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Classification of rolling element bearing fault using artificial neural network

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ABSTRACT

The paper presents a new approach to the classification of rolling element bearing faults by implementing Artificial Neural Network. Diagnostics of rolling element bearing faults actually represents the problem of pattern classification and recognition, where the key step is feature extraction from the vibration signal. Characterization of each recorded vibration signal is performed by a combination of signal's time-varying statistical parameters and characteristic rolling element bearing fault frequency components obtained through the frequency spectrum analysis method. The experimental data is collected for four bearings at three different speeds. The sensor is located at three different positions for each bearing. Both time domain and frequency domain signals were measured. Thus the data was three time spectrums and three frequency spectrums for each speed for a bearing. The entire data set comprised of 72 (6 x 3 x 4) data. The time domain signal was comprised of 8192 samples and extracting these features from a huge data set was difficult. To overcome this difficulty the 8192 samples were split into 32 bins each containing 256 samples. The entire process of splitting and evaluating the seven features was coded in MATLAB. From these seven features the most suitable features for explaining the intensity of the defect is discussed.

Introduction

Among the other mechanical components, researchers pay great attention to the rolling element bearings due to their unquestionable industrial importance. Different techniques are employed in the studies related to the rolling element bearings. Brian and Robert (2000) have discussed in their paper about the vibrations induced by a defect in the inner raceway of bearing. In order to obtain the experimental data the outer ring of the bearing is modified. A sensor is integrated into the outer raceway of the bearing and it is interfaced with a computer to acquire the data. They have developed a finite element model and compared the results obtained from the experimental setup. Zeki Kiral and Hira Karagulle (2003) have mentioned basically three different ways of loading in machinery: constant amplitude–constant direction (gearing forces), constant amplitude–varying direction (unbalanced forces) and varying amplitude–varying direction (joint forces). The second form is considered in the previous sections. The third type of loading, varying amplitude–varying direction is also frequently encountered in applications and hence is analyzed with regard to its effect on the defect detection methods. David Brie (2000) stated the effects of load distribution on bearings and has obtained experimental data for a single-point defect on the inner race of the driving shaft ball bearing. The two main reasons making the bearing vibration signal analysis difficult are the effect of the load distribution and the approximate knowledge of the contact angle. He has concluded that two main facts result from the time-frequency analysis. First one deals with the periodicity of the impulse train. The second point is mainly concerned with the vibration transmission through the bearing. Su and Lin (1992) have proposed a vibration model considering a bearing assembly with the defect-induced pulse train as the system input and the bearing vibration at the outer race or bearing housing as the system output. It is assumed that the system is a linear one, with time-invariant coefficients. Radivoje and Tatjana (2002) have analyzed that the internal geometry is changed due to wear. Consequently, diameters of balls and inner raceway decrease, and diameter of outer ring raceway increases. With change of these dimensions the internal radial clearance of the bearing increases, owing to what the load distribution between rolling elements becomes more unequal. The mathematical relation between rolling bearing life and dynamic load rating, external load, linear wear rate, total number of rolling elements is established in this paper. Zeki Kýral and Hira Karagulle (2006) in their paper have proposed a method based on the finite element vibration analysis for defect detection in rolling element bearings with single or multiple defects on different components of the bearing structure using the time and frequency domain parameters. Gunhee Jang and Seong-Weon Jeong (2004) have presented an analytical model to investigate vibration due to ball bearing waviness in a rotating system supported by two or more ball bearings. This research presents the principal frequencies, their harmonics and the sideband frequencies resulting from the waviness of rolling elements of ball bearing. Choudhury and Tandon (1998) have discussed about the fundamental frequencies generated by rolling bearings with simple formulae. They have stated that these frequencies cover a wide range and can interact to give very complex signals. This is often further complicated by the presence of other sources of mechanical, structural or electromechanical vibration on the equipment. The bearing equations assume that there is no sliding and that the rolling elements roll over the raceway surfaces. Zeki Kiral and Hira Karagulle (2003) have analyzed the vibration data and different parameters such as Root Mean Square (RMS), Crest Factor (CF) and kurtosis are assessed with regard to their effectiveness in the detection of bearing condition. Garcia et al (2007) have used Discrete Wavelet Transform (DWT) for feature extraction. The extracted

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features from the DWT are used as inputs in a neural network for classification purposes. Nalinaksh et al (2000) have described a method to identify faults in rotating machinery using neural networks. Hajnayeb et al (2008) in their paper have improved the performance and speed of artificial neural network based ball-bearing fault detection expert systems by eliminating unimportant inputs and changing the ANN structure. An algorithm is used to select the best subset of features to boost the success of detecting healthy and faulty ball.

Existing literatures and methodologies are available only for bearing vibration monitoring using time and frequency spectrum data. Several works has been carried out in the field of condition monitoring using Artificial Neural Networks. Also they have implemented time and frequency domain in neural nets. However the usage of time domain signal features in bearing vibration analysis is still obscure. The present work considers the features extracted from the time domain signals and the classification is done based on those features. This is done to classify a normal and defective bearing with the help of time domain features.

1. Problem formulation and Methodology

The localized defect and distributed defect are formed in bearing by wear, flaking, smearing, corrosion, rough treatment during assembly in housing, radial loads acting on the bearing. Study of bearing defects is done by the following ways

- A defect can be introduced into the bearing by spark erosion, scratches indentation, etc. and the bearing's vibration response can be measured.
- The bearing housing can be used for measuring shock waves when defects pass through the testing region.
- The fault frequencies of the bearing under test can be measured using a vibration analyzer.
- The theoretical fault frequency values of a defective bearing can be calculated using the fault frequency formulae.
- With time wave form and frequency spectrum analysis the nature and the amplitude of the defect can be identified.

The time waveform and frequency spectrum in this work is done as an initial process for finding the defect and its intensity. Artificial neural networks (ANN) are used for several applications in the field of Engineering. Here, it is developed for condition monitoring the bearing vibration levels. Condition monitoring is of two phase, first to identify whether the bearing is defective or normal and second one is to identify the intensity of the defect.

The neural network system focuses on the above said objectives. The two most popular networks namely Radial Basis Function Network (RBFN) and Probabilistic Neural Network (PNN) for classification are used in this work. In the present work, the PNNs were created, trained and tested using MATLAB.

Experimental Setup

The experimental setup shown in figure-1, comprises of lathe fitted with specially fabricated arrangement to hold a circular plate. Lathe is used as a media since it is possible to achieve variable speed. The fabricated arrangement consists of circular plate for holding the outer race of the bearing. This circular plate is rotated by three rods bolted to the face plate of the lathe head stock. The shaft is held stationary by holding its one end with a non-revolving centre at the head stock and the other end with the tailstock's centre. A tapered roller bearing (535/532A) was used for each test.

The location of the sensor plays a significant role in detecting an impulse from the defect. Therefore the signals are measured by placing the accelerometer in three positions Horizontal, vertical and axial directions. The test bearings were loaded in the setup and the system was run for 20 minutes prior to measurement. This pre-run heats up the bearing components and then the vibration response of the system was measured. A dual channel vibration analyzer is used for measuring the system's vibration response. The time and frequency domain signals were measured for the system at three speeds for four different bearings.

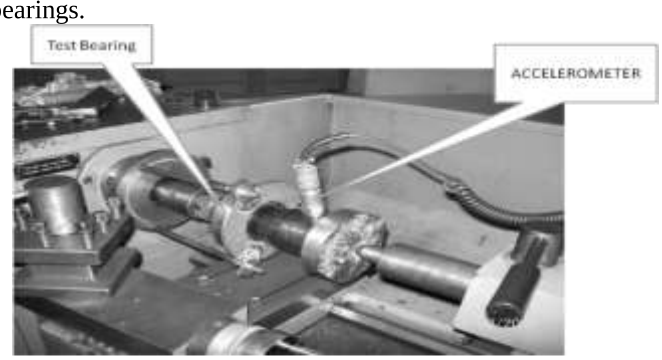

Figure.1 Experimental Setup with Test Bearing and Accelerometer

The time domain and frequency domain analyses are widely accepted for detecting malfunctions in bearings. The frequency domain spectrum is more useful in identifying the exact nature of defect in the bearings and the time spectrum is used for identifying the intensity of the defect. The experimental results have to be compared with that of the theoretical characteristic frequencies calculated for a defective bearing. The fault frequencies of a bearing relates to the elements (rolling elements, inner race, outer race, cage) in the bearing.

The experimental data is collected for four bearings at three different speeds. The sensor is located at three different positions for each bearing. Both time domain and frequency domain signals were measured. Thus the data was three time spectrums and three frequency spectrums for each speed for a bearing. The entire data set comprised of 72 (6 x 3 x 4) data. The presence of a defect can be established with the frequency spectrum but the intensity of the defect cannot be uniquely defined with the RMS value alone. Hence the time spectrum features were extracted. The following are the seven features which are used to define the intensity of the defects in a bearing, Maximum value, Overall RMS value, Mean Value, Variant, Kurtosis, Crest factor and Clearance factor. The time domain signal was comprised of 8192 samples and extracting these features from a huge data set was difficult. To overcome this difficulty the 8192 samples were split into 32 bins each containing 256 samples. The entire process of splitting and evaluating the seven features was coded in MATLAB. From these seven features the most suitable features for explaining the intensity of the defect is discussed.

Neural Networks for Classification

The pattern classification theory has been a key factor in fault diagnosis methods development. Some classification methods for process monitoring use the relationship between a set of patterns and fault types without modelling the internal processes or structure of an explicit way. Nowadays, the ANN's constitute the most popular method. The human learning process may be partially automated with ANN's, which can be configured for a specific application, such as pattern recognition or data classification, through a learning process. An artificial neuron is composed for some connections, which receive and transfer information, also there is a net function designed for collect all information (weights x inputs + bias) and send it to the transfer function, which process it and produces an output. The process is illustrated in Figure 2. There are two mean phases in the ANN's application: the learning or training phase and the testing phase. The learning phase is critical because it determines the type of future tasks able to solve. Once trained the network, the testing phase is followed, in which the representative features of the inputs are processed. After calculated the weights of the network, the values of the last layer neurons are compared with the expected output to verify the suitability of the design.

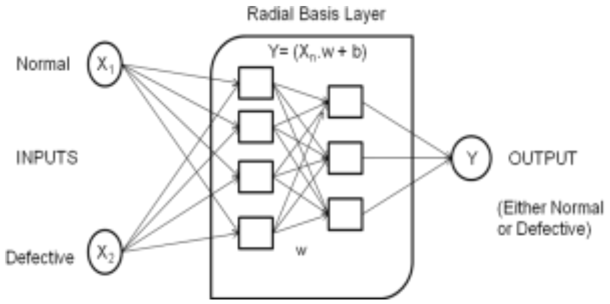

Figure 2 Neural Network Architecture

For the above the feature extracted from the time signal. The time domain signal was comprised of 8192 samples and extracting these features from a huge data set was difficult. To overcome this difficulty the 8192 samples were split into 32 bins each containing 256 samples. Therefore the final data set obtained for each of the seven parameters was 1152. That is, the Final data set, 1152 = 32 (Bins) x 3(Speeds) x 3(Sensor locations) x 4(Bearings)

The classification was done to sort the normal bearing from the defective one. Two networks were tested for this classification purpose. From the above said data set 864(24 x 3 x 3 x 4) data were used for training the network and 288(8 x 3 x 3 x 4) was used for testing the network. The two most popular networks namely Radial Basis Function Network (RBFN) and Probabilistic Neural Network (PNN) for classification are used in this work. In the present work, the PNNs were created, trained and tested using MATLAB.

Results and discussion

The first step in condition monitoring is to identify whether the bearing is defective or normal. Though the experimental results are enough for the above said purpose, a pattern classification system which can act involuntarily has to be inherited for condition monitoring. To fulfill this purpose artificial neural network were used in this project for classification.

The classification of bearing based on its condition was done using the features extracted from the time domain signals. However, the functioning of neural networks is effective on using large number of data sets. For this purpose all the time domain features were used.

Inputs to the Neural Network

The inputs to neural network are the features extracted from the time domain signals. The table 2 lists the time domain features for bearing 1 at a particular speed for a sensor position. The formula for calculating these features are given in appendix 1. Similarly, the features were calculated for three speeds and three sensor locations.

Targets for the Classification Network

The table 1 shows the targets assigned to the neural network input parameters for normal and defective bearing. The targets for the classifier network is set as '1' for a normal bearing and '2' defective bearing. The parameters were assigned the targets depending upon the condition of the bearing. The neural network was done in MATLAB environment with two networks (RBFN and PNN). The code for training and testing the network of an axial time waveform is given in appendix 2. The selection of these two networks was based on the previous literatures and their functioning efficiency as classifiers. The two networks were tested and the results are discussed in the next section.

Neural Network Classification Results

The parameters listed in the previous section were used for classification purpose with the corresponding targets mentioned previously. The two networks used here were RBFN and PNN. Both these networks were tested by varying the spread value. Also the number of input parameters (extracted time features) used for testing were varied and those results are also discussed.
The test results in table 3 show that PNN as the most successful network among the two. The tests were conducted for several other spread values and the most suitable spread value which has the highest success rate was found to be 0.1. The corresponding success rates are discussed in the table. The features used in neural network vary from single to all the seven features. The results show higher success rate on using single feature whereas it was minimum when all the seven parameters were used. The significant aspect to be noted in the results table is the test No. 14. The features numbered 2, 5, 6 (i.e. Crest factor, RMS value, Variant) showed 100% test success in PNN. This due to the fact that these features had values which do no correlate with each other. Also, there were considerable variations in their values in each data set. This resulted in better training of the network and ultimately better test results were achieved.

Conclusion

The results discussed in the previous chapters arrive at three conclusions. First, the presence of a defect in the bearing was discussed. This was done with the help of time and frequency spectrum. The element in which the defect is present was examined with the help of frequency spectrum. The defect intensity was also examined using time spectrum. However, the unclear nature of time analysis led to feature extraction.

Next, the features extracted cleared the doubts in obtaining intensity from the time spectrum. From the result the most defective to the least defective bearing was classified. Thus the feature extraction proves to be good indicator of defect intensity. Finally, neural networks were used to classify the bearing's condition. The classification results showed whether the bearing is normal or defective. The output from the neural network can be used for online condition monitoring.

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Table 1 Targets for Neural Network

Bearing No.	TARGETS FOR INPUT PARAMETERS						
	Clearance	Crest Factor	Kurtosis	Maximum Value	Mean Value	RMS Value	Variant
1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2
3	2	2	2	2	2	2	2
4	2	2	2	2	2	2	2

Table 2 Inputs to the Neural Network

Sl. no	Clearance	Crest factor	Kurtosis	Maximum value	RMS value	Variant	Mean value
1	3.93377	2.338364	3.621464	5.584	1.933973	5.70251	3.740253
2	2.386514	1.057098	2.599332	5.5096	2.74948	27.1649	7.559638
3	3.426314	1.980926	3.378461	4.5603	1.883703	5.29968	3.548336
4	2.313875	0.999157	3.121539	5.7888	2.884412	33.5667	8.319833
5	3.06103	2.173668	2.683456	3.6482	1.661341	2.81689	2.760054
6	1.960849	0.864245	3.158704	5.3793	2.99581	38.7415	8.974875
7	3.46506	2.249549	2.998557	4.3369	1.755826	3.71678	3.082925
8	2.361699	1.03534	3.393918	5.9563	2.881427	33.0969	8.302619
9	3.42885	1.840102	2.421499	4.3369	1.890963	5.55488	3.575741
10	2.333169	1.067927	3.750883	5.9563	2.852079	31.1078	8.134356
11	3.480162	1.71025	2.758907	5.007	2.079931	8.57108	4.326111
12	2.605358	1.097561	2.245671	5.8818	2.768671	28.7185	7.665539
13	3.85092	1.532663	2.935272	5.9191	2.325888	14.9148	5.409756
14	3.97627	1.686102	5.281759	8.5994	2.699366	26.0116	7.286579
15	2.981582	1.322989	2.418439	5.0815	2.365257	14.7527	5.594442
16	2.98309	1.291917	2.606505	5.7888	2.543212	20.0774	6.467925
17	3.005414	1.307681	2.947156	6.161	2.604671	22.1972	6.78431
18	2.578081	1.462321	2.541811	4.4858	2.194113	9.41010	4.814133
19	2.451681	0.94324	2.381476	5.3607	2.821149	32.2997	7.958883
20	3.21288	1.732918	2.753921	4.9326	2.090813	8.10206	4.371499
21	3.079505	1.221469	3.23415	7.3337	2.905034	36.0480	8.439223
22	3.662547	2.170959	3.225435	5.2676	1.95207	5.88738	3.810578
23	2.185821	0.923792	2.964371	5.6213	2.94979	37.0275	8.701262
24	2.691393	1.720513	2.229066	3.5924	1.834668	4.35966	3.366007
25	2.424856	1.027971	2.851432	6.5705	3.017898	40.8540	9.107708
26	3.832714	2.49058	3.464152	5.0442	1.804963	4.10188	3.257892
27	2.354052	1.007264	3.564647	6.2727	2.98578	38.7813	8.914882
28	3.774554	2.285491	3.587189	5.2118	1.895491	5.20015	3.592887
29	2.138669	0.936905	2.992746	5.6585	2.948109	36.4763	8.691345
30	3.45407	1.915507	3.137169	5.007	2.000942	6.83262	4.003768
31	2.266324	0.950691	2.382048	5.5468	2.883713	34.0412	8.315801
32	3.707334	1.833419	3.503719	6.161	2.238458	11.2922	5.010694

Table 5.8 Neural Network Classification Results

Test No	Features	Network	Success Rate
1	1	RBFN	92%
		PNN	100%
2	2	RBFN	92%
		PNN	100%
3	3	RBFN	92%
		PNN	100%
4	4	RBFN	92%
		PNN	100%
5	5	RBFN	92%
		PNN	100%
6	6	RBFN	92%
		PNN	100%
7	7	RBFN	92%
		PNN	100%
8	1, 2	RBFN	92%
		PNN	100%
9	2, 5	RBFN	92%
		PNN	100%
10	2, 6	RBFN	92%
		PNN	100%
11	5, 6	RBFN	92%
		PNN	100%
12	1, 2, 3	RBFN	83%
		PNN	92%
13	1, 3, 5	RBFN	83%
		PNN	92%
14	2, 5, 6	RBFN	92%
		PNN	100%
15	5, 6, 7	RBFN	83%
		PNN	92%
16	1, 2, 3, 4, 5, 6, 7	RBFN	62.5%
		PNN	75%