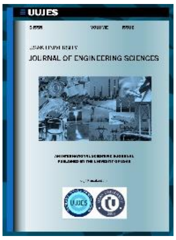

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Research article

CLASSIFICATION OF HELICAL GEAR FAULT LEVELS USING FREQUENCY COMPONENT BASED STATISTICAL ANALYSIS WITH ANN

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Abstract

Gearboxes that are frequently used as power transmission elements are experienced various faults over time. The pitting fault, which is one of these faults, is usually caused by insufficient lubrication and overloading. Detecting pitting fault and identifying different pitting levels are challenging subjects in gear fault detection. This study aims to propose a method to classify the different levels of pitting fault in helical gearbox. It is known that gear defects illustrate themselves in vibration signal at gear mesh frequency (GMF) and its harmonics. As the severity of faults on the tooth surface grows, the amplitude of these frequencies usually increases in the frequency spectrum. Frequency component based statistical analysis (FCSA) method is utilized to obtain stronger indicators for fault classification. In this study, frequency component based statistical analysis calculates the mean, standard deviation, RMS and Kurtosis values of narrowband gear vibrations obtained around the GMF and its harmonics in order to detect these increases in the frequency spectrum. Moreover, these statistical parameters are then used as an input for training and testing of artificial neural network (ANN) for classification of pitting faults. Furthermore, the pitting fault is detected and different pitting levels are classified. It has been found that the proposed approach is quite beneficial for not only detection, but also classification of pitting fault levels in helical gearboxes.

Keywords: *ANN; fault classification; helical gear; pitting; vibration; spectrum analysis.*

1. Introduction

Maintenance of mechanical systems in order to reduce cost and downtime is an important issue in the industry. When a fault develops and cannot be noticed in its early stages, it may

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result in much worse situations such as loss of production, damage to machine parts, and unexpected downtime. For this reason, an enterprise uses a variety of maintenance methods to ensure that the plant can maintain its operation without interruption.

Maintenance strategies can be examined in two main groups as unplanned maintenance and planned maintenance. In unplanned maintenance strategy, the machine is allowed to run until a failure occurs, and no pre-determined action is taken to prevent failure. This type of maintenance can only be considered if the machine is inexpensive to replace, and the failure does not significant other damage. Planned maintenance is divided into two sub-groups as regular preventive maintenance and predictive maintenance. In the preventative maintenance, the maintenance and repair of the machine parts is carried out in a predetermined period of time. In predictive maintenance approach, however, machines are no longer maintained according to a damage-based policy, but rather depending on their condition. To determine, evaluate, and predict machine condition and to accurately diagnose any fault, information is extracted from regularly monitored parameters such as vibration, temperature and other process parameters.

Mechanical power transmission systems have great importance for industrial applications. A gearbox is one of the most widely used equipment among the mechanical power transmission systems. Gear systems are used to transfer rotation or power transmission from one shaft to another in desired ratios and high efficiency. These factors can be satisfactorily achieved if there is no fault in the gears. Whenever a defect occurs in a gear system (e.g. pitting, abrasive wear, bending fatigue cracks) the performance of the gears deteriorates. As a result, motion or power transfer cannot be achieved as demanded. When a gear fault initiates and cannot be detected in its early phase, this may be responsible in occurrence of upcoming serious faults. In entirety, gear related failures comprise 60% of faults in gearboxes, and 24% of gearbox failures are caused by ineffective maintenance action [1]. Consequently, gearbox condition monitoring has considerable importance to decrease failures and to ensure permanence of process.

Gear faults can be detected by a variety of condition monitoring techniques such as vibration analysis [2,3,4], lubricant analysis [5,6], infrared thermography [7], acoustic emission [8,9], motor current signature analysis [10], and etc. Among these techniques, vibration analysis is widely used for condition monitoring of gearbox. For any failure in a gearbox, there will be most likely an effect in its vibration signal [11]. Therefore by measuring and analyzing vibration of a gearbox, it is possible to determine the type of failure and severity of the defect [12]. On the other hand, vibration signals measured from gearbox are mostly affected by severe noise. This causes complexity in fault detection of the gearbox by using traditional vibration analysis methods such as time domain, frequency domain and time-frequency analysis [13,14]. Thus, more recently, machine learning techniques such as artificial neural network (ANN) [15,16], support vector machine (SVM) [17], genetic algorithm (GA) [18] are proposed to solve fault detection problems. Studies show that it is possible to interpret the condition of the machine with the help of these methods. For this reason, these classification methods have gained more importance in recent years. Recently, Backpropagation Neural Network (BPNN) is widely used to solve fault diagnosis problems. This method has been innovated by Rumelhart and McClelland [19] and developed as a diagnosis method by Sorsa et al. [20]. McCormick & Nandi [21] used the method for classification of the rotating machine condition. Samanta & Al-Balushi [22] used back propagation algorithm for fault diagnosis of a machine coolant system. Kang et al. [23] used frequency spectrum of vibration signals for diagnosis of electric motor bearing faults by using BPNN. The algorithm is also used to monitor gear conditions in several works [24, 25, 26, 27].

This paper focuses on the early detection of localized pitting damages in a helical gearbox using Backpropagation Neural Network (BPNN) and Frequency component based statistical analysis (FCSA). In this study, FCSA and BPNN are applied together for the first time with six prevalent fault related statistical parameters. These statistical parameters are determined from frequency spectra of vibration signals and used as inputs to classifier ANN for multi-class recognition.

2. Theoretical background

2.1. Statistical parameters

In this study, six statistical feature parameters are considered for the detection of pitting in a helical gear. Statistical features applied to the vibration signals in frequency domain are: mean, root mean square (RMS), peak to peak, crest factor, skewness and kurtosis as shown in Table 1. Herein, x, x_i, σ and N denote vibration data, a sample indexed by "i", standard deviation, and total number of samples respectively.

Table 1 Equations of statistical parameters.

Mean Value	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$
RMS Value	$RMS(x) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i^2)}$
Peak to Peak Value	$P_P = \max(x) - \min(x)$
Crest Factor Value	$F_C = \frac{P_P}{RMS(x)}$
Skewness Value	$Sk(x) = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3\right]}{\sigma^3}$
Kurtosis Value	$Kr(x) = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4\right]}{\sigma^4}$

2.2 Frequency component based statistical analysis

Frequency component based statistical analysis (FCSA) using time domain analysis and frequency domain analysis together is a sophisticated vibration analysis method as shown in Fig. 1. It is known that the distinctive gear frequencies such as GMF, its sidebands and harmonics are seen in the frequency spectrum. As the severity of faults on the tooth surface grows, the amplitude of these frequencies usually increases in the frequency spectrum. This method aims to detect these abnormal increases in the amplitude of these distinctive gear frequencies. For this purpose, the method calculates total values of statistical parameter (SP) of these frequencies within a bandwidth. Firstly, distinctive gear frequencies are specified. FCSA value is then computed using total statistical parameter value of bands as given in Eq. (1) where $B_1, B_2, \ldots, B_N$ stand for the considered frequency bands.

$$FCSA = \sqrt{{SP_{B_1}}^2 + {SP_{B_2}}^2 + \ldots + {SP_{B_N}}^2} \tag{1}$$

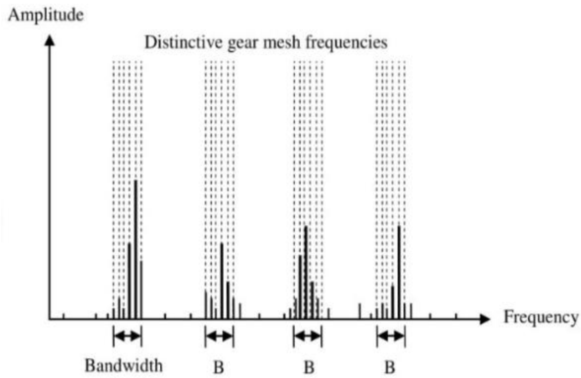


Fig. 1 Implementation of FCSA for helical gearbox.

2.3 Artificial neural network

Artificial neural networks (ANNs) are the computer systems that can learn with samples and determine how to react against surrounding incidents. Backpropagation neural network (BPNN) is used in this work which is the supervised learning algorithm and is widely used in ANNs for diagnosis of faults systems. BPNN was created, trained and tested by Matlab neural network toolbox. The training algorithm is Levenberg-Marquardt backpropogation (LMBP). BPNN has consisted of three layers: input, hidden and output, as shown in Fig. 2. The number of nodes in the input layer is equal to the number of feature for this network. They are determined as six parameters in this study. The number of nodes in the hidden layer is thirteen and the number of output nodes is four. The number of neurons in the hidden layer is tested up from two-nodded hidden layer to twenty-five nodded hidden layers. The best result is given by 13 neurons. This result also overlaps with the Kolmogorov theorem. This theorem states that, if input layer has n nodes, then the hidden layer has $2n$+1 nodes [28, 29].

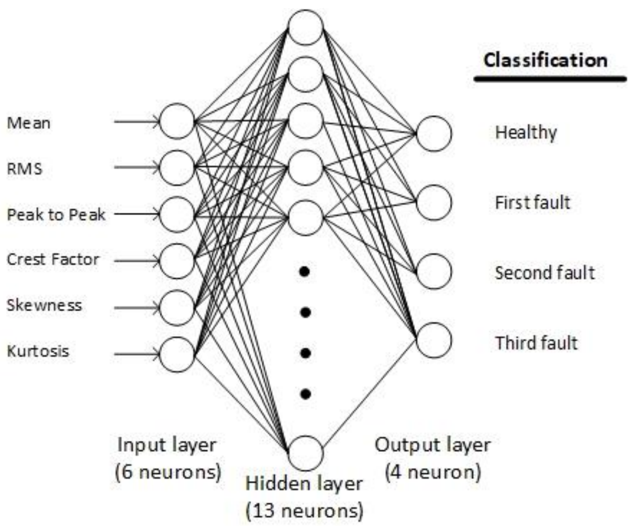


Fig. 2 Architecture of artificial neural network.

In this study, the results obtained from the experiments performed by changing the percentages of the data to be used in the training, validation and test sections were compared with each other. As a result of these comparisons, at least 50 % of the data were decided to be used in the training section of the network to learn the system. The training dataset was selected randomly from samples. In similar studies [20, 30, 31], amount of data separated for the training section can vary between 50 % and 85 % of all data.

To train network, the samples are divided into three sets, randomly, the first set is for training the network, the second set is for validate the network and the third one is for testing the performance of the network. The transfer functions of tansig and purelin are used in the hidden layer and output layer, respectively. In this study, a MSE of 10-7 and epoch of 1000 are used.

3. Experimental setup

During testing, a two-stage industrial helical gearbox is used. The system has a 2.2 kW 3 phase AC motor as drive and 2.2 kW DC load generator as resistance, as shown in Fig. 3. The gearbox was loaded by a DC motor the output of which was used to feed an adjustable resistor bank; the 2.2 kW load capacity of the DC was much lower than that of the gearbox used, which is nearly 8.1 kW. For this reason, the face width of the pinion test gear was reduced from 12 mm to 4 mm so that it could be tested at reasonably high load [1]. The AC motor and DC generator are connected by belt pulley mechanisms to avoid unwanted effects of misalignment. The drive pinion at the first stage has 29 teeth meshing with a 40-tooth wheel. The pinion gear at the second stage, driven directly by a 40-tooth wheel, has 13 teeth meshing with a 33-tooth wheel. The operation conditions of experiments are shown in Table 2.

Table 2 Operation conditions of experiments.

Drive pinion gear speed:	2679 rpm–44.65 Hz
Sampling frequency:	15 kHz
Sampling time:	30 sec.
Gear mesh frequency for the first stage of the gearbox (1X):	1295 Hz
Gear mesh frequency for the second stage of the gearbox (1Y):	424 Hz
Total sampling data for each condition:	450000 data
The total number of drive pinion gear rotations over 30 sec:	1339 turns

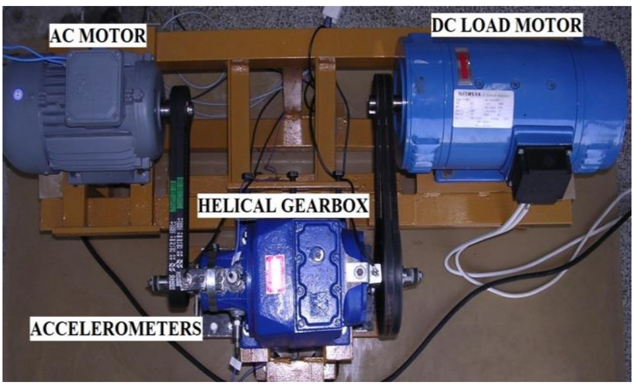
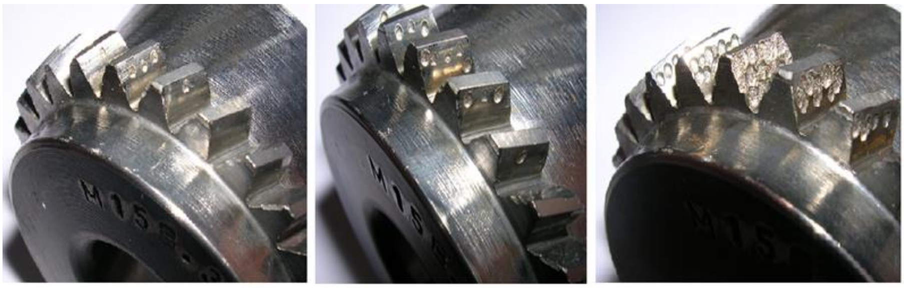


Fig. 3. Experimental test setup with helical gearbox.

The simulated surface fault, which is intended to replicate a real pitting, was introduced onto the tooth surfaces of the input pinion gear at the first stage using an electro-erosion machine. In the initial stage, few pitting faults are formed on gear surface. Subsequently, more faults reproduced on the teeth in such a way as to increase the severity of the failure. To represent the early stage of surface damage, five circular pits (whose diameter and depth are approximately 0.7 mm and 0.1 mm, respectively) were seeded onto three neighboring teeth as shown in Fig. 4(a). In order to represent the advancement of fault, the number of defected tooth was then increased to five and additional pits were also introduced as shown in Fig. 4(b). At the final stage of the fault development, the number of pits was increased on the same gear teeth during which the surface of the center tooth was completely covered by severe pitting marks as illustrated in Fig. 4(c). In the experiment, a classification for a healthy and three different faulty conditions is implemented.



(a) (b) (c)

Fig. 4. Faults on helical gears: (a) Fault level 1, (b) fault level 2, and (c) fault level 3.

4. Analysis and results

Synchronous time averaging was applied the raw signal to enhance repetitive features and to eliminate unwanted noise. The averaged vibration signals are obtained for every 10 turns of input pinion gear. Fig. 5 shows the frequency spectra of one of averaged helical gear vibrations for each gearbox stage. It can be seen a high peak at 1295 Hz and 2590 Hz in the spectra, which are the first and second gear mesh frequencies for the first stage of the gearbox.

In case of the existence of faults, this shows itself as an increase at harmonics of GMF and their sidebands on the frequency spectrum. Therefore, frequency spectra must be examined specifically around those frequencies in order to determine the effects of severity of faults. The enlarged form of the frequency spectrum around these frequencies is shown in Fig. 6.

Fig. 6 shows the presence of several pairs of the sidebands whose amplitudes are associated with the severity of faults. It is important to note that these families of sidebands are centered on two GMF components. It can be seen from Fig. 6 that the amplitudes of the GMF components and their sidebands vary with the degree of fault severity. For the first GMF, except for the first fault, there is a linear relationship between fault severity and the resulting GMF amplitude. For the second GMF, the amplitude of the first fault is higher than that of healthy condition and third fault. However, sideband amplitudes occurring around the second GMF exhibit a linear increase with the advancement of fault severity.

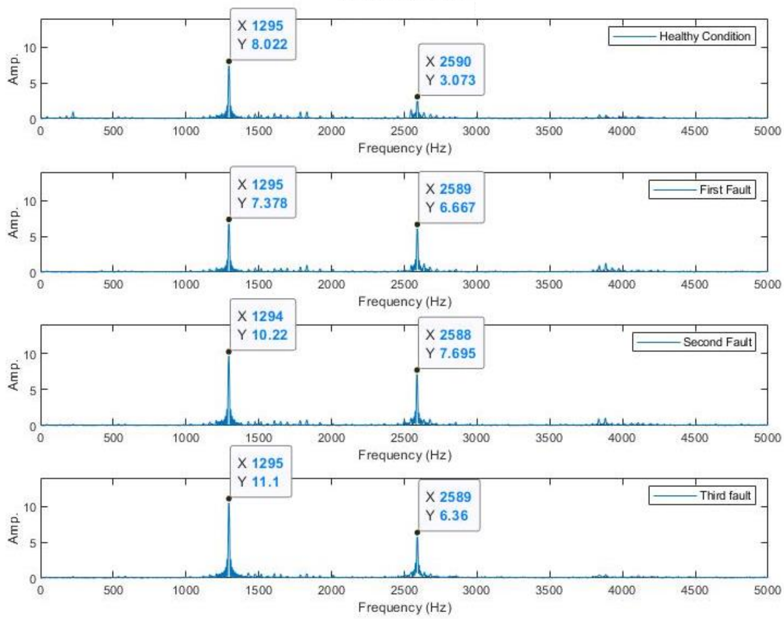


Fig. 5. Frequency spectra of averaged vibration signals for gears with conditions from healthy to third level faulty.

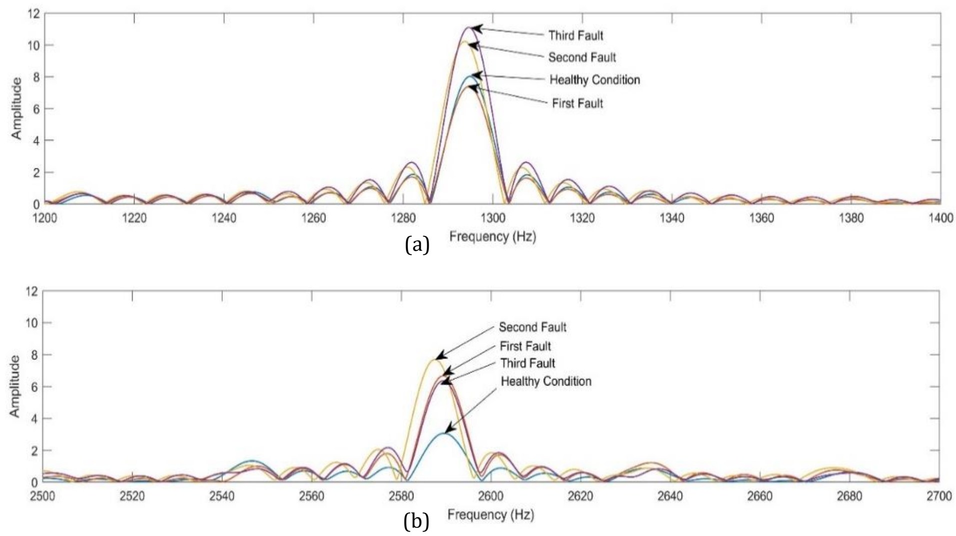


Fig. 6. Frequency spectra examined around the (a) first and (b) second GMF for all fault conditions.

FCSA method is developed because it is considered that the exploring of changes of the statistical parameters on frequency spectrum for specific frequencies gives more detail about the severity of faults when compared to the other methods. The number of GMF harmonics is taken two (first and second GMF) in this study. The bandwidth used in FCSA method was selected as by examining frequency spectrum of healthy helical gearbox before implementation of the method. The bandwidth was chosen as 100 Hz considering the number of sidebands and the decrease in amplitude of them. Fig. 7 shows six statistical parameters (RMS, peak to peak, mean, kurtosis, skewness, crest factor) calculated from averaged vibration signals whose spectra are shown in Fig. 6.

The classification method proposed in Section 2.3 is applied in order to classify the vibration signal according to the fault severity. The total number of drive pinion gear rotations over sampling duration (30 sec) is 1339 turns. The number of averaged signals is 133 because the averaged vibration signals are obtained for every 10 turns of pinion gear. Therefore, 133 sets of data were obtained for each condition. After all sets were combined, the total number of sets was 532. The 266 sets were then selected randomly for training ANN. The random 133 sets were selected as validation part of ANN and the other random 133 sets were selected as test data.

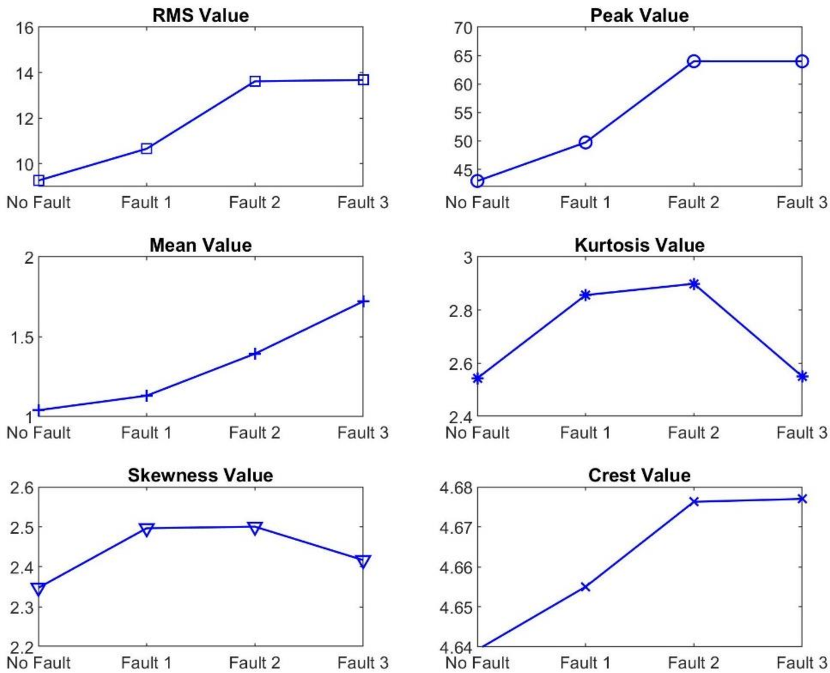


Fig. 7. Frequency based statistical features of averaged vibration signals.

Mean square error performance of the network is given in Fig. 8. The value of mean square error is 0.010258 and the total number of epoch is 43 at the end of the validation of the network. The plots of the training, validation, test and all performance confusion matrices are shown in Fig. 9.

The target values of outputs are varied from 1 to 4 in this work. The fault severity conditions of the helical gear (which are healthy, first fault, second fault and third fault) are assumed 1, 2, 3 and 4, respectively. In Fig. 9, the diagonal cells in green indicate the number of sets classified correctly and the off-diagonal cells in red indicate the number of sets classified wrongly by the ANN. The last cell in blue indicates the total percentage of sets classified correctly. From Fig. 9, it can be seen that the test of ANN has 95.5 percent accuracy in fault classification on helical gearbox.

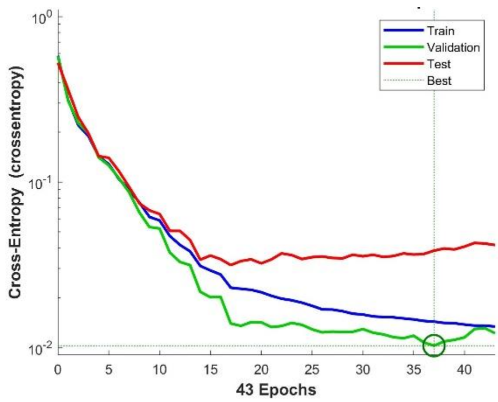


Fig. 8. Mean square error performance of the network (Best validation performance is 0.010258 at epoch 37).

Fig. 9. The confusion matrices for training, testing, validation and all phases.

5. Conclusions

In this study, the frequency component based statistical analysis is applied to the vibration signals of the helical gears in order to determine the progress of the pitting fault. To eliminate the non-repetitive errors in the vibration data, time synchronous average is applied. The statistical parameters are determined by applying FCSA on FFT signal. The statistical results obtained from FCSA are applied to ANN for classification of pitting fault progression of helical gear, and then BPNN is created, trained and tested using Matlab. Applied ANN model achieved 95.5% success in classification.

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