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Application of cepstrum and neural network to bearing fault detection †

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Abstract

This paper proposes an integrated system for motor bearing diagnosis that combines the cepstrum coefficient method for feature extraction from motor vibration signals and artificial neural network (ANN) models. We divide the motor vibration signal, obtain the corresponding cepstrum coefficients, and classify the motor systems through ANN models. Utilizing the proposed method, one can identify the characteristics hiding inside a vibration signal and classify the signal, as well as diagnose the abnormalities. To evaluate this method, several tests for the normal and abnormal conditions were performed in the laboratory. The results show the effectiveness of cepstrum and ANN in detecting the bearing condition. The proposed method successfully extracted the corresponding feature vectors, distinguished the difference, and classified bearing faults correctly.

***Keywords*:** Fault classification; Cepstrum; Machine condition monitoring (MCM); Artificial neural network

1. Introduction

Machine condition monitoring (MCM) is an area of increasing importance in the manufacturing industry. The bearing of the rotating machines, which has been commonly used in the industry for decades, is one of the machines' most important elements and is commonly the reason for the equipment breakdown. Zarei mentioned in [1] that more than 40% of motor failures are bearing-related. Bearing fault detection and identification have been substantially investigated, and many algorithms have been proposed during the past few decades. Several methods have been used to analyze the vibration signal in order to extract effective features for bearing fault detection. Among them, Heng and Nor [2] used statistical data such as mean value and standard deviation to monitor the bearing conditions; Li et al. [3] and Ye et al. [4] trained an artificial neural network (ANN) from the frequency and amplitude data of the bearing system; Goddu et al. [5] applied fuzzy logic inference rules to judge the bearing conditions; Zarei [1] and Eren [6] used the wavelet packet transform to decompose the vibration signals; Cheng [7] and Yu [8] used the empirical mode decomposition (EMD) and Hilbert spectrum to analyze the experiment data and moved away from the non-stationary mode of bearing faults. Feature extraction is one of the most important factors in pattern recognition problems. The process involves deriving new features from raw data in order to reduce the dimensionality of data presented to the classifier while improving the classification efficiency. In this paper, we will present a new, efficient, and fast feature-extracting method for detecting and discriminating general motor bearing faults from a segment of pattern. For machine condition monitoring signal analysis, ANN and the cepstrum coefficient method were utilized in this study.

The term "cepstrum" was first introduced by Bogert [9] and mainly applied to speech recognition [10]. It has since become an accepted terminology to refer to the inverse Fourier transform of the logarithm

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of a signal's power spectrum. The cepstrum of a signal is defined as the inverse Fourier transform of the log power spectrum of a signal [11], and cepstrum coefficients are the measurements of the spectrum. Cepstrum coefficients are derived from the linear predictor coefficients [9], which are extracted from each frame by the auto-correlation method and Durbin's recursive procedure. The ANN has potential applications in automated detection and in the diagnosis of machine conditions [12]. By combining these two techniques, a reliable automatic motor fault diagnosis system employing cepstrum transform to extract features from segmented motor vibration information is proposed. Faults are classified according to the features extracted from the segmented data using ANN. In addition to normal motor testing (NOR), the proposed system is designed to distinguish four faults, including an unaligned bearing axis, and loose bearing accessories such as pedestals, shims, and wedges. To verify our methods, laboratory testing data were used for processing in this study.

Based on the features of input fault pattern, the decision-making process of the ANN is holistic, and it is suitable for the classification of fault monitoring data. Different network topologies and powerful learning strategies are used to solve nonlinear problems. [13]. For the present application, back propagation with momentum was used to train the feed forward neural network. Every fault with forty different segmented motor vibration data was collected for ANN evaluation of this system. Twenty signals from each category were used as training sets for the network, with the remaining signals used for testing.

To address the issues discussed above, this paper is organized as follows. Cepstrum-based feature extraction method is addressed in Section II. The ANN used for the classification task in this study is described in Section III. Section IV provides some discussions based on experimental results. The advantages and limitations of the cepstrum-based feature extraction method are concluded in Section V.

2. Cepstrum coefficient extraction algorithm for motor-bearing vibration signal

The characteristics of an unknown motor vibration signal were compared with those in the database. In this study, we proposed utilizing cepstrum techniques to extract and compare the characteristics of bearing fault signals. The algorithm in Fig. 1 contains three major steps: (i) start point detection, (ii) feature extraction, and (iii) feature comparison. After these steps, the characteristics of a motor vibration signal will be classified and used to recognize possible bearing faults. There are two major portions in the cepstrum extraction algorithm: first is to build up the template database, and the second is to identify the unknown signals.

For those motor vibration signals with already known symptoms, the processes shown at the left column in Fig. 1 are to extract the characteristics from the signals and save them as standard reference templates. Each signal will go through the start point detection and feature extraction processes before their characteristics are saved into the standard reference template database. For unknown signals, usually collected through real-time motor condition monitoring, the processes shown in the right column of Fig. 1 will be used to extract the characteristics. These characteristics will be compared to the template in order to distinguish possible symptoms if the signals contain any abnormalities. Detailed descriptions for each step will be discussed in the following sections.

2.1 Start point detection of segment data

The motor vibration signal is wholly saved as standard reference or used for comparison; therefore, processing of more data is required. Based on the characteristics of a motor monitoring signal, it is necessary to extract proper features for comparative recognition. We divide the meaningful block of motor vibration data for processing. First, as a starting point of segment data, the peak positions are found by a threshold value and a moving window. The procedures are described as follows.

Step 1. Estimate a maximum peak value of the first wave from the motor vibration signal during a time interval (about 2 s). The 50% peak value is chosen to be an initial amplitude threshold.

Step 2. Use the initial amplitude threshold to search for the waveform's next peak value in a 0.125-s searching window. When the peak position is found, add a time interval (about 0.0625 s) to determine the the next starting point of the next searching window.

Step 3. Repeat step 2 until the first five positions and peak values of waveform are found.

Step 4. Average these five peak values to obtain the average amplitude threshold.

Step 5. Move the search window and estimate other

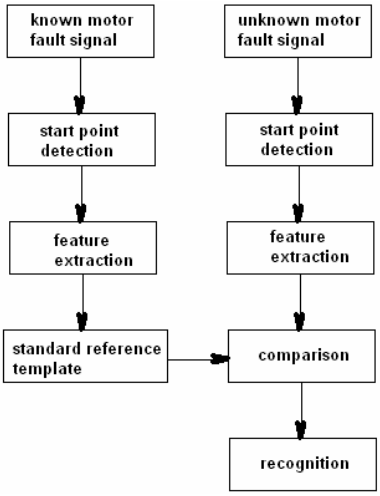

Fig. 1. Systemic block diagram for cepstrum extraction algorithm.

wave peak positions with 70% of this average amplitude threshold. Choose one peak position, which is defined to be the starting-point of the meaningful motor fault data, and the following 1,500 points (about 0.125 s) of data for the feature extraction process. The length of processing data, used to classify the bearing faults, is chosen according to the mechanic's suggestions.

2.2 Feature extraction

The procedures of feature extraction, shown in Fig. 2, include three steps: (i) Signal Segmentation, (ii) Linear Predict Coding (LPC) Coefficient Extraction, and (iii) Cepstrum Coefficient Extraction.

First, the meaningful segment vibration data need to be divided into multi-frames. All the feature extractions were based on one frame as a unit to get the corresponding feature vector. The segment data was divided into 10 frames. Hence, each frame was composed of 150 points (12.5 ms) for extracting 10 cepstrum feature coefficients. The data in each frame were multiplied by a Hamming window of 25 ms, resulting in a 50% overlapping between one frame and the next in order to maintain the continuity of bearing fault signals as follows:

$$X(n) = \begin{cases} S(n) * W(n) & 0 \le n \le N-1 \\ 0 & others \end{cases} \tag{1}$$

$$W(n) = \begin{cases} 0.54 - 0.46 * \cos(\frac{2n\pi}{N-1}) & 0 \le n \le N-1 \\ 0 & others \end{cases} \tag{2}$$

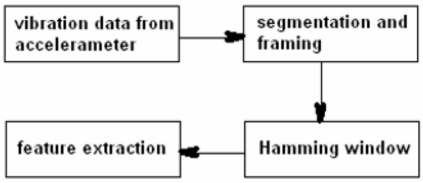

Fig. 2. Feature extraction steps.

where *S (n)* is the motor vibration original signal, *W (n)* is the Hamming window function, *X (n)* is the n^{th} output result, and *N* is the length of the window.

Secondly, the LPC coefficients will be analyzed to obtain the cepstrum coefficients. The linear prediction technique has been proven to be very useful in providing an efficient representation of the speech signals [13-15]. The basic idea of the linear prediction coding is that a hypothetical motor vibration sample can be predicted by linear combination of previous *p* samples. The LPC coefficient is aimed at reducing the variation between an actual motor vibration sample and a predicted sample to a minimum to find the best predictor for linear combination [13]. The actual motor vibration data sequence *X (n)* can be approximated by another sequence $\tilde{X}(n)$ which is determined by a unique set of predictor coefficients and the past *p* samples *X (n)*. That is

$$\tilde{X}(n) = \sum_{k=1}^{p} \alpha_k X(n-k) \tag{3}$$

where *p* is the number of order predicted by LPC and α_k is the k^{th} linear predictive coefficients (LPC). The difference between the actual vibration sequence and the predicted sequence is generally named residual error *e (n)* and is expressed as the following:

$$e(n) = X(n) - \tilde{X}(n) = X(n) - \sum_{k=1}^{p} \alpha_k * X(n-k) \tag{4}$$

The weighting coefficient α_k in Equation (4) can be determined by minimizing the mean squared residual error, and the best prediction can be obtained by setting

$$\frac{\partial e^2}{\partial \alpha_k} = \tilde{0} \ \text{ for } \ 1 \le k \le p \tag{5}$$

and obtaining

$$\frac{\partial e^2}{\partial \alpha_k} = 2\sum_n X(n)*X(n-k) + 2\sum_n \sum_{j=1}^{p} \alpha(k)*X(n-j)*X(n-k) \tag{6}$$

Eq. (6) can be re-arranged as the following matrix form:

$$\begin{bmatrix} R_0 & R_1 & R_2 & R_{p-1} \\ R_1 & & & \vdots \\ \vdots & & & \vdots \\ R_{p-1} & R_{p-2} & \cdots & R_0 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_p \end{bmatrix} = -\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_p \end{bmatrix} \tag{7}$$

where R_k is a short-time autocorrelation coefficient of *X(n)*. The variables $\{\alpha_k \mathrm{i}\}$ can be solved by using Durbin's recursive procedure. The cepstrum coefficient is generally defined as the inverse Fourier transform of the spectrum over a short interval, which can be expressed in the following equation as

$$X(k) = \sum_{n=0}^{N-1} X(n)e^{-\frac{2\pi}{N}kn} \qquad 0 \le k \le N-1 \tag{8}$$

$$C(n) = F^{-1}\log|X(k)| = \frac{1}{N}\sum_{k=0}^{N-1}\log|X(k)|e^{j\frac{2\pi kn}{N}} \qquad 0 \le n \le N-1 \tag{9}$$

where *X(k)* is the Fourier transform of the motor vibration signal *X(n)*. The spectral features of envelope and minute changes in vibration signals can be presented by using cepstrum analysis to avoid the complicated calculation in Eq. (9). Generally, cepstrum coefficient can be derived from previous LPC coefficients through the following recursive procedure:

$$C(n) = \alpha(n) + \sum_{k=1}^{n-1}\left(\frac{k}{n}\right)C(k)\alpha(n-k) \qquad 1 \le n \le p \tag{10}$$

where *α(n)* is the obtained LPC linear prediction coefficient, *C(n)* is the target cepstrum coefficient, and *n* is the order of the cepstrum coefficient. We can get a 10-element vector [*C(0), C(1), C(2),…, C(9)*] that represents the feature vector of this frame, and it can be used to do the feature comparison in the next section. There are no significant differences in cepstrum coefficient for the prediction order *n* which is larger than 10. The cepstrum features of segment motor vibration data divided into 10 frames is defined by

$$Cep\_Feature[i][j], \begin{cases} 1 \le i \le 10 \\ 1 \le j \le 10 \end{cases} \tag{11}$$

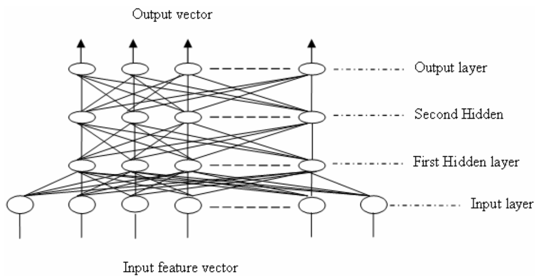

Fig. 3. Architecture of the neural network.

where *i* is the frame number and *j* is the order of cepstrum coefficient of the *i-th* frame.

3. Detection using ANN classification

ANN is probably one of the most common classifiers in use today. In this section, a supervised artificial neural network (ANN) is developed to recognize and classify the cepstrum features of segment motor vibration signals. Since the classification of arrhythmia is a complicated problem, we used a feed-forward neural network with two hidden layers as shown in Fig. 3. All neurons were defined as sigmoid activation functions. The input layer consisted of nodes for motor vibration measurements, and in the subsequent hidden layers, the process neurons with the standard sigmoid activation functions were used. The output layer contained four neurons to distinguish the motor vibration signals into five classes.

The neural network was trained by the back propagation algorithm (BPA) with the selected vibration segments as its inputs and the weights of neurons as its outputs. The BPA is a supervised learning algorithm, in which a sum square error function is defined, and the learning process aims to reduce the overall system error to a minimum.

The output units have weights $W^3_{i,j}$, and the hidden units have weights $W^1_{i,j}$ and $W^2_{i,j}$. During the training phase, each output neuron compares its computed activation y_k with its target value d_k to determine the total square error E for the pattern with that neuron,

$$E = 1/2\sum_{k=1}^{m}(d_k - y_k)^2 \tag{12}$$

where m is the number of output neurons, k represents the k^{th} neuron. By using BPA, the network has been trained with moderate values of learning rate and momentum. The weights will be updated for every training vector. The training will be terminated when the sum square error reaches a minimum value.

The weights are randomly assigned at the beginning and progressively modified backward from the output layer to the input layer to reduce the overall system error. The weight update is in the direction of "negative descent" to maximize the speed of error reduction. For effective training, it is desirable that the training data set be uniformly distributed throughout the class domains. The available motor vibration data will be used repetitively until the error comes to a minimum. Hence, an algorithm containing three steps, namely, (i) setting random weights, (ii) training recursion and (iii) classification steps, is used to obtain the correct class.

Step 1: Setting initial weight data and biases. Initially, we set all the weights in the net to a random number between 0 and 1.

Step 2: Training recursively. The cepstrum features of segment motor vibration data [x_0, x_1, x_2,…,x_{n-1}] will be fed into the input layer and will set the target vector. Since this ANN is designed to be a classifier, only one of five output neurons will be set as one and others will be zero. For instance, if the motor vibration data is classified to be the first class, the vector of output neurons will be [1,0,0,0,0], so [1,0,0,0,0] denotes the normal condition, [0,1,0,0,0] denotes the unaligned bearing axis, [0,0,1,0,0] denotes the loose bearing pedestal, [0,0,0,1,0] denotes the loose bearing shim, and [0,0,0,0,1] denotes the loose bearing wedge. The ANN weights and biases are adjusted to minimize the least-square error. The minimization problem is solved by the gradient technique, in which the partial derivatives of E with respect to weights and biases have been calculated using the generalized delta rule. This is achieved by back-propagation (BP) of the error. Convergence is sometimes faster if a momentum term is added to the weight update formula. In the back-propagation with momentum, the weights for training step t+1 are based on the weights at training steps t and t-1. The weight update formulas for BP with momentum are

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j x_i^{'} + \alpha\Delta w_{ij} \tag{13}$$

where $w_{i,j}(t)$ is the weights from hidden layer or input layer to node j at step t, $x_i^{'}$ can be input or output at node i, η is the learning factor, α is the momentum, δ_j is the error items at node j, and $\Delta w_{ij} = [w_{ij}(t) - w_{ij}(t-1)]$. There are two cases:

(i) If j is the node of output layer, then

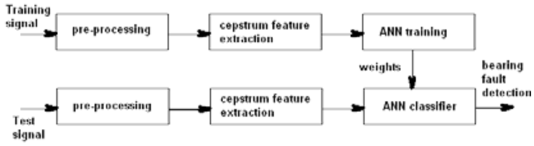

Fig. 4. Block diagram of the bearing fault classifier.

$$\delta_j = y_j(1-y_j)(d_j - y_j) \tag{14}$$

where y_j is the output value at node j, and d_j is the target value at node j.

(ii) If j is the node of hidden layer, then

$$\delta_j = y_j(1-y_j)(d_j - y_j) \tag{15}$$

where k is the total number of nodes at the layer where node j is. The weights and biases are assigned some initial random values and updated in each iteration (called an epoch) until the net has settled down to a minimum.

Step 3: Testing and classification: By using back propagation algorithm, the network has been trained with moderate values of learning rate (η) and momentum (α). The weights are updated for every training vector, and the termination bearing a condition that the sum square error reaches a minimum value. The following steps are performed for arrhythmia recognition:

The segment of motor vibration signal considered for analysis consists of 1,500 points of data for feature extraction processing.

Cepstrum coefficients are calculated and transferred to -100 elements vector.

Feature vector is given as input to the neural network, which has an optimal set of weights.

Classification of the input data set is carried out by the trained neural network.

4. Results and discussion

Motor vibration records with normal bearing and different types of bearing faults were collected from the laboratory for analysis. We utilized the database of the acceleration signals for (i) normal condition, (ii) un-aligned bearing, (iii) loose bearing pedestal, (iv) loose bearing wedge, and (v) loose bearing shim. After filtering high-frequency noise and lower-frequency drifting, the start-point was located and meaningful signals were treated as the input segment of feature extraction, as shown in Fig. 5. Ten frames

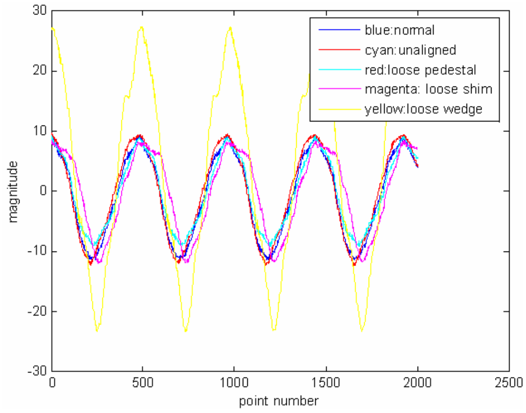

Fig. 5. Acceleration signals for (i) normal condition, (ii) unaligned bearing, (iii) loose bearing pedestal, (iv) loose bearing wedge, and (v) loose bearing shim.

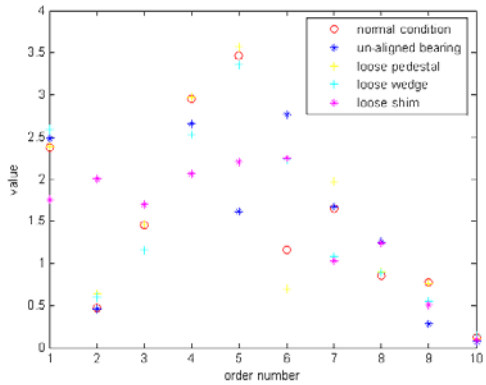

Fig. 6. The cepstrum coefficients of five classes.

were generated with Hamming windows and then 100 cepstrum coefficients were obtained. The cepstrum features of five bearing fault signals are compared in Fig. 6.

One can easily find the difference in cepstrum coefficient of the five bearing fault signals in the first frame from Fig. 6. The special feature of the cepstrum analysis is that it allows for the separate representation of the spectral envelope and fine structure. The block diagram of cepstrum analysis for extracting spectral envelope and fundamental period is shown in Fig. 7. In this study, it was demonstrated that the neural network combined with the cepstrum transform feature extraction provided an excellent combination in automatic bearing fault diagnosis.

It is believed that the combination of cepstrum with the neural network provides a good solution for automatic fault detection system in the future. Forty-segment input data with the same bearing fault signal

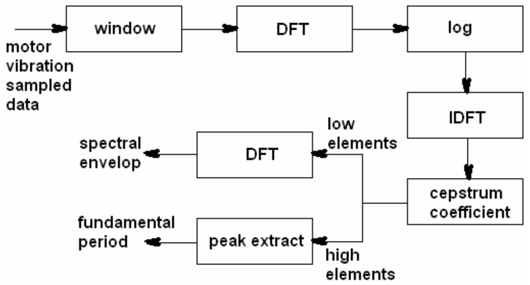

Fig. 7. Block diagram of cepstrum analysis for extracting spectral envelope and fundamental period.

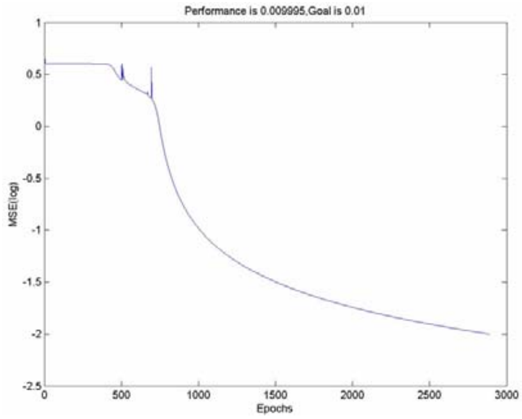

Fig. 8. The training performance of the network.

were appropriately arranged to be the training and testing patterns. Each segment consists of 1,500 data samples. Two hundred bearing fault patterns were collected from the experimental data for the ANN training and evaluation of this system. A sample of the training performance for the network is shown in Fig. 8. The best multi-layer perceptron (MLP) structure found in the experiments was 100-20-20-4.

Table 1 lists the results of the ANN model used in the bearing fault classification. The accuracy of a bearing fault classifier was defined as the ratio of the number of segment data correctly classified to the total number of data tested. The accuracy of classification in the testing mode was 100%, that is, all 20 testing data sets were correctly classified to the corresponding classes. Table 2 shows the result of the proposed method used in the classification of bearing fault. There are a total of 100 testing data sets used to test the accuracy of the trained neural network to diagnose different motor bearing faults. Table 3 shows the output vector of the neural network for the bearing faults diagnosis scheme. The results demonstrate that with proper processing of the measured data and pos-

Table 1. Back-propagation bearing fault models.

Architecture	100-20-10-4
η	0.3
α	0.1
*SSE	<0.01
Epochs	2885
Training sets (**cc %)	100
Testing sets (cc %)	100

*SSE is sum square errors; **cc % is accuracy.

Table 2. Overall performance of the proposed method.

Method	cepstrums+ANN
Number of arrhythmia types	5
Training accuracy in %	100
Testing accuracy in %	100

Table 3. Test sample and its output.

Test sample	Output Vector of ANN
Normal condition	[0.9496, 0.0347, 0.0000, 0.0086, 0.0000]
Unaligned bearing axis	[0.0222, 0.9361, 0.0036, 0.0201, 0.0094]
Loose bearing pedestal	[0.0000, 0.0013, 0.9693, 0.0270 ,0.0263]
Loose bearing shim	[0.0259, 0.0185, 0.0003, 0.9555, 0.0213]
Loose bearing wedge	[0.0008, 0.0000, 0.0315, 0.0291, 0.9493]

sible training procedure, the proposed method can diagnose bearing faults with the desired accuracy.

The proposed cepstrum and ANN techniques can also extract real-time features and classify them to database-referred feature patterns to effectively detect the occurrence of sudden bearing faults in the MCM field.

5. Conclusion

In this article, a cepstrum-based feature extractor and ANN techniques were proposed for the extraction and classification of features from raw vibration data. They were successfully applied to the problem of bearing fault classification. Experiments showed that this algorithm was effective in finding a nonlinear mapping between five bearing conditions. Different features were correctly classified to the corresponding classes, resulting in a classification accuracy of 100%. On the other hand, when a long-term machine condition monitoring was required for a rotor machine, the algorithm was valid only if its normal signal block was accessed and saved into its own database. Comparing the extraction of real-time feature with that of a database-referred feature, the algorithm was able to detect the occurrence of sudden bearing faults effectively.

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