Chapter 5

Fault Diagnosis Based on Artificial Neural Network

This Chapter proposes the expert system for accurate fault detection of bearing. The study is based upon advanced signal processing method as wavelet transform and artificial intelligence technique as Artificial Neural Network (ANN) and K-nearest neighbor (KNN), for fault classification of bearing. An adaptive algorithm based on wavelet transform is used to extract the fault classifying features of the bearing from time domain signal. These features have been used as inputs to proposed ANN models and the same features have also been used for KNN. Dedicated experimental setup was used to perform the test upon the bearing. Single data set for four fault conditions of bearing is collected to train ANN and KNN. The processed and normalized data was trained by using backpropagation multilayer perceptron neural network. The results obtained from ANN are compared with KNN, ANN results proved to be highly effective for classification of multiple faults.

5.1. Introduction

The crucial component of modern rotating machinery is rolling element bearing. Fault in any one of the components of bearing can lead to catastrophic failure of the whole system. Accordingly, robust fault diagnosis scheme of bearing reasonably benefits the rotating machinery system by avoiding the premature removal of the bearing from the service. Vibration based diagnostic technique was extensively used technique for the assessment of health of the bearing and provides an easy approach in analyzing the signal response due to the defective rolling element bearing. Diagnosis of fault of rolling element bearing is considered to be an effective, when the characteristic fault features from the vibration signal response are obtained accurately, making it possible to understand the exact faulty nature of the bearing. To obtain characteristic fault features from the raw vibration signals, some of simple signal/data processing techniques have to be applied to process the raw signal such as kurtosis, crest factor, mean, standard deviation, root mean square (RMS) value of time domain signal and FFT (fast fourier transform) of frequency domain. However, the term raw vibration signal provides clear insight about its processing, so as to obtain exact fault features. Thereby, advanced signal processing methods such as wavelet transforms, empirical mode decomposition, and expert systems such as support vector machine (SVM), artificial neural network (ANN), fuzzy logic techniques etc has gain importance from past few years. Advanced signal processing techniques removes the background noise effect, speed fluctuation effect and smearing effect. Vibration signals obtained from defective bearing are considered to be non-linear and non-stationary in nature [1]. Thus, difficulty lies in extracting the fault information from the vibration signal. However, advanced signal processing techniques such as continuous wavelet transform helps in determining the fault characteristic of bearing from a non-stationary and non-linear signal. Therefore, present study is paying attention on the application of the wavelet transform which is a time-scale domain analysis for extracting the faulty features from the vibration signals obtained from defective bearing [2]. The inherent complexity of vibration waveform makes it difficult to classify the faults, thus expert data-driven technique such as ANN combined with advanced signal processing technique such as wavelet transforms (WT), efficiently performs the fault diagnosis of rotating machinery and its critical component such as bearings.

WT is an efficient technique to deal with non-linearity of signal and it is effective in analyzing the machine failures that are transient in nature [3]. Mori et.al [4] applied the discrete wavelet transform (DWT) to predict the occurrence of spalling in the rolling element bearing. Shibata et.al [5] used WT to analyze the acoustic signals generated by bearings. The significant application of WT is denoising of raw vibration signal, which leads to the enhancement of condition monitoring process of rotating machinery [6-7]. Fault diagnosis of rotating machinery are categorized into four major levels including: detection of the existing damage, localization, quantification of the damage severity and estimation of the remaining life, respectively [8]. In order to perform the efficient fault diagnosis of system, it is highly recommended to automatize the diagnosis procedures. Over the past few years, for automatizing the procedure of fault diagnosis and providing the decision about bearing health state, some of the significant tools have been developed such as ANN, SVM, genetic algorithm (GA). These tools provide the basis for automatic fault feature diagnosis. Among the various automatic feature diagnosis method, ANN proved to be more efficient and reliable for diagnosing the faulty features due to the outperforming advantages such as it involves non-linear behavior and unstable processes for complex systems. ANN is highly useful for adaptive systems.

Various researchers had applied ANN methods to diagnose the rolling element bearing faults [9-10]. Zhiqiang Chen et.al [11] studied the fault diagnosis of bearing based upon three deep neural network models (Deep Boltzmann Machines, Deep belief networks and stacked auto-encoders) to identify the fault condition of rolling bearing. Jian chen et.al [12] used multi-layer-based perceptron (MLP) ANN system to solve the problem of intelligent big-end bearing knock fault diagnosis in Internal combustion (IC) engine. They applied two MLP networks, one for fault detection and one for fault severity identification. Thus, ANN has found vast application in a fault detection, fault severity and fault classification. Unlike, the other ANN models which classified single point fault of bearings, the proposed ANN model, classifies multiple point faults (faults on two different components of bearing) along with single point fault of bearing, which proved to be the novelty of this research work. In this chapter, vibration-based monitoring technique is used to obtain the vibration signals from the different conditions of defective bearing. A combination of wavelet transforms and time domain analysis techniques are used to extract the fault features from the raw vibration signal. Then, feed forward neural network and K-nearest neighbor (KNN) is applied upon the extracted features to classify the faults. The performance of ANN is compared with another classifier KNN. The performance of classification is compared between two classifiers, to determine the potential of classifiers in classifying various faults of bearing.

5.2. Fault Diagnosis Technique

Figure 5.2. describes the flow diagram of the proposed rolling element bearing fault diagnosis system. Here applications of WT, ANN and KNN are briefly introduced for obtaining effective fault diagnosis of bearing.

5.2.1 Wavelet Transform

WT is considered to be one of the most potential non-stationary signal processing technique. It has been enormously studied and largely applied in a fault diagnosis of rotating machinery. It is being realized by means of inner product principle of signal and wavelet base. Since wavelet transform have more choices on basis function to match a specific fault symptom, it is highly beneficial for fault related feature extraction [15,16]. The theory of wavelet has been originated from the idea of dilaton and translation and wavelet transform similar to fourier transform also uses inner product transform to analyze the non-linear contents of signal by a pre-determined wavelet basis. The selection of wavelet basis is a significant step while performing wavelet transform upon the weak signals. Since the wavelet transform uses the inner product to analyze the signal. The inner product is defined as follows

$$< X(t), Y(t) >= \int_{-\infty}^{+\infty} X(t)Y^{*}(t).dt \tag{5.1}$$

The superscript* implies conjugate transposition, whereas, $< X(t), Y(t) >$ stands for operation of calculating a generalized inner product between X(t) and Y(t). In a field of mechanical fault diagnosis, inner product theory in introduced from the general expansion of signals. Any given signal can be expressed and expanded in different ways. Therefore, a signal 'x' in space of ψ can be expressed as follows:

$$x = \sum_{n \in z} a_n \psi_n \tag{5.2}$$

where, $\{\psi_n\}n \in z$ is a set of fundamental functions in space of ψ . If $\{\varphi_n\}n \in z$ is the perfect sequences in ψ space, then according to the Equation 5.2, all signals can be expressed in space ψ .Now a set of dual functions, whose expansion co-efficient can be gained by basis function is given as

$$a_n = \int x(t)\, \varphi_{\tilde{n}}^{*}(t).dt =< X, \psi_{\tilde{n}} > \tag{5.3}$$

$$a_n = \sum_{t \in z} x(t)\varphi_{\tilde{n}}^{*}(t).dt =< X, \psi_{\tilde{n}} > \tag{5.4}$$

The above expansion co-efficient are used to reconstruct the signal, where $\varphi_{\tilde{n}}$ represents the analytic function and φ_n represents the synthesis function. From Equation (5.2) a larger result of a_n develops a close relationship in between the signal 'x' and the dual functions

$\Psi_n^{\sim}$. The success of mechanical fault diagnosis lies in extracting the pragmatic and accurate features from the original signals. Therefore, seeking the mode mostly similar to the basis function, is essence of mechanical fault diagnosis system. In fault diagnosis, the most essential step is to construct the most suitable basis function and obvious signal features. Therefore, extracting the decisive features from the signal through inner product transform is the basis of the accurate condition monitoring and fault diagnosis [17]. Wavelet transform shares the perfect local properties in both time and frequency domain. In the wavelet transform, the wavelet basis function is a mother wavelet. A function of two variables is obtained by comparing the signal to the mother wavelet at various scales and positions. For mechanical fault diagnosis two major wavelet-based methods are used: wavelet decomposition based and wavelet filter-based method. Both methods use the wavelet basis function into a different form, for a signal processing of the time domain signal. The wavelet basis function necessarily implements the wavelet transform. Wavelet basis function is defined as small wave of oscillating waveform which concentrates its whole energy in short time. Traditionally wavelet transform can be divided into three category as continuous wavelet transform (CWT), Discrete wavelet transform (DWT) and wavelet packet transform (WPT). A general wavelet dictionary is given as

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \quad (5.5)$$

Now calculating the inner product operation of $W_f(u,s) =< f, \psi_{u,s} >$,the wavelet transforms of $f = X(t)$ is given by

$$W_f(u,s) = \frac{1}{\sqrt{s}}\int X(t)\Psi\left(\frac{t-u}{s}\right)dt \quad (5.6)$$

If 's' means a continuous variable, then $W_f(u,s)$ is defined as CWT while if $s = a^j$, 'a' is the scale parameter, then $W_f(u,s) = W_f(u,j)$ is defined as DWT. In detail CWT and DWT is given by equation

$$CWT(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\bar{\psi}\left(\frac{t-b}{a}\right) dt \quad (5.7)$$

where a and b are the scales and positions parameters respectively. ψ denotes the mother wavelet. Mother wavelet $\bar{\psi}$ is defined as

$$\psi(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (5.8)$$

Now DWT is derived from the discretization of CWT and is given by

$$DWT(j,k) = \frac{1}{\sqrt{a^j}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-a^j k}{a^j}\right) \quad (5.9)$$

where a and b are replaced by a^j and $a^j k$.

In the present Chapter, WT is used to process each raw vibration signal to extract three essential time domain parameters at 5 levels. The three-time domain parameters selected are mean, peak and standard deviation. They are given as

(5.10)

$$Mean = \sum_{n=1}^{N} \left(\frac{y(n)}{N}\right) \quad (5.11)$$

$$Peak = max|y(n)| \quad (5.12)$$

$$Standard\ deviation = \sqrt{\sum_{n=1}^{N} \frac{(y(n)-mean)^2}{N-1}}$$

Denoising of raw vibration signal based upon the wavelet transform, consists of three basic steps

1] Decomposition of vibration signals over an orthogonal wavelet basis using WT to get detailed co-efficient.

2] Suppress the detailed co-efficient through thresholding and keeping the co-efficient of suitably chosen level intact.

3] Reconstruction of the signal by applying the inverse WT to thresholded co-efficient. The signal obtained by such a procedure is the denoised signal. In this work Db8 wavelet was used while performing the WT of raw vibration signal. Figure 5.1 Shows the denoised vibration signals of defective conditions of bearing obtained by the application of wavelet transform upon raw vibration signal.

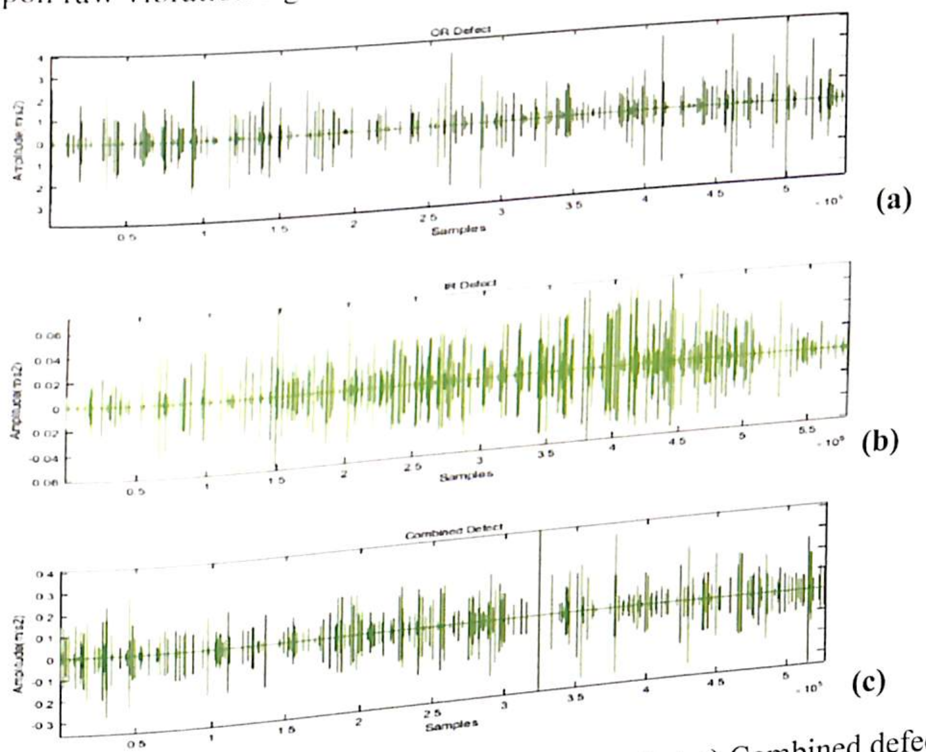


Figure 5.1 WT denoised vibration signals a) OR defect b) IR defect c) Combined defect.

5.2.2 Artificial Neural Network

ANN is a computational model, which is an interconnected assembly of simple processing elements, units and nodes. In many ANN structures, processing of the information has been carried out using single neuron, which leads to slow computation. Computational capabilities of these single neuron systems are limited by the nature of the signal function, and by the lack of a layered architecture.

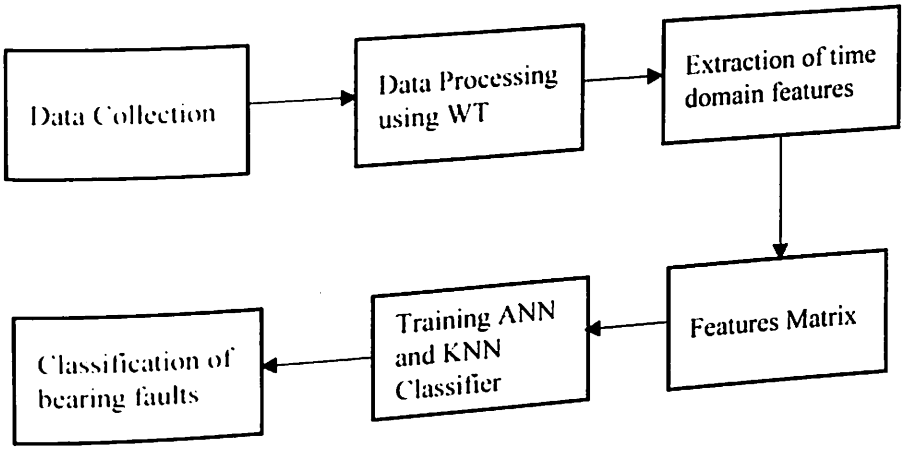


Figure 5.2 Flow diagram of proposed fault diagnosis system

Therefore, layering drastically increases the computational power of the system Computational capability of the neural network increases using a non-linear function with appropriate layering of neurons for fast computationally viable network architecture. One such network is a feed forward neural network, referred as multilayer perceptron (MLP). MLP is based upon a back-propagation algorithm running behind it. The general idea of back propagation for MLP is to reduce global error over the entire training set. The developed MLP network architecture is computed using MATLAB neural network toolbox [13] using five inputs and one output variable. The output vector response determines classification of faults. Any ANN architecture is considered to be efficient, when the difference between the target and the ANN output is minimized. Similarly, the performance of ANN also dependent upon the training process and mainly upon the suitable selection of the training algorithm. There are various algorithms available for training feed forward neural network, such as the standard backpropagation algorithm and levenberg-Marquardt (LM) algorithm. Back-propagation algorithm is reported to be most suitable for non-linear data. In the process of developing ANN models, the selection of weights and threshold values are random, therefore the ANN models formed using the same layers and same neuron quantities exhibits the different performance values after training process.

Table 5.1 Conditions of bearing fault.

Fault Size(mm) (Width×Depth)	Fault location	Fault Name
0.5×0.3	Outer race, Inner race.	0.5×0.3OR, IR.
0.75×0.5	Outer race, Inner race.	0.75×0.5OR, IR.
1.0×0.75	Outer race, Inner race.	1.0×0.75OR, IR.
1.0×0.5	Outer race, Ball.	1.0×0.5 CD.

This leads to different classification performance during the evaluation of fitness value. To prevent such a situation, in this work, ANN models are developed using different number of neurons in hidden layer (n_h = 15,20,30) for all the classes of bearing faults described in Table 5.2 and ANN model corresponding to that number of neurons is selected, which determines the best performance during evaluation of fitness value. Small number of inputs leads to faster training requiring far less iterations [14]. By performing the training and testing with different number of hidden neurons, ANN model for fault class- outer race and inner race, and for fault class-combined defect, is developed with 20 number of neurons whereas for all defect fault class condition, ANN model is developed with 15 number of neurons, using a single hidden layer. The objective of the ANN is to minimize mean square error (MSE). Here each variable in the vectors was normalized between 0 and 1 by dividing each variable by variable maxima.

5.2.3 K-Nearest Neighbor

KNN is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (minimum distance). The process of KNN is divided into two phases: the training set and the test phases. The training set trains the objects of different classes of interest. In training phase, a model is constructed from the training instances and classification algorithm finds relationships between predictors and targets. In testing phase, the model is tested based on a test sample whose class labels are known but not used for training the model. The KNN uses standard Euclidean distance to find the nearest neighbors of an example. According to the value of K and the distances, the classification of the example is performed.

5.3 Experimental Setup

The experimental setup used for this study is as shown in Figure.3.5. The test rig operates with a 3-phase AC servo motor of 1 HP capacity. In this study also, self-aligned ball bearings 1204 ETN9 of SKF were used in a bearing test setup. In the experimental studies, the defects on the components of the bearing (i.e outer race defect, inner race defect, and combined defect) were artificially generated using electro-discharge machining process, by using the dimensions as described in Table 5.1. To perform effective studies of fault diagnostic, series of experiments were conducted with varying sizes of defects. Photographs of sample inner race defect, outer race defect, and combined defect are shown in Figure 5.3. Generally, in bearing defects occurs at loading zone [8]. Therefore, defects are seeded in loading zone of bearing. Vibration acceleration signals were collected for different defective conditions of the bearing with two load conditions (no load and 50 N load) and with two different speed conditions (1500 rpm and 3000 rpm). Here the experimental data were collected two times to be able to reproduce training data. In this way a feature set of 480 features is developed (15×4×2×2=480). Here pre-amplified tri- accelerometer of Kistler 8076 k make with the sensitivity of 102.0 mv/g was used for obtaining the vibration signals. The tri-accelerometer was mounted directly on the housing of defective bearing. OR 35 real time multi-analyzer of 8 channels was used for acquisition and analysis of vibration signals. Vibration signals features and its fault classification operation of bearing are executed in MATLAB.

(a) (b) (c)

Figure 5.3 Sample Photographs of Defects (a) Outer race (b) Inner race (c) Combined defect.

Table 5.2: - ANN Model Performance for fault classifications.

Fault case	Neurons in hidden layer	MSE Value		R Value	
		Training	Testing	Training	Testing
OR & IR	15	4.43840×10^{-7}	5.30349×10^{-5}	9.99991×10^{-1}	9.99904×10^{-1}
	20	7.29874×10^{-6}	9.99824×10^{-1}	8.24936×10^{-4}	9.99998×10^{-1}
	25	1.58482×10^{-4}	3.90236×10^{-3}	9.99965×10^{-1}	9.99998×10^{-1}
Combined defect	15	2.61246×10^{-5}	3.43807×10^{-5}	9.99686×10^{-1}	9.99963×10^{-1}
	20	4.03186×10^{-10}	1.05952×10^{-6}	9.99999×10^{-1}	9.99999×10^{-1}
	25	2.86554×10^{-12}	7.63672×10^{-3}	9.99999×10^{-1}	9.72554×10^{-1}
All defect	15	1.67400×10^{-10}	1.10584×10^{-6}	9.99999×10^{-1}	9.9997×10^{-1}
	20	1.21457×10^{-10}	2.27960×10^{-6}	9.99999×10^{-1}	9.9999×10^{-1}
	25	1.34664×10^{-8}	1.94998×10^{-3}	9.99999×10^{-1}	9.9289×10^{-1}

5.4. Results and Discussions

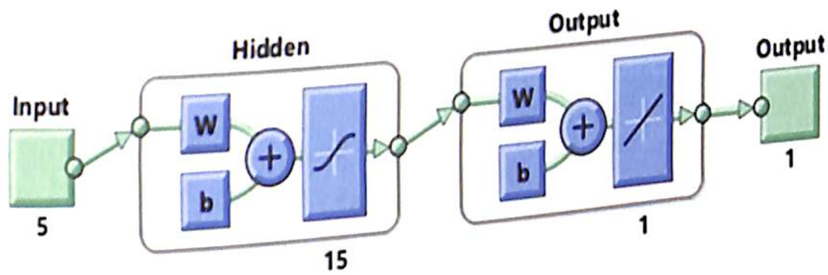
In the present work, the vibration signals are denoised using wavelet transform db8 wavelet upto five levels. After denoising, the features of time domain such as mean, peak and standard deviation was extracted at all five levels for proposed defect conditions of bearing. Thus, total 480 features were extracted and normalized from different defective condition of bearings. Out of these extracted features, 80% of data were used for training purpose and 20% of data were used for testing purpose. The three types of time domain features were extracted, along with two different speed conditions and two different loading conditions were used as input to ANN and KNN. The data sets have been allocated randomly. The input signals were normalized between 0 and 1 before feeding them into ANN and KNN model.

5.4.1 ANN implementation

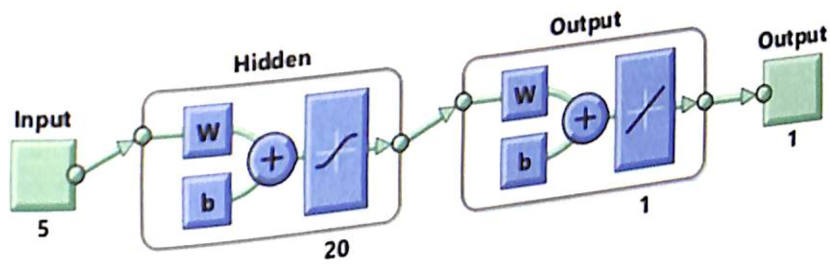
In ANN, the output vector was developed using single output node. Output vector of the ANN determines the faulty condition of bearing. Here, the dimension of the output vector classifies the fault condition of bearing. Three different fault cases were considered for classification procedure as given in Table 5.2.

The first fault case was for OR and IR. Second fault case was for combined defect (Combination of OR defect and Ball defect) and third fault case was for all defect condition (OR and IR, Combined defect). The dimension of output vector was taken as 1 and 0. A dimension of '1' represents the presence of the fault corresponding to particular fault condition of particular fault class, whereas dimension '0' represents the presence of fault to another fault condition of same fault class. In this work for ANN, multi-layer perceptron (MLP) network training based on a back-propagation algorithm was used. The number of hidden layers(n_h), neuron number of each hidden layer (n_{neuron}) and the iteration of training stage(epoch) have a great impact upon the performance of back propagation neural network.

So, following parameters were set during the training and testing of network for all conditions of bearing. The default setting of parameters are as follows: n_h=1, n_{neuron}= *15,20,25, lrate=1.0, maximum epochs=1000* and activation function of the hidden layer is sigmoid function.



(a)

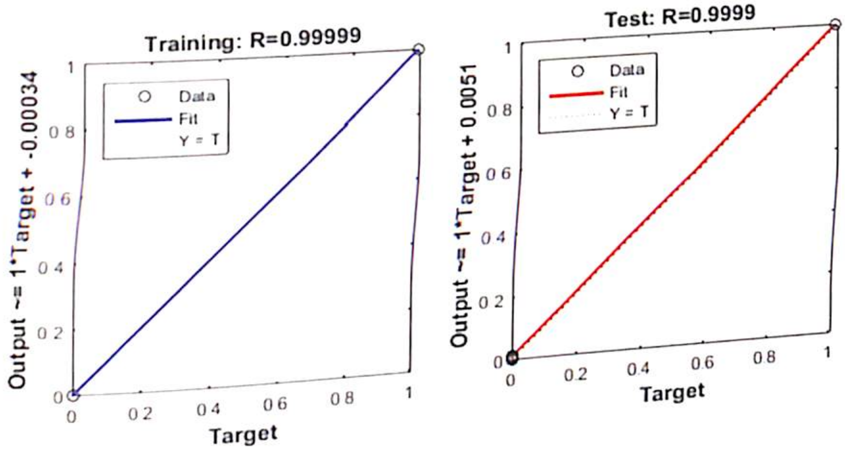


(b)

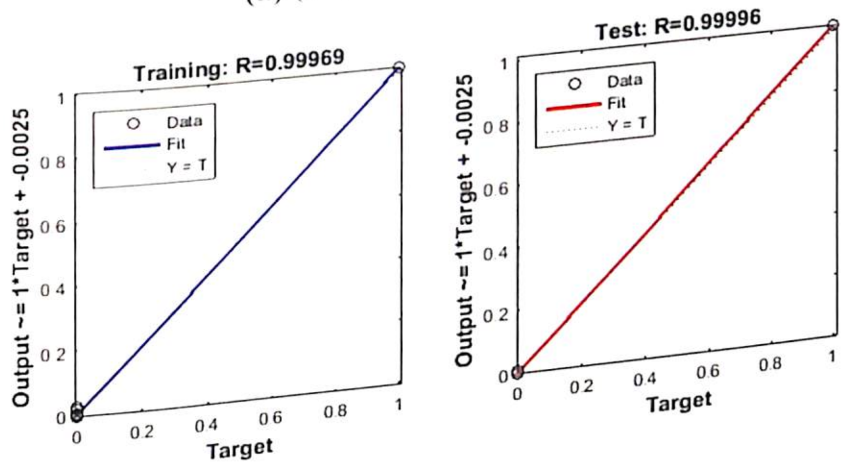
Figure 5.4 ANN Architecture for the classification of vibration data (a) OR-IR, and combined defect (b) All defect.

A mean square error of 10^{-4} and minimum gradient of 10^{-10} were used. The training process of network would stop if any one of the conditions is met. Here MATLAB neural network toolbox was used to train the MLP neural network. These networks have been trained using logisc transfer function between input and output layer and hard limit transfer function between hidden layer and output layer. The performance of ANN models is evaluated in terms of MSE and regression value(R-value).

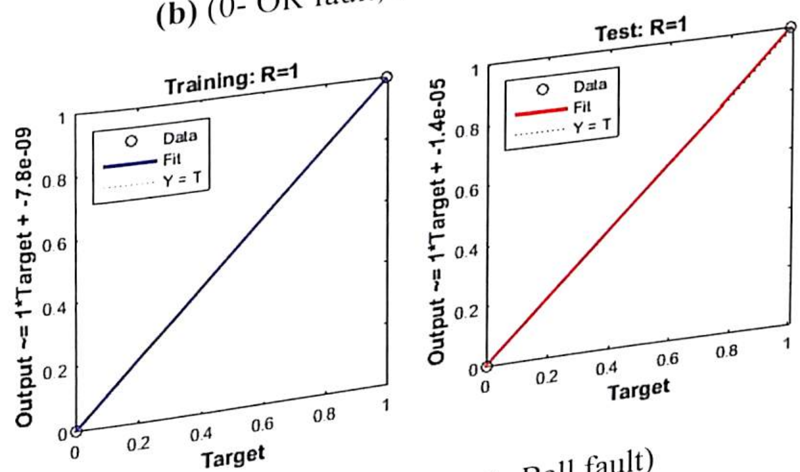
The number of hidden neurons was used as a procedure to obtain the best ANN architecture model for each conditions of bearing. ANN Performance models for all three-fault class of the bearing are illustrated in Figure 5.4. The ANN models in Figure 5.4 represents the best ANN model among the number of hidden neurons used for training and testing.



(a) (0-OR fault, 1- IR fault)

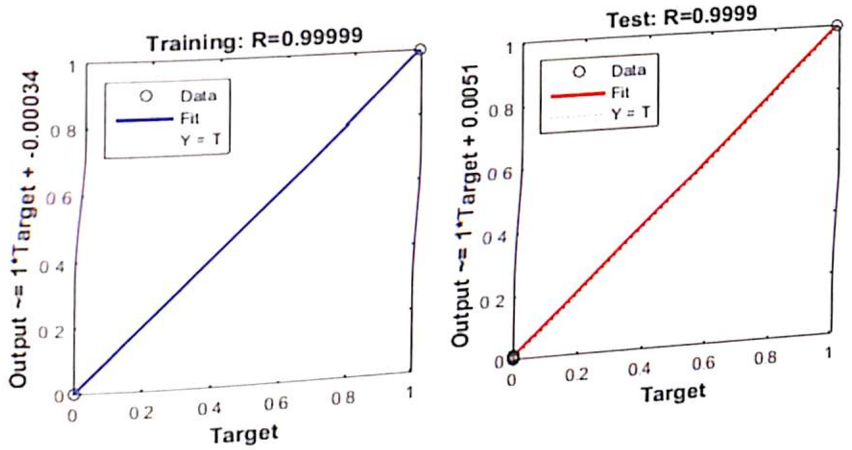


(b) (0- OR fault, 1- Ball fault)

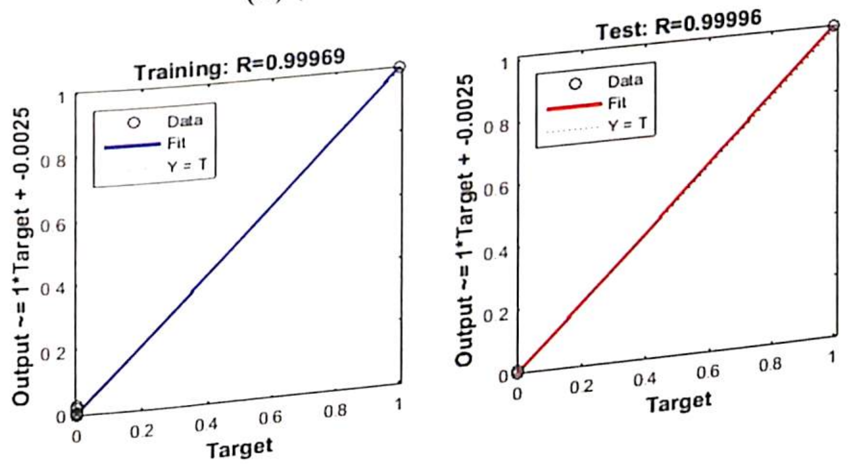


(c) (0-OR and IR fault, 1- Ball fault)

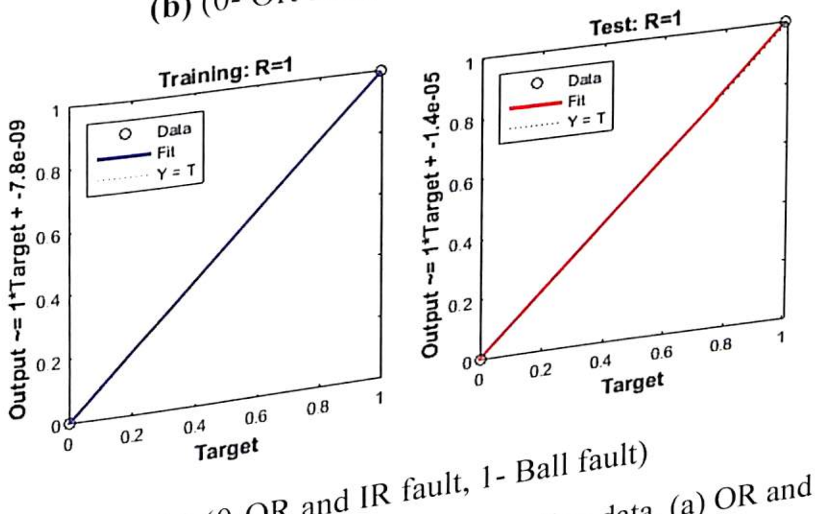
Figure 5.5 ANN performance for classification of vibration data. (a) OR and IR defect (b) Combined defect (CD) (c) All defect the bearing are illustrated in Figure 5.4. The ANN models in Figure 5.4 represents the best ANN model among the number of hidden neurons used for training and testing.



(a) (0-OR fault, 1- IR fault)



(b) (0- OR fault, 1- Ball fault)



(c) (0-OR and IR fault, 1- Ball fault)

Figure 5.5 ANN performance for classification of vibration data. (a) OR and IR defect (b) Combined defect (CD) (c) All defect

From the Figure 5.4, for first and second fault class, 15 number of hidden neurons provide the best result in the form of least MSE and R-value close to 1, whereas for third fault class ,20 number of hidden neurons provides the best result in the form of MSE and R-value. Parameters, training and test performances are given in Table 5.2. From Table 5.2, it is clearly observed, that the significant faults of the bearing (outer race fault, inner race fault, and combined fault) can easily distinguished by using single hidden layer in ANN architecture for the proposed fault location. Figure5.5 shows the regression plot of ANN output and target values for each classification cases. From Figure5.5, it is inferred that regression value close to 1 and least MSE, as well target values indicate that ANN model classifies the fault successfully. In Figure5.5 (a), 0 represents OR fault whereas 1 represents IR fault. Figure 5. 5 (b), presents the ANN output for second fault class, where 0 represents OR fault and 1 represents ball fault.

Similarly, in Figure5.5(c), 0 represents OR and IR fault, whereas 1 represents combined fault. High performance being observed for third fault class compared to other fault classes in terms of better MSE and R-value.

5.4.2 KNN implementation.

In KNN, we consider each of the characteristics in the training set as a different dimension in some space and take the value an observation has for this characteristic to be its co-ordinate in that dimension, so getting a set of points in space. We can then consider the similarity of two points to be the distance between them in this space under some appropriate metric. The distance between the data points is calculated using distance function. The various distance functions available in KNN are Euclidean, manhattan, mahalanobis etc. In this work Euclidean distance function as described earlier is used to calculate the distance between data points for its similarities. Higher distances indicate higher dissimilarities. The advantage of using Euclidean distance as similarity measure, is that many data points with the same class are close to each other according to distance measure in many local areas. Here the training data used by the classifier provides decision boundaries for fault classes as shown in Figure5.6. As can be seen from the figure outer race faults and inner race faults are very close to each other. Hence, as per the principal of KNN, these faults are easily classified in one class, whereas the combined fault features are largely separated from kernel boundaries, therefore it cannot be classified into one class.

Thus, performance of the ANN in classifying the multiple faults (or combined faults) is better than the KNN. Therefore, ANN can be taken as effective classification technique to classify multiple faults.

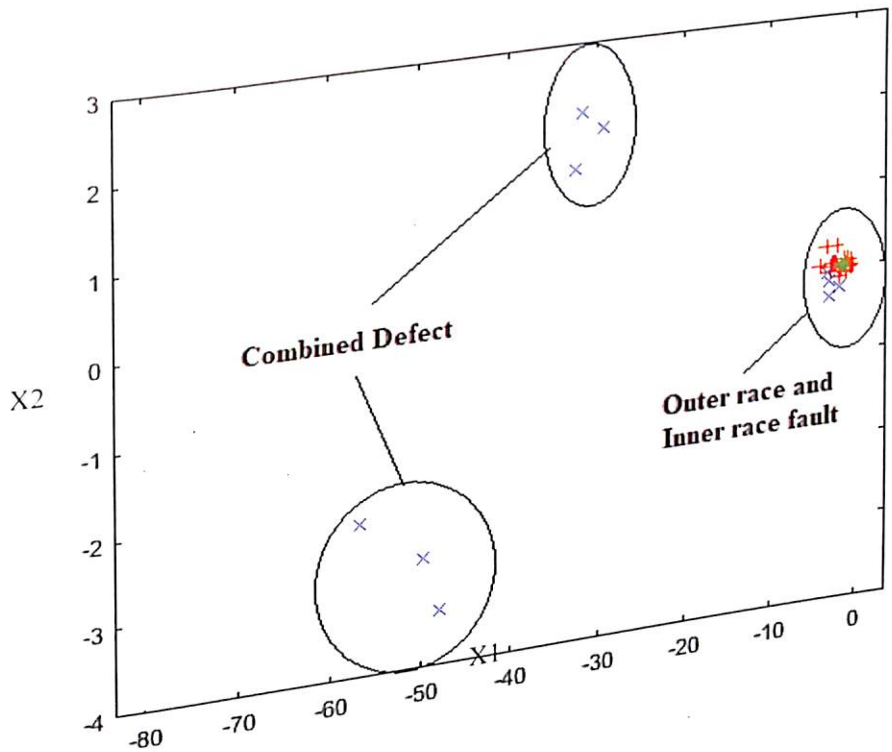


Figure 5.6 KNN Classification of faults.

5.5. Conclusion

This chapter describes the method of fault diagnosis of rolling element bearing for its various components. Here wavelet transform is used as a significant tool in denoising the signal and extracting the sensitive time domain parameters. ANN and KNN is used to classify the faults by successfully training and testing the data obtained from wavelet transform. Five significant features were used as inputs to ANN and KNN model. ANN model provides 99% success for classifying OR-IR and CD fault class and 100% for all fault class. KNN classifiers proves to be effective for classifying single point faults (OR-IR fault) and not so effective in classifying the multiple faults (Combined fault). Regression value close to 1 and low MSE values proved the accuracy of ANN prediction and estimated very close corresponding target fault. The proposed ANN model proved to be highly effective in classifying the multiple faults as described in second fault class. Therefore, such ANN model can be used for diagnosing multiple faults and can be used as a novel approach for specific diagnostic problem.

The next chapter provides deep insights about classifying faults with the help of sensor fusion. The present chapter classifies fault only with single sensor thus loses the accurate fault related characteristics obtained from multiple sensors.

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