Detection of Combined Gear-Bearing Fault in Single Stage Spur Gear Box Using Artificial Neural Network

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Abstract

Gears and bearings are important components of almost every machines used in industrial environment. Hence detection of defect in any of these must be detected in advance to avoid catastrophic failure. This paper aims to address the effect of bearing defect on gear vibration signature and effect gear defect on bearing vibration signature. Also its purpose is to make vibration analysis of single stage spur gear box, when both gear and bearing are defective. A condition monitoring set up is designed for analyzing the defect in outer race of bearing and damaged tooth of gear. MATLAB is used for feature extraction and neural network is used for diagnosis. In the literature, many authors have analyzed defects in bearings and gears separately. But it is found that the real situation may be more complex. The work presents a laboratory investigation carried out through an experimental set-up for the study of combined gear–bearing fault. This paper proposes a novel approach of damage detection in which defects in multiple components are analyzed using vibration signal.

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1. Introduction

Rotating machinery plays an important role in any industry while bearings and gears are inevitable part of any rotating machinery. So detection of defects in gears and bearings is the most important task for maintenance engineer using condition based maintenance in their plant. A lot of research has been done on defect detection of gears and bearings but all the researchers focused on single or multiple defects in a gear or bearing. D.J. Ewins [1] have presented an overview of the vibration problems which are experienced in gas turbines such as resonance, instability from aerodynamic forces or from rotor dynamics. By tune design the vibrations can be managed so as to
avoid the most serious resonance which is done by ensuring the critical frequency crossings do not exist in the running speed range. N. Tandon et al [2] have reviewed the vibration and acoustic measurement methods for the detection of both localized and distributed defects in rolling element bearings in time domain and frequency domain. V. N. Patel et al [3] worked on the detection of defects existing on races of deep groove ball bearing in the presence of external vibrations using envelope analysis and Duffing oscillator. Xiaoyuan Zhang and Jianzhong Zhou [4] have proposed a novel procedure based on ensemble empirical mode decomposition (EEMD) and optimized support vector machine (SVM) for multi-fault diagnosis of rolling element bearings. Sait et al. [5] summarized the different methods of defect detection in gears using condition monitoring by vibration analysis. Loutas et al [6] utilized acoustic emission (AE) and vibration measurements for single stage gear box and different conventional as well as advanced features are compared for its diagnostics capacity. Daming Lina et al [7] used an approach to extract useful condition indicators (covariates) from raw vibration signals and developed optimal maintenance policies for the gearboxes. Mohit Lal and Rajiv Tiwari [8] developed an identification algorithm to estimate parameters of multiple faults in a turbine-generator system model based on the forced response information. D.J. Bordoloi and Rajiv Tiwari [9] have used statistical features in frequency domain for the multi-fault classification of gears using support vector machine (SVM). D.P. Jena, et al. [10] established a robust technique of acoustic signal processing for detection and localization of multiple teeth defect in geared systems using features extracted from wavelet transform and artificial neural network (ANN) for diagnosis. N. Saravanan and K.I. Ramachandran [11] have analysed the gear defects such as face wear, tooth breakage by extracting features using discrete wavelet transform and ANN is used as classifier. N. Sawalhi and R. B. Randall [12] have studied the combined gear /bearing simulation model to understand the interaction between them.

In this work a novel thing is that, the more complex but real situation is considered where the combined defect in gear and bearing i.e. defects in multiple components are analyzed using vibration signal. The literature provides the analysis in time domain, frequency domain and time-frequency domain. Here an attempt is made to make use of the important and most significant features of gear and bearings in each domain. These features extracted from vibration signals are used by a classifier called artificial neural network for fault diagnosis.

2. Methodology

Any vibration signal measured by accelerometer is a mixture of bearing and gear signal. Since the first aim of this work is to find the effect of gear defect on bearing signature and bearing defect on gear signature. Hence it is necessary to understand how these signals are generated. The vibration signal generated by a bearing fault can be described by combining Braun’s and McFadden’s models [13]. The vibration induced by shaft rotation & gear mesh is denoted by s(t), and the vibration by a bearing fault is b(t),

\[ s(t) = \sum_j A_j \cos(j \omega_s t + \phi_j), \]

\[ b(t) = \sum_k B_k e^{-\left(\frac{t-kT}{\alpha}\right)} \cos[\omega_n (t-kT)] . U(t-kT) \]  

Where, \( j \) is the shaft order number, \( A_j \) and \( \phi_j \) are amplitude and phase, respectively, at \( j^{th} \) order and \( \omega_s \) is the shaft rotation frequency (in rad /sec). In the bearing signal shown in Eq. (2), \( T \) is the characteristic fault period (i.e., the reciprocal of the fault frequency 2p /\( \omega_n \)), and \( \omega_n \) the structure resonant frequency exited by bearing fault, \( \alpha \) denotes the time constant for the exponential decay of the resonant oscillations, which is determined by system damping, and \( U(t) \) is a unit step function. \( B_k \) represents the peak amplitude of \( k^{th} \) impulse produced by the bearing fault. When the bearing fault is small, the amplitude of \( b(t) \) can be much less than that of \( s(t) \). The shaft synchronous signal \( s(t) \) and bearing fault induced signal \( b(t) \) can be mixed together in both additive and multiplicative (by a factor of \( s = 0 \sim 1 \)) forms, resulting a signal

\[ x(t) = s(t) + b(t) + s \times s(t) b(t) = s(t) + [1 + s.s(t)] \times b(t) \]

In practice, the actual measured signal will be the convolution of signal \( x(t) \) with the system’s transmission path
function h(t) plus measurement noise. Hence, the measured vibration signal is usually expressed by

$$y(t) = x(t)\tilde{h}(t) + n(t)$$

where, $\tilde{h}$ denotes the convolution operation, and $n(t)$ is the measurement noise which is assumed random. Since the actual measured vibration is the combined vibrations of gear and bearing hence a novel methodology is required to be developed for detection of more real and complex situation in transmission machinery.

The methodology followed in this work consists of design and development of a condition monitoring test rig where it is possible to introduce the defect in gear/bearing/rotor system. The vibration data acquisition in time and frequency is done by using FFT analyser. The defects are produced on gear and bearing and statistical features are extracted from time and frequency domain signal using MATLAB. This data is then utilized for diagnosis of defects using artificial neural network.

2.1. Experimentation

Fig. 1 shows the condition monitoring test rig used for the vibration study of the combined gear and bearing fault. The test rig consists of a single stage spur gear box having gears made from steel with a module of 2.11 mm, pressure angle 20°, pinion teeth 26, gear teeth 46, and 20 mm face width. Also it consists of a shaft with rotor disks and the support bearings. The shaft at one end is connected to a drive unit consisting of a 0.5 HP D.C. motor, 2.6 amp, 230 volt, maximum speed = 2880 rpm and voltage regulator for changing the speed through a flexible coupling. The motion is transmitted to the dynamometer (an arrangement to apply load on gear box) unit by a single stage spur gearbox with a speed ratio of 1.77:1 through a V- Belt drive. The axes of the gears are supported by two ball bearings of 6004 type each. The basic parameters of the test rig were fixed after considering the relations between operating speed and frequencies of vibrations along with the limitations of the measuring and analyzing equipment available. Also general manufacturing considerations are taken into considerations. The locations of the sensor mountings are marked with letters A to J as shown in Fig. 1, for example at A : Axial Driving end, B : Vertical at Left Bearing Block, H/I : Radial at gear box shaft, and at J : Frame etc.

A single accelerometer having sensitivity 100 mV/g (g=9.81m/s²) was placed on gear box casing at location H in radial (vertical) direction to measure the vibration amplitude in displacement, velocity and acceleration with the help of a 4 channel fast Fourier transform (FFT) analyser. The sampling frequency used was 16384 Hz and recordings of 4 sec duration were obtained. Vibration readings were collected for a range of frequency 6400 Hz, number of lines 12800, 2 averages and in hanning FFT window. The first channel was dedicated for the accelerometer signal, while the speed was measured by using laser tachometer.

Seeded fault in bearing and gear are as shown in Fig. 2. Local circular defect of 0.8 mm in size on outer race of the bearing was created by electric discharge machining (EDM) as indicated in Fig. 2 (a), while the defective pinion was created by removing one teeth completely as shown in Fig. 2 (b). If any one of the element of a bearing is
defective the entire bearing will be replaced, therefore here only a single defect on outer race is considered for analysis. Consequently, the classification here was aimed to determine whether the gear/bearing or both were defective.

To analyse the effect of gear and bearing fault, the data is collected for the following conditions such as good gear and good bearing (G), good gear and defective bearing (DB), defective gear and good bearing (DG) and defective gear and defective bearing (DGB). In each case there were about thirty signals acquired for a constant shaft speed of 1000rpm (16.6 Hz) and different torques like 1.22 Nm, 1.83Nm and 2.45 Nm on belt type of dynamometer. In the present study results from a representative test conducted at a healthy pair of gears and bearings shall be presented and discussed along with the defective gear and bearing.

### 2.2. Feature extraction

The vibration signals acquired during the tests were processed with significant efforts. The primary aim here was to calculate a number of statistical parameters in time and frequency domain and check their diagnostic capacity for the actual condition monitoring of gears and bearings. In the literature, research groups involved in long term gear and bearing testing using number of sensors at different locations. They have mainly used higher order moments and their combinations to form diagnostic parameters with interesting behavior during the tests. In this work, various features were extracted from single sensor to save the time and money. Table 1 shows conventional features from the time and frequency domain that were calculated from the collected vibration waveforms. They are typical statistical moments and their combinations.

![Photographic view of Seeded fault in bearing and gear](image)

**Fig. 2. Photographic view of Seeded fault in bearing and gear**

### 2.3. Statistical parameters

The statistical parameters from the time and frequency domain were calculated, as explained below with reference to Table 1. $x(n)$ is a signal series for $n = 1, 2, \ldots, N$, where $N$ is the number of signal samples and $y(m)$ is the Fourier transform for $m = 1, 2, \ldots, M$, where $M$ is the number of spectrum lines, $f_m$ is the frequency value of the $m$th spectrum line. Parameter $p_1$ is the mean of the signal, $p_2$ is standard deviation, $p_4$ the root mean square, $p_5$ is obviously the absolute maximum of the signal, $p_6$ and $p_7$ are the third and fourth moments (Kurtosis) whilst $p_8$ the crest factor, $p_9$ – $p_{11}$ result as a combination of previous parameters all calculated by the signal in time domain. Similarly, $p_{12}$ is the mean, $p_{13}$ the variance and so on from $p_{14}$ – $p_{24}$ are extracted in the frequency domain.

According to the set of signals collected, each bearing and gear state is represented by a set of vibration signals. These signals must be processed in order to be replaced by a vector of parameters to simplify the classification procedure. So, the above features which include the most important information contained in the signal were extracted in order to prepare the matrices of learning and testing for the neural networks. Frequency analysis has become a fundamental tool for vibration signal processing [6].
3. Effect of bearing defect on gear signature

To study the effect of bearing defect on gear signature, the signature in good condition was compared with the defective bearing signature i.e. to observe the peaks of gear mesh frequency signal and its harmonics and the sidebands. Fig. 3 (a) is for good condition and Fig. 3 (b) is for defective bearing, comparison clearly indicates that the gear vibration signatures changes appreciably due to presence of bearing defect, there are more number of peaks observed in Fig. 3 (b) between 0 to 434Hz i.e. gear mesh frequency (GMF) because of defective bearing while the magnitude of all the gear mesh frequency harmonics increases. While if Fig. 3 (c) is compared with Fig. 3 (d) it is observed that the gear mesh frequency amplitude is higher than previous also the sidebands are clearly visible which may misleads the observer about gear defect. While the Fig. 3 (e) and (f) shows the bearing defect frequencies, Fig. 3 (f) indicates the higher amplitude of outer race defect frequency (BPFO) at 59.48Hz.

4. Effect of gear defect on bearing signature

To study the effect of gear defect on bearing signature, the signature in good condition was compared with the defective gear signature i.e. to observe the peaks of bearing defect frequency signal and shaft harmonics. It is observed from the Fig. 4 (a) and (b) that the amplitude of outer race defect frequency (BPFO) at 59.8 Hz is more in defective gear signature. Also the peak amplitudes at shaft frequency 16.69 Hz and its harmonics are observed to be higher as compared to good condition. Generally bearing defects are identified by envelop analysis hence the envelop spectrum of good and defective gear signature was compared but no appreciable change in envelop spectrum is observed at bearing defect frequencies but the same shaft harmonics amplitude are more than good signature.

5. Combined gear-bearing fault identification system

The main impact of this work is to generate neural network that can detect the combined state of gears and bearings simultaneously whereas most of previous neural networks have focused mainly on gears or on bearings alone [4, 8, 9, 10, 11]. Here the supervised network is utilized, called feed-forward network trained with back propagation, which uses a set of input vectors and a set of associated desired output vectors called target vectors. The basic training process consists of four steps as, assemble the training data, create the network object, train the network, and simulate the network response to new inputs. The Features extracted from vibration signals are stored as a set of input vectors and depending upon the condition of gear box a set of target vectors. These two variables are stored as input matrix and the target matrix in MATLAB workspace.

The next step was to create a network and train it until it has learned the relationship between the given inputs and targets. The network used with back-propagation is the three-layer feed-forward network. For each faults namely good bearing and good gear, defective bearing and good gear, defective gear and good bearing, and defective gear and defective bearing for various loading conditions, a total of 120 samples, thirty feature vectors consisting of twenty four feature value sets were collected from the experiment for each condition. Twenty-five samples in each class were used for training and 5 samples are reserved for testing ANN. Training was done by selecting three layers neural network, of that one is input layer, one hidden layer and one output layer. The numbers of neurons in the hidden layer were varied and the values of number of neurons, RMS error and number of epochs along with percentage efficiency of classification of various faults using ANN are computed. The neural network is designed with MATLAB and ANN tool box with twenty three neurons, one hidden layers and four outputs neurons.

The architecture of the artificial neural network is as follows- Network type: Forward neural network trained with feed back propagation, Transfer function: Sigmoid transfer function in hidden and output layer, Training function: TRAINLM (Levenberg-Marquardt), Adaption learning function: TRAINGDM, Performance function: MSE, number of hidden layers:1, and Number of neurons in hidden layer:3. The network is created with above parameters.
5.1. Result of ANN

To check the results of network after training, the performance plot was observed. This plot shows the mean squared error of the network starting at a large value and decreasing to a smaller value. In other words, it shows that the network is learning. The plot has three lines, because the 120 input and targets vectors are randomly divided into three sets. 60% of the vectors are used to train the network. 20% of the vectors are used to validate how well the network generalized. Training on the training vectors continues as long as the training reduces the network’s error on the validation vectors. After the network memorizes the training set, training was stopped. This technique avoids the problem of overfitting, which plagues many optimization and learning algorithms. Finally, the last 20% of the vectors provide an independent test of network generalization to data that the network has never seen. The overall training testing and validation found to be the best fit with $R = 0.99934$ while the only 16 number of iterations were required for this.

6. Results and discussions

After training the network, it was used for testing the samples using simulation of network. To improve the accuracy of results the numbers of hidden neurons are increase from 2 to 10. The better results are obtained by a network created with 3 neurons in hidden layer, the performance of which for different fault conditions are as reported in Table 2 for two new samples. Performance of ANN in percentage prediction of gear box faults using above networks was found successful for classifying the faults namely G, DB, DG and DGB respectively. The overall average efficiency of entire classification using ANN was found to be 99.99%. Using this neural network it is possible to detect the combined/multiple defects in transmission system with 99.99% accuracy.

Table 1. Statistical Parameters [6]

<table>
<thead>
<tr>
<th>Time Domain parameters</th>
<th>Frequency Domain parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1 = \frac{\sum_{n=1}^{N} x(n)}{N}$</td>
<td>$p_12 = \frac{\sum_{n=1}^{M} y(n)}{M}$</td>
</tr>
<tr>
<td>$p_2 = \sqrt{\sum_{n=1}^{N} (x(n) - p_1)^2}$</td>
<td>$p_13 = \frac{\sum_{n=1}^{M} (y(n) - p_{12})^2}{(M-1)}$</td>
</tr>
<tr>
<td>$p_3 = \sqrt{\frac{\sum_{n=1}^{N} x(n)}{N}}$</td>
<td>$p_14 = \frac{\sum_{n=1}^{M} (y(n) - p_{12})^3}{M(\bar{y}_{12})}$</td>
</tr>
<tr>
<td>$p_4 = \sqrt{\frac{\sum_{n=1}^{N} x(n)^2}{N}}$</td>
<td>$p_15 = \frac{\sum_{n=1}^{M} (y(n) - p_{12})^4}{M(p_{12})}$</td>
</tr>
<tr>
<td>$p_5 = \max[x(n)]$</td>
<td>$p_16 = \frac{\sum_{n=1}^{M} f_{n_1}(m)}{\bar{y}_{m_1}(y(m))}$</td>
</tr>
<tr>
<td>$p_6 = \frac{\sum_{n=1}^{N} (x(n) - p_3)^3}{(N-1)p_3^2}$</td>
<td>$p_17 = \frac{\sum_{n=1}^{M} (f_{n_1} - p_{16})^2y(m)}{M}$</td>
</tr>
<tr>
<td>$p_7 = \frac{\sum_{n=1}^{N} (x(n) - p_4)^3}{(N-1)p_4^2}$</td>
<td>$p_18 = \frac{\sum_{n=1}^{M} f_{n_1}^2y(m)}{\bar{y}_{m_1}^2y(m)}$</td>
</tr>
<tr>
<td>$p_8 = \frac{p_1}{p_4}$</td>
<td>$p_19 = \frac{\sum_{n=1}^{M} f_{n_1}^2}{\bar{y}<em>{m_1}f</em>{n_1}^2}$</td>
</tr>
<tr>
<td>$p_9 = \frac{p_1}{p_3}$</td>
<td>$p_20 = \frac{\sum_{n=1}^{M} (f_{n_1} - p_{16})^2}{\sum_{m=1}^{M} f_{n_1}^2}$</td>
</tr>
<tr>
<td>$p_{10} = \frac{p_3}{p_1}$</td>
<td>$p_21 = \frac{p_{16}}{M^2}$</td>
</tr>
<tr>
<td>$p_{11} = \frac{\sum_{n=1}^{N} x(n)}{\sum_{n=1}^{N} x(n)}$</td>
<td>$p_22 = \frac{\sum_{n=1}^{M} (f_{n_1} - p_{16})^2}{M^2}$</td>
</tr>
<tr>
<td>$p_{23} = \frac{\sum_{n=1}^{M} (f_{n_1} - p_{16})^2}{M^2}$</td>
<td></td>
</tr>
<tr>
<td>$p_{24} = \frac{\sum_{n=1}^{M} (f_{n_1} - p_{16})^2y(m)}{M^2}$</td>
<td></td>
</tr>
</tbody>
</table>

As discussed in section (3) and (4) the effect of one component defect over other component is appreciable since all these components are connected to each other [12]. Even though every component is having its own frequency of vibration still the amplitude of this frequency is important to know the severity of vibration. The overall vibration collected by sensor is adding the effect of all the defects present in different components of system; hence the analysis of individual component may not provide the actual picture of the condition of machine, so one should go
for analyzing the combined defects/multiple defects. The same is attempted in this work and found satisfactory results for the combined fault as well.

Fig. 3. Vibration response of defective bearing compared with good condition (with Torque, shaft speed = 1000 rpm)

Fig. 4. Vibration response of defective gear compared with good condition (with Torque, shaft speed = 1000 rpm)
Table 2. Performance of ANN in percentage prediction of defect type

<table>
<thead>
<tr>
<th>CONDITION</th>
<th>G</th>
<th>DB</th>
<th>DG</th>
<th>DGB</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAMPLE 1</td>
<td>99.99</td>
<td>100</td>
<td>99.99</td>
<td>100</td>
</tr>
</tbody>
</table>

7. Conclusion

Experimental vibration studies with locally defective deep groove ball bearings, missing tooth gears and combined gear-bearing defect have been carried out and reported in this paper by applying radial loading on the gear-bearing test rig. Based on the studies reported herein, the following conclusions have been drawn: (i) It is observed from above analysis of seeded faults that the set up prepared for analyzing the combined defects in gear-bearing system is working satisfactorily. (ii) With defective bearing, the higher vibration peaks at gear mesh frequency and its harmonics with side bands are observed, compared to good condition. (iii) With defective gear, the higher vibration peaks at bearing defect frequencies are observed, compared to good condition. (iv) Overall vibration increases in presence of bearing defect, gear defect and combined gear-bearing defects in comparison to healthy condition of gear box. (v) Vibration signal statistical parameters, such as RMS, Standard deviation, Kurtosis, crest factor etc. values increases while the derived parameters like p21, p23 decreases with increase in defects in gear-bearing system. (vi) The ANN based defect classifier using the above mentioned statistical parameters as neurons are effective in defect identification. (vii) This is a novel thing that the multiple defects in a gear-bearing system can also be detected using trained neural network.

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References