INTELLIGENT FUSION FOR AEROENGINE WEAR FAULT DIAGNOSIS

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Abstract: Four common oil analysis techniques, including the ferrography analysis (FA), the spectrometric oil analysis (SOA), the particle count analysis (PCA), and the oil quality testing (OQT), are used to implement the military aeroengine wear fault diagnosis during the test drive process. To improve the precision and the reliability of the diagnosis, the aeroengine wear fault fusion diagnosis method based on the neural networks (NN) and the Dempster-Shafter (D-S) evidence theory is proposed. Firstly, according to the standard value of the wear limit, original data are pre-processed into Boolean values. Secondly, sub-NNs are established to perform the single diagnosis, and their training samples are dependent on experiences from experts. After each sub-NN is trained, diagnosis results are obtained. Thirdly, the diagnosis results of each sub-NN are considered as the basic probability allocation value to faults. The improved D-S evidence theory is applied to the fusion diagnosis, and the final fusion results are obtained. Finally, the method is verified by a diagnosis example.

Key words: wear fault diagnosis; data fusion; neural network; D-S evidence theory; aeroengine

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INTRODUCTION

The oil analysis method is an important technique in the machine fault diagnosis because of its sensitivity to and effectiveness in the machine wear fault detection. Each oil analysis method has its own advantages, but the detection rate of a single method is limited[1]. In this paper, four conventional oil analysis techniques are combined for the wear fault diagnosis, including the ferrography analysis (FA), the spectrometric oil analysis (SOA), the particle count analysis (PCA), and the oil quality testing (OQT). Furthermore, the fusion diagnosis based on multi-source data is important to improve the wear diagnosis precision. However, how to fully utilize the information of each oil analysis method is the essence of the fusion diagnosis. Currently, many researchers study the problem[2, 3].

In this paper, the neural network (NN) and the Dempster-Shafter (D-S) evidence theory are applied, the wear fault diagnosis of a certain type of military aeroengine during the test-drive process is targeted, and a fusion diagnosis method based on NN and the D-S evidence theory is presented. Finally, an example shows that the new method can provide more correct and reliable decision support for the aeroengine condition evaluation in a test.

1 WEAR FAULT FUSION DIAGNOSIS FLOW CHART

The basic steps for the aeroengine wear fault fusion diagnosis are as follows:

(1) Wear faults are detected;

(2) The diagnosis result of each analysis method is integrated;

(3) Fusion results are obtained. Fig. 1 shows the flow chart of the aeroengine wear fault fusion diagnosis. Each module is explained in detail below.

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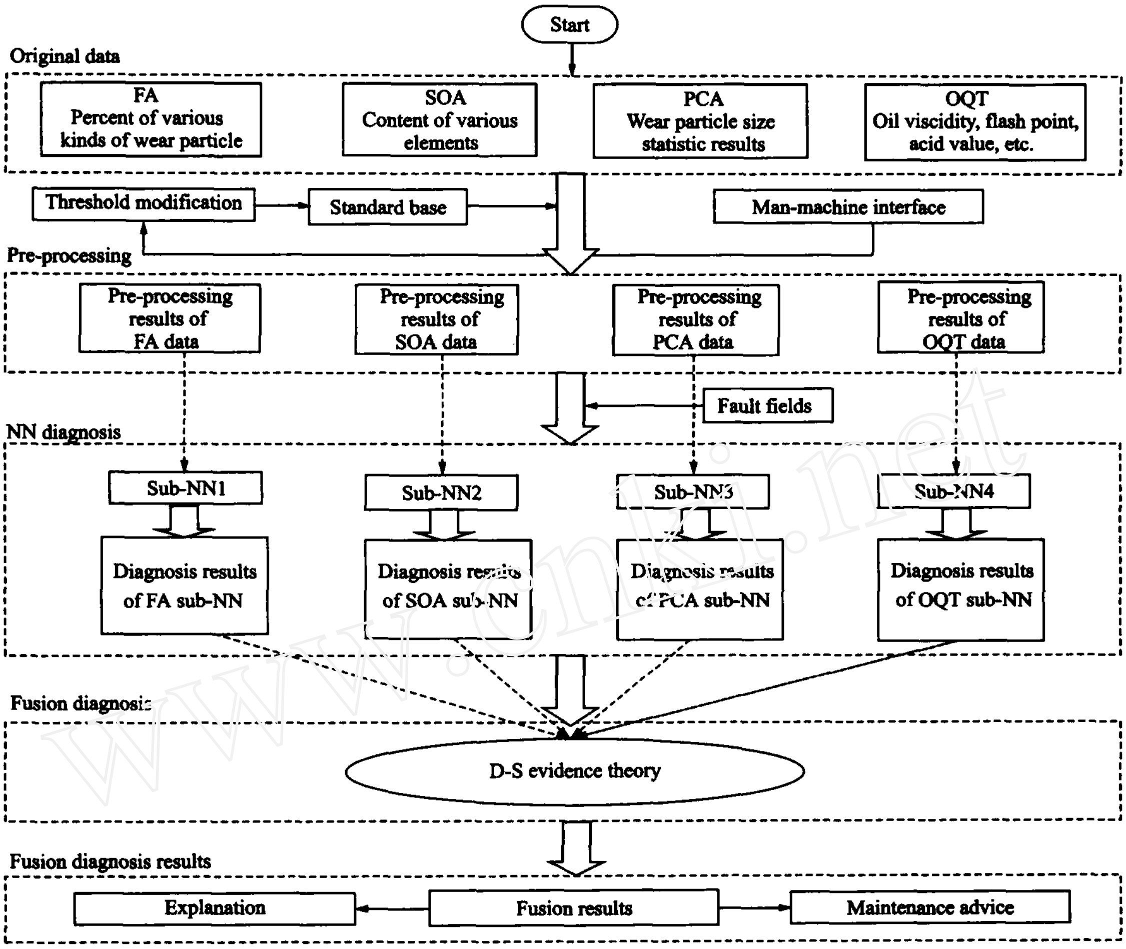

Fig. 1 Flow chart of aeroengine wear fault fusion diagnosis

2 PRE-PROCESSING OF ORIGINAL DATA

Due to the different values and units of original data obtained by various analysis methods, the subsequent analysis and processing become very difficult. Therefore, original data must be pre-processed before the fusion diagnosis. The processing method is to compare original data with standard limits. If exceeding the limit, the value is 1; otherwise 0. Accordingly, original symptom data are converted into Boolean values of 0 and 1.

Original data from FA depend on the percents of various kinds of wear particles. Their pre-processed values are as follows: (1) If spherical wear particles exceed the limit, $S_{F1}=1$; otherwise, $S_{F1}=0$. (2) If laminar wear particles exceed the limit, $S_{F2}=1$; otherwise, $S_{F2}=0$. (3) If fatigue chunk wear particles exceed the limit, $S_{F3}=1$; otherwise, $S_{F3}=0$. (4) If cutting wear particles exceed the limit, $S_{F4}=1$; otherwise, $S_{F4}=0$. (5) If severe rubbing wear particles exceed the limit, $S_{F5}=1$; otherwise, $S_{F5}=0$. (6) If red oxide wear particles exceed the limit, $S_{F6}=1$; Otherwise, $S_{F6}=0$. (7) If black oxide wear particles exceed the limit, $S_{F7}=1$; otherwise, $S_{F7}=0$.

For the aeroengine studied in this paper, elements Fe, Cr, Ni, Mo, Cu, V, Zn, Al and Ti are selected as the materials of the SOA diagnosis, and their contents form the original data of the SOA diagnosis. However, for other machines, the structure and materials of a friction set are different. Hence, the selected elements are different too. The Boolean value S_{S1} is used to represent whether Fe content exceeds the standard value. If the content exceeds the standard value, S_{S1} is 1; otherwise 0. In the same way, Boolean values S_{S2}, S_{S3}, S_{S4}, S_{S5}, S_{S6}, S_{S7}, S_{S8} are used for Cr, Ni, Mo, Cu, V, Zn, Al and Ti contents, respectively. After pre-processing, data from SOA are composed of S_{Si} (i= 1, 2, ⋯, 9).

According to the NASA 1638 standard, in PCA, the wear particle number can be obtained in given size ranges, which are 5—15μm, 15—25μm, 25—50μm, 50—100μm and over 100 μm. According to the particle number in each size range, only the Boolean value S_{C1} can be obtained, denoting whether the oil contamination exceeds the standard value, because particle number in each size range cannot correspond to engine fault modes

Original data by OQT include movement viscidities at 250 ℃, 200 ℃, 100 ℃, 0 ℃, - 40 ℃ and - 54 ℃, the condensation point, the flash point, the acid value, the impurity content, and the water content Depending on the relation with engine faults, after pre-processing, the following Boolean values are obtained: (1) S_{P1}, representing whether the movement viscidity exceeds the standard value If exceed, S_{P1}= 1; otherwise, S_{P1} = 0; (2) S_{P2}, representing whether the impurity content exceeds the standard value If exceeds, S_{P2}= 1; otherwise, S_{P2}= 0; (3) S_{P3}, representing whether other indexes exceed the standard values If exceed, S_{P3}= 1; otherwise, S_{P3}= 0

3 NN SINGLE DIAGNOSIS

NN has a strong nonlinear mapping ability and some generalization abilities It is widely applied to the fault diagnosis In this paper, three-layer NN is used to perform a single diagnosis of oil analysis data, and it is trained by the back propagation (BP) algorithm.

Sub-NN for the single diagnosis includes: FA sub-NN, SOA sub-NN, PCA sub-NN, and OQT sub-NN. The input of each sub-NN is Boolean values, obtained after original data are pre-processed, and the output is final wear faults Through the fault analysis, the wear faults of the engine are classified into seven types as follows: (1) Normal (F_1); (2) Bearing severe wear (F_2); (3) Bearing fatigue failure (F_3); (4) Gear fatigue over-loading (F_4); (5) Gear agglutination or scratching (F_5); (6) Oil contamination exceeding the standard value (F_6); (7) Oil quality exceeding the standard value (F_7).

Tables 1-4 show training samples obtained by the experience and the knowledge of field experts Training samples of FA sub-NN [4] are shown in Table 1, and those of SOA Sub-NN, PCA Sub-NN and OQT Sub-NN are shown in Tables 2-4, respectively.

The parameters of each Sub-NN structure are: FA sub-NN 7-20-7, SOA sub-NN 9-10-7, PCA sub-NN 1-8-7, OQT sub-NN 3-8-7. The variable step-size learning is adopted in each sub-NN. The training precision is 0.01, and the momentum coefficient is 0.9 In order to improve the generalization ability of NN, the Gaussian noise N (0, 0.01) is add to each training sample

In Table 1-4, F_{Fi} (i= 1, 2, ⋯, 7) are the diagnosis results of seven fault types by FA sub-NN, F_{Si} (i= 1, 2, ⋯, 7) are the diagnosis results of seven fault types by SOA sub-NN, F_{Ci} (i= 1, 2, ⋯, 7) are the diagnosis results of seven types faults by PCA sub-NN, and F_{Pi} (i= 1, 2, ⋯, 7) are the diagnosis results of seven fault types by OQT sub-NN.

Table 1 FA sub-NN training samples

Item	S_{F1}	S_{F2}	S_{F3}	S_{F4}	S_{F5}	S_{F6}	S_{F7}	F_{F1}	F_{F2}	F_{F3}	F_{F4}	F_{F5}	F_{F6}	F_{F7}
Value	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0.5	0	0	0	0
	0	1	0	0	0	0	0	0	0	0.6	0	0	0	0
	0	0	1	0	0	0	0	0	0	0.8	0.6	0	0	0.6
	0	0	0	1	0	0	0	0	0.8	0	0	0.8	0.6	0
	0	0	0	0	1	0	0	0	0	0	0	0.9	0	0.6
	0	0	0	0	0	1	0	0	0	0	0	0	0	0.8
	0	0	0	0	0	0	1	0	0	0	0	0	0	0

Table 2 SOA sub-NN training samples

Item	S_{S1}	S_{S2}	S_{S3}	S_{S4}	S_{S5}	S_{S6}	S_{S7}	S_{S8}	S_{S9}	F_{S1}	F_{S2}	F_{S3}	F_{S4}	F_{S5}	F_{S6}	F_{S7}
Value	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0.7	0	0	0.9	0	0
	0	1	0	0	0	0	0	0	0	0	0.9	0	0	0.1	0	0
	0	0	1	0	0	0	0	0	0	0	0.9	0	0	0.1	0	0
	0	0	0	1	0	0	0	0	0	0	0.9	0	0	0.1	0	0
	0	0	0	0	1	0	0	0	0	0	0.9	0	0	0.8	0	0
	0	0	0	0	0	1	0	0	0	0	0.9	0	0	0.7	0	0
	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0

Table 3 PCA sub-NN training samples

Item	S_{C1}	F_{C1}	F_{C2}	F_{C3}	F_{C4}	F_{C5}	F_{C6}	F_{C7}
Value	0	1	0	0	0	0	0	0
	1	0	1	0	0	1	1	0

Table 4 OQT sub-NN training samples

Item	S_{P1}	S_{P2}	S_{P3}	F_{P1}	F_{P2}	F_{P3}	F_{P4}	F_{P5}	F_{P6}	F_{P7}
Value	0	0	0	1	0	0	0	0	0	0
	1	0	0	0	1	1	1	1	0	1
	0	1	0	0	1	0	0	1	0	1
	0	0	1	0	0	0	0	0	0	1

4 FUSION DIAGNOSIS BASED ON D-S EVIDENCE THEORY

4.1 D-S evidence theory

The D-S evidence theory[5] is the most common method for the decision-level fusion. And the generalized Bayes theory is established by the human logic.

4.1.1 Distinguishing frame

Defining that the parameter θ is a event and all its values compose the set Θ, named the distinguishing frame, 2^{Θ} is the power set of Θ, which consists of all subsets of Θ.

4.1.2 Basic probability value

The function m: $2^{\Theta}\rightarrow[0, 1]$ is the basic probability allocation (BPA), then

(1) $m(\Phi)=0$, where Φ is the null set;

(2) $\sum_{A\subset\Theta} m(A)=1$, where A is the focus element and $m(A)$ the basic probability value.

For an arbitrary assumption, the belief degree is $\mathrm{Bel}(A)$, $A\in 2^{\Theta}$. It is defined as the sum of basic probabilities of all subsets in A, $\mathrm{Bel}(A)=\sum_{B\subset A} m_i(B)$. Generally, the belief function cannot be added together.

4.1.3 Composing rules of D-S evidence theory

Various evidences possess various BPA functions due to different sources. Ref. [5] presented a method to incorporate data. For n brief functions Bel_i ($i=1, 2, \cdots, n$), their own BPAs are m_i ($i=1, 2, \cdots n$). Then after integration, the belief function is $\mathrm{Bel}=\mathrm{Bel}_1\oplus\mathrm{Bel}_2\oplus\cdots\oplus\mathrm{Bel}_n$.

BPA of the subset A is

$$m(A)=m_1\oplus m_2\oplus\cdots\oplus m_n=\frac{1}{1-k}\sum_{A_i\cap B_j\cap C_l\cap\cdots=A} m_1(A_i)m_2(B_j)\cdot m_3(C_l)\cdots \quad (1)$$

where $k=\sum_{A_i\cap B_j\cap C_l\cap\cdots=\Phi} m_1(A_i)m_2(B_j)m_3(C_l)\cdots$. It is a constant, which reflects conflict degrees between n evidences under the same assumption. The coefficient $\frac{1}{1-k}$ is called the normalization factor, which can prevent the probability from being allotted to the null set Φ.

If $k=1$, then $1-k=0$, Eq. (1) cannot be adopted. Same, when $k\rightarrow 1$, the conflict degree of evidences is high. Thus, results deviate from the truth. Ref. [6] pointed out that since conflict evidences cannot be decided, they must be considered as the unknown region. Then, a new composing formula is proposed, the probabilities of the evident conflict are all assigned to the unknown region. The improved formula for two-evidence sources is as follows[6]

$$\begin{cases} m(\Phi) = 0; \\ m(A) = \sum_{A_i \cap B_j = A} m_1(A_i) m_2(B_j) \qquad A \neq \Phi, X \\ m(X) = \sum_{A_i \cap B_j = X} m_1(A_i) m_2(B_j) + k \end{cases} \tag{2}$$

Compared with Eq. (1), in Eq. (2), the normalization factor $\frac{1}{1-k}$ is eliminated, and the factor k reflects the conflict degree to $m(X)$. When $k=0$, Eq. (2) is identical to the D-S evidence theory—Eq. (1). Though Eq. (2) can compose high conflict evidences, it completely negates conflict evidences. Therefore, when composing more than two evidences, sometimes, results can be unaccepted[7]. Ref. [8] introduced the mean support degree of the evidence set, i. e. $q(A) = \frac{1}{n}\sum_{1 \le i \le n} m_i(A)$. Then, the evidence conflict probability k is assigned to A according to the scale. Therefore, better composing results can be obtained by the following composing formula

$$\begin{cases} m(\Phi) = 0 \\ m(A) = \sum_{A_i \cap B_j \cap C_l \cdots = A} m_1(A_i) m_2(B_j) \cdot \\ \qquad m_3(C_l) \cdots + kq(A) \\ k = \sum_{A_i \cap B_j \cap C_l \cap \cdots = \Phi} m_1(A_i) m_2(B_j) m_3(C_l) \cdots \end{cases} \tag{3}$$

In this paper, Eq. (3) is used to carry out the fusion diagnosis.

4.2 Application of D-S evidence theory in wear fault fusion diagnosis

Aeroengine wear fault diagnosis approaches used in this paper include FA, SOA, PCA, and OQT. And seven types of faults are $F_i (i=1, 2, \cdots, 7)$. In evidence composing formulas—Eqs. (1-3), all evidences are effective. However, each oil analysis method has its own localization, and can provide no-support for some faults. For example, OQT cannot provide any support to the fault C. Though the diagnosis result of OQT sub-NN is '0' or '1', it cannot be denoted if the oil contamination exceeds the standard value. Therefore, if the effectivity of evidences is not considered in the fusion procedure, an error occurs. In order to solve this problem, a matrix is introduced.

$$\begin{array}{c c} & \begin{array}{cccc} \mathrm{FA} & \mathrm{SOA} & \mathrm{PCA} & \mathrm{OQT} \end{array} \\ \begin{array}{c} F_1 \\ F_2 \\ F_3 \\ F_4 \\ F_5 \\ F_6 \\ F_7 \end{array} & \left\{ \begin{array}{cccc} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right\} \end{array} \tag{4}$$

where, '1' means that the method is effective for detecting the corresponding fault, and its single sub-NN diagnosis result is considered in the fusion; and '0' indicates that the approach is not effective for detecting the fault, and its sub-NN diagnosis result is neglected during the fusion and the conflict computation. Using the matrix, the obtained fusion diagnosis results are more effective and reliable.

In this paper, a fault corresponds to a distinguishing frame. And a double assumption is taken, i. e. a fault appears

5 EXAMPLES

An example is used to verify the effectiveness of the proposed new method. FA symptom data are supposed to be (0, 0, 0, 1, 0, 0, 0), which indicates that spherical wear particles, laminar wear particles, fatigue chunk wear particles, severe rubbing wear particles, red oxide wear particles and black oxide wear particles are normal, but cutting wear particles are in a large number. SOA symptom data are (0, 1, 0, 0, 0, 0, 0, 0, 0), which denotes that Fe, Ni, Mo, V, Cu, Zn, Al and Ti contents are normal, while the Cr content exceeds the standard value. PCA symptom data are (1), indicating that the oil contamination exceeds the standard value. OQT symptom data are (0, 0, 1), indicating that the movement viscidity and the impurity content are normal, but other indexes exceed the standard value.

The single diagnosis result of each sub-NN is shown in Table 5.

Furthermore, the bearing severe wear and the gear agglutination and scratching are analyzed, respectively. The bearing severe wear presents weak conflict, as shown in Table 6; and the gear agglutination presents great conflict, as shown in Table 7. From fusion results, when evidences present great conflict, the fusion result is in the middle of two fused values; when evidences present weak conflict, which means they support each other, the fusion result is higher than two fused values. Obviously, fusion results accord with the practical situation. Other faults can be analyzed in the same way, and results are shown in Table 5. In Table 5, after introducing the matrix of the effectivity, non-effective evidences can be ignored, and more reasonable and reliable results are obtained.

Table 5 Results of single and fusion diagnoses

Fault	FA sub-NN	SOA sub-NN	PCA sub-NN	OQT sub-NN	Fusion result
Normal	0	0	0	0	0
Bearing severe wear	0.8	0.9	1	0	0.972
Bearing fatigue failure	0.000 1	0	0	0	0
Gear fatigue over-loading	0	0	0	0	0
Gear agglutination or scratching	0.8	0.1	1	0	0.662 67
Oil contamination exceeding standard value	0.6	0	1	0	1
Oil quality exceeding standard value	0.000 1	0	1	1	1

Table 6 Weak conflict fusion analysis

Fault	FA Sub-NN	SOA Sub-NN	PCA Sub-NN	Conflict	Fusion result
With bearing severe wear	0.8	0.9	1	0.28	0.972
Without bearing severe wear	0.2	0.1	0	0.28	0.028

Table 7 Great conflict fusion analysis

Fault	FA Sub-NN	SOA Sub-NN	PCA Sub-NN	Conflict	Fusion result
With gear agglutination or scratching	0.8	0.1	1	0.92	0.662 67
Without gear agglutination or scratching	0.2	0.9	0	0.92	0.337 333

It should be pointed out that the example does not come from the practical aeroengine test data. The reasons are: (1) Four oil analysis approaches, i.e. FA, SOA, PCA and OQT, can hardly be simultaneously carried out in a practical aeroengine test due to the limit of oil analysis test conditions; (2) To establish the standard limit and diagnosis samples for each oil analysis approach, a lot of oil analysis tests need to be performed. But at present, the accumulation of such data from aeroengine test-drives is very small. Therefore, the intelligent fusion diagnosis method of aeroengine wear faults presented in this paper can only be verified by simulated data made in theory. Many researches need to be made in practice.

6 CONCLUSIONS

(1) Four common oil analysis methods, i.e. FA, SOA, PCA and OQT, are used to conduct the fusion diagnosis of a certain type of military engine wear fault diagnosis during the test drive process in order to improve the diagnosis precision.

(2) The fusion diagnosis method is based on NN and the D-S evidence theory. BPNN is used to carry out the single diagnosis, and the improved D-S evidence theory is used to complete the fusion diagnosis.

(3) The example shows that the new method is correct and effective.

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航空发动机磨损故障的智能融合诊断

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摘要: 运用了4种最常用的滑油分析技术——铁谱分析、光谱分析、颗粒计数分析及理化指标分析, 同时结合发动机试车台监测数据, 提出了运用神经网络和D-S证据理论对发动机试车状态进行融合诊断的方法。首先依据各种分析方法的标准磨损界限值, 将原始数据进行了预处理, 转换成故障征兆的布尔值; 其次, 建立了各子神经网络的拓扑结构, 并依据专家经验建立各子系统的输入征兆与故障论域的映射关系, 由此获得了各子神经网络的训练样本, 对各网络成功训练后, 利用神经网络实现各子网络的诊断并得到了中间诊断结果; 然后, 将每种方法的神经网络诊断结果作为各故障模式的基本概率分配值, 利用改进的D-S证据理论, 实现了对神经网络诊断结果的融合, 由此获得了最终的融合诊断结果; 最后, 通过算例证明了该方法的有效性。

关键词: 磨损故障诊断; 数据融合; 神经网络; D-S证据理论; 航空发动机

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