# Fault Diagnosis on Bevel Gearbox with Neural Networks and Feature Extraction

Tayyab Waqar[1], Mustafa Demetgul[1], Cemal Kelesoglu[1]
[1]*Department of Mechatronics Engineering, Faculty of Technology, Marmara University, Goztepe, Istanbul, Turkey*
*tayyabwaqar@gmail.com,*

***Abstract*—In recent years, early fault detection and diagnosis of gears have become extremely important due to requirement to decrease the downtime on production machinery caused by the failures. For that reason, researches have been done for the early detection of faults through the analysis of their vibration signals. Modern day machines, due to their complexities, can have many vibration generating sources in addition to noises. Therefore it is important that the vibration signal of faulty gear to be recognized and recovered for the diagnostics. In this paper Back-Propagation neural network has been used for the classification of RPM and oil level related gearbox faults that can occur during operation. With the help of Power spectrum technique, signal was more refined in order to make the feature selection process much more accurate.**

***Index Terms*—Back-propagation artificial neural network, Bevel gears, fault detection, fast Fourier transform, mean, mesh frequency, oil level, power spectrum, rpm, vibration analysis.**

## I. INTRODUCTION

Rotating machinery, which is one of the most basic and important equipment, plays a very important role in any kind of industry [1], [2]. The majority of these machines are operated by the means of gears, and bearings which can become faulty with their usage and can affect the performance of the machine and can even result in their breakdown [3]. These causes of machine downtime result in loss of production, upon which the whole industry depends.

Gearboxes are considered to be one of the earliest machine parts. It has been in use for thousands of years. It is a fundamental part on most types of machinery in order to change the shaft speed, the torque and the power. Also, in some types of machinery such as helicopter or aircraft, the role of gearbox is extremely important as its failure may lead to the loss of assets and even human life [4].

Nowadays, modern rotating machinery is getting more complex which requires the system to be more reliable with low cost of production and high maintenance [5]. To achieve this, accurate fault diagnosis of machine failure is required. The diagnosis of machine faults has evolved a lot from the early days when the maintenance meant only to repair a machine only after the fault has occurred in it. The current era is of predictive or condition based maintenance. It can be defined as maintenance actions taken based on the information acquired from the target measurement. The effectiveness of this type of maintenance is measured based on the accurate diagnostic strategies. For this purpose vibration monitoring is widely used in order to detect rotating machinery failures [6]–[8].

Through vibration monitoring we can detect, locate, and distinguish between the different failures in a machine. Results from purpose built gearbox test rigs for condition monitoring showed that vibration signal analysis was able to detect an eccentricity on just one of the gears [9], [10]. In 2003, Reimche and Südmersen demonstrated that analysis of the vibration signal is able to detect the eccentricity on one of the gears [11].

In 1994 Choy and fellow researchers developed a signature analysis scheme to study and identify the characteristics of vibration signal of a gear system using time averaging and spectrum analysis. Simulating varying degrees of wear and pitting damage, could provide a comprehensive database of gear fault detection to study and characterize the vibration signal of the gear system [12].

During condition monitoring using vibration analysis, early stage faults on spur gear teeth were identified and an approximately linear decreasing relationship between tooth mesh stiffness and time was found [13], [14].

In gearbox health monitoring and fault detection, the scalogram based parameter (frequency variation) provides the most useful basis for monitoring of localized pitting gear damage [15].

In the wind power industry, vibration monitoring is used routinely to detect faults in bearings and gears. Sensors are mounted on the bearing housing to detect the unique characteristic vibration signatures for each gear mesh or bearing, which depends on the geometry, load, and speed of the components [16].

An artificial neural network based fault diagnosis system for gearbox concluded that using Genetic algorithm is better than UTA [17].

A combination of Hilbert and wavelet packet transforms based model for the gearbox fault detection has been proposed with result showing effective detection in early gearbox faults [18].

In 2004 I. Yesilyurt presented the applications of four time-dependent parameters (e.g. the instantaneous energy, mean and median frequencies, and bandwidth) based upon the use of spectrogram and scalogram, and compared their

Manuscript received April 16, 2015; accepted August 18, 2015.
This work was supported by the Marmara University's Research and Project Department under the grant FEN-E-120314-0065.

abilities in the detection and diagnosis of localized and wear gear failures [19].

In 2009, N. Saravanan and fellow researchers presented the use of decision tree for selecting best statistical features that will discriminate the fault conditions of the gear box from the signals extracted using vibration signals. A rule set was formed from the extracted features and fed to a fuzzy classifier. They also presented the usage of decision tree to generate the rules automatically from the feature set. A piezo-electric transducer was used to get the vibration signals for the following conditions – good bevel gear, bevel gear with tooth breakage, bevel gear with crack at root of the tooth, and bevel gear with face wear of the teeth for various loading and lubrication conditions. A fuzzy classifier was built and tested with representative data. The results were found to be encouraging [20].

In 2014, Hemantha Kumar and colleagues used FFT and Bayes net classifier for the fault detection on bearings and stated the results to be encouraging [21]. In 2014, an intelligent diagnostic method for gear fault detection was presented by Qingrong Fan and colleagues, and they were able to classify 82 % of the gear pitting faults correctly [22]. Saravanan used a combined approach, Hilbert transform and Support Vector Machine, for the fault detection in bevel gear with 100 % accuracy [23].

The objective of this study is to present a method which can be used to identify fault features of bevel gearbox accurately and effectively from complicated continuous vibration and sound signals. Raw data was collected with the help of data acquisition module. This data was then pre-processed for the signal processing with the help of Mean. By taking the mean of the raw data and then subtracting it from the raw data, a refined signal was prepared for the processing. Later on, Fast Fourier Transform has been applied on that data. By using Power spectrum, feature selection process was further refined. It helped in achieving a near perfect signal for the selection of features.

Mean and Fast Fourier transform techniques has been used for the feature extraction purposes from the raw data. Back-Propagation artificial neural network has been used for the classification of faults. In total 7 different oil levels and rpm related conditions were generated. The performance of the system was monitored over 25 different experiments.

## II. Gears

Gears permit the transfer of energy between two shafts. The process is important in that components of a system can be designed for maximum efficiency, with the gears acting as the interface between the components. Specific uses for gears are to change speeds in a system, change direction of rotation, and transmission of power [19].

### *A. Bevel Gears*

The bevel gear is often used to transfer power from one shaft to another when shafts are at $90^0$. The teeth of these gears are formed on a conical surface and normally the two shafts would be at right angles to each other and “intersect” at the apex of the cone. Bevel gears have teeth that are cut straight, and are all parallel to the line pointing to the apex of the cone on which the teeth are based [20]. However, they cannot be used for parallel shafts and can be noisy at high speeds [18].

### *B. Faults in Gears*

Gears tend to operate with the teeth of one engaging the teeth of another to transmit power without slippage. When the teeth are meshed, driving one gear (e.g. with an electric motor) will force the other to turn, transmitting power but allowing the rotational speed and direction of rotation to be changed. It is very important to be familiar with the common gear faults in order to perform gear’s fault diagnosis successfully. Normally, Gear failures tend to occur when a gear is working under high stress conditions [24]–[29]. Normal gear faults are:

– Root Cracking;
– Pitting;
– Scoring;
– Scuffing;
– Distributed Gear defects i.e. Adhesive wear, Abrasive wear, Surface inaccuracy, and Misalignment.

## III. Fault Detection

Basically, Machine fault detection can be stated as whether a machine has a fault or not. The whole process of fault detection can be simplified as in Fig.1:

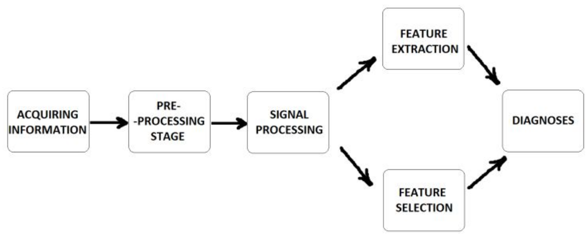


Fig. 1. Fault detection process.

First of all, raw information about the working part is collected through sensor. It can be done through mechanical measurements (vibration, acoustic emission and/or temperature), Electrical readings (Current and Voltage), and Tribology. This acquired raw data must then be pre-processed in order to reduce the dimension of it thus making the signal processing stage more accurate. During the signal processing stage, features are extracted and then selected from the pre-processed acquired data in order to detect what kind of fault can be present in that particular part.

## IV. Signal Processing Techniques

### *A. Fast Fourier Transform*

Fourier series provides an alternate way of representing data; instead of representing the signal amplitude as a function of time, we represent the signal by how much information is contained at different frequencies. Fourier analysis is important in data acquisition as it allows us to isolate certain frequency ranges.

In signal processing, it is more common to deal with digital signals that by definition are discrete. Consider a sequence x(n), periodic in N, in time-domain and the discrete time Fourier series (DFTS) are defined as:

$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) e^{-\frac{i2\text{®}}{N}kn}, \tag{1}$$

$$x(n)=\sum_{n=0}^{N-1} X(k)e^{\frac{i2\text{®}}{N}kn}, \tag{2}$$

where X(k) a periodic sequence in frequency-domain, and is as x(n) periodic in N.

### B. Mean

Mean can be defined as the average value of a signal. In signal processing, it is generally used to make the process of feature extraction more accurate. It can be defined mathematically as

$$\overline{x}=\frac{1}{N}\sum_{i=0}^{N-1} x_i, \tag{3}$$

where $\bar{x}$ is the mean of signal, $x_i$ is the signal and N is the total number of samples.

### C. Gear Mesh Frequency

Gear mesh frequency is the frequency at which teeth on the pinion come into contact with teeth on the bull gear. It is simply defined as the number of teeth on the gear times the rotational frequency of the gear. The vibration monitored on a faulty gear generally exhibits a significant level of vibration at the tooth. Gear Meshing Frequency and its harmonics of which the distance is equal to the rotational speed of each wheel as shown in Fig. 2.

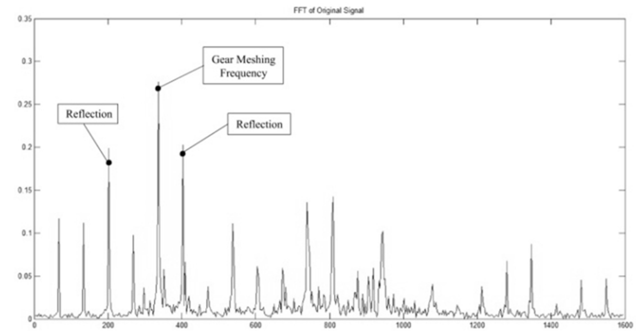


Fig. 2. Mesh frequency.

### D. Power Spectrum

Periodic signals give peaks at their fundamental frequencies and their harmonics. Power spectrum tells us how much of the signal is present at these frequencies. It gives a plot of portion of a signal's power at specific frequencies.

### E. Artificial Neural Network

An artificial neural network is a computational model which is based on the structure and operation of a biological neural network. Similar to a biological network, a neural network learns based on inputs and outputs.

Most applications of artificial neural networks use multi-layer perceptron network training with back-propagation algorithm. A typical multi-layer perceptron network, Fig. 3, is constructed with layers of neurons. Each neuron in a layer computes the sum of its input (x) and puts it through an activation function (f). Its output (o) can be written mathematically as

$$o=f^2\left(W^1 f^1\left(W^1 x+b^1\right)+b^2\right), \tag{4}$$

where W is weight and b is bias vector.

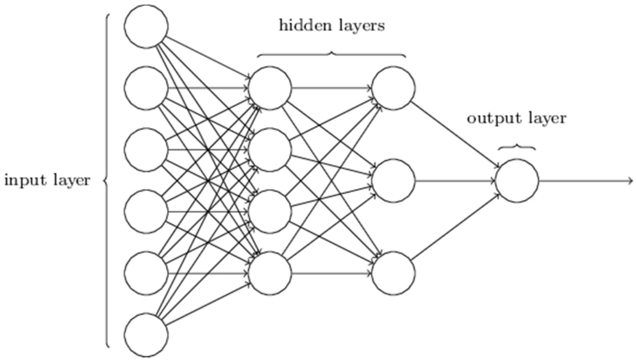


Fig. 3. Neural network model.

The neural network used in this study, which is shown in Fig. 4, had 8 inputs parameters, 45 hidden layer neurons and one output parameter; which is used to indicate the nature of fault. The 8 input parameters were the mesh and harmonic frequencies from the microphone and accelerometer for both rpm and oil level.

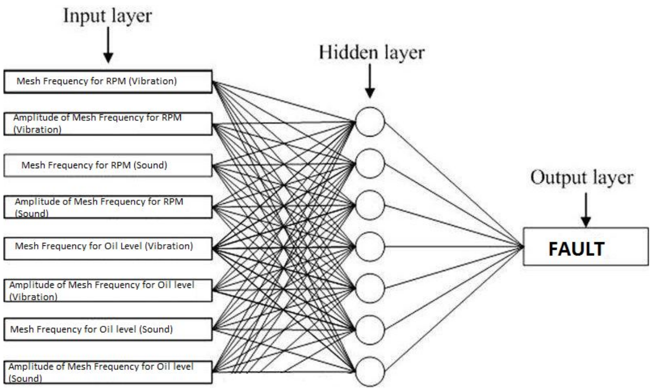


Fig. 4. Neural Network Model showing inputs and outputs.

## V. EXPERIMENTAL SETUP

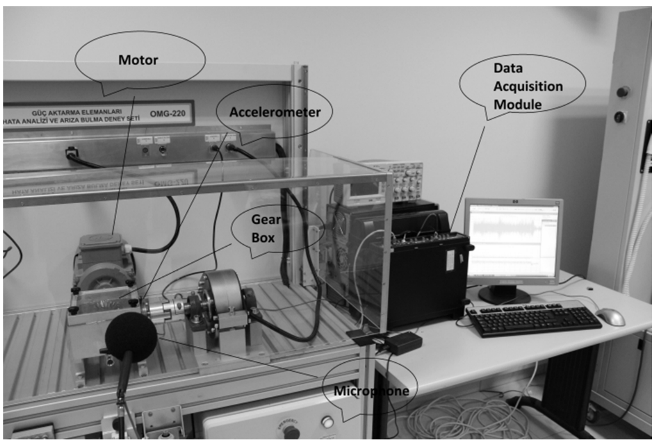


Fig. 5. Experimental setup.

The experiments were performed on a test rig, Fig. 5, built specifically for the diagnosis of rotating machinery, especially gears. The signals are measured by two sensors which were connected directly to a Pulse Type 7533 data acquisition and analyser module for data logging and analysing purposes.

Test rig used for this study had an effective speed range of 100 rpm–5000 rpm provided by a 3 phase AC motor. Bevel gears were used as test bearings for this study.

*A. Sensors*

A total of two sensors were used for the measurement of signals in this study. One was accelerometer and other was microphone.

The accelerometer (Endevco 7253B-10), which was used for the detection of vibrations, was placed directly on the housing of gears. It had a frequency band of 10 Hz to 25.6 kHz and a sensitivity of 10 mV/ms$^2$.

A 1/2-inch microphone (Bruel & Kjaer model no. 4189L001) was used for the detection of sound signals. It has a frequency range of 6 kHz to 20 kHz.

The signals from the both sensors were fed to Breul & Kjaer Pulse Type 7533 data acquisition and analysing module. Raw data were collected through Pulse 10.2 software and MATLAB was used for the signal processing purposes.

## VI. RESULTS

*A. Research Methodology*

The whole procedure is depicted by the flow diagram in Fig. 6. Raw data, from the microphone and accelerometer, was collected for two different operating conditions. One was based on different revolution speeds of gears while the other was different oil levels. The vibration and sound data of gears are analysed at 4 different speeds (1200 rpm, 1500 rpm, 1800 rpm and 2100 rpm) and 3 different oil levels (130 ml, 250 ml and 850 ml).

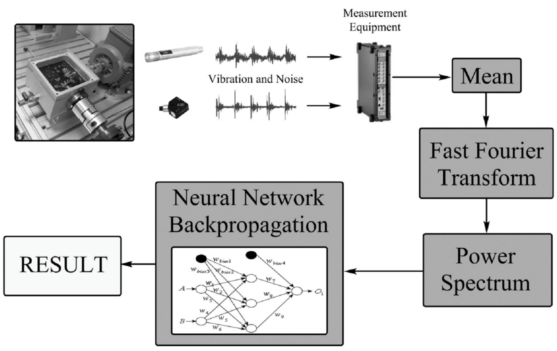


Fig. 6. Flow diagram.

The raw data collected for the rpm and oil level can be seen in Fig. 7.

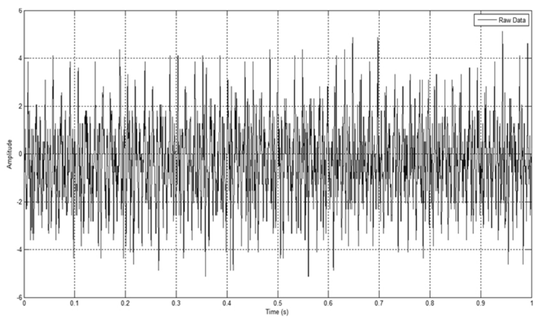


Fig. 7. Raw signal.

This raw data, collected through the data acquisition module, is then pre-processed, by taking the mean value Fig. 8, before the feature extraction processes.

After getting the mean of the raw signal, the feature extraction process is performed by using Fast Fourier Transform. The resulting signals from FFT for both vibration and sound from different RPM and oil levels can be seen in Fig. 9–Fig. 12.

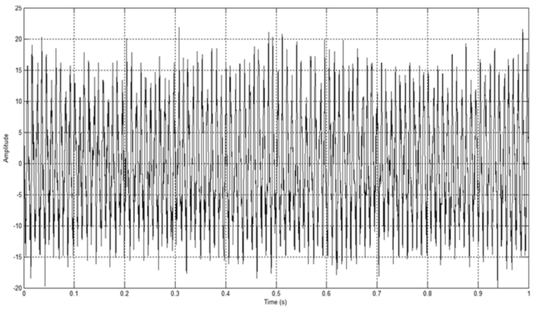


Fig. 8. Mean of raw signal.

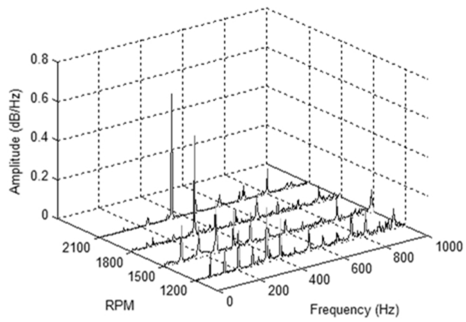


Fig. 9. FFT of vibration signal from different rpm.

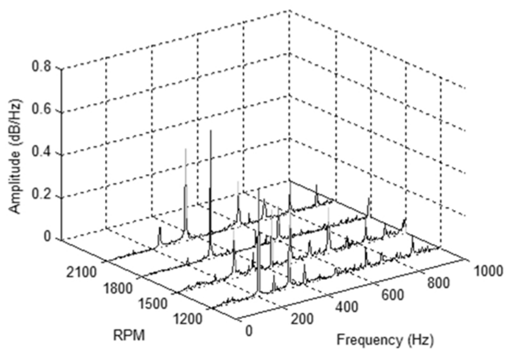


Fig. 10. FFT of sound signal from different rpm.

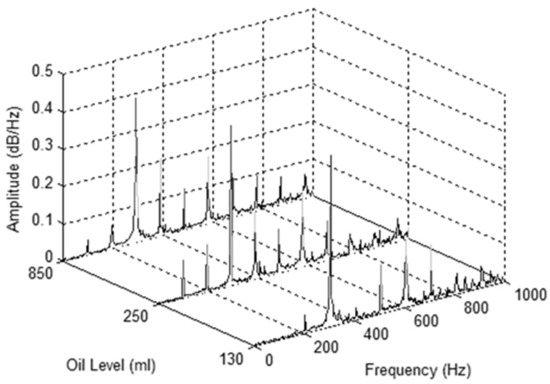


Fig. 11. FFT of vibration signal from different oil level.

The feature selection procedure is further refined with the help of Power spectrum in Fig. 13–Fig. 16. Power spectrum shows us how much of the signal is present at these frequencies. It gives a plot of portion of a signal’s power at specific frequencies. For different oil levels, the mesh frequency was at 250 Hz, whereas it fluctuated in between 200 Hz and 400 Hz for different rpm values. Power spectrum helps us in further refining the feature extraction process. Extracted feature are then used for the fault detection purposes.

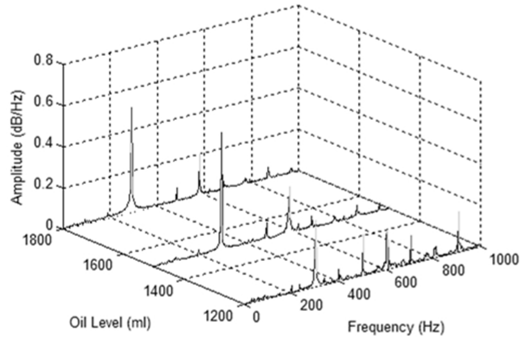


Fig. 12. FFT of sound signal from different oil level.

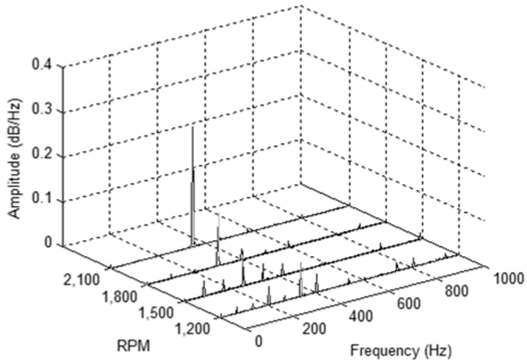


Fig. 13. Power Spectrum of vibration signal from different rpm.

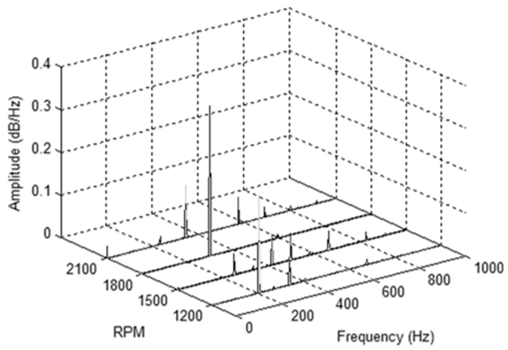


Fig. 14. Power Spectrum of sound signal from different rpm.

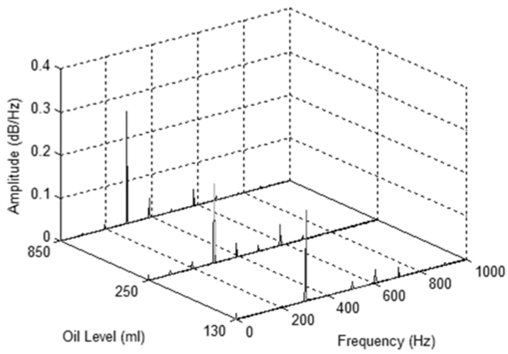


Fig. 15. Power Spectrum of vibration signal from different oil level.

A multi-layer perceptron artificial neural network, which has 45 hidden layer neurons, has been used for the classification purposes of faults in this study. The model consists of a total of 8 inputs based on which it is able to classify 7 different faults successfully. The multi-layer perceptron artificial neural network is created, trained and simulated with MATLAB.

Total of 25 experiments were performed. The results of these experiments were divided for training (70 %), and test (30 %). After the training, artificial neural network was presented with 8 experimental results for tests which the neural network has never experienced before. The performance of that test can be seen in Fig. 17 and Table I.

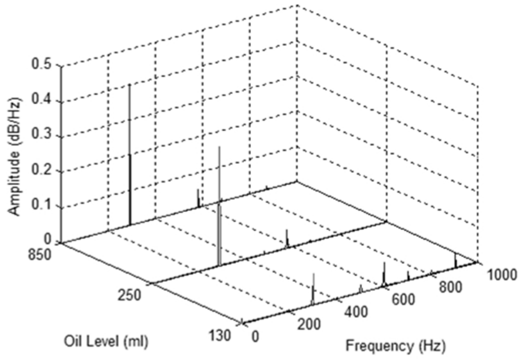


Fig. 16. Power Spectrum of sound signal from different oil level.

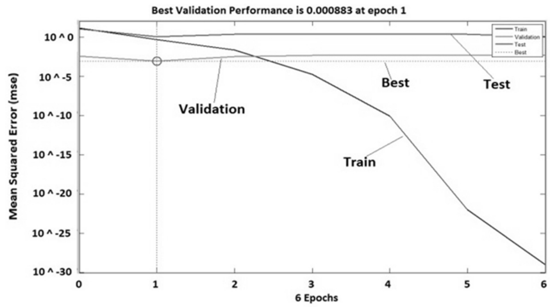


Fig. 17. Training of neural network.

TABLE I. PERFORMANCE OF NEURAL NETWORK.

| Hidden Layer Neurons | All | Training | Test |
|---|---|---|---|
| **5** | 0.7608 | 0.81763 | 0.74613 |
| **10** | 0.86409 | 0.9994 | 0.46697 |
| **15** | 0.49045 | 0.99938 | 0.13097 |
| **20** | 0.82131 | 0.94342 | 0.46951 |
| **25** | 0.89829 | 1 | 0.89339 |
| **30** | 0.94016 | 0.99708 | 0.86659 |
| **35** | 0.91267 | 0.99984 | 0.79778 |
| **40** | 0.97575 | 0.99999 | 0.88867 |
| **45** | 0.93954 | 0.95357 | 0.96534 |
| **50** | 0.4035 | 0.89348 | 0.11748 |

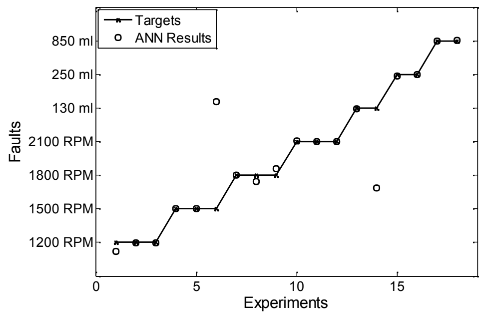


Fig. 18. Result of training preformed on neural network model showing the fault detection performance of it.

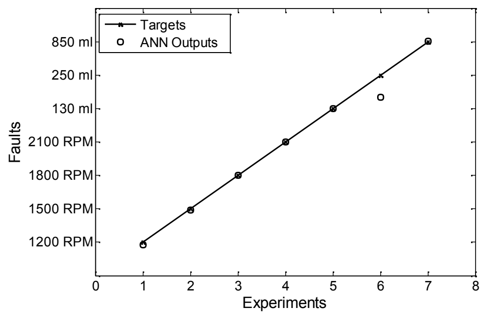


Fig. 19. Result of tests performed on neural network model showing the fault detection performance of it.

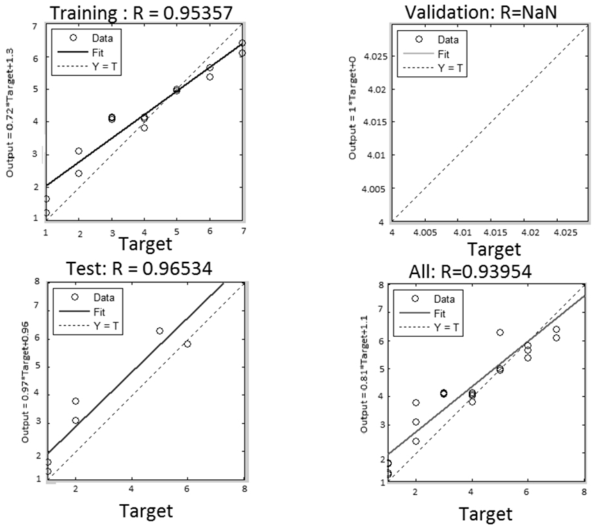


Fig. 20. Correlation coeffiecient of neural network's performance.

As can be seen in the Table I, the best performance was achieved when the numbers of hidden layer neurons were 45. The results of the tests are presented in Fig. 18. In total 25 tests were performed and neural network was able to correctly predict 21 out of them. The overall accuracy of the model is 93.954 %. Training and Test results can be seen in Fig. 18 and Fig. 19 respectively, whereas regression is shown is Fig. 20.

## VII. Conclusions

An approach for the diagnosis of different type of faults in gear by using Mean, Fast Fourier Transform, Power spectrum and Neural Network has been presented in this paper. The different vibration and sound signals produced during the normal and error related operations of gears have been collected through different sensors. This data is then studied for feature detection and feature selection processes. Later on, some random data was presented to the designed neural network model and its performance was monitored. Inputs, based on 8 different parameters, were presented to the developed model, and it was able to detect and classify 96.53 % correctly. This shows that the research techniques used in this study were efficient enough to extract useful information from raw data for the analysis purposes so that it can be used in fault detection of gears.

## References

[1] A. Muszynska, *Rotor dynamics*, CRC Press —Taylor & Francis Group: Boca Raton, 2005.

[2] M. L. Adams, *Rotating Machinery Vibration from Analysis to Troubleshooting*. Marcel Dekker: New York, 2000. [Online]. Available: http://dx.doi.org/10.1201/9780203902165

[3] S. Ericsson, N. Grip, E. Johansson, L. E. Persson, R. Sjoberg, J. O. Stromberg, "Towards automatic detection of local bearing defects in rotating machines", *Mechanical Systems and Signal Processing*, vol. 19, pp. 509–535. [Online]. Available: http://dx.doi.org/10.1016/j.ymssp.2003.12.004

[4] J. Yu, "Early fault detection for gear shaft and planetary gear based on wavelet and hidden Markov modeling", Ph.D. dissertation, Dept. Mech. & Industrial Eng., University of Toronto, 2011.

[5] A. K. B. Mahamad, "Diagnosis, classification and prognosis of rotating machine using artificial intelligence", Ph.D. dissertation, Dept. Computer Science & Electrical Eng., Kumamoto University, 2010.

[6] Z. Kiral, H. Karagulle, "Simulation and analysis of vibration signals generated by rolling element bearing with defects", *Tribology International*, vol. 36, pp. 667–678, 2003. [Online]. Available: http://dx.doi.org/10.1016/S0301-679X(03)00010-0

[7] S. Orhan, N. Akturk, V. Celik, "Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: comprehensive case studies", *NDT&E International*, vol. 39, pp. 293–298, 2006. [Online]. Available: http://dx.doi.org/10.1016/j.ndteint.2005.08.008

[8] J. D. Wu, C. C. Hsu, "Fault gear identification using vibration signal with discrete wavelet transform technique and fuzzy-logic inference", *Expert Systems with Applications*, vol. 36, pp. 3785–3794, 2009. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2008.02.026

[9] M. Cairns, "The condition monitoring of a Spur gearbox using noise and vibration measurements and correlation", M.S Thesis, Cranfield University, UK, 1991.

[10] P. Vayionas, "Design and build of a gearbox test rig for condition monitoring through vibration analysis", M.S Thesis, Cranfield University, Cranfield, 1991.

[11] W. Reimche, U. Sudmersen, "Basics of vibration monitoring for fault detection and process control", *Rio de Janeiro, Brazil*, vol. 6, 2003, pp. 2–6.

[12] F. K. S. Choy, J. J. Huang, R. F. Zakrajsek, "Vibration signature analysis of a faulted gear transmission system", 106623. AIAA-94-2937, University of Akron, University of Akron, 1994.

[13] R. Serrato, M. M. Maru, L. R. Padovese, "Effect of lubricant viscosity grade on mechanical vibration of roller bearings", *Tribology International*, vol. 40, no. 8, pp. 1270–1275, 2007. [Online]. Available: http://dx.doi.org/10.1016/j.triboint.2007.01.025

[14] J. D. Smith, "A new diagnostic technique for asperity contact", *Tribology International*, vol. 26, no. 1, pp. 25–27, 1993. [Online]. Available: http://dx.doi.org/10.1016/0301-679X(93)90035-Y

[15] H. Ozturk, "Gearbox health monitoring and fault detection using vibration analysis", Ph.D. dissertation, Dept. Mech. Eng., Dokuz Eylul University, Dokuz Eylul, 2006.

[16] M. Lucente, *Condition monitoring system in wind turbine gearbox*, KTH, Stockholm, Sweden, 2008.

[17] A. Hajnayeb, A. Ghasemloonia, S. E. Khadem, M. H. Moradi, "Application and comparison of an ANN-based feature selection method and the genetic algorithm in gearbox fault diagnosis", *Expert systems with Applications*, vol. 38, pp. 10205–10209, 2011. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2011.02.065

[18] X. Fan, M. J. Zuo, "Gearbox fault detection using Hilbert and wavelet packet transform", *Mechanical systems and Signal processing*, vol. 20 pp. 966–982, 2005. [Online]. Available: http://dx.doi.org/10.1016/j.ymssp.2005.08.032

[19] I. Yesilyurt, "The application of the conditional moments analysis to gearbox fault detection-a comparative study using the spectrogram and scalogram", *NDT & E International*, vol. 37, no. 4, pp. 309–320, 2004. [Online]. Available: http://dx.doi.org/10.1016/j.ndteint.2003.10.005

[20] N. Saravanan, S. Cholairajan, K. I. Ramachandran, "Vibration-based fault diagnosis of spur bevel gearbox using fuzzy technique", *Expert Systems with applications*, vol. 36, no. 2, part 2, pp. 3119–3135, 2009.

[21] H. Kumar, T. A. Kumar, M. Amarnath, V. Sugumaran, "Fault detection of bearing through vibration signals using Bayes classifiers", *Int. J. Computer Aided Engineering and Technology*, vol. 6, no. 1, 2014.

[22] Q. Fan, K. Ikejo, K. Nagamura, M. Kawada, M. Hashimoto, "Diagnosis for gear tooth surface damage by empirical mode decomposition in cyclic fatigue test", *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, vol. 8, no. 3, 2014. [Online]. Available: http://dx.doi.org/10.1299/jamdsm.2014jamdsm0039

[23] S. Natarajan, "Gear box fault diagnosis using Hilbert transform and study on classification of features by support vector machine", *International Journal of Hybrid Information Technology*, vol. 7, no. 4, pp. 69–82, 2014.

[24] J. Shigley, C. Mischke, *Mechanical Engineering Design*, NY McGraw Hill Book Co., Inc., 1989.

[25] D. W. Dudley, *Gear Handbook*. NY, McGraw-Hill Book Co. Inc., 1962.

[26] H. E. Merritt, *Gears.* Pitman Press, 1954.

[27] E. Alban, *Systematic Analysis of Gear Failures*. American Society of Metals. Metals Park, Ohio, 1985.

[28] J. D. Smith, *Gears and their vibration: a basic approach to understanding gear noise*, NY: Marcel Dekker, Inc., 1983.

[29] S. K. Al-Arbi, "Condition monitoring of gear system using vibration analysis", Ph.D. dissertation, University of Huddersfield, 2012.