17th IMEKO TC 10 and EUROLAB Virtual Conference
“Global Trends in Testing, Diagnostics & Inspection for 2030”
October 20-22, 2020.

VAE Deviation for Detecting Bearing Anomalies

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***Abstract* –Anomaly of rotating machines are usually inferred from vibration measurements. However, it is not easy to determine the normal range for conventional crest factor or primary component analysis. In this paper, we try to use the Artificial Neural Network technique to make judgments based on the degree of deviation from the learned normal range. Specifically, we evaluated VAE which compresses the measured sensor data into the latent space of smaller number of dimensions with standard normal distributions. We propose an anomaly score which indicates the deviation from the center of the normal distribution using linear VAE calculation and dimensionality compensation. The proposed anomaly score shows good performance with several test data sets and measured real data sets.**

Keywords –Variational Auto-Encoder, Bearing Anomaly Detection, Anomaly Score, Latent Space.

I. INTRODUCTION

Anomaly detection of rotating equipment such as pick-and-place machines, robots, machine tools, pumps, fan blowers, etc. is the key technology for stable operation of equipment and improved operation.

The most common means for detecting the state of a rotating device is to measure the vibration of the device with a vibration sensor such as an accelerometer. The device condition can be represented by an anomaly score which is derived from the normal vibration waveforms or frequency spectra. This anomaly score will make it possible to predict the time of fault. Further, when the score rises, a precise diagnosis of the vibration waveform can be triggered and the cause of the anomaly can be analyzed.

As an anomaly score, several quantities have been used so far such as the peak value, root mean square (RMS) value, crest factor, skewness, and kurtosis of the time waveform of vibration. However, anomalous vibrations of rotating equipment can be caused by various situations such as misalignment, imbalance, gear meshing, pump cavitation, bearing vibration, and damage. As a result, various waveforms and frequency spectra appear. Any simple quantity cannot be an accurate indicator of the degree of anomaly. Further, even if a quantity or a combination of such quantities that can accurately express the anomaly degree is found for a specific usage case, it may not be suited for other cases. It must be reviewed and adjusted for specific application cases.

Recently, methods for diagnosing factory equipment have been developed using various machine learning and deep learning methods [1,2]. There are also researches specialized in bearings whose conditions inevitably change during operations, such as data analysis methods that extract and classify features using normal and abnormal vibration data for supervised learning, and cluster analysis using many observation data for unsupervised learning [3]. However, in actual equipment, vibration data etc. vary greatly depending on usage conditions such as load. So, it is difficult to prepare data for judging individual normality/abnormality in advance [4].

Therefore, it is practical that the observed value in the early stage of operation of the device is treated as normal data. Observed data during operation is analyzed, and the deviation degree from the normal data is used as an anomaly score. Specifically, variational auto-encoder (VAE [5]) can be employed to transform the observed data into a standard normal distribution in a smaller dimensionality [5-8] and to calculate the anomaly score corresponding to the deviation from the center of distribution in a way of unsupervised learning. The authors tried the VAE method exhaustively, and propose a method to calculate the anomaly score with linear VAE processing and compensation for latent space dimensionality.

Section 2 shows the basics of VAE and the method of calculating the anomaly score. Section 3 shows the details of the processing. Section 4 shows the results for the simulated and measured data. And Section 5 concludes.

II. VAE AND PROPOSED ANOMALY SCORE

VAE performs information compression with the encoder that maps multidimensional input values into a latent space of a small number of dimensions (Fig.1). In order to properly compress the information, the decoder returns the compressed data back to the original dimensions while minimizing the loss function such as square error. Furthermore, by adding Kullback-Leibler divergence term to the loss function, the distribution in the latent space is trained to be the standard multidimensional normal distribution. Therefore, when VAE is well trained with normal data, the distribution in the latent space becomes very close to the standard normal distribution. Data after the learning period, which may include anomalies, is to be evaluated by a multidimensional deviation in the latent distribution. It is expected that anomalies will deviate significantly from the standard normal distribution. Therefore, the degree of anomaly can be evaluated by the deviation from the origin of the latent space.

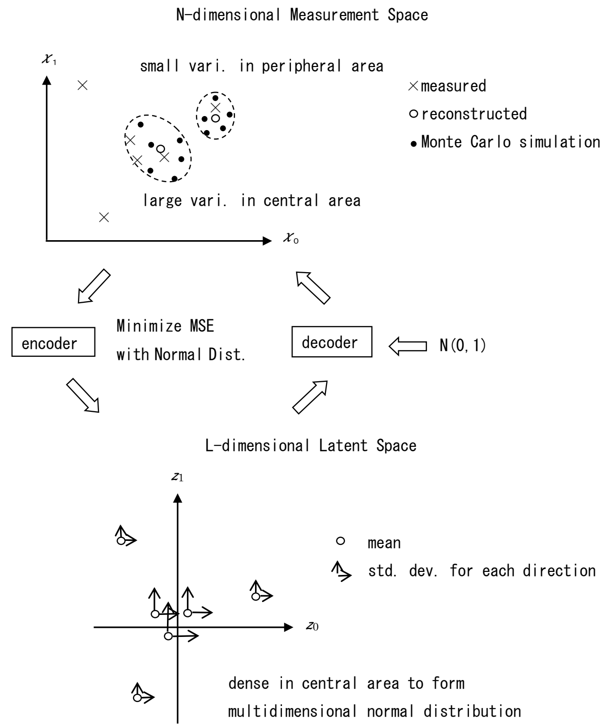

Fig. 1. VAE and latent space.

In the case of anomaly detection of bearings, it is usual to acquire vibration waveforms using acceleration sensors. Data is collected at regular intervals (e.g. 10 minutes) with some sampling frequency (e.g. 20 kHz). Since features often appear in frequency spectrum, VAE learning is performed by converting waveforms into frequency amplitude spectra. If we input newly acquired data to the learned encoder, we can obtain the anomaly score for that data (Fig. 2).

The anomaly score is calculated by the following formula as the VAE deviation (V_D) from the origin.

$$V_D = \sqrt{\frac{1}{D_{cmps}} \sum_{i=1}^{D} \left(\frac{x_i - \overline{x_i}}{\sigma_i}\right)^2}, \tag{1}$$

where D is the dimensionality of the latent space, D_{cmps} is the dimensionality compensation described later, x_i is the value of dimension i in the latent space, and $\overline{x_i}$ and σ_i are the mean and the standard deviation of the distribution along the dimension i.

If there is no correlation between the basis functions (i.e. input data patterns corresponding to each latent dimension), it can be calculated as Euclidean distance (D_{cmps}=1). However, if there is correlation in part or in full, the summed part in the square root of V_D increases in proportion to the number of dimensions. The correlation coefficient between basis functions is calculated as follows.

$$R(f_i, f_j) = \frac{1}{N} \sum_{n=1}^{N} f_i(n)\, f_j(n), \tag{2}$$

where N is the number of frequency components (the number of input sequence to VAE), f_i is a basis function corresponding to the dimension i, of which the mean is zero and the variance is normalized to one. A signal component that matches one of the basis functions affects all dimensions by this correlation coefficient.

As a result, the effect of the following total value D_{cmps} appears in the square root of the anomaly score. To compensate for it, it is necessary to divide by D_{cmps} when calculating the anomaly score. D_{cmps} is one when all basis functions are orthogonal (no correlation), and is equal to D when all the basis functions are same.

$$D_{cmps} = \frac{1}{D} \sum_{i=1}^{D} \sum_{j=1}^{D} R^2(f_i, f_j) \tag{3}$$

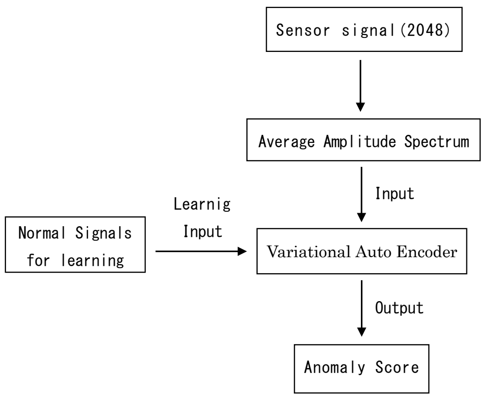

Fig.2. Processing flow.

III. VAE PROCESSING DETAILS

Since the measured values may be noisy, averaging is desirable as the preprocessing. The loss function of VAE is non-linear and the input value to VAE has the optimum range. Therefore, we converted the whole input values into the standard normal distribution. If the input has a large dynamic range, it may be desirable to perform non-linear compression such as a logarithmic compression and then perform the conversion to the standard normal distribution (used in the case of IMS data described later).

The structure of VAE is set to three layers (each one for the input layer, the intermediate layer, and the output layer) referring to the Keras example [9] (Fig. 3). All of the activation functions are set to be linear in order to obtain the anomaly score that changes linearly with respect to the input. For this reason, the distribution in the VAE latent space is close to but may not be exactly the standard normal distribution.

The number of inputs of the encoder and the outputs of the decoder is 512 (the number of frequencies in the FFT result). As for the intermediate layer, the smaller the number of units, the shorter the calculation time and the smaller the memory usage. It is better to use a small number within a range that shows sufficient expressiveness. As a result of examination using test data (D-1 in section 4.1), 16 is selected as the value which shows a sufficient margin within the stable range.

Ideally, the number of dimensions of the latent space must be adjusted to the number of independent components of the target signal, but the larger it is, the more the processing time and the memory usage. As a result of examination using the test data (D-1), there are cases where a change cannot be detected with one dimension. We select two for dimensionality, as almost the same temporal change is obtained as the anomaly score for three or more dimensionality. The units in the latent layer in Fig. 3 mean that there are two units in two dimensions because these are values corresponding to the average output and the standard deviation output for each dimension.

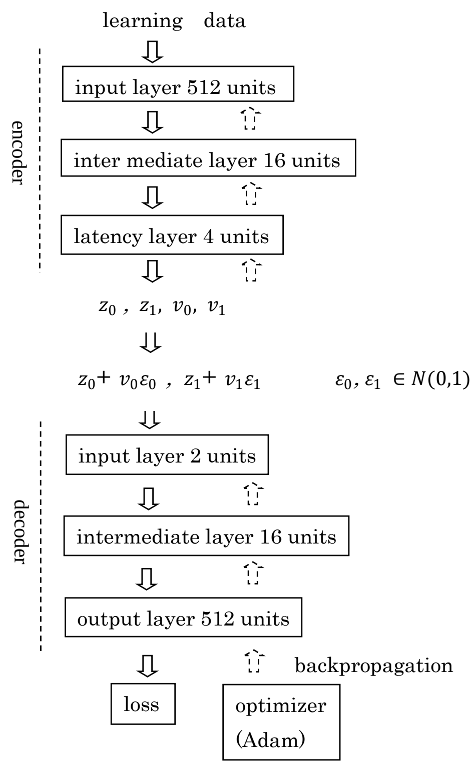

Fig.3. VAE structure.

It is necessary to set the number of times of learning (epoch) for VAE that sufficiently converges. Checking the actual convergence state (loss change), we set 1000 as a sufficient learning epoch. As for the learning batch size, the larger the number, the shorter the learning time. However, if it is large, the result may vary greatly and stable results may not be obtained, so we select one for the batch size.

IV. TEST DATA AND RESULTS

We determined the hyperparameters of VAE as described in the previous section, using the measured data D-1 (D-1 and D-2 are provided by Device & System Platform Development Center Co., Ltd.) as the training and test data. To evaluate the anomaly score, 80% of data are used to train VAE from the beginning part of each data, and the whole sequence of each data are fed to the VAE encoder to obtain the anomaly score change.

A. Test Data: Harmonics with white noise

In order to confirm that the anomaly score with the selected hyperparameters can properly show anomalies, we applied it to a simple signal, a vibration signal consisting of three overtone frequency components (125 Hz as the fundamental tone) with 10% amplitude perturbation and with white noise (Fig.4). The amplitude ratios of the three tones and the noise was set to 4:6:2:1.

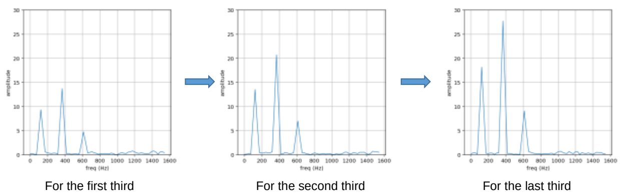

Fig.4. Test signal: Harmonics with white noise.

The time signal of this spectrum is duplicated three times with amplitude change of 1, 1.5 and 2. The peak and the RMS increase in proportion to the amplitude (Fig.5). The crest factor (i.e. peak/RMS) and the envelope crest factor are getting smaller rather than larger, because the RMS is increasing irrelevant to the peaks owing to the constant noise (Fig.6). The envelope crest factor is calculated with creating the envelope of the time waveform. VAE uses the first 1/3 period as the learning data (Fig.7). The second 1/3 period and the last 1/3 period show rises by the same amount (corresponding to 0.5 times amplitude increase). The dashed purple line indicates the triple of the standard deviation, above which can easily be judged as anomaly.

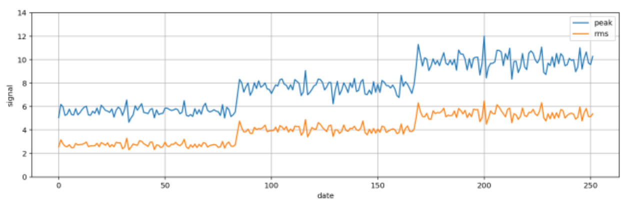

Fig.5. Peak and RMS of Harmonics.

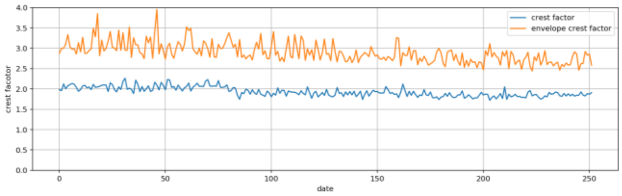

Fig.6. Crest factor and envelope crest factor of test signal Harmonics.

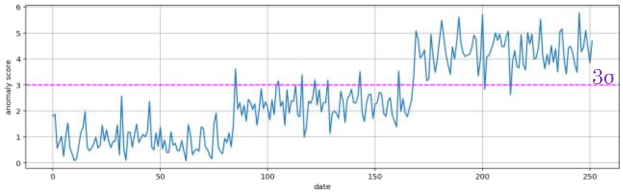

Fig.7. VAE anomaly score of test signal Harmonics.

As another test signal, we raised the fundamental tone of the same signal in Fig.4, 125 Hz, 131.25 Hz and 137.5 Hz in 5% increasing steps. Of course, the peak, RMS, the crest factor, and the envelope crest factor do not change (Fig. 8-9). However, VAE shows large stepwise changes (Fig. 10), although the changes are not proportional to the frequency changes.

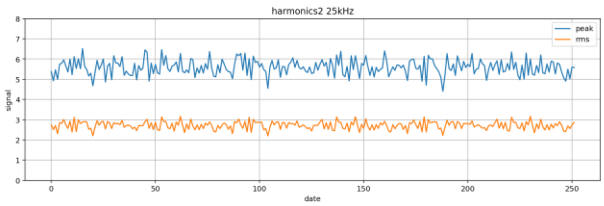

Fig.8. Peak and RMS of Harmonics with frequency change.

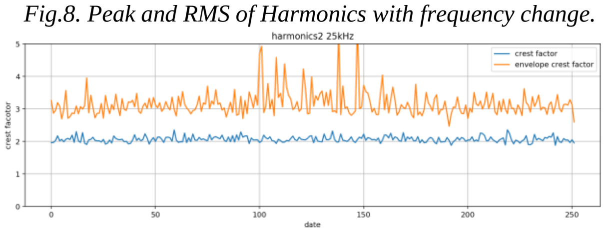

Fig.9. Crest factors of Harmonics with frequency change.

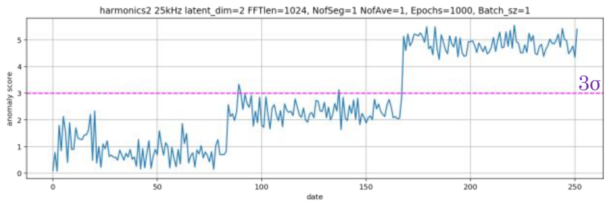

Fig.10. VAE anomaly score of Harmonics with frequency change.

B. Test Data: CWRU

We applied VAE to a noisy signal obtained by real bearing measurement (X105_DE of CWRU public data with periodic impact [10]). As the CWRU data is continuous measurement data, we divided them into sections of 1024 time points and processed as separate sampling data. To add variations to the data, we changed the amplitude in three steps (1, 2 and 3) for different continuing parts of data.

The peak and RMS show clear change of amplitude (Fig.11). No significant change can be identified in the crest factor and the envelope crest factor (Fig.12). VAE used the first third of the data for learning. Although the fluctuation of Fig. 13 is large, the center of the fluctuation corresponds the amplitude change of 1, 2, 3.

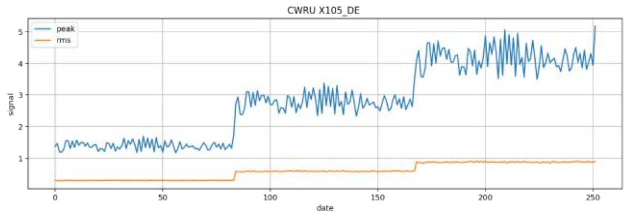

Fig.11. Peak and RMS of stepwise changed cyclic impact.

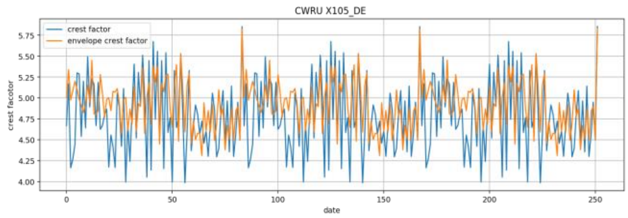

Fig.12. Crest factors of stepwise changed cyclic impact.

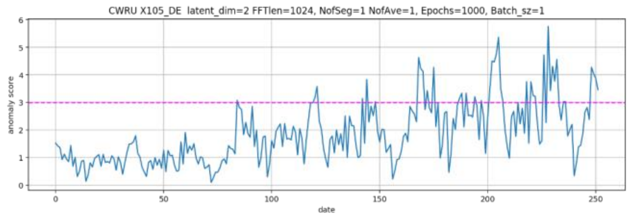

Fig.13. VAE anomaly score of stepwise changed cyclic impact.

C. Test Data: D-1

We applied VAE to the measured bearing data, of which the condition is known. The real measurements collected 2048 points with sampling at 25 kHz, every four hours. To average the amplitude spectra, FFT was applied three times for three segmented 1024 point data from 2048 points. The averaged amplitude spectra were input to the VAE encoder.

The peak, the RMS, the crest factor and the envelope crest factor show clear changes (Fig. 14-15). Actually, the tested bearing was replaced at around 2020-03-12, and the pillow block was replaced at around 2020-03-21. The anomaly score also shows the similar change (Fig.16). The hyperparameters of the VAE were searched using this data to output stable anomaly scores as described in the previous section.

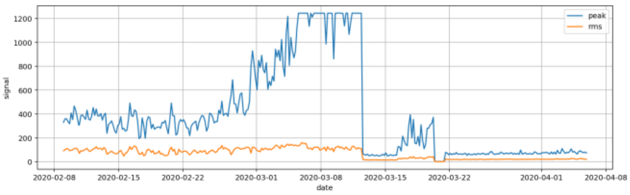

Fig.14. Peak and RMS of test signal D-1.

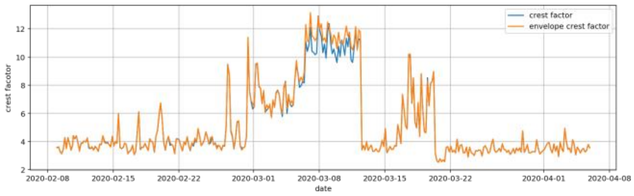

Fig.15. Crest factor and envelope crest factor of test signal D-1.

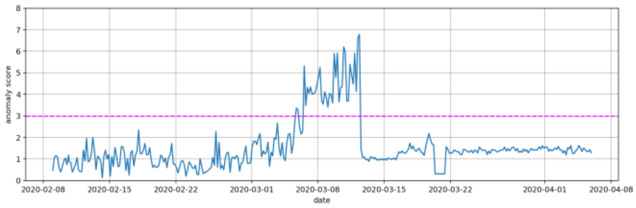

Fig.16. VAE anomaly score of test signal D-1.

D. Test Data: D-2

We also applied VAE to another measurement data set D-2 which was obtained using a bearing different from D-1. VAE in Fig.19 shows clear changes which are not so clear in the peak/RMS (Fig.17) and the crest factors (Fig.18). Especially, anomaly score changes in the early stage show the initial fluctuations, and the middle table shape shows some anomaly state which is not so clear in the other four plots. Also, the tail of the anomly score indicates the continuing and rising anomalous state.

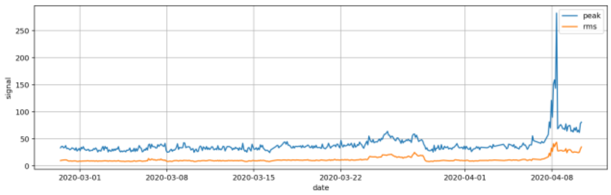

Fig.17. Peak and RMS of test signal D2.

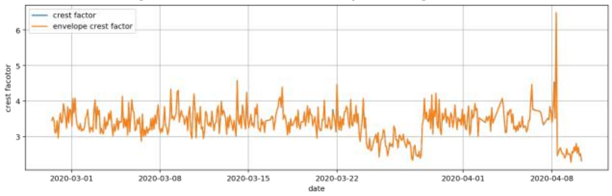

Fig.18. Crest factor and envelope crest factor of test signal D-2.

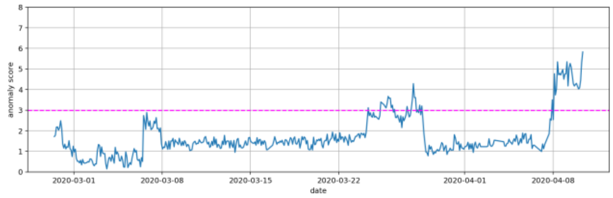

Fig.19. VAE anomaly score of test signal D-2.

E. Test Data: IMS

We also applied another measured bearing data (IMS data [11], 1st_test bearing 4 x sensor). The 20480-point data (20 kHz sampling) is divided into twenty 1024 intervals and the average amplitude spectrum of them was applied to the VAE encoder. Since the signal spectrum has a strong line property, the amplitude spectrum was logarithmically compressed to flatten the amplitude distribution.

The three results (Fig. 20-22) show similar change in a broad sense. In VAE, the leading data (150 samples) are used for learning. The rise of VAE anomaly score at the final stage is clearer than others.

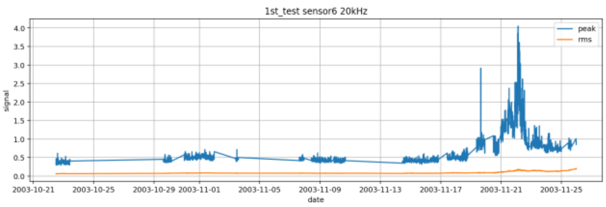

Fig.20. Peak and RMS of IMS-1-4x.

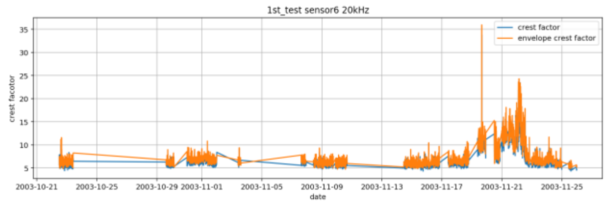

Fig.21. Crest factors of IMS-1-4x.

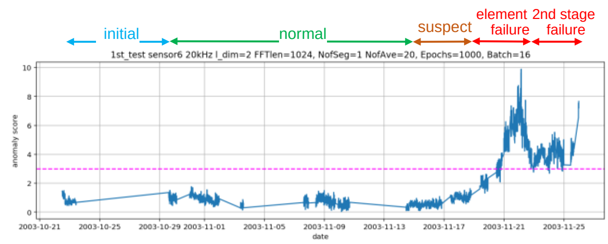

Fig.22. VAE anomaly score of IMS-1-4x.

V. CONCLUSION

The proposed structure of VAE and calculation method of anomaly score have shown its effectiveness for tested cases: three frequency component cases of amplitude change and frequency change; periodic signal case; actual bearing measurement cases. The proposed anomaly score reflects the measured data linearly, and its effectiveness was confirmed for tested cases. The hyperparameters chosen for typical measured data are also applicable to other similarly conditioned data. The most important feature of the method is the unsupervised learning scheme and the capability of real time anomaly inference by learning only the data of the initial normal operation period.

VI. ACKNOWLEDGMENTS

The authors are grateful to Device & System Platform Development Center Co., Ltd. for providing the measured data and for commenting on the results. Also, the authors would like to thank the Case Western Reserve University Bearing Data Center and the Center for Intelligent Maintenance Systems, University of Cincinnati for providing their data sets publicly.

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