

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ABSTRACT Nuclear Power Plant (NPP) have increasing demand to improve safety and reliability of air compressors with various fault diagnosis methods. Fault diagnosis methods may provide early fault warning information for air compressors rapidly and give a reference for maintenance, especially for the serious faults affecting security strongly. In this work, a method framework of fault diagnosis system based on the Vibration Observation Window (VOW) for air compressors is proposed. The VOW constructs a dynamic vibration tensor which presents the operating state of air compressors according to the real time vibration data, strengthens the association among the monitoring data in spatial domain and time domain. Thus, dynamic characteristic, which reflects the fault information, can be contained in the dynamic vibration tensor explicitly. For proving the advantage of VOW method, we compare the performance between the fault diagnosis system with VOW and the fault diagnosis system without VOW based on different hardware environments: embedded computer, and high speed Industrial PC. The results show that the VOW method can both improve the performance of the vibration fault diagnosis system of NPPs in different hardware environments.

INDEX TERMS Air compressors, fault diagnosis, vibration tensor, nuclear power plants, VOW method.


I. INTRODUCTION

As critical mechanical systems in Nuclear Power Plants (NPPs), safety is of prime importance for air compressors, and closely related to the mechanical state. Various kinds of faults, which may occur in any components of air compressors, have a major impact on security of NPP operation and experiment. Moreover, aged air compressors in NPPs are more vulnerable to aging-related faults [1]. This becomes a major concern as existing NPPs on average are over 30 years old [2], and similar problems may happen in some special nuclear reactors. Therefore, fault diagnosis systems are necessary for air compressors operation.

Over the past few decades, various diagnosis methods, including model-based methods [3], [4], data-driven methods

and signal-based methods [5], have been applied in fault diagnosis. For example, Kalman filters and parameter estimation which belong to model-based methods [6], [7], artificial neural networks and partial least squares which belong to data-driven methods [8], [9], time-frequency analysis and wavelet transform which belong to signal-based methods [10], etc.

Model-based method is the first method used for the fault diagnosis of complex mechanical system, where, analytical redundancy is the core concept that most model-based methods are based on [11]. For model-based methods, the normal behavior of a system needs to be described by the mathematical model. Based on the model, output variables of the system can be estimated analytically from other correlated measurements. The idea can be extended to analytically estimate other quantities such as model parameters and system states. The differences between the analytically estimated quantities and the actual measurements are called residuals.

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Faults result in violations of the normal relationships represented in the model, leading to statistically abnormal changes in the residuals, so that faults can be detected by testing these residuals statistically [12]. However, the accurate models are necessary, which is difficult to be built. In addition, faults that have not been considered in the modeling stage may not be detected at all. Further, robustness against disturbances and modeling uncertainties has to be considered [13].

Signal-based and data-driven methods do not rely on precise dynamic models of systems. Actually, signal-based methods can be regarded as special data driven methods. They make decisions by comparing features extracted from a signal or state data with baseline characteristics that are considered to be normal, where, features in both frequency domain and time domain have been used. With the development of artificial intelligence, multivariate statistical methods are also used for signal-based method gradually. For the fault diagnosis of the rotating machinery based on signal-based method, analysis in time-domain, frequency-domain, and time-frequency domain [14]. The methods like fast Fourier transform (FFT) [15], wavelet transformation (WT) [16], empirical mode decomposition (EMD) [17], ensemble empirical mode decomposition (EEMD) [18], empirical wavelet transform (EWT), wavelet packet transform (WPT) [19], variational mode decomposition (VMD), stochastic resonance, sparse decomposition, etc., were suggested worldwide.

However, with the continuous development of computer, sensor and manufacturing technology, the modern mechanical systems have shown a new trend of large-scale, complex and distributed [20], so that traditional signal-based methods cannot adapt to the complexity of modern mechanical systems. As a typical branch of data-driven methods, machine learning method was developed during past decades to teach machines how to handle data more efficiently. some of the broadly practiced machine learning algorithms are artificial neural networks (ANNs) [21], principal component analysis (PCA) [22], support vector machines (SVM) [23], [24], k nearest neighbors (KNNs) [25], singular value decomposition (SVD) [26]. In recent years, some fault deep learning methods represented by convolutional neural networks (CNNs) were also presented, for example, the motor bearing, self-priming centrifugal pump, and axial piston hydraulic pump fault diagnosis systems based on CNNs [27], and the bearing and pump fault diagnosis system based on TCNNs [28].

For air compressors of NPPs, these methods on above lead to benefits for safe and efficient operations: assist with decision making correctly and timely; enhance safety margins; enhance equipment reliability; optimize the maintenance schedule. However, for the reason of complicated operational mechanism, it is impossible to build a whole dynamic model of air compressors for model-based fault diagnosis; meanwhile, huge amounts of state variable measured in air compressors will enhance the complexity and reduce the process rate of the signal-based fault diagnosis method. Therefore, the data-driven method based on machine learning for air

compressors fault diagnosis of NPPs is worthy of further research.

In this work, a method framework of fault diagnosis system based on the Vibration Observation Window (VOW) for air compressors is proposed. The VOW constructs a vibration tensor which presents the operating state of air compressors according to the real time vibration signal. Actually, the VOW is a kind of special feature enhancement method. For different from traditional data-driven fault diagnosis methods, the VOW can strengthen the association among the monitoring data in spatial domain and time domain, and simplifies the diagnosis process of air compressors with large monitoring data. And then, the operation state of air compressors can be diagnosed by existing fault diagnosis methods accurately and rapidly.

The rest of this study is organized as follows: In Section II, the basic concepts of VOW method for data organization are presented. Section III describes the experiment setup based on real air compressors in NPPs, where two different hardware environments are considered, one is embedded computer, and the other is high speed Industrial PC. Section IV shows the experiment result of fault diagnosis, and the result analysis from the view of accuracy and calculation speed is also given. At last, it has a brief conclusion in Section V.

II. VOW METHOD

A. DATA ORGANIZATION

Consider an air compressor with n vibration sensors, which can measure the accelerated velocities under the rectangular coordinate system. The sampling period of each sensor is T . The data series presenting the vibration state of air compressors can be shown in figure 1. Where, \mathbf{V}_{ij} means the vibration data series in direction $j(j = x, y, z)$ of i th vibration sensor. v_{ij}^k means the k th vibration data in \mathbf{V}_{ij} . We introduce an observation window with the size of $3n \times m$ to cover the data series, the \mathbf{V} containing the vibration data from T_0 to $T_0 + mT$ can be built.

If the data flow direction is defined as shown as the gray arrow in figure 1, \mathbf{V} will become a tensor. So that, at time $T_0 + mT$, the dynamic vibration tensor \mathbf{V}_{T_0} can be built, which contains the all of the vibration data from T_0 to $T_0 + mT$. The tensor \mathbf{V}_{T_0} will be regarded as the analytic target of the fault diagnosis.

Fault diagnosis of air compressors can be reduced to the classification problem about \mathbf{V}_{T_0} . For this purpose, the classification function of the vibration tensor can be given as:

$$\eta_i = Clf(\mathbf{V}_{T_0}) \quad (i = 1, 2, 3, \dots) \quad (1)$$

where, Clf means the classification function. η_i means the i th classification of \mathbf{V}_{T_0} . Actually, Eq.1 provides a normal form of the vibration diagnosis based on VOW method, that is, as the sample analyzed in this work, \mathbf{V}_{T_0} belongs to the sample space; as the classification of system faults, η_i belongs to the classification space. For \mathbf{V}_{T_0} of each moment T_0 , the fault diagnosis system based on VOW method can calculate

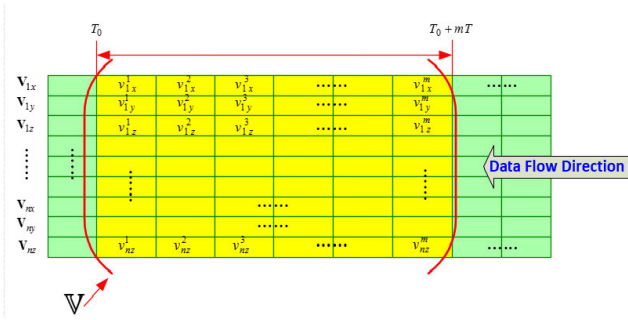


FIGURE 1. Data series and observation window with the size of $3n \times m$.



FIGURE 2. Typical Industrial PCs.

η_i , which means the current state belongs to the normal steady-state or fault state.

B. CLASSIFICATION

According to the equation 1, the fault diagnosis of air compressors can be converted to the classification problem of tensors. It is obvious that, Convolutional Neural Networks (CNNs) based on deep learning is one of suitable methods for tensors classification. However, the training and operation of CNNs may need a lot of computational resources, so that hardware system for air compressor vibration fault diagnosis should have a high computational performance in real time. Contrast to deep learning methods, classical machine learning methods, such as binary classification, K-nearest neighbor (KNN) and support vector machine (SVM), only need fewer computational resources.

Generally, two kinds of hardware systems are used for NPPs, one is Industrial PCs (IPCs) with high computational performance; the other is embedded computers with little computational performance. Therefore, an appropriate classification method needs to be chosen for different hardware system.

1) IPC

IPCs have become a firmly established part of various industrial environments. The advantages of IPCs are extremely high arithmetic speed, excellent scalability and flexibility. Together with associated software, IPCs are at the core of wide range of control or calculation task, such as motion control, processes or logistics systems, networking of system components, data acquisition, or image processing (figure 2 [29]). It is obvious that IPCs also have the ability to diagnosis vibration fault based on complex CNNs in real time.

CNN are typical feedforward deep neural networks, which extract the characteristics of input data by constructing

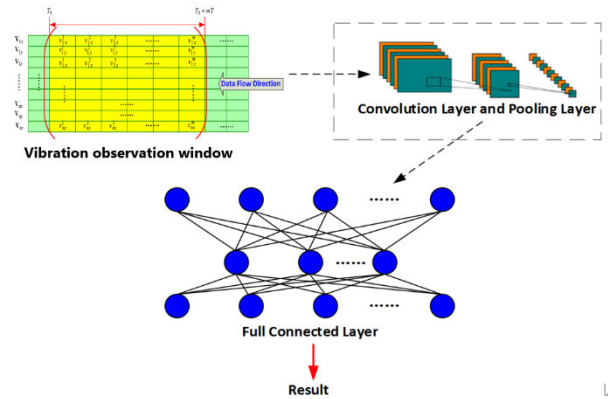


FIGURE 3. The structure of VOW-CNN.

multiple filters, and then carries out convolution and pooling processing to extract the potential topological data characteristics. Finally, the processed information is classification by the multi-layer perceptron, that is full connected layer.

Figure 3 shows the complete structure of VOW-CNN, which contains VOW, convolution layer, pooling layer, and full connected layer. The characteristics implying in the tensor can be extracted by convolution layers and pooling layers. The function of the fully connected layer is to integrate the features after multiple convolution layers and pooling layers, obtaining the high-level meaning of the features and then use it for classification. The structure of VOW-CNN is similar with the classical feed-forward neural network (figure 3), where the detail expression can be shown as equation 2:

$$N_n^{l+1} = f \left(\sum_{m=1}^l W_{n,m}^{l+1} x_m^l + b_n^{l+1} \right) \quad (2)$$

where, N_n^{l+1} is the output of n th neural cell in $(l+1)$ th layer. x_m^l means the input of m th neural cell in the l th layer. $W_{n,m}^{l+1}$ means the weight of m th neural cell in the l th layer connected to the n th neural cell in the $(l+1)$ th layer. b_n^{l+1} means the bias of n th notes in the $(l+1)$ th layer.

Usually, the ReLU activation function can be used for the hidden layer of full-connected layer, which can be shown as equation 3:

$$ReLU(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (3)$$

where, $ReLU$ means the ReLU activation function.

SoftMax function can be regarded as the activation function in output layer:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}} \quad (4)$$

where, p_i means the output of i th neural cell in the output layer. z_i means the input of i th neural cell in the output layer. k means the number of the neural cells in the output layer.

Actually, the SoftMax function reflect the probability of the classification. k neural cells in output layer means that the



FIGURE 4. Typical embedded computer.

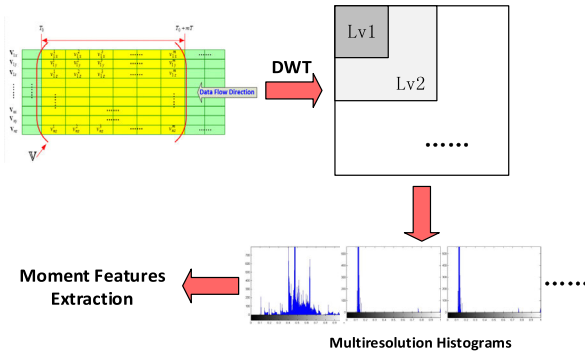


FIGURE 5. Process of feature extraction for vibration tensor.

vibration states need to be classified into k ICs. If the output probability of i th neural cell is the maximum probability of all the output probability in the output layer, the current vibration state will be classified into i th IC.

2) EMBEDDED COMPUTER

The distributed processing units (DPUs) is a kind of classical control-oriented embedded computer system, which are used for NPPs widely (figure 4 [30]). DPUs have lower power consumption, appropriate volume and lower manufacturing cost. While, they cannot diagnose vibration faults based on complex CNNs because of the little computational performance. Classical machine learning methods are more suitable for the vibration diagnosis in DPUs.

For a classification process based on classical machine learning method, the first step is feature extraction. As mentioned in section I, the VOW method associates the monitoring data in special domain and time domain, so that the pixel feature can be extracted from the tensor \mathbf{V}_{T_0} . For reducing computational complexity, a method based on multiresolution histogram is used for feature extraction of vibration tensor in this section, which can be shown as figure 5.

This method based on multiresolution histogram can reflect the change of amplitude and vibration spatial distribution of different sensors in \mathbf{V}_{T_0} . First, the vibration tensor \mathbf{V}_{T_0} is processed by 2D Discrete Wavelet Transform (DWT) [31], [32]:

$$\mathbf{W}_{V_k} = DWT_k(\mathbf{V}_{T_0}), \quad k = 1, 2 \dots L \quad (5)$$

where, DWT_k is the 2D DWT operator, k is the decomposition level of 2D DWT, \mathbf{W}_{V_k} is the approximation with k level

decomposition. Then an approximation sequence of \mathbf{V}_{T_0} in different resolutions can be given as:

$$\mathbf{W}_{V_k} = (\mathbf{W}_{V_0} \quad \mathbf{W}_{V_1} \quad \dots \quad \mathbf{W}_{V_L}) \quad (6)$$

Accordingly, the multiresolution histograms $(\mathbf{H}_{W_0} \quad \mathbf{H}_{W_1} \quad \dots \quad \mathbf{H}_{W_L})$ of \mathbf{W}_{V_k} can be built:

$$\mathbf{H}_{W_k} = (h_{k1} \quad h_{k2} \quad \dots \quad h_{kn_0}), \quad k = 1, 2 \dots L \quad (7)$$

Moment features of multiresolution histograms can be extracted from \mathbf{H}_{W_k} to represent the feature of \mathbf{V}_{T_0} , shown as equation 8:

$$\begin{cases} m_{ck}^1 = \frac{1}{H_k} \sum_{j=1}^{n_0} g_j h_{kj} \\ m_{ck}^p = \frac{1}{H_k} \sum_{j=1}^{n_0} |g_j - m_{ck}^1|^k h_{kj}, p = 2, 3 \\ m_{rk}^1 = \frac{1}{n} \sum_{j=1}^{n_0} h_{kj} \\ m_{rk}^p = \frac{1}{n} \sum_{j=1}^{n_0} |h_{kj} - m_{rk}^1|^p, p = 2, 3 \end{cases} \quad (8)$$

where, m_{ck}^p means the p th moment feature in the column direction of \mathbf{W}_{V_k} . m_{rk}^p is the p th moment feature in the row direction of \mathbf{W}_{V_k} , g_j is j th decomposition level. Then, the feature vector \mathbf{F}_{T_0} at time $T_0 + mT$ of \mathbf{W}_{V_k} can be built, (9), as shown at the bottom of the next page.

Based on the feature vector \mathbf{F}_{T_0} , vibration faults of air compressors can be diagnosed by lightweight classical classifier, including KNN, SVM, and binary classification. The performance of these classifiers with VOW will be tested and compared in section VI.

III. EXPERIMENTAL SETUP

The experiments are performed on a type of air compressor used for Nuclear Power Plant. 2 vibration sensors in different locations of the air compressor provide real time vibration signals, which can be shown as figure 6. Vibration signals are acquired by the distributed control system (DCS).

For testing the performance of VOW, it is realized based on an additional IPC or embedded Distribution Process Unit (DPU), which can be shown as figure 7. The IPC is connected with the DCS by a special embedded DPU in the DCS. The special DPU is also communicates with other DPUs in the DCS, acquires vibration signals through data transmission network based on TCP/IP, and extracts the vibration tensor. The IPC acquires the vibration tensor through PROFIBUS-DP. In the IPC, the method based on VOW-CNN is executed, and the classification results are transmitted to the DPU backward. At the same time, the DPU is also used for test the performance of classical machine learning methods with VOW. Timing sequence of vibration diagnosis in one period can be shown as figure 8, which means the IPC and DPU must make diagnosis in one period T in order to receive the diagnosis result from the DCS in real time.



FIGURE 6. Vibration sensors in different locations in air compressor.

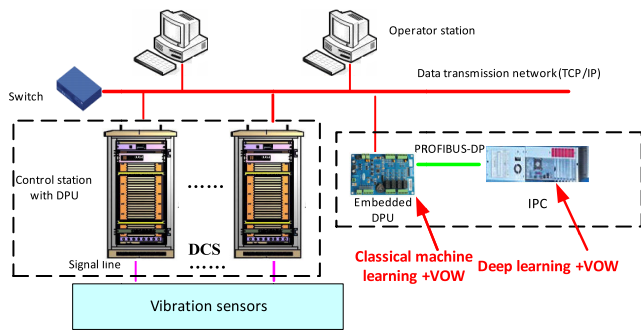


FIGURE 7. Hardware architecture based on IPC and DPU.

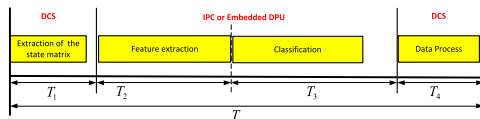


FIGURE 8. Timing sequence of vibration diagnosis in one period.

The structure dimension of the CNN merged in the IPC can be shown as figure 9. In addition to the feature tensor generated by The CNN contains one convolution layer (5 × 49 × 6), one Relu layer (5 × 49 × 6), one pool layer (4 × 48 × 12), and two full connected layers (10 and 7 nodes respectively). Kernels with 2 × 2 size are used for the convolution and pooling process. The strides in the convolution and pool layer are also set to 1.

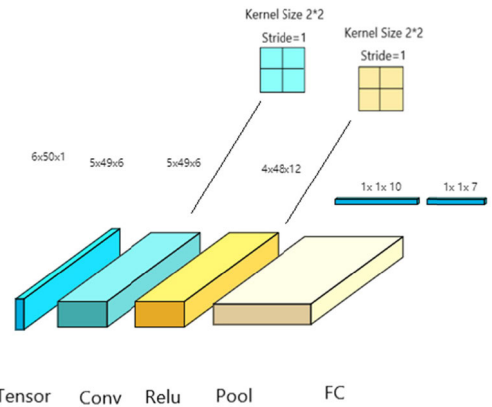


FIGURE 9. Structure sizes and parameters in CNN used in experiment.

TABLE 1. Simulation industry conditions.

ID of IC	Description	Sampling period/Observation window size
IC-1	normal	0.5s/50
IC-2	Seat wear of discharge valve	0.5s/50
IC-3	Crack of discharge valve	0.5s/50
IC-4	Spring break of discharge valve	0.5s/50
IC-5	hydrops in air cylinder	0.5s/50
IC-6	bolt looseness	0.5s/50
IC-7	filter clogging	0.5s/50

IV. RESULTS AND DISCUSSION

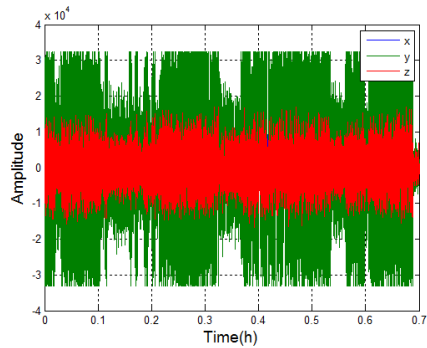
A. IC INTRODUCTION

In this work, 6 fault ICs and 1 normal IC are considered, including normal (IC-1), seat wear of discharge valve (IC-2), crack of discharge valve (IC-3), spring break of discharge valve (IC-4), hydrops in air cylinder (IC-5), bolt looseness (IC-6) and filter clogging (IC-7). All of the ICs are shown as table 1. The corresponding ID of fault type of each simulation IC is also contained.

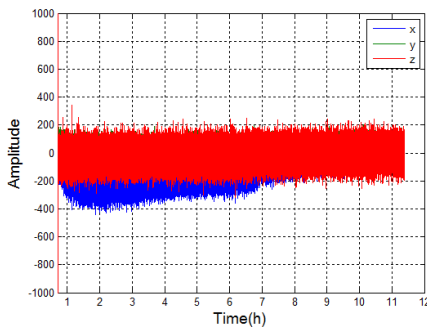
With the vibration experiment of the air compressor, the vibration data in less than 12 hours is acquired (figure 10-11), which is divided into two parts: train set and validation set. Degenerated components are installed to present failures at different times.

According to figure 10-11, more than 240000 vibration signals are acquired during the 12 hours. Each vibration tensor has 50 time-domain samples based on the 0.5s sampling period, and 6 signal group (vibration signals in x, y, z direction of 2 sensors). Thus, the size of each vibration tensor is 50 × 6. It can also be found that the state of the air compressor changed consistently, so that the vibration fault diagnosis in real time is necessary.

$$F_{T_0} = (m_{x1}^2 \quad m_{x1}^3 \quad m_{y1}^1 \quad m_{y1}^2 \quad m_{y1}^3 \quad \dots \quad m_{xL}^2 \quad m_{xL}^3 \quad m_{yL}^1 \quad m_{yL}^2 \quad m_{yL}^3) \quad (9)$$

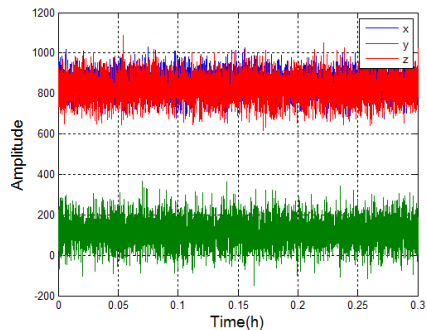


(a) 0h-0.7h

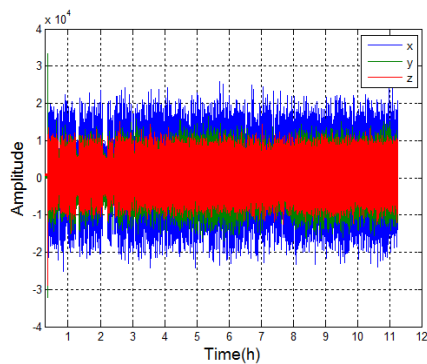


(b) 0.7h-12h

FIGURE 10. Vibration signal from sensor 1.



(a)



(b)

FIGURE 11. Vibration signal from sensor 2.

B. RESULTS AND COMPARISON OF VOW-CNN

Based on the IPC, the training process of VOW-CNN method can be given as figure 12. As mentioned on above, the vibra-

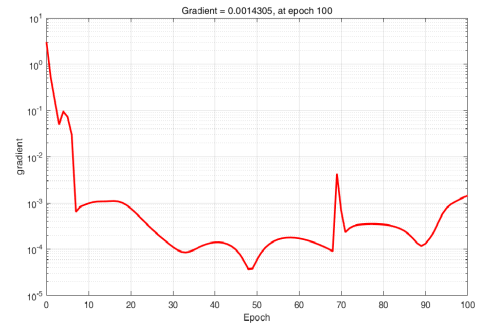
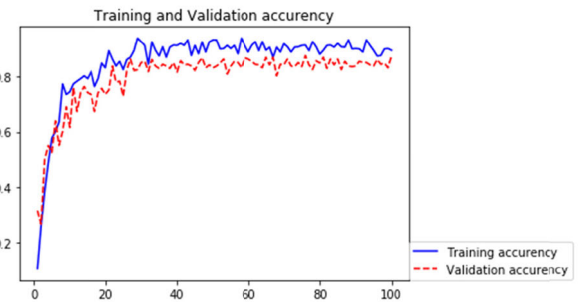


FIGURE 12. Training process of VOW-CNN (100 iterations).



(a)



(b)

FIGURE 13. Accuracy and loss during training and validation process.

tion data is divided into two parts: train set and validation set. There are about 120000 normal signals and 70000 fault signals in the training and validation set, and 30000 normal signals and 20000 fault signals in the test set respectively. The signal in training set is reconstructed by the VOW, and the tensor from VOW is applied to train the proposed CNN directly. The validation set is used to optimize parameters and evaluate the performance of VOW-CNN.

During the training process, the predicted value is obtained by using forward propagation firstly. Then, the chain derivative of the back-propagation algorithm is used to calculate the partial derivative of the loss function with respect to each weight. The weight in each neural cell is updated by using gradient descent method. The training and validation accuracy can be shown as figure 13 (a), accordingly, the training

TABLE 2. Simulation industry conditions for VOW-CNN test.

ID of IC	Description	maximum length of lag time	Number of Samples
IC-1	normal	2.4s	46941
IC-2	Seat wear of discharge valve	10.4s	3790
IC-3	Crack of discharge valve	9.2s	4463
IC-4	Spring break of discharge valve	1.2s	3105
IC-5	hydrops in air cylinder	5.4s	3120
IC-6	bolt looseness	3.6s	2679
IC-7	filter clogging	3.2s	3652

and validation loss can be shown as figure 13 (b), where, 100 iterations are implemented during the training process. It is obvious that after 100 iterations, the accuracy and loss converge significantly. The training and validation process show that the fault diagnosis system based on VOW-CNN method has the accuracy of more than 80%.

For testing the performance of VOW-CNN method in the IPC, extra 72000 vibration signals are test online in 4 hours, which contain about 50000 normal signals and 22000 fault signals. For introducing faults, fault components are implemented. The test results can be shown in Table 2 and 3. Take the fault IC-7 as the example, the output of fully connected layer is shown as figure 14 during 1 hour after the fault introduction, where 7 nodes are adapted to present the different ICs (shown as figure 15). In the initial phase, the normal filter is replaced by the clogging filter in the air compressor. Accordingly, the output of node 7 enhances rapidly, and becomes greater than the output of mode 1-6. It shows that the fault diagnosis system based on VOW-CNN method has identified the most fault signals accurately, although some normal signals are diagnosed as fault conditions, which may due to the unbalanced distribution of IC classifications. Not only for IC-7, IC-1~IC-6 have all similar fault diagnosis processes.

Some brief analysis can also be given as follows based on the results of VOW-CNN method. For the most of the ICs, the fault diagnosis system has good precision and recall rate. However, the test recall rate of fault IC-6 (bolt looseness) is lower than other ICs significantly. One possible reason is that number of sensors is small, so that the classifier cannot acquire sufficient information from original data. Moreover, the long sampling period of the fault diagnosis system (0.5s) may reduce the diagnosis accuracy. Beside the measurement process, the feature of IC-6 may also be an important factor for IC-6 diagnosis. Actually, bolt looseness is not an independent fault. It may also be caused by other abnormal vibration, including seat wear, crack, and filter clogging. When bolt looseness occurs, the fault diagnosis system is hard to recognize whether the bolt looseness is independent. On the other hand, the test precision rate of IC-2 and IC-7 are lower than other ICs significantly, because of the unbalance samples distribution. On the other hand, the maximum length of false-alarm or lag time also shows the impact of diagnosis loss

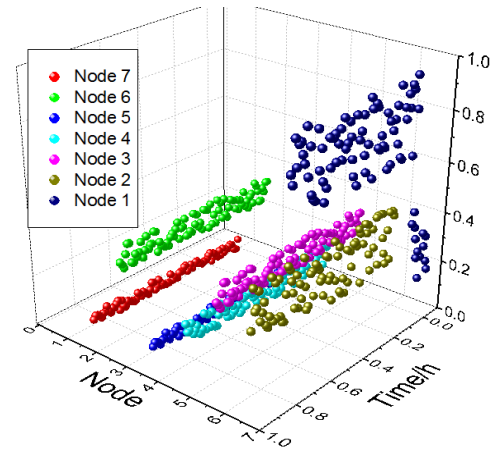


FIGURE 14. Output of fully connected layer in IC-2.

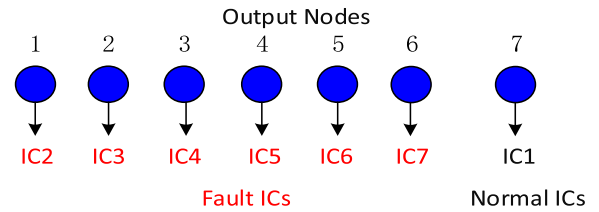


FIGURE 15. Structure of output nodes in fully connected layer.

TABLE 3. Confusion matrix of VOW-CNN.

		PREDICTED CLASS							Recall
		IC1	IC2	IC3	IC4	IC5	IC6	IC7	
Actual Class	IC1	42216	812	1274	373	486	845	935	89.93%
	IC2	661	3095	27	0	0	7	0	82.45%
	IC3	726	196	3519	0	0	22	0	75.52%
	IC4	335	0	0	2770	0	0	0	89.20%
	IC5	641	0	0	0	2479	0	0	79.47%
	IC6	694	51	79	121	0	1711	23	63.85%
	IC7	380	12	0	0	31	47	3182	91.65%
Precision		91.37%	74.29%	71.83%	84.87%	82.74%	65.00%	76.86%	

on air compressor operation. IC-2 (seat wear of discharge valve) and IC-3 (crack of discharge valve) have longer lag time, which means seat wear and cracking are not significant in the initial phase of the fault (traditional machine learning methods with VOW have also similar result, which can be shown as section IV C).

It is well known that CNNs are very adept at extracting two-dimensional signal features, therefore, it is necessary to compare the proposed VOW-CNN method with the typical CNN method without VOW. The typical CNN without VOW tested in this section also contains convolution layer, pooling layer and fully connected layer. The same number of the nodes in these three layers as the VOW-CNN is configured (figure 16). Figure 17 shows the precision on about 50000 tests of VOW-CNN and CNN. Different from classical machine learning methods on section IV C, CNN method has a better precision,

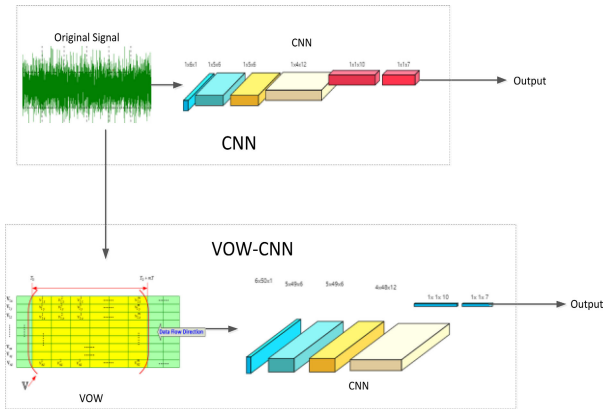


FIGURE 16. The comparison between VOW-CNN and typical CNN.

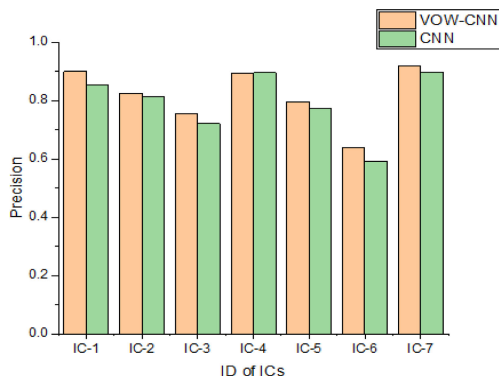


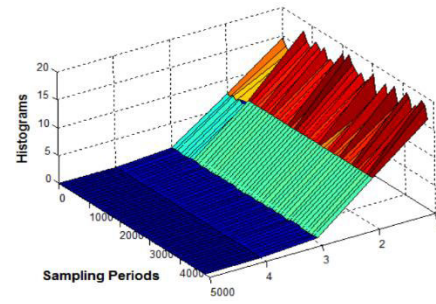
FIGURE 17. The precision with 50000 tests among the VOW-CNN and typical CNN.

and the performance in most of fault conditions is closed to VOW-CNN. However, for the normal condition IC-1 and combination fault IC-6, CNN without VOW has a lower precision, which means CNN generates more false alarms than VOW-CNN, and has a bad performance in combination faults.

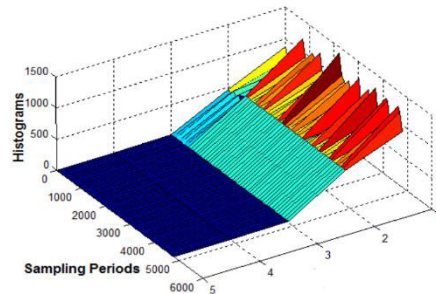
C. RESULTS AND COMPARISON OF TRADITIONAL MACHINE LEARNING METHOD WITH VOW

A lot of typical machine learning method can be used for fault classification based on the embedded DPU. For ease of analysis, KNN, SVM and binary classification are regarded as the candidate classification methods. Similar to VOW-CNN in the IPC, for testing the performance of VOW-KNN, VOW-SVM and VOW-Binary classification methods in the DPU, extra 72000 vibration signals are introduced online in 4 hours.

For the classical machine learning method based on the VOW, vibration fault features need to be extracted separately. According to the algorithm in section II B, from 0h-12h, multiresolution features of the vibration tensor in VOW, which are regarded as features, can be shown as figure 18, which contain 2 decomposition levels. On the other hand, for the test of classical machine learning methods without VOW, the



(a) Level 1



(b) Level 2

FIGURE 18. Features of vibration tensor from 0h-12h in different decomposition levels.

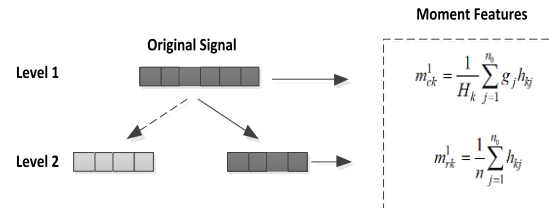


FIGURE 19. The moment feature extraction and classification process of original signal.

TABLE 4. Time performance of VOW-classical machine learning test.

Method	maximum length of lag time	Average program running time
VOW-KNN	12.1s	103ms
VOW-SVM	10.7s	175ms
VOW-Binary Classification	17.2s	71ms

original 6-D vibration vector is also need to extract features similar to the machine learning method with VOW. For this purpose, 1-D moment features are extracted according to the process of figure 19.

Figure 20-22 show the precision on the 72000 tests of classical machine learning methods with VOW compared with machine learning methods without VOW. In the table 4, the fault diagnosis process all can be executed during one diagnosis period of the DPU (500ms), where, VOW-SVM has maximum average program running time (175ms). It can

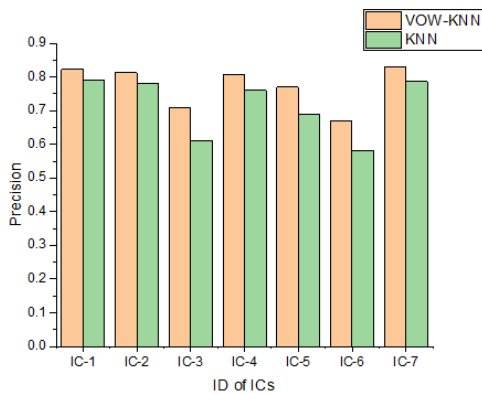


FIGURE 20. The precision comparison between VOW-KNN and KNN.

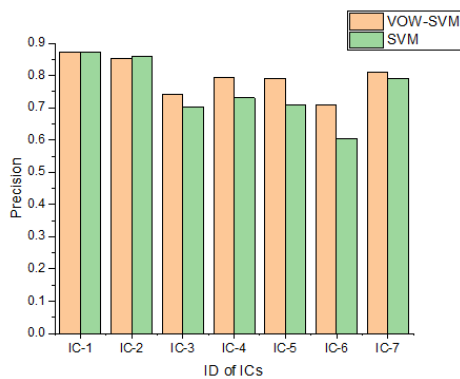


FIGURE 21. The precision comparison between VOW-SVM and SVM.

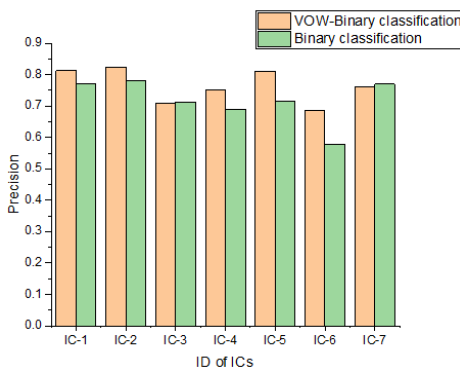


FIGURE 22. The precision comparison between VOW-Binary classification and binary classification.

be found that in figure 20-22, the test precision of machine learning methods without VOW has a lower precision than machine learning methods with VOW in IC-1~IC-7, which means VOW can represent more information about fault ICs effectively. For the three methods in figure 20-22, the similar characteristic to the CNN method in section IV B is presented: the diagnosis accuracy of IC-6 is lower than other ICs significantly. This reason has been analyzed in section IV B briefly. Beside on IC-1, the classical machine learning method with VOW can acquire better diagnosis accuracy for IC-2, IC-4 and IC-7 than other ICs, because faults of the discharge valve and filter have striking features

than other faults, and can be recognized linearly and easily. Moreover, the VOW-SVM has the best diagnosis accuracy in the three classical machine learning methods with VOW, because of the non-linear and robust characteristics.

V. CONCLUSION

In this work, a method framework of vibration fault diagnosis system based on VOW method for air compressors has been researched. In the VOW method, vibration tensor is used to describe the air compressors state in current. Actually, the VOW is a kind of special feature enhance method. Different from classical data-driven fault diagnosis methods, the VOW method can strengthen the association among the monitoring data in spatial domain and time domain, and simplifies the diagnosis process of air compressors with large monitoring data. Considering the hardware characteristic in NPPs, we compare the performance between the fault diagnosis system with and without VOW based on different hardware environments: the embedded DPU in DCS, and the high speed IPC. In the high-speed IPC, the CNN is used for fault classification, and the vibration tensor in VOW is regarded as the input of the CNN. In the DPU, three kinds of classical machine learning methods are used, where multiresolution histogram can be extracted from the VOW as the feature.

The effectiveness of VOW method is verified by the actual air compressor in NPPs, and the industrial field application mode of the VOW method is also given. The online test show that the fault diagnosis system based on IPC and DPU both have good test accuracy and response speed, which indicate that the VOW can both improve the performance of the vibration fault diagnosis system of NPPs based on different classification methods.

However, the experiment result also shows that the inadequacy of the method framework for combination faults. As a typical example, the test accuracy of fault bolt looseness is lower than other ICs significantly, because bolt looseness is not an independent fault. In future work, the fault diagnosis based on VOW method needs to be improved further:

- (1) improving the feature extraction ability of combination faults;
- (2) reducing the maximum length of undetected time based on different classification methods, including deep learning and classical machine learning.

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