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Online Monitoring Technology by Analysis of Highly Accurate Vibration Waveform to Diagnose Abnormality of Machines†

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Abstract:

JFE Steel Group has developed a diagnostic system that determines early abnormalities by processing vibration waveforms by using statistical methods for journal bearings, reciprocation machines and low-speed rotary machines. The developed system was applied to the production facilities and its marketing started at the same time. To date, the companies have succeeded in detecting early abnormalities of journal bearings of induced draft fan motors in converters and reciprocation rotation machines such as the loss of the inhalation valves and the exhalation valves of plunger pumps.

1. Introduction

The JFE Steel Group positions equipment diagnosis technology as a necessary and indispensible technology for equipment control, and has been involved in development in this field for more than 30 years. The developed technologies are applied to the steel manufacturing equipment and are also marketed outside the JFE Group. In particular, JFE began development of vibration diagnosis technology for rotary machines from an early date and has made continuous improvements in this technology[1)]. This paper introduces diagnosis technologies for journal bearings, reciprocation machines, and low-speed rotary machines, with which early judgment of abnormalities was difficult using conventional techniques.

2. Development of Machine Abnormality Diagnosis Technology by Highly Accurate Waveform Analysis

Vibration abnormality judgment is generally a pass/fail judgment which is made by measuring vibrational velocity, acceleration, etc. and comparing the result with standard values specifying, in advance, peak, root mean square (rms), and other values. With this technique, pass/fail judgment technologies have been established for roller bearings and other parts of high-speed rotary machines which operate under constant speed and load conditions. However, with journal bearings, reciprocation machines, and low-speed rotary machines, abnormality judgments were difficult due to deviations in vibration values, the fact that vibration values do not display large changes until the terminal stage of the abnormality, and similar factors. Therefore, the authors developed a diagnosis system in which parameters obtained from measured waveforms are extracted, new parameters which capture the distinctive features of the waveforms are formed by statistical techniques such as principal component analysis, Kullback information, etc., trend control is performed using the change in the waveform due to equipment abnormalities as a parameter, and abnormality judgments are made on this basis.

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2.1 Vibration Diagnosis Technology by Dimensional-Nondimensional Integrated Parameter Using Principal Component Analysis

2.1.1 Extraction of dimensional-nondimensional parameter

In this technique, first, as shown in **Table 1**, dimensional parameters (peak, rms, mean value, rotation frequency element value, etc.) and nondimensional parameters (wavy rate, peak-to-rms ratio, impact index, skewness, Kurtosis, etc.) are extracted[2)].

2.1.2 Execution of principal component analysis

Principal component analysis is a multivariate analysis technique and is used to extract the controlling components when it can be thought that multiple parameters (factors) control abnormal events (results). The results of linear combination of nondimensionalized parameters, also including dimensional parameters, are called principal components, and are specified so as to maximize variance of the principal components (**Fig. 1**). Concretely, the direction of the first principal component is determined so as to maximize the variance of the measured value X for the data under normal conditions (Group A). Because the linear combinations are made in such a way as that deviations increase, if these are compared with the measured data, it is possible to distinguish an abnormality as a group (Group B) which is clearly different when that group diverges from the normal group.

Table 1 Example of dimensional parameter and nondimensional parameter

Kind of parameter	Parameter
Dimensional parameter	The maximum value, Root mean square value, Mean value, Rotation frequency element value ×n; ×1/2; ×1/3; ×0.4, Frequency element value of bearing defect
Nondimensional parameter	Wavy rate, Peak-to-rms ratio, Impact index, Skewness, Kurtosis

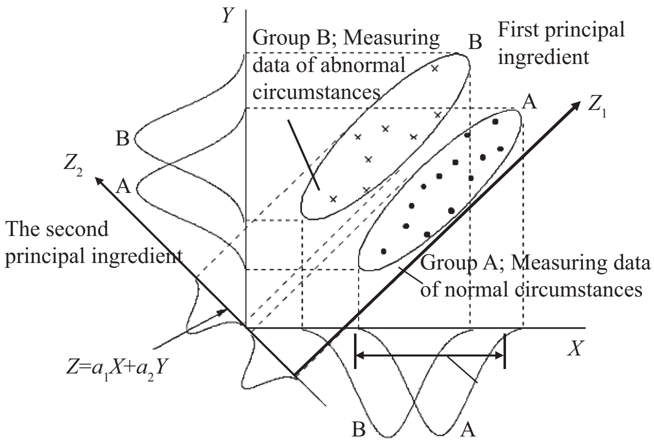


Fig. 1 At the image of the principal component analysis (two variables X and Y)

2.1.3 Formation of integrated parameter

The principal component Z_i (population) obtained under a normal condition, as described above, is assumed to follow a regular distribution. The statistical quantity χ^2 comprising N samples taken independently from this population follows a chi square distribution with $N-1$ degrees of freedom (from the theorem of chi square distribution).

$$\chi^2 = \frac{(N-1)s^2}{\sigma^2} \quad \cdots\cdots (1)$$

χ^2: chi square value
N: number of samples
s^2: sample variance
σ^2: population variance

Here, if the n samples extracted from the population are called X_1, X_2, X_n, the sample variance s^2 is expressed by

$$s^2 = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}_i\right)}{(N-1)} \quad \cdots\cdots (2)$$

Because the population variance σ^2 of the principal component Z_i is equal to the eigenvalue λ_i, the following equation is obtained when X_i and $\overline{X}_i$ in Eq. (2) are replaced with Z_i and $\overline{Z}_i$, respectively[3)],

$$\chi^2 = \sum_{i=1}^{n}\left\{\frac{Z_i - \overline{Z}_i}{\sqrt{\lambda_i}}\right\}^2 \quad \cdots\cdots (3)$$

Z_i: i-th principal component
$\overline{Z}_i$: mean value of i-th principal component Z_i
λ_i: eigenvalue of i-th principal component

The two sides of Eq. (3) are divided by χ^2 (φ, α):

$$S = \frac{1}{\chi^2(\phi, \alpha)} \sum_{i=1}^{\phi}\left\{\frac{Z_i - \overline{Z}_i}{\sqrt{\lambda_i}}\right\}^2 \quad \cdots\cdots (4)$$

φ: degree of freedom of χ^2 distribution
α: significance level

In this technology, this value is defined as the dimensional-nondimensional integrated parameter S.

Figure 2 shows the relation between the significance level α and the normal range of the dimensional-

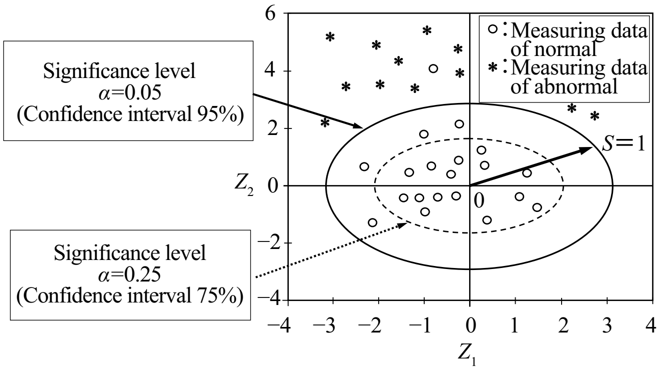


Fig. 2 Relation between significance level α and state amount S normal range

nondimensional integrated parameter S. Among the data taken under a normal condition, the normal range is designated by the significance level α. For example, when α=0.05, the confidence interval is 95% (range of 95% of normal data). Because the center of the ellipse is S=0 and a point on the ellipse is S=1, the region where $S \leq 1$ can be considered the region where a normal condition is confirmed. The distance of the measured data from the normal data is evaluated using the dimensional-nondimensional integrated parameter S, and judgments of equipment abnormality are made by trend control of this S value.

2.2 Vibration Diagnosis Technology Using Kullback Information

2.2.1 Extraction of amplitude probability density function

The amplitude probability density function $P(x)$ is extracted from the measured vibration waveform.

Figure 3 shows an image of extraction of the amplitude probability density function.

The amplitude probability density function $P(x)$ is normalized by the root mean square (rms) value of the vibration waveform, the peak of amplitude is divided by the number of segments d and the result is considered to be the segment width, and the original waveform of the density function is obtained by counting the number

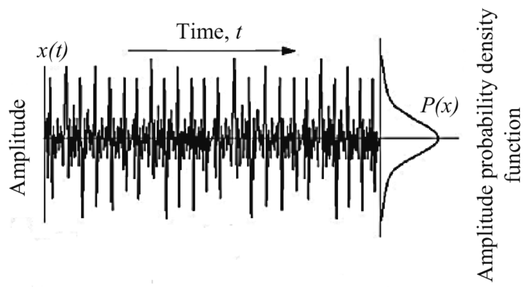


Fig. 3 Extraction image of amplitude probability density function

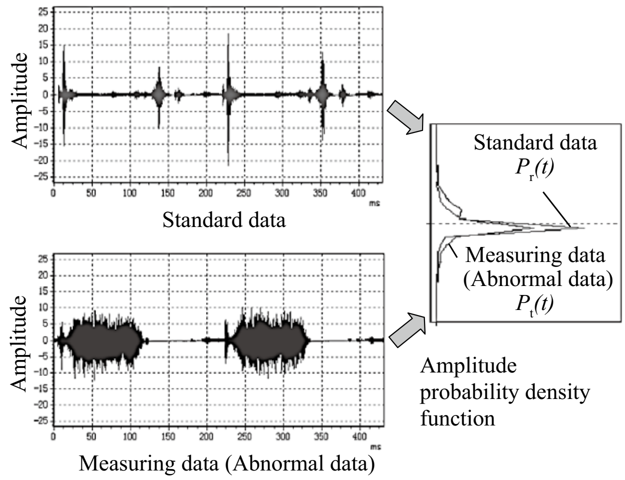


Fig. 4 Extraction image of amplitude probability density function of standard data and measuring data

included in each width. In actual abnormality diagnosis, as shown in **Fig. 4**, the amplitude probability density functions $P_r(t)$ and $P_t(t)$ are extracted from the standard data under a normal condition and the measured data when an abnormality is judged, respectively.

2.2.2 Quantification of change in probability density function

Next, in order to quantify changes in the amplitude probability density function, the Kullback-Leibler divergence of symmetry type (hereinafter, ID value)[4] is obtained.

$$\mathrm{ID} = \int \{P_r(t) - P_t(t)\} \log \frac{P_r(t)}{P_t(t)} \mathrm{d}t \qquad \cdots\cdots(5)$$

$P_r(t)$: Amplitude probability density function of standard data (normal data)
$P_t(t)$: Amplitude probability density function of measured data (abnormal data)
t: time (ms)

The ID value is calculated from the amplitude probability density function of standard data (normal data),

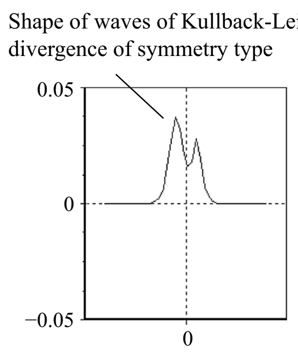


Fig. 5 Example of shape of waves of Kullback-Leibler-divergence of symmetry type (ID)

$P_r(t)$ and the amplitude probability density function of measured data (abnormal data), $P_t(t)$ obtained in Fig. 4 using Eq. (5).

Figure 5 is an example of calculation of the ID information waveform from the waveform in Fig 4. The fact that the difference between the standard data and the measured data is expressed by the ID information waveform can be confirmed. Furthermore, the ID value is the area when the value of the waveform in Fig. 5 is integrated.

3. Basic Experiment Evaluation by Highly Accurate Vibration Waveform Analysis

An off-line test device was prepared using a multistage centrifugal pump, as shown in **Fig. 6**. Vibration sensors, AE (acoustic emission) sensors, etc. were installed on the bearing part, and a burning (seizure) detection test of the journal bearing was performed.

The pump used in this experiment was a multistage centrifugal pump (motor: 5.5 kW, bearing metal: WJ1, bearing lubricant: turbine oil (VG-46)). First, data collection was performed for a given time under a normal condition at a speed of 1 460 min^{-1}. A burning test was then performed by draining the oil from the discharge hole at the bottom of the bearing casing and applying a load by inserting a 0.1 mm shim in the bearing bolted joint to cause eccentricity.

Figure 7 shows the relationship between test time and the results of measurement of the velocity peak value (VEL-P), acceleration peak value (1/5ACC-P), and acceleration rms value (ACC-R), and change magnification of AE. Beginning 27 min after the start of the test, a squeaking metal contact sound due to seizure occurred for about 2 min. This is an initial-period phenomenon in burning. During this period, it was difficult to judge abnormality because the values of the conventional parameters such as VEL-P, 1/5ACC-P, ACC-R, AE, etc. increased temporarily, but then immediately decreased to their original levels. With the developed technology using the *S* value (parameter integrating dimensional and nondimensional parameters), the *S* value rose sharply, although with variations, beginning 20 min after the start of the test, which was 7 min earlier than the conventional parameters, confirming that early abnormality detection is possible using the *S* value. After 58 min, the metal contact sound became continuous and was accompanied by a burning smell. Therefore, the pump was stopped 68 min after the start of the test, and the experiment was ended. **Photo 1** shows the appearance of the shaft bearing after the end of the experiment.

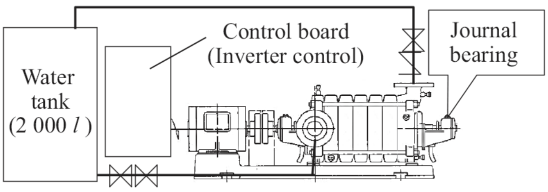
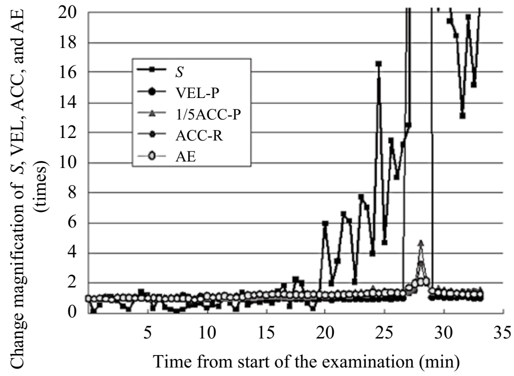


Fig. 6 Outline of basic examination evaluation device



S: Parameter that integrates having dimensionparameter and nondimension parameter
VEL-P: Velocity-Peak
1/5ACC-P: 1/5Acceleration-Peak
ACC-R: Acceleration-Root mean square value
AE: Acoustic emission

Fig. 7 Journal bearing burning test result

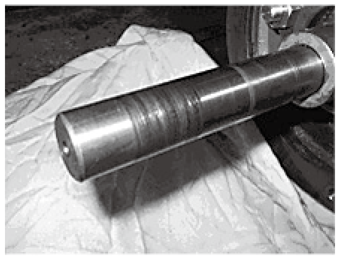


Photo 1 Shaft photograph after burning examination ends

4. Verification with Actual Machines

4.1 System Outline

Figure 8 shows a block diagram of the system when applied to actual equipment. Vibration sensors are installed on the bearings and other parts of each unit of equipment, and vibration waveform data are collected periodically by a prototype high-speed data collection device. The data are transmitted to a data collection personal computer at a cycle of 20 times per minute. The data collection personal computer transmits the data to the monitoring server, enabling clients (maintenance section, production section) to check the data in the server.

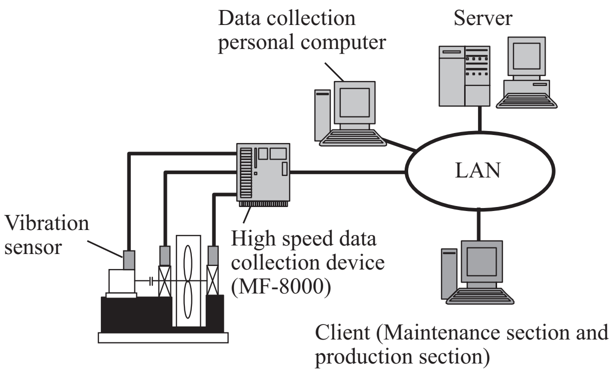


Fig. 8 Block diagram of system of making to real machine

4.2 Main Features

With this system, it is possible to perform high-speed sampling at 26–38.4 kHz. Therefore, fabrication of the prototype high-speed data collection device, which can collect waveforms for a maximum 30 seconds period, enabled adequate waveform sampling for parameter formation by statistical techniques, even with low-speed rotary machines.

4.3 Examples of Application to Actual Machines

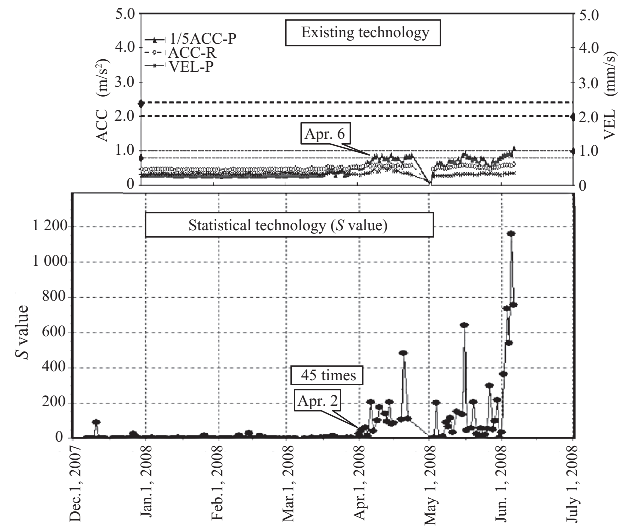
Next, this section introduces two examples of early abnormality detection in an induced draft fan (IDF) motor (journal bearing) in converters and a plunger pump (reciprocation machine) in a plate mill, where the developed technology was used in actual machines. In low-speed rotary machines, a defect was also successfully detected in an inner ring scratch in a bearing of a reduction gear (24 min^{-1}) of a blast furnace raw material charging conveyer, etc.

4.3.1 Example of IDF motor in converter

First, an example of an IDF motor in a converter will be introduced. **Figure 9** is a trend management graph of data sampled from a vibration sensor installed on the journal bearing of an IDF motor in a converter.

With the conventional technique, the acceleration caution value was exceeded on April 6, but thereafter, there was no large increase and the trend remained around the caution value. Accordingly, recognition of the fact that this was an abnormality may have been delayed. In contrast, the dimensional-nondimensional integration parameter S used in the statistical technique rose to 45 times the normal value on April 2 and showed large rises thereafter, although with variations.

Therefore, when all parameters were checked in order to investigate the cause of the rise in the S value, it was judged that acceleration-rotation frequency (ACC-fr), acceleration-impact index (ACC-IP), etc. increased



1/5ACC-P: 1/5Acceleration-Peak
ACC-R: Acceleration-Root mean square value
VEL-P: Velocity-Peak
S: Parameter that integrates having dimension parameter and nondimension parameter

Fig. 9 Tendency management graph of IDF motor in converter (Average data of day)

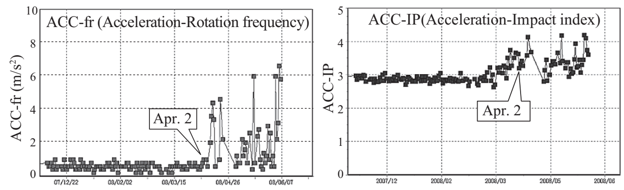


Fig. 10 Each parameter change IDF motor in converter abnormality detects it

beginning on April 2, and impact vibration of the rotation frequency was occurring (**Fig. 10**). From the above, light metal contact, backlash in the bearing housing, or similar trouble was considered possible, and wear of the oil ring contact part was also conceivable. An open inspection was performed, and misalignment of the half contact part of the oil ring was confirmed. After repair, the vibration decreased.

4.3.2 Example of plunger pump for descaling in plate mill

Next, an example of a plunger pump used in descaling in plate mill will be presented. Vibration sensors were installed at a total of 12 locations, including 10 suction and discharge valves (5 each) on the plunger pump body and 2 crankshaft bearings, and detection of abnormalities in the reciprocal motion of the pump was attempted (**Fig. 11**).

Figure 12 shows the trend management graph and acceleration waveform when a suction valve abnormality was detected. Abnormality judgment was difficult

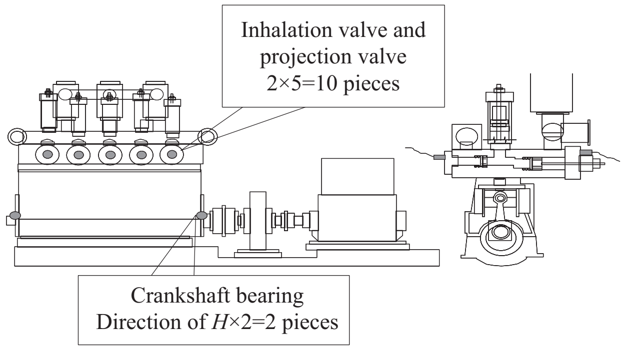


Fig. 11 Vibration sensor installation situation of main body of plunger pump of plank factory

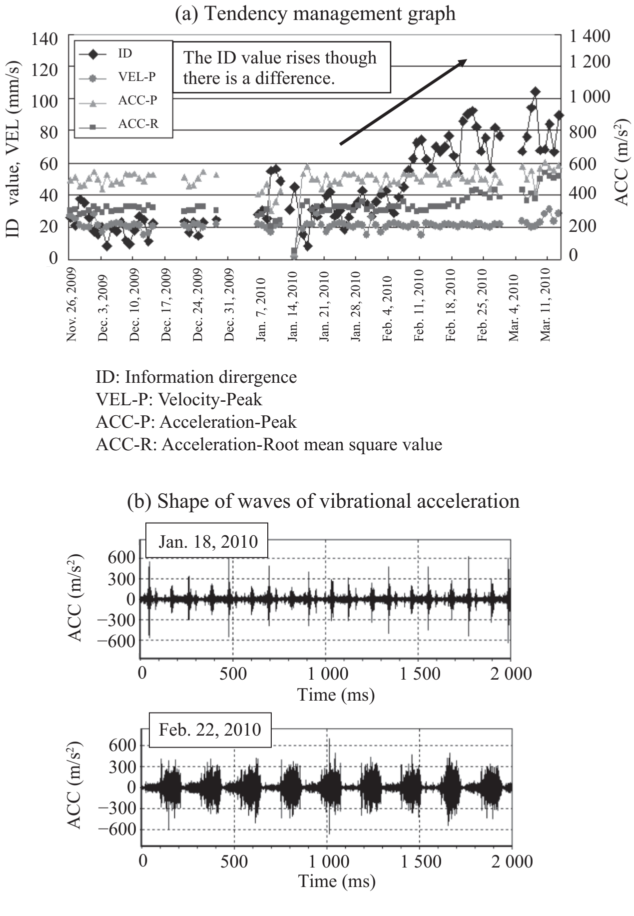


Fig. 12 Tendency management graph and vibration acceleration wave type when inhalation valve abnormality is detected

because the root mean square (rms) value (ACC-R) of vibration acceleration in the conventional method showed a slight increase, but this was limited to less than 2 times the normal value and did not reach the caution value. In contrast, the Kullback-Leibler divergence of symmetry type (ID) information value showed a clear rising tendency and exceeded 100 times the normal value, although with variations. When the acceleration waveform was checked, leak vibration after the valve was closed, which could not be observed on January 18, was found on February 20. As a result, the valve was replaced during scheduled maintenance.

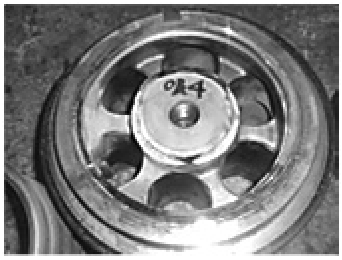


Photo 2 Detached inhalation valve (loss on seat side)

Photo 2 is a photograph of the suction valve after removal. Large loss had occurred on the seat face. The ACC-R value used in the conventional method rose very slightly around February 20. In contrast to this, the ID value in the statistical technique began to rise in the first part of February, confirming the superiority of the ID value.

5. Conclusion

This research confirmed that processing of vibration waveforms by statistical techniques such as principal component analysis, Kullback information, etc. enables dramatically earlier abnormality judgment than conventional techniques in judgment of abnormalities in actual machines such as journal bearings, reciprocation materials, low-speed rotary machines, and others which were difficult to judge abnormalities using conventional techniques.

JFE Mechanical has begun outside sales of a high performance monitoring device called "Condition Eye" [5] incorporating this technology and has already received inquiries.

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