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Development of EBP–Artificial neural network expert system for rolling element bearing fault diagnosis

Pratesh Jayaswal[1], S.N. Verma[2] and A.K. Wadhwani[3]

Abstract

The objective of this work is to develop techniques to automate the condition-based maintenance procedure. It is observed that vibration signals are capable of alarming the malfunctions in machineries. In order to overcome the shortcomings in the traditional vibration analysis using time-domain and frequency-domain features, two new approaches based on wavelet transform, artificial neural network and fuzzy rules are proposed for detecting and localizing defects in rolling element bearings. The two expert systems are developed and tested with the use of vibration signals collected from the bearing housing of an experimental setup. Experiment results show that the proposed approaches are sensitive and reliable in detecting defects on the outer race, inner race and rolling elements of bearings. The proposed approaches may be used for other fault diagnoses such as gear faults, coupling faults, belts in industries. It is also expected from the obtained results that the generalized defect detection will be easier in future by using the proposed approaches via other parameters such as noise, temperature, lubricant analysis in addition to used vibration signals.

Keywords

Artificial neural network, condition based maintenance, condition monitoring, fault diagnosis, rolling element bearing

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1. Introduction

The prevention of potential damage to machinery is necessary for the safe, reliable operation of process plant. Failure prevention can be achieved by sound specification, selection, review and design audit routines. Bloch and Geitner (1983) has concluded that when failures do occur, accurate definition of root cause is an absolute prerequisite to the prevention of future failure events.

Condition-based maintenance (CBM) is an attractive concept that says the proper time for performing maintenance ought to be determinable by monitoring condition and/or performance, provided of course, that a readily monitorable parameter of deterioration can be found. The probabilistic element in failure prediction is therefore reduced or, indeed, almost eliminated, the life of the item maximized and the effect of failure minimized.

Davies (1998) has suggested that because of widespread use in industrial machinery, rolling element bearings for example, have received considerable attention in respect of condition monitoring. For the present work one healthy and three faulty bearings were used. Defects were enforced to simulate faults and tests were subsequently conducted to identify these faults.

A number of signatures are generally analyzed during condition monitoring of machines such as vibration signature, acoustic pattern, temperature pattern, and oil condition. Among these, vibration signature analysis seems to be the most promising one because

[1]Department of Mechanical Engineering, Madhav Institute of Technology and Science, Gwalior, India.
[2]Department of Mechanical and Industrial Production Engineering, University Institute of Technology, Rajiv Gandhi Technical University, Bhopal, India.
[3]Department of Electrical Engineering, Madhav Institute of Technology and Science, Gwalior, India.

Corresponding author:
Pratesh Jayaswal, Department of Mechanical Engineering, Madhav Institute of Technology and Science, Gwalior, India
Email: pratesh_jayaswal@yahoo.co.in

it is the first responsive signature to give rise to other machine signature. Capturing the signature properly can give a better machine health estimate. Antifriction bearings failure is a major factor in the failure of rotating machinery. Amarnath et al. (2004) have concluded that antifriction bearing defects may be categorized as localized and distributed. The localized defects include cracks, pits, and spalls caused by fatigue on rolling surfaces. The distributed defect includes surface roughness, waviness, misaligned races, and off-size rolling elements. These defects may result from manufacturing and abrasive wear. Major research is carried out with a single defect introduced at a specific location such as the outer race, the inner race, the ball or the cage. The single fault gives an impulsive response resulting in variation in characteristics such as kurtosis, crest factor, etc. that are used as fault signature. These characteristics which have impulsive response become nonresponsive as the fault severity or spread increases. Therefore multiple point defect and generalized defect diagnosis is not straightforward. In this work an attempt is made for multiple point defect diagnosis.

In the present work a brief review of previous work done by several researchers and application of signature analysis techniques is covered. The two approaches are developed by using Error Back Propagation (EBP)–Artificial Neural Networks (ANN) for the rolling element bearing fault identification. Initially an experimental setup is developed for the purpose of collecting vibration signatures as a condition monitoring parameter. The other signals noise and temperature were also collected for reference.

The first approach is developed by using Elliptic filter and EBP–Artificial Neural Network and the other with the help of wavelet packet transform, fuzzy logic and EBP–neural network.

2. Vibration analysis

Source identification and fault detection from vibration signals associated with items which involve rotational motion, such as gears, rotors and shafts, rolling element bearings, journal bearings, flexible couplings, and electrical machines depend upon several factors: (i) the rotational speed of the items, (ii) the background noise and/or vibration level, (iii) the location of the monitoring transducer, (iv) the load sharing characteristics of the item, and (v) the dynamic interaction between the item and other items in contact with it. The main causes of mechanical vibration are unbalance, misalignment, looseness and distortion, defective bearings, gearing and coupling inaccuracies, critical speeds, various forms of resonance, bad drive belts, reciprocating forces, aerodynamic or hydrodynamic forces, oil whirl, friction whirl, rotor/stator misalignments, bent rotor shafts, defective rotor bars, and so on (Norton and Karczub, 2003). Renwick and Babson (1985) demonstrate that the predictive maintenance using vibration analysis has achieved meaningful results in the successful diagnosis of machinery problems. The benefits of such programs include not only evident cost-benefits such as reducing machinery downtime and production losses, but also the more subtle long-term cost benefits that can result from accurate maintenance scheduling. Wegerich et al. (2003) developed a nonparametric modeling technique by smart signal, and they demonstrate the use of this approach for detecting faults in rotating machinery via extracted features from vibration signals. Lei et al. (2003) present a damage diagnosis approach using time series analysis of vibration signals for structural health monitoring as a benchmark problem.

Sohn and Farrar (2001) presented a procedure for damage detection and localization within a mechanical system solely based on the time series analysis of vibration data. Sahinkaya et al. (2001) worked on fault detection and tolerance in synchronous vibration control of rotor magnetic bearing systems. A simple and effective algorithm has been developed to build fault detection and tolerance capabilities into the open-loop adaptive control of the synchronous vibration of flexible rotors supported or equipped with magnetic bearings. Lebold et al. (2000) presented a review of vibration analysis methods for gearbox diagnostics and prognostics. This review listed some of the most traditional features used for machinery diagnostics and presented some of the signal processing parameters that impact their sensitivity.

Verma and Balan (1998) present a fundamental study on the vibration behavior of electrical machine stators using an experimental model analysis and suggest that vibration level even at resonance can be reduced by designing the electromagnetic forces to have circumferential mode associated with corresponding resonance. Ocak and Loparo (2004) present algorithms for estimating the running speed and the bearing-key frequencies of an induction motor using vibration data that can be used for failure detection and diagnosis. Plenge et al. (2004) developed optical inspection techniques for vibration analysis and defect indication in railways.

In rolling element bearing failure analysis, the low-frequency phenomenon is the impact caused by a defect of a bearing. The high-frequency carrier is a combination of the natural frequencies of the associated rolling element or even of the machine (Jun and Lias, 2007). There are a number of factors that contribute to the complexity of the bearing signature. First, variation in bearing geometry and assembly, which make impossible to precisely determine bearing characteristics frequencies. Second, locations of bearing defects cause different behavior in the transient response of the signal, which is easily buried in wide band response and noisy signals. Third, the signature appears to be very different with the same type of defect at different stages of damage. Finally, operating speed and loads of the shaft greatly affect the way and the amount a machine vibrates. Several researchers have worked on the subject of rolling element bearing defect detection and diagnosis through vibration analysis. Time-domain, frequency-domain, time-frequency-domain based on Short-Time Fourier Transform (STFT), wavelet transform and advanced signal processing techniques have been implemented and tested (Jayaswal et al., 2008a). Time-domain analysis focuses on direct dealing with the time-domain waveform of vibration signals. The indices like RMS, peak value, and crest factor are often used to quantify the time signal. The statistical parameters such as kurtosis and skewness value are robust to varying bearing operating conditions and are good indicators of incipient defects. The disadvantage, however, is that as the defect spreads across the bearing surface the values of these parameters drop back to normal (Sun et al., 2004).

2.1. Time-domain signature analysis technique

Time-domain vibration signals, if understood properly, can yield an enormous amount of information. Identifying some characteristics that are not readily observed can be highlighted by this technique. Various time-domain techniques can be used in machine condition monitoring and these are as follows.

2.1.1. Waveform. Waveform analysis consists of recording the time history of the event on a storage oscilloscope or a real time analyzer. Apart from an obvious fundamental appreciation of the signal, it is useful in the study of non-steady conditions and short transient impulses. Waveform analysis can also be useful in identifying vibrations that are non-synchronous with shaft speed. In machine cost down analysis waveform can indicate the occurrence of resonance. A typical vibration waveform is shown in Figure 1 for a balls defected bearing.

2.1.2. Indices. Indices are also used in vibration analysis. The peak value, RMS level and their ratio crest factor are often used to quantify the time signal. The peak level is not a statistical quantity and hence may not be reliable in detecting damages in continuously operating systems. The RMS value, however, is more satisfactory for steady-state applications. Equations (1) and (2) are generally used to calculate the peak value and RMS value for a time-domain signal.

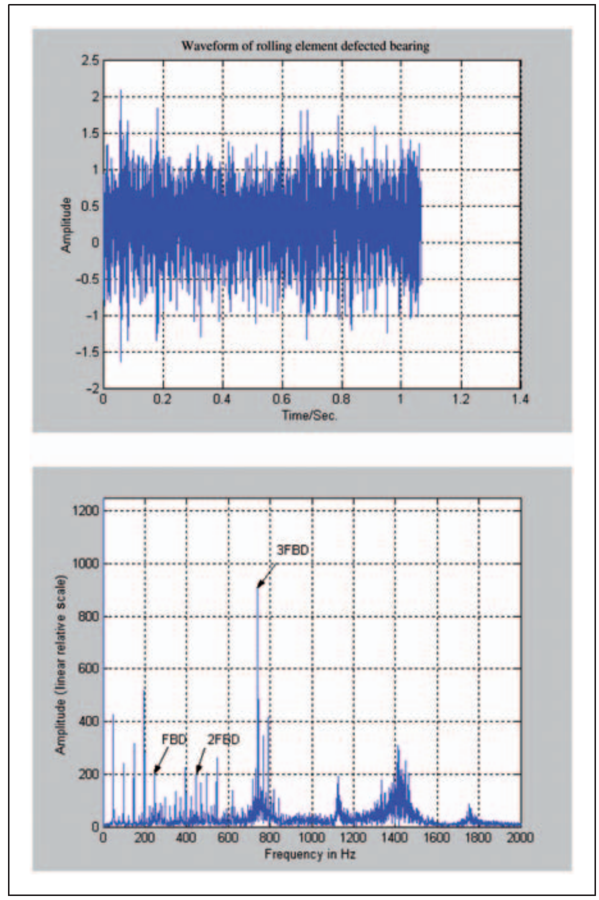

Figure 1. A typical waveform and its FFT spectrum of balls defected bearing vibration signal.

$$\text{Peak Value} = \mathrm{A}_{\max} \tag{1}$$

$$\text{RMS} = \sqrt{\frac{\sum_{n=1}^{N} [A(n)]^2}{N}} \tag{2}$$

2.1.3. Crest factor. The simplest approach to measure defects in the time domain is using the RMS approach. However, the RMS level may not show appreciable changes in the early stages of gear and bearing damage. A better measure is to use "crest factor." which is defined as the ratio of the peak level of the input signal to the RMS level as shown in equation (3). Therefore, peaks in the time series signal will result in an increase in the crest factor value. This feature is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth breakage on a gear or a defect on the outer race of a bearing. The crest factor feature is not considered as a very sensitive technique.

$$\text{Crest Factor} = \text{Peak Level}/\text{RMS Level} \quad (3)$$

Here: A_{max} = Maximum amplitude value in the time domain,
A (n) = Amplitude of the nth digitized point in the time domain, N = Number of point in time domain.

2.1.4. Statistical methods. Statistical analysis can also be carried out on time-domain data. The probability density is the probability of finding instantaneous values within a certain amplitude interval, divided by the size of the interval. All signals will have a characteristic probability density curve. These curves if derived from machinery vibration signals can subsequently be used in machine condition monitoring.

2.1.5. Probability density moments. The shape of the probability density curve can be described by a series of single-number indices. The indices are the moments of the curve and these are analogues to mechanical moment about the centroid of a plane.

2.1.6. Kurtosis (K). Kurtosis as explained in equation (4) is defined as the fourth moment of the distribution and measures the relative peakedness or flatness of a distribution as compared to a normal distribution. Kurtosis provides a measure of the size of the tail of distribution and is used as an indicator of major peaks in a set of data. As a gear wears and breaks this feature should indicate an error due to the increased level of vibration. The equation for kurtosis is given by:

$$\mathrm{K} = \frac{\sum_{n=1}^{N}[y(n)-\mu]^4}{N^*(\sigma^2)^2} \quad (4)$$

2.1.7. Skewness (S). Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution of dataset is symmetric if it looks the same to the left and right of the center point. Equation (5) is used to calculate the value of skewness.

$$\mathrm{S} = \frac{\sum_{n=1}^{N}[y(n)-\mu]^3}{N^*(\sigma^3)} \quad (5)$$

Here: y (n) = Data, n = 1,2,3 --------- N,
N = Total No. of data Samples,
μ = Mean,
σ = Standard Deviation.

2.2. Frequency-domain signature analysis technique

Digital fast Fourier analysis of the waveform has become the most popular method of deriving the frequency-domain signal. The signature spectrum so obtained can provide valuable information with regards to machine condition.

2.2.1. Signature spectrum. Spectral analysis of bearing signal is the most useful diagnostic and fault detection technique, but it requires details about the bearing geometry and the operating conditions. This technique supports identifying the various discrete frequencies if the bearing vibration signals are not submerged in background noise. Outer race defects tend to dominate because the vibrations generated here have the shortest path to the measurement transducer. Also, vibration levels increase with defect size. The frequency-domain spectrum of the vibration signal reveals frequency characteristics of vibrations if the frequencies of the impulse occurrence are close to one of the bearing characteristic frequencies, such as ball pass inner race frequency, ball pass outer race frequency, ball spin frequency, cage defect frequency as shown in equations (6) to (9). Then it may indicate a defect-related fault in the bearings.

The outer race defect frequency (FOD) or the ball pass outer race frequency is given by

$$FOD = (n/2)(N/60)\left[1-\left(\frac{bd}{pd}\right)\cos\phi\right] \quad (6)$$

The inner race defect frequency (FID) or the ball pass inner race frequency is given by

$$FID = (n/2)(N/60)\left[1+\left(\frac{bd}{pd}\right)\cos\phi\right] \quad (7)$$

The ball defect frequency (FBD) or ball spin frequency is given by

$$FBD = \left(\frac{pd}{bd}\right)(N/60)\left[1-\left(\frac{bd}{pd}\right)^2\cos^2\phi\right] \quad (8)$$

The cage defect frequency (FCD) is given by

$$FCD = \tfrac{1}{2}(N/60)\left[1-\left(\frac{bd}{pd}\right)\cos\phi\right] \quad (9)$$

Where: ϕ is the contact angle, pd is the pitch diameter, bd is the ball diameter, n is the number of balls and N is the shaft rotational speed in rpm (ROR). The FFT spectrum of ball defected bearing vibration signal is shown in Figure 1. In this figure three peaks corresponding to ball defected frequency and its resonant frequencies are present, with other peaks due to the presence of background noise (Jayaswal et al., 2008b).

Fast Fourier Transform is used in conventional frequency-domain signature analysis technique for conversion of a time-domain signal into a frequency-domain signal. Other frequency-domain techniques generally used are the calculation of power spectral density, band-pass analysis, and envelope analysis.

2.2.2. Band-pass analysis. Band-pass analysis is yet another technique of reducing the quantity of data made available in a spectrum to manageable proportions. The technique involves monitoring of a band of frequencies either broad or narrow, in which defect frequencies of components are anticipated, known as discrete frequency monitoring. The frequency of interest in the detection of bearing faults is the modulating frequencies because the resonant frequency of housing is high and the number of spectral lines is limited. It is difficult if not impossible to resolve sidebands. The band-pass technique allows one to get a direct measure of the frequency of the modulating signal (MacInerny and Dai, 2003). The purpose of band-pass filtering is to reject the low frequency high amplitude signals associated with unbalance, misalignment, looseness and due to random noise. Band-pass analysis is a technique of reducing the quantity of data made available in a spectrum to manageable proportions. Thus the band-pass filtering technique can be employed to extract the features of the defected bearing for further fault categorization

2.2.3. Envelop spectrum. The analysis of envelop spectra involves spectral analysis of the envelope or amplitude modulation component of a time history. It is particularly useful for providing diagnostic information concerning early damage to rolling element bearings. In the early stages of a bearing fault, the impulses produced by the fault are very short in duration and the energy associated with the impulses is distributed over a very wide frequency range. Because of this, frequency analysis in the range of the fundamental bearing frequencies will often not reveal any early stages of bearing faults. The envelope of the time history, however, contains information about the impact rate and the amplitude modulation. Discrete faults along the inner and outer races of a rolling element bearing generate impulses at a rate which corresponds to the contact with the rolling element. Discrete faults along the inner race rotate in and out of the loaded zone, generating the amplitude modulation. These faults can be detected by spectrum analysis of the envelop spectrum peaks.

The envelope signal is generated by the following procedure as shown in Figure 2(a). The bearing vibration time history is octave band-pass filtered around a bearing resonance to reduce components that are unrelated to the bearing and the signal is enveloped (amplitude demodulation) by full-wave rectification and low pass filtration or via Hilbert transformation. Then, the spectrum of envelope signal is analyzed. It can be easily seen in Figure 2(b), and in Figure 1, that background noise is eliminated with the help of demodulation.

The fast Fourier transform has the drawback that when a signal is nonstationary or noisy, even in FFT, time information is lost. Many researchers have used short-time Fourier transform (STFT) to overcome the time information loss problem although low resolution problems exist in STFT. The wavelets transform is currently used to overcome both the time information and low resolution problems. A major advantage of the wavelets transform is that this method can exhibit the local features of the signals and give account of distribution of energy over frequencies which changes from one instant to the next (Jayaswal et al., 2008c).

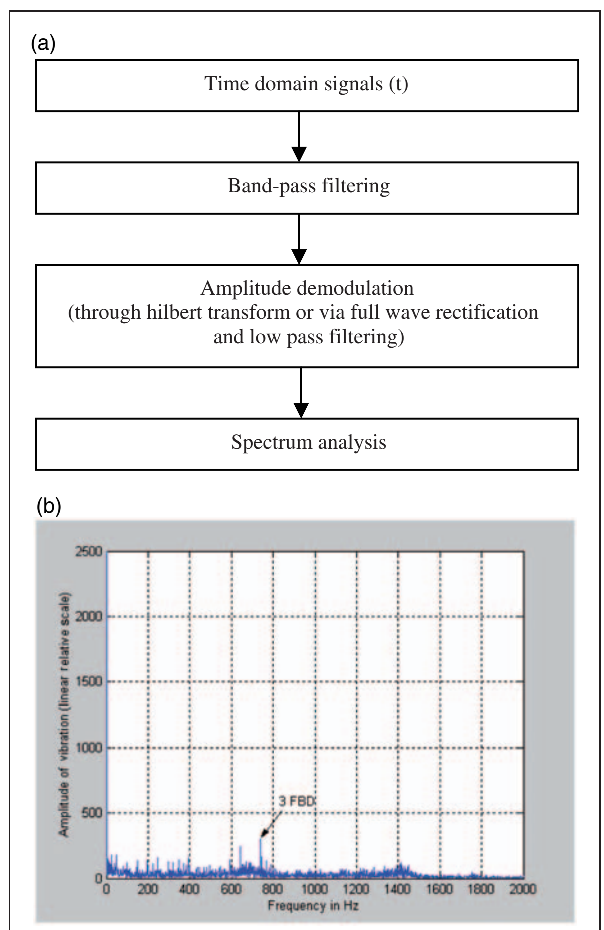

Figure 2. (a) General procedure of envelope analysis; (b) a typical spectrum after envelope analysis.

The confidence of the bearing fault diagnosis can be improved by using a range of failure indicators including performance indices, oil analysis, thermography and motor current readings in conjunction with vibration analysis. Theses indicators are generally assimilated and analyzed by human experts. But the computational expert systems which are based on neural network, fuzzy logic, rule based logic and hybrid techniques, are being used to automate the process.

3. ANN, fuzzy logic and wavelet transform in fault diagnosis

With the development of soft computing techniques such as artificial neural network (ANN) and fuzzy logic, there is a growing interest in applying these approaches to the different areas of engineering. These systems gained popularity over other methods, as they are model-free estimators capable of synthesizing nonlinear and noisy systems. Fuzzy logic was developed as a way of representing, manipulating, and utilizing uncertain information (information that is usually expressed in linguistic terms). The recent surge of interest is in merging or combining NN and fuzzy logic system into a functional system to overcome their individual weaknesses. Wavelet analysis is an emerging field of mathematics that has provided new tools and algorithms for the type of problems encountered in process monitoring.

The monitoring and diagnosis of machinery is a well-established discipline, but much progress remains to be made in automating diagnosis as well as developing low-cost reliable technologies that can be applied cost-effectively in the majority of production environment. Developments in micro-technology and artificial intelligence have driven the trends toward more extensive onboard diagnostics. Recent systems have relied on artificial intelligence techniques to strengthen the robustness of diagnostics systems. Four artificial techniques have been widely applied as expert systems, neural networks, fuzzy logic, and model-based systems (Mann et al., 1995). Different kinds of artificial intelligence methods have become common in fault diagnosis and condition monitoring. For example, fuzzy logic and neural networks have been used in modeling and decision making in diagnostics schemes. Neural networks-based classifications are used in diagnosis of rolling element bearings.

Shikari and Sadiwala (2004) worked on automation in condition-based maintenance using vibration analysis. In this work, the importance of intelligent systems in CBM is focused. Dyke (1998) describes an example of the application of the DLI engineering ExpertAlert expert automated diagnostics system to successfully diagnose machine tool spindle bearing problems. Sima (1995) proposes a strictly neural expert system architecture that enables the creation of the knowledge base automatically by learning from example inferences. Badyopadhya et al. (n.d.) have developed an expert system for real-time condition monitoring using vibration analysis for turbine bearing. Poyhonen et al. (2002) have applied support vector classification to fault diagnostics of an electrical machine.

Zhenya et al. (1992) proposed a multilayer feed forward network-based machine state identification method. They represent certain fuzzy relationships between the fault symptoms and causes, with high nonlinearity between the input and the output of the network. The rolling element bearing signals were investigated by Jun and Lias (2007), according to the principle that the wavelet can extract the signal envelope. A wavelet-based self-information extracting envelope method was applied, and application of the method demonstrates that the method is effective to extract the rolling bearing signal envelope and is useful to analyse the bearing faults (Jun and Lias, 2007).

Four approaches based on bispectral and wavelet analysis of vibration signals are investigated as signal processing techniques for application of a number of induction motor rolling element bearing faults by Yang et al. (2003). A general methodology for machinery fault diagnosis through a pattern recognition technique is developed by Sun et al. (2004) – this involves data acquisition, feature extraction, mapping for feature fusion, and piecewise-linear classification and diagnosis. They conclude that to increase the sensitivity and reliability of pattern recognition, one is encouraged to include as many feature parameters as possible without concern for the redundancy or numerical singularities.

Satish and Sharma (2005) demonstrate a novel and cost-effective approach for diagnosis and prognosis of bearing faults in small and medium-size induction motor. In this work, a fuzzy back-propagation network was developed by combining neural network with fuzzy logic to identify the present condition of the bearing and to estimate the remaining life of the motor.

Fan and Zuo (2006) proposed an effective method to extract the modulating signal and to detect the early gear fault. In this new fault detection method, a combination of Hilbert transform and wavelet-packet transform were used. Both simulated signals and real vibration signals collected from a gearbox dynamics simulator were used to verify the proposed method.

Duraisamy et al. (2004) have described a comparative study of membership functions for design of a fuzzy logic fault diagnosis system for single-phase induction motor.

Intelligent systems cover a wide range of techniques related to hard science such as modeling and control theory, and soft science such as artificial intelligence.

Intelligent systems, including neural networks, fuzzy logic, and wavelet techniques utilize the concepts of biological systems and human cognitive capabilities. These three systems have been recognized as a robust alternative to some of the classical modeling and control methods (Becerikli, 2004).

3.1. Wavelet transforms

Wavelet transform (WT) is a mathematical approach that decomposes a time-domain signal into different frequency groups. Wavelet algorithms process data at different scales and resolutions. If we look at a signal with a large "window", we should notice gross features. Similarly, if we look at a signal with a small window, we should notice detailed features. The wavelet transform involves the use of a prototype wavelet function, called an analyzing wavelet or mother wavelet. The temporal analysis is performed with a contracted, high frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion, data operation can be performed using just the corresponding wavelet coefficients. If we further choose the best wavelets adapted to our data, or truncate the coefficients below a threshold, then data is sparsely represented. This makes wavelets an excellent tool in the field of fault diagnostic.

3.2. Neural networks

According to the DARPA Neural Network Study, a neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes.

According to Haykin (1994) a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

ANNs have been used in an increasing number of real-world problems of considerable complexity. Their most important advantage is in solving problems that are too complex for conventional technologies, like problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well-suited to problems that people are good at solving, but for which computers are not. These problems include pattern recognition and forecasting (which requires the recognition of trends in data).

Neural networks are a different paradigm for computing: von Neumann machines are based on the processing/memory abstractions of human information processing, neural networks are based on the parallel architecture of animal brains. Neural networks are a form of multiprocessor computer system; with simple processing elements a high degree of interconnection simple scalar messages adaptive interaction between elements.

A biological neuron may have as many as 10,000 different inputs, and may send its output (the presence or absence of a short-duration spike) to many other neurons.

Neurons are wired up in a 3-dimensional pattern. Real brains, however, are orders of magnitude more complex than any artificial neural network so far considered.

A neural network is a computing system made up of simply, highly interconnected processing elements (neurons). The computing system processes information by its dynamic state response to external inputs. By this definition, two main elements make up a neural network, i.e processing elements and interconnections. The structure of a neural network is defined by the interconnection architecture between the processing elements, the rules that determine whether a processing element will fire, and the rules governing changes in the related importance of individual interconnections to a processing element's input. It is constructed and modified by training of the network. A neural network is usually divided into three parts: the input layer, the hidden layer and the output layer. In classification, the input layer has n processing elements which represent n elements of a feature vector and the neurons in the output layer represent the pattern class of conclusion. The hidden layer to the neural network allows it to develop its own representation of the mapping from inputs to outputs.

Neural network technology is based on the massive parallelism (a large number of neurons working simultaneously) and high connectivity of the neurons, which differentiate it from conventional computing. Each neuron in a network receives input signals from several other neurons, and in turn passes a single signal to other neurons through weighted connections feeding into a summation box. The output signal passes through several pathways to provide an input signal to other neurons. The connection between any two neurons is called a synapse, through which neurons send and receive messages to each other. Some of the connections are stronger than others based on the adaptive coefficients often referred to as weights. Operating individually, a neuron lacks computational strength; however, the high connectivity among neurons provides the strength and speed that make neural nets such a powerful algorithm. Multi-layer perceptron (MLP) is perhaps the most popular network architecture in use today, developed originally by Rumelhart and McClelland (1986). Important parameters in MLP design include the number of hidden layers and the number of units in each layer (Haykin, 1994; Bishop, 1995).

Back propagation algorithm, a generalization of the least mean square (LMS) method, is used to train MLP networks with an approximate steepest descent algorithm, in which the performance index is the mean square error (Fausett, 1994; Patterson, 1996). Modern second-order algorithms such as conjugate gradient descent and Levenberg–Marquardt (Shepherd, 1997) are substantially faster (e.g. an order of magnitude faster) in some applications, but more complicated than back propagation. Back propagation provides a way of using examples of a target function to find the coefficients that make a certain mapping function approximate the target function as closely as possible.

The mapping function used in back-propagation is the computation carried out by a fully connected feed-forward network. Each node in the input layer brings into the network the value of one independent variable. The nodes in the hidden layer calculate the weighted sum of the inputs using its unique connection strengths as weights (included in the sum is a threshold, or bias). Next, the hidden node computes a sigmoid function of its sum. The sigmoid function limits the value to a certain range. Each hidden node then sends the results to the output node. Each output node performs a similar calculation and outputs the resulting value as an estimate of the independent variable it represents. The nature of the mapping carried out by the network depends on the values of the weights.

3.3. Fuzzy logic and rule-based logic

Fuzzy logic has proven ability in mimicking human decisions, and the bearing fault diagnosis problem has typically been solved by an experienced engineer. Fuzzy logic is promising for automation in the area of bearing vibration diagnosis if the input data is well processed Goddu et al. (1998). The advantages of the fuzzy logic approach include the possibility of changing the linguistic rules into decisions by copying the procedure and thinking of a human analyzer. The rules that include uncertainty and inaccuracy are changed into numbers describing the severity or the probability of fault. The rules and membership functions can be tuned so that the sensitivity of the system is good. Fuzzy logic systems address the imprecision or vagueness in input-output descriptions of systems using fuzzy sets. Fuzzy sets have no crisp boundaries and provide a gradual transition between membership and non-membership of elements in a set. A fuzzy set can be defined mathematically by assigning to each possible individual in the universe of discourse, a value representing its grade of membership in the fuzzy set. This grade corresponds to the degree to which that individual is similar or compatible with the concept represented by the fuzzy set (Rajasekaran and Vijaylakshmi, 2004). Fuzzy logic applies fuzzy set theory to data, where fuzzy set theory is a theory of classes with unsharp boundaries and the data belongs in a set based on its degree of membership. The membership value can be any value between 0 and 1. The advantage of applying fuzzy logic to condition-based maintenance is that it is flexible, making allowances for unanticipated behavior. Defining the fuzzy logic model requires inputs, outputs and rules.

4. Experimental setup and data acquisition

In the present work the vibration signatures were collected from bearing housing of an experimental setup. The experimental setup was designed to evaluate the bearing signatures in healthy and different faulty conditions as inner race, outer race, ball defect under the constant speed and operating conditions. To fulfill the requirements of our purpose a speed control unit is provided to maintain the constant speed, flexible coupling for the easy removal of the shaft from the experimental setup to mount or dismount the test bearing. Two rotating disks of same dimension and same material are also provided to maintain the shaft in loaded condition. This experimental setup was used to predict faults in antifriction bearings. The setup consists of a shaft with two rotors, which is supported on two self aligning double row ball bearings. An induction motor coupled with a flexible coupling drives the shaft. A self-aligning double row ball bearing is mounted at the driver and the free end. The various components of the experimental setup are listed as follows: Shaft, Rotors, Self aligning ball bearing, Flexible coupling, Motor $-0-0.55$KW, $220-240$V.

The shaft of the experimental setup was driven by a DC motor through a flexible coupling. The test rolling elements bearing SKF 1205EKTN9/C3 were mounted in housing and loaded by two rotating discs of the same materials and the same dimensions. A CSI 359 accelerometer and 2400 Dynamic signal Analyzer are employed to collect the vibration signals. Four rolling element bearings, one healthy and three with different

Table 1. Different defect details for three faulty bearings

S.No.	Bearing name	Bearing defect	Location of defect Number of defects	Defect size
1	Faulty-1	Ball defect	2 balls in one row, one by one	1*1mm, 0.1mm, deep
2	Faulty-2	Inner race defect	3 Defects at each row. 3 mm distance, both rows with defects	1*1mm, 0.2 mm, deep
3	Faulty-3	Outer race defect	3 Defects at each row. 3 mm distance, both rows with defects	1*1mm, 0.2mm, deep

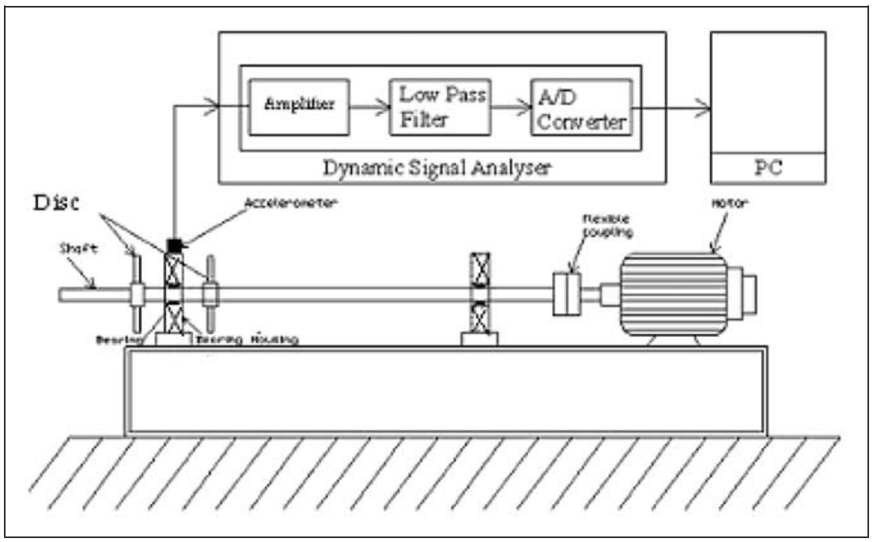

Figure 3. Experimental setup and data acquisition.

defects, are tested. The parameters of the above self-aligning double row ball bearings are: number of balls at each row 13, diameter of ball 7.5 mm, medium diameter 38.5 mm and contact angle 0 degree. The experiments are carried out for four bearings numbered healthy, faulty-1 (rolling elements defected defect), faulty-2 (inner race defect), and faulty-3 (outer race defect) as discussed in Table 1.

The calculated fault frequencies for bearing are FID = 385 Hz, FOD = 261 Hz, FBD = 245 Hz. The vibration signals are collected at a constant shaft rotational speed FOR = 2890 rpm and constant loading from each bearing configurations. The data were collected using an accelerometer placed in the radial direction to the loading of the bearing. The above signals were filtered by a low pass filter of cut-off frequency of 3000 Hz and digitized at the sampling frequency of 7680 Hz with the use of dynamic signal analyzer. The vibration acceleration data in the form of an analog signal is collected from bearing housing through accelerometer and the output of accelerometer is transferred in a signal analyzer. The signal is sampled and converted into a discrete signal in a dynamic signal analyzer as shown in Figure 3. This discrete signal is then transferred and stored in a personal computer for the purpose of analysis. Data is collected for healthy, faulty-1, faulty-2 and faulty-3 bearings.

5. Expert system-I

This section outlines a neural-network-based rolling contact bearing condition monitoring system (Expert System-I) for healthy and three fault state classification. The vibration processed data were fed to a back propagation neural network to be trained. The developed diagnostics system was then tested to predict various bearing conditions. In the present work an artificial neural network is used as a fault detection tool for bearing fault identification. For artificial neural network design, an error back propagation algorithm with linear transfer function for input layer and sigmoidal transfer function for hidden and output layer is used. Training and testing data were collected from the bearing housing for one healthy and three faulty bearings of the experimental setup. The schematic block diagram of the diagnostic system is given in Figure 4. It consists of a vibration data acquisition and processing unit, a filtering unit, a feature extraction

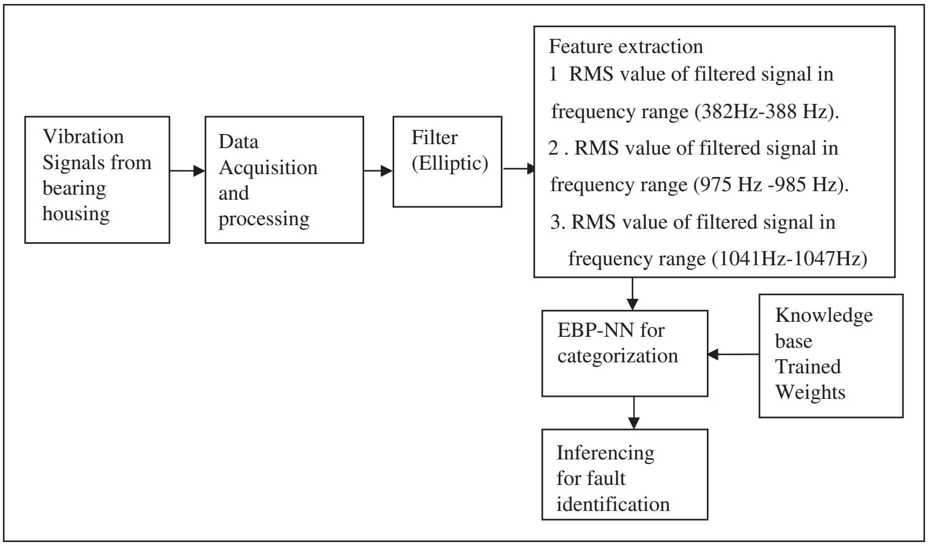

Figure 4. Diagnostics system (Expert system-I).

unit, an EBP-ANN unit, and an inferencing unit for the fault identification. Vibration time signals stored in a personal computer are filtered with a band-pass filter at three nodes corresponding to three fault frequencies as outer race defect frequency (FOD), inner race defect frequency (FID), and ball defect frequency (FBD). RMS value of the filtered time-domain signal of each node is used as training data; 75% data is used for training the network. The developed network is then tested with 25% of the dataset

5.1. Feature extraction

It was observed during investigation that in the predominance of other faults the fault characteristic in which we are interested may not find its sufficient representation. Filtering the signal around the expected fault frequency may be the solution to extract the representation of fault for the analysis and prediction. Filtering a signal leave signal component of interest and all other signal components subsided within some tolerances depending on the efficiency of the filter. The pass-band analysis is a helpful technique of reducing the quantity of data made available in a spectrum to manageable proportions. The technique involves monitoring only a band of frequencies, either broad or narrow, in which defect frequencies of components are anticipated. In the present work, vibration acceleration signal of each bearing is filtered in three frequency bands using MATLAB filter (Elliptic Filter) corresponding to inner race defect frequency (± 3), ball defect frequency (± 5) fourth harmonic, outer race defect frequency (± 3) fourth harmonic. RMS value of these three filtered signals is used as a feature vector (parameters of diagnostic importance to train and test the EBP-NN for fault identification. Parameters are used as:

1. RMS acceleration values of filtered signal in frequency range (382 Hz–388 Hz)
2. RMS acceleration values of filtered signal in frequency range (975 Hz–985 Hz)
3. RMS acceleration values of filtered signal in frequency range (1041 Hz—1047 Hz).

The RMS values of each bearing condition at each frequency band are shown in Tables 2 to 5.

5.2. Knowledge base generation

In general, human knowledge is vague and imprecise. Human thinking and reasoning frequently involves inexact information. An expert system should, therefore, be able to cope with such inexact and incomplete information. The knowledge base is at the heart of the fault diagnosis system as it provides the reference values for normal and fault categories. The knowledge base is created from an experimentally obtained database. A major bottleneck in a building expert system is the process of acquiring the required knowledge in the form of production rules. Some of the weights of the parameters are embedded in the knowledge base after training the network with known cases. Initially these weights are selected randomly. Then these weights are used in the construction of production rules. The RMS values of four bearing conditions (known cases) at each filtering band is used for the generation of the knowledge base.

Each data input pattern uses a normalized array scaled in a range of 0.1 to 0.9. The values of each pattern are normalized for efficient processing by

Table 2. RMS values of healthy bearing signals, filtered in three frequency band

S. No.	Ball pass frequency band	Inner race ball pass frequency band	Outer race ball pass frequency band
1	0.01944	0.01358	0.01032
2	0.01795	0.01287	0.00839
3	0.01384	0.01328	0.00939
4	0.01547	0.01722	0.01161
5	0.01795	0.01616	0.00888
6	0.01955	0.01727	0.01115
7	0.01509	0.01564	0.01197
8	0.01979	0.02268	0.00820
9	0.01322	0.01545	0.01251
10	0.01818	0.01532	0.01179
11	0.01695	0.01262	0.01100
12	0.01806	0.01591	0.01336
13	0.01493	0.01192	0.00972
14	0.01695	0.01310	0.00671
15	0.01565	0.01194	0.00688

Table 3. RMS values of outer race, defected bearing signals filtered in three frequency band

S. No.	Ball pass frequency band	Inner race ball pass frequency band	Outer race ball pass frequency band
1	0.01856	0.01767	0.04842
2	0.01751	0.01743	0.07428
3	0.01475	0.01261	0.07905
4	0.01891	0.01821	0.02338
5	0.01691	0.01592	0.06531
6	0.01948	0.01774	0.06849
7	0.02085	0.01688	0.07242
8	0.02079	0.01742	0.07643
9	0.01816	0.01333	0.07501
10	0.02022	0.01453	0.07051
11	0.01686	0.01768	0.07187
12	0.01901	0.01643	0.07572
13	0.02030	0.01609	0.07269
14	0.01997	0.01778	0.07515
15	0.01711	0.01802	0.07604

Table 4. RMS values of inner race defected bearing signals filtered in three frequency band (reproduced)

S. No.	Ball pass frequency band	Inner race ball pass frequency band	Outer race ball pass frequency band
1	0.01205	0.01998	0.00932
2	0.01860	0.01792	0.00783
3	0.01558	0.02278	0.00895
4	0.01527	0.02158	0.00878
5	0.01920	0.02460	0.01075
6	0.01270	0.02292	0.00985
7	0.01414	0.02387	0.01161
8	0.01284	0.02076	0.00783
9	0.01487	0.02411	0.00767
10	0.01584	0.02728	0.00838
11	0.01399	0.02331	0.00938
12	0.01473	0.02482	0.01013
13	0.01619	0.02314	0.00914
14	0.01501	0.02399	0.00721
15	0.01475	0.02206	0.00932

Table 5. RMS values of rolling element defected bearing signals filtered in three frequency band (reproduced)

S. No.	Ball pass frequency band	Inner race ball pass frequency band	Outer race ball pass frequency band
1	0.01703	0.01503	0.00892
2	0.01592	0.01228	0.00957
3	0.01736	0.00923	0.00853
4	0.01674	0.01140	0.00890
5	0.01353	0.01188	0.01037
6	0.01406	0.00782	0.01035
7	0.01376	0.00657	0.00982
8	0.01357	0.01561	0.01408
9	0.01524	0.01604	0.00799
10	0.01346	0.01097	0.00745
11	0.01604	0.01123	0.00901
12	0.01406	0.01621	0.00964
13	0.01600	0.01379	0.01089
14	0.01558	0.01391	0.00804
15	0.01162	0.01171	0.00788

the network. The normalization is carried out using a linear mapping given as

$$X = \frac{(X_r - X_{N\min}) * (X_{N\max} - X_{N\min})}{(X_{\max} - X_{\min})} + X_{N\min}$$

Where X is the normalized variable, X_r is the real value of the variable before normalization, X_{max} and X_{min} are the maximum and the minimum values of the variable before normalization and X_{Nmax} and X_{Nmin} are the maximum and minimum values of the variable after normalization.

The training of EBP-NN was performed by taking various network architectures. It was found that the architecture with three nodes at the input layer, eight nodes at the hidden layer, three nodes at the output layer and linear transfer function at the input layer nodes, that sigmoidal transfer function at hidden and outer layer nodes converges fast and give minimum training error, and therefore a single layer 3-8-3 EBP-NN models is trained to diagnose various categories of faults. The network is trained with the normalized dataset having three input data as an RMS value of filtered signal at three nodes to inner race defect frequency (± 3), ball defect frequency (± 5) fourth harmonic, outer race defect frequency (± 3) fourth harmonic and three output sets corresponding to the respective fault. Data is feed forwarded in the network from input to output layer, the difference is checked with the targeted output and the error is back propagated to adjust synaptic weight between the output-hidden layer and the input-hidden layer. The process is repeated until the sum of the square error become less than 0.1.

5.3. Methodology

ANN should be so designed that it should give minimum error for the whole set of input values in the work space which it represents. During training, after initializing, weights between layers are to be adjusted every epoch to give lesser error than the previous epoch. Since in multilayer ANN the error surface is near elliptical, so the steepest distant method is chosen for weight adjustment during training. Since in our case we are working with the known target values during training we have chosen the error back propagation algorithm to propagate the error back to each node to adjust the weight between nodes.

The EBPNN model, which is an optimizing procedure based on gradient descent that adjusts the weights to reduce the system error is hierarchical, i.e., the network always consists of at least three layers of neurodes. The model illustrated below has three layers of neurodes; namely the input, output and the middle layer neurodes.

The input layer has three inputs, the outputs of the input layer neurodes are the same as the inputs. The numbers of middle layer neurodes are decided by a trial and error method, which is optimized to eight for training the experiments conducted in this work. The output layer has three neurodes, which is assigned as in Table 6. The outputs of the output layer neurodes have either a value of 0.1 or 0.9.

Every input layer neurode is connected to each of the middle layer neurodes, by inter-layer connections. Every connection carries a weight factor, which is initially assigned by a random generator algorithm. The weights are scaled in the range of –1 to + 1. The output and the middle layer neurodes are also connected similarly. The same random generator also initially generates the weights on these connections. These inputs are fed to the input layer of the EBPNN. Each of the outputs of the input layer neurodes is multiplied with the weights, on the inter-layer connections of a middle layer neurode and form the input to the middle layer neurode. A sigmoid activation function is used that transforms the input value of the middle layer neurodes to a scaled output. Following through the network, these outputs from the middle-layer neurodes are treated as inputs to the output layer neurodes. The summation of the product of all the middle layer outputs and the inter-layer connection weights to an output layer neurode forms the input to that output layer neurode, where the same sigmoid activation function is applied and the output is computed. This output is compared to the assigned (targeted) value of each output node and the difference in the actual and computed outputs is calculated, which forms the error at the output layer. This procedure constitutes the forward flow of the back propagation model. The error computed is back propagated through the same network by changing the weights on the neurodes. To change the weights Delta vector is computed. With the updated weights, the error is calculated again, the next training set is taken and the error is adjusted, and the iterations are carried out until the error is minimized.

Table 6. Targeted output for output layer nodes

S. No.	State of bearing	Node-1	Node-2	Node-3
1.	Healthy	0.9	0.9	0.9
2.	Inner race defect	0.9	0.1	0.1
3.	Outer race defect	0.1	0.9	0.1
4.	Ball defect	0.1	0.1	0.9

The EBP-NN model with architecture 3-8-3 was used with different learning rates and momentum factors. The best diagnostic parameters were obtained by those models whose learning rate $\eta = 0.08$ and sigmoidal gain $\lambda = 0.8$ respectively. ANN is trained with 60 sets of data for training and 16 sets of data for testing. The result of training and testing are represented by Figure 5 in illustrating that the target sum of the square error is achieved during batch training in 116,675 epochs.

The network has been successfully tested for bearing condition identification for healthy bearing, inner race defect bearing, outer race defect bearing, and ball defect bearing categories. The results for 16 cases are shown in Table 7 and Figure 6.

6. Expert system-II (Neural fuzzy expert system)

The Expert system-II uses fuzzy concepts and EBP-NN for Rolling Contact Bearing fault diagnostics. The fuzzy concepts account for the uncertainty or imprecision in the experimental observations in both the healthy and faulty conditions. The schematic block diagram of the Expert system-II is given in Figure 7. It consists of a vibration data acquisition and processing unit, wavelets decomposition unit, and feature extraction unit for frequency-domain parameters. The system includes a fuzzification unit, an EBP-ANN unit and an inferencing unit for fault identification. To handle uncertainties in symptoms descriptions and data, fuzzy logic and fuzzy NN have emerged as a helpful tool in expert system based diagnosis. The diagnostic system as shown in Figure 7 is used to detect the bearing condition according to the fault on the bearing component. The vibration signals stored as explained in Section 4 are used. The EBP-NN used for pattern recognition and fuzzy logic is used to reduce the uncertainty. The four output nodes of EBP-NN are selected. The fuzzified values for each bearing condition are values between 0 to 1. The input values at nine nodes of input layer of EBP-NN are also fuzzifed values of vibration features. The input values of input layers are also between 0 to 1. The if and then fuzzy rules are used to find the fuzzified value of each vibration feature.

The first block of Expert system-II is data acquisition, and processing is used to capture the vibration signals of bearings and for processing purpose. The 50 datasets for each bearing condition is stored with the help of experimental setup.

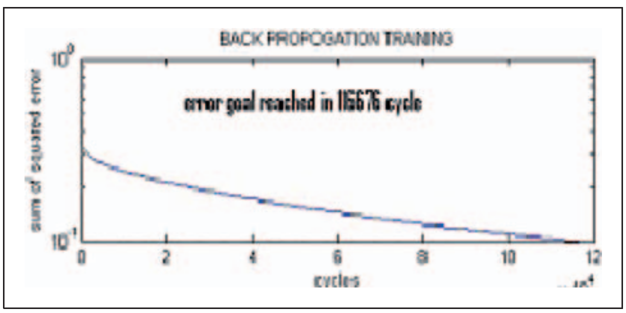

Figure 5. Result of training and testing.

6.1. Features for diagnostics importance

In building an expert system, one of the major problems encountered is to extract the knowledge (information) from human experts/measured data. That is why identification and encoding of the knowledge are the two most complex and arduous tasks encountered in the construction of an expert system. The stored vibration signals are used to determine the features for diagnostics importance.

Table 7. The output of EBP-NN system and bearing condition results of 16 test data

Input to EBP-NN (before normalization)			Output of EBP-NN			
Node-1	Node-2	Node-3	Node-1	Node-2	Node-3	Fault identification
0.01872	0.01306	0.00988	0.9014	0.9367	0.9470	Healthy bearing
0.01469	0.01099	0.00769	0.9062	0.9457	0.9485	Healthy bearing
0.01337	0.01130	0.00946	0.9061	0.9462	0.9487	Healthy bearing
0.01622	0.01047	0.01049	0.9023	0.9429	0.9495	Healthy bearing
0.01549	0.02551	0.00886	0.8994	0.0761	0.0751	Inner race defect bearing
0.01244	0.02325	0.00956	0.8994	0.0764	0.0754	Inner race defect bearing
0.01322	0.02165	0.00847	0.8995	0.0784	0.0774	Inner race defect bearing
0.01375	0.02320	0.00960	0.8995	0.0780	0.0769	Inner race defect bearing
0.01658	0.01645	0.07106	0.1110	0.8874	0.0913	Outer race defect bearing
0.01748	0.01755	0.08176	0.1069	0.8933	0.0922	Outer race defect bearing
0.02337	0.01396	0.07882	0.0964	0.9085	0.0978	Outer race defect bearing
0.01926	0.01873	0.07705	0.1103	0.8881	0.0913	Outer race defect bearing
0.01757	0.00898	0.00959	0.0975	0.0925	0.9046	Ball defect bearing
0.01458	0.01218	0.00788	0.0978	0.0996	0.8975	Ball defect bearing
0.01538	0.01099	0.01115	0.0975	0.0994	0.8977	Ball defect bearing
0.01386	0.00910	0.00924	0.0976	0.0959	0.9012	Ball defect bearing

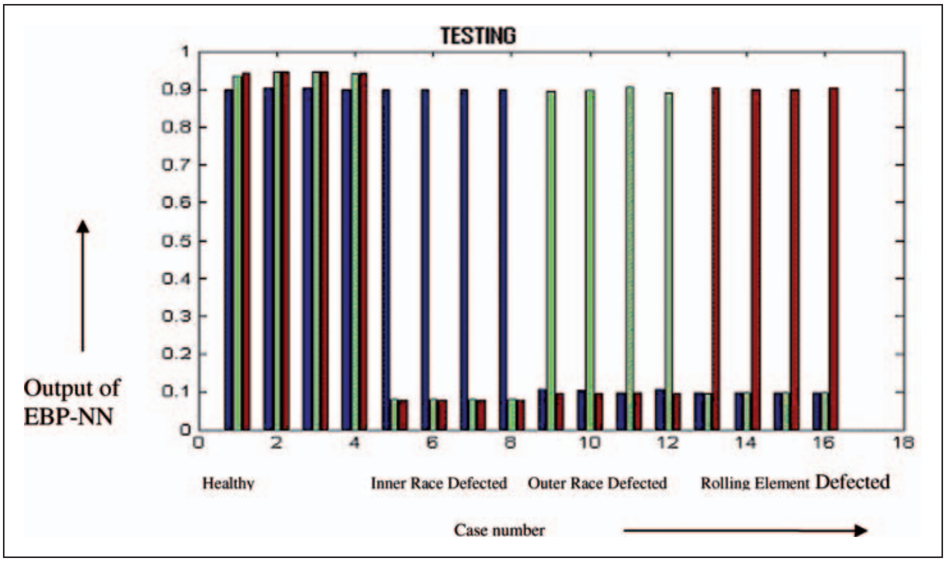

Figure 6. Plot showing testing result.

Features were extracted through wavelets packet transform of vibration signals dataset of 40 signals for each bearing condition. The wavelet decomposition is done up to 62 nodes with the help of MATLAB software. The RMS value of each bearing (healthy, inner race defected, outer race defected, balls defected) signal at 62 nodes or vectors is determined. The 22 nodes were selected for further fault categorization out of 62 nodes through consideration of available fundamental characteristics frequencies and its multiple frequencies. A further four nodes are selected through Fisher criteria as 8, 10, 18 and 36 node, where the difference is higher for mean, max, min RMS values.

The RMS (max and min) values are determined at 8, 38, 10, 18 selected decomposition vectors and stored as a feature for the generation of the knowledge base. The same 40 known vibration signals are used to determine the Median Frequency (FMED), Power at Median Frequency, Maximum Frequency (F_o), Maximum Power, Area from the Power spectrum curve generated by MATLAB algorithms.

The following algorithms or equations are used to determine the features for the input to next step of fuzzification.

(a) RMS value of the decomposed signal

The RMS value of the decomposed signal is calculated by using the following equation

$$X_{RMS} = \sqrt{(1/N)\sum_{n=1}^{N}[x(n)]^2}$$

Where, N is the number of samples and x(n) is the discrete time signal. The decomposition of the original signal is determined using db-8 wavelet.

(b) Frequency-domain parameters

The power spectral density, PSD, describes how the power (or variance) of a time series is distributed with frequency. Mathematically, it is defined as the Fourier transform of the autocorrelation sequence of the time series. An equivalent definition of PSD is the squared modulus of the Fourier transform of the time series, scaled by a proper constant term.

Frequency-domain features like median frequency, power at median frequency, maximum frequency, maximum power and area under the power spectrum curve of the vibration signal provide additional information in the assessment of fault diagnosis. The variation in the values of these parameters is used to find the change in the state of the fault, i.e the change from the healthy or the faulty state. The features are defined as follows:

(i) Median frequency (FMED) – calculated as the frequency at which the power spectrum is divided into two regions of equal power.
(ii) Power at median frequency – defined as power spectral estimate at median frequency
(iii) Maximum frequency (F_o) – calculated as the frequency at which the power is maximum.
(iv) Maximum power – the maximum power in the signal.
(v) Area – the area under the power spectrum curve.

The values of each feature are stored for the input to the next block of Expert system-II, i.e. fuzzification unit.

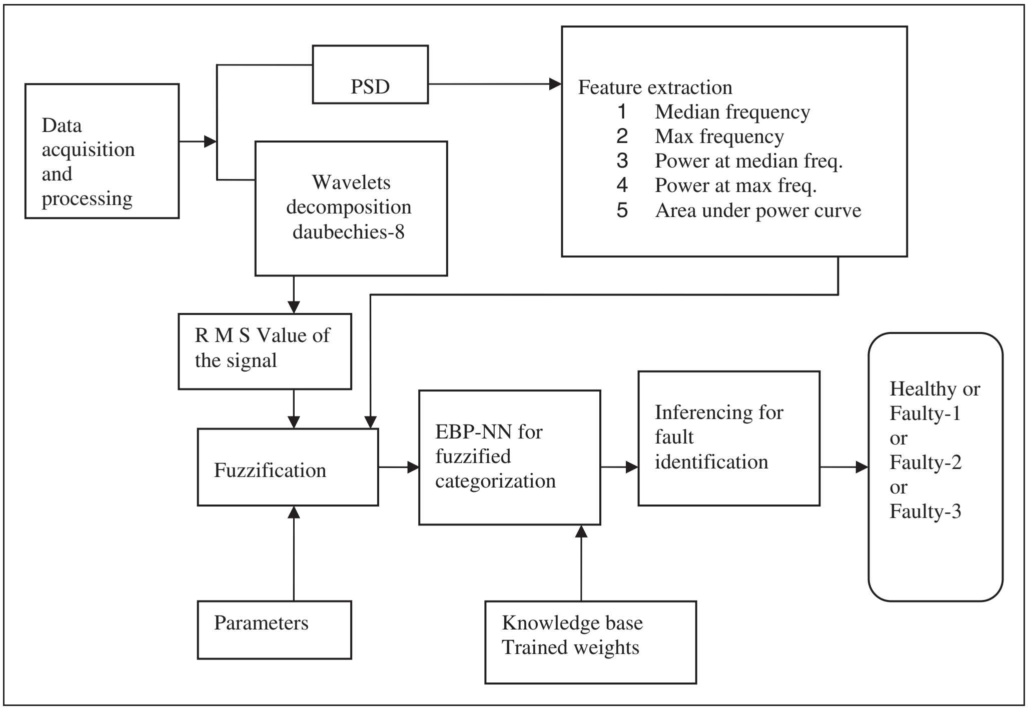

Figure 7. Block diagram of Expert system-II for bearing condition identification.

The knowledge base is the heart of the expert system as it provides the reference values of various time and frequency-domain parameters for healthy and outer race defected, inner race defected and balls defected bearing conditions. Proper design and implementation of the knowledge base significantly affects the performance of the expert system. The knowledge base acquires information on all bearing conditions to establish the relationship among the parameters. The relationships are stored as numerical values ranging from 0 to 1. By using lower, median and upper values, the triangular membership function is generated for applying the fuzzy concept for each time and frequency-domain parameters.

A total of nine features are used as five features from power spectrum density and four features as RMS value at nodes 8, 38, 10, 18 of wavelet packet decomposition.

The steps for the generation of the knowledge base are as follows:

1. Take the lower, upper and maximum occurrence value for the first parameter as WPT node 8 RMS value for healthy condition.
2. Three forms of membership function, i.e. triangular, Gaussian and bi-Gaussian are studied for fuzzification of RMS value of decomposed signals and frequency-domain parameters. Outside of these, the triangular memberhip function is used as it gives linear normalized fuzzified healthy or faulty index for the experimental parameter value. Construct the triangular membership function for each parameter separately.

Fuzzification of each parameter by using following equation:

If the value of the parameter is between (max to min) then fuzzified value of parameter is 0

3. Store the fuzzified values.
4. Repeat 1 to 3 for all frequency-domain and WPT parameters.
5. Repeat the 1 to 3 for the other three bearing conditions by using following equations:

If the value of the parameter is between (max to min) then fuzzified value of the parameter is 0.25.

The fuzzification equation is used for the outer race defected bearing condition:

If the value of the parameter is between (max to min) then fuzzified value of parameter is 0.75.

The fuzzification equation is used for Ball defected bearing:

If the value of the parameter is between (max to min) then the fuzzified value of the parameter is 1.

The (max to min) values are stored values of each feature in four bearing conditions.

In the present work we have used error back propagation artificial neural network (EBP-NN). The training of EBP-NN was performed by taking various network architectures. It was found that the architecture with nine nodes at the input layer, 12 nodes at the

Table 8. Targeted output for output layer nodes

State of bearing	Node-1	Node-2	Node-3	Node-4
Healthy	0.9	0.9	0.9	0.9
Inner race defect	0.9	0.1	0.1	0.1
Outer race defect	0.1	0.9	0.1	0.1
Ball defect	0.1	0.1	0.9	0.1

Table 9. Classification results of Expert system-II

Bearing condition	Accuracy
Healthy	90.88%
Outer race defected	88.33%
Inner race defected	83.67%
Ball defect	86.78%

hidden layer, four nodes at the output layer and linear transfer function at the input layer nodes, sigmoidal transfer function at the hidden and outer layer nodes converges fast and give minimum training error, therefore a single layer (9-12-4) EBP-NN models is trained to diagnose various categories of faults. The network is trained with the stored fuzzified dataset. Finally the inferencing unit is used for fault identification, the healthy, ball defect, the inner race defected and the outer race defected can be found directly.

The 40 vibration signals for each condition were used for feature extraction in the frequency domain and RMS value of wavelet decomposition and the parameters were fuzzified and the normalized value data was feed forwarded in the network from the input to the output layer; the difference is checked with the targeted output as shown in Table 8 and the error is back propagated to adjust synaptic weight between the output hidden layer and the input hidden layer. The process is repeated until the sum of the square error becomes less than 0.1.

The performance of this expert system for bearing fault diagnosis was tested through a remaining 10 vibration signals for each bearing condition as healthy bearing, inner race defect bearing, outer race defect bearing, and ball defect bearing categories. The expected and actual values at the output nodes are checked. The bearing condition identification results are shown in Table 9. As can be seen, the approach Expert system-II is capable of highly accurate diagnosis. In addition, although the method only achieved 83.67% accuracy at detecting inner race defects and 86.78% at ball defect conditions, the 90.88% accuracy at healthy condition and 88.33% at outer race defects will ensure that the bearing is more closely monitored as it approaches the outer race defect.

7. Conclusions

The work presented in this paper aims to develop alternative techniques to conventional and individual soft computing methods for detecting the bearing conditions. The neural networks are good at learning things and performing nonlinear mapping of numerical information whereas the main task of fuzzy logic is classification of linguistic and ambiguous information. Hence two approaches as Expert system-I and Expert system-II for the detection of bearing conditions are developed and tested, which can greatly avoid the disadvantages of individual AI approaches.

In Expert system-I the technique of using neural network for the bearing fault prediction using a filtered signal has been successfully developed and tested for the fault diagnostics of an inner race fault, an outer race fault, and ball fault categories. With this technique, excellent results have been achieved with minimum data. Due to the very high probability of bearing defects this method of non-destructive testing and prediction is of great importance in bearing fault finding. In Expert system-II WPT and PSD data is used for training and testing to interpret vibration signals of bearings in order to diagnose the bearing condition. Below are the outcomes drawn from the present work:

(i) Neural networks can be effective diagnostic tools for bearing faults through an appropriate knowledge base. The feasibility of using EBP-NN for bearing faults identification has been established. Using band-pass filters can enhance the capability of such systems to identify spread faults in rolling element bearings.
(ii) An expert-system-based fault diagnosis approach for a bearing fault using fuzzy and neural network is presented. The experiments have demonstrated that this approach can successfully diagnose the bearing condition and the accuracy is good compared with conventionally EBPNN based fault diagnosis.
(iii) A better ability of a hybrid system has been demonstrated with the use of fuzzy rules, ANN, and wavelets decomposition.
(iv) The further improvement in this expert system can be done with the use of other symptoms of bearing as temperature and noise.

Further research should be done to find out fault characteristics' relationship with different fault severity, spread and the probable range of fault frequency and the harmonics where faults may present themselves. Also research should be done to find out the characteristics with a better response so that the network could be trained for the range of speed with the range of faults. The other parameters such as lubricant properties, temperature, and noise can be incorporated to develop diagnostics system with the help of the NN and fuzzy logics. Wavelets transforms can also be used for features extraction from the vibration signals.

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