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Rolling bearing fault diagnostics using artificial neural networks based on Laplace wavelet analysis

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Abstract

A study is presented to explore the performance of bearing fault diagnosis using three types of artificial neural networks (ANNs), namely, Multilayer Perceptron (MLP) with BP algorithm, Radial Basis Function (RBF) network, and Probabilistic Neural Network (PNN). The time domain vibration signals of a rotating machine with normal and defective bearings are preprocessed using Lapalce wavelet analysis technique for feature extraction. The extracted features are used as inputs to all three ANN classifiers: MLP, RBF, and PNN for four-class: Healthy, outer, inner and roller faults identification. The procedure is illustrated using the experimental vibration data of a rotating machine with different bearing faults. The results show the relative effectiveness of three classifiers in detection of the bearing condition with different learning speeds and success rates.

Keywords: Bearing Fault detection, Wavelet Transform, Laplace Wavelet Kurtosis (LWK), Kurtosis Factor, Neural Networks, Multilayer Perceptron (MLP) , Radial Basis Function RBF, Probabilistic Neural Network (PNN).

1. Introduction

The predictive maintenance philosophy of using vibration information to lower operating costs and increase machinery availability is gaining acceptance throughout industry. Since most of the machinery in a predictive maintenance program contains rolling element bearings, it is imperative to establish a suitable condition monitoring procedure to prevent malfunction and breakage during operation. The hertzian contact stresses between the rolling elements and the races are one of the basic mechanisms that initiate a localized defect. When a rolling element strikes a localized defect an impulse occurs which excites the resonance of the structure. Therefore, the vibration signature of the damaged bearing consists of an exponentially decaying sinusoid having the structure resonance frequency. The duration of the impulse is extremely short compared with the interval between impulses, and so its energy is distributed at a very low level over a wide range of frequency and hence can be easily masked by noise and low frequency effects. The periodicity and amplitude of the impulses are governed by the bearing operating speed, location of the defect, geometry of the bearing and the type of the bearing load.

The rolling elements experience some slippage as they enter and leave the bearing load zone. As a consequence, the occurrence of the impacts never reproduce exactly at the same position from one cycle to another, moreover when the position of the defect is moving with respect to the load distribution of the bearing, the series of impulses is modulated in amplitude. However, the periodicity and the amplitude of the impulses experience a certain degree of randomness (Kiral and Karagulle, 2003, Tandon and Choudhury, 1997, Antoni and Randall, 2002 and Mcfadden and Smith, 1989). In such case, the signal is not strictly periodic, but can be considered as cyclo-stationary (periodically time-varying statistics), then the cyclic second order statistics (such as cyclic-autocorrelation and cyclic spectral density) are suited to demodulate the signal and extract the fault feature (Antoniadis and Glossiotis, 2001 and Li and Qu, 2003). All these make the bearing defects very difficult to detect by conventional FFT- spectrum analysis which assumes that the analyzed signal to be strictly periodic.

The wavelet transform provides a powerful multi-resolution analysis in both time and frequency domain and thereby becomes a favored tool to extract the transitory features of non-stationary vibration signals produced by the faulty bearing (Qiu *et al.*, 2006, Shi *et al.*, 2004 and Rubini and Meneghetti, 2001). The wavelet analysis results in a series of wavelet coefficients, which indicate how close the signal is to the particular wavelet. In order to extract the fault feature of signals more effectively an appropriate wavelet base function should be selected. Morlet wavelet is mostly applied to extract the rolling element bearing fault feature because of the large similarity with the impulse generated by the faulty bearing (Vass and Cristalli, 2005, Lin and Qu, 2000 and Nikolaou and Antoniadis, 2002). The impulse response wavelet is constructed and applied to extract the feature of fault vibration signal in (Junsheng *et al.*, 2007). A number of wavelet-based functions are proposed for mechanical fault detection with high sensitivity in (Wang, 2001).

The Laplace wavelet is a complex, single sided damped exponential function formulated as an impulse response of a single mode system to be similar to data feature commonly encountered in health monitoring tasks. It has been applied to the vibration analysis of an actual aircraft for aerodynamic and structural testing (Lind, and Brenner), and to diagnose the wear fault of the intake valve of an internal combustion engine (Yanyang *et al.*, 2005). ANNs are proposed to solve the non-linear system identification problems by learning due to training samples, and have been widely used in the automated health detection and diagnosis of machine conditions using features extracted from vibration signals. The appropriate pre-processing of the measurement data enables the exclusion of the data, which are less correlated to the bearing condition. Consequently, the minimization of the training vector, and thus reduction of NN-training time and computation cost can be obtained. The normalized features of the vibration signal in frequency domain which includes the peak amplitude, peak RMS and power spectrum are used as inputs to MLP-ANN for bearing fault detection and classification (Liu and Mengel, 1992). Distinguishing the normal from defective bearings with 100% success rate and classify the bearing conditions into six states with success rate of 97% are achieved with ANN structure of 3:12:1 (3 input nodes, 12 hidden nodes and 1 output node) .

The MLP-NN trained with supervised error propagation technique and an unsupervised learning NN were used by (Subrahmanyam and Sujatha, 1997) for rolling bearing defects classification. The optimal architectures of the network had been selected by trial and error process. The signals were processed to obtain various statistical parameters in time and frequency domains (i.e. peak value, standard deviation, autocorrelation, kurtosis). The extracted parameters are used as input vectors to train the NN. The networks were able to classify the ball bearing into different states with 100% reliability. The unsupervised learning network has been found to be extremely fast, about 100 times faster that the supervised back propagation learning network.

The vibration frequency spectrum features and the time domain characteristics are applied as NN input vectors for automatic motor bearing fault diagnosis (Li *et al*., 2000). The extracted features are the spectrum amplitude at bearing fault frequencies in frequency domain and the maximum and mean value of the vibration amplitude in time domain. The NN is with three output nodes representing three bearing conditions namely, bearing looseness, inner race fault, rolling element fault.

Until now there are two approaches to combine WA and NNs. The first is to employ wavelet analysis to provide a characteristic vector of input sample for NNs, i.e. to take WA as a preprocessing unit, and the second is to assemble wavelet and NNs directly, i.e. to apply the wavelet base function (with scale and translation) as a network neuron activation functions. The most dominant wavelet transform coefficients using Db4 wavelet function are applied by (Paya and Esat, 1997) as input vectors to the MLP-ANN rolling bearing classifier. Both single and multiple faults were successively detected and classified into distinct groups. The ANN and wavelet techniques are combined by (Wang. and Vachtsevanos, 2001) to prognosticate the remaining useful life time of rolling bearing which enhance the Condition Based Maintenance (CBM) process. The maximum time domain and power spectral of three dimensional vibration signals have been used as input features to the ANN. The Mexican hats wavelet has been used as hidden nodes activation function. The Genetic Algorithm (GA) technique is applied by (Ray and Chan, 2001) to select the relevant features from the processed wavelet coefficients using the complex Morlet wavelet as a mother wavelet function. Five cases of bearing faults and one normal bearing case have been used to evaluate the proposed technique. The wavelet contour map is used as input features to an ANN-MLP with 19 input nodes, 5-60 hidden nodes, and 4 output nodes to serve as automated wavelet map interpretation. The misclassification rate number of testing pattern was used to assess the performance of the MLP classifier applied for mechanical vibration signal fault features diagnosis. The misclassifications rate reduces significantly when the number of hidden nodes increases from 5 to 20 and above 20 the improvement slows down (Chen and Wang, 2002).

The characteristic features of time domain vibration signals of rotating machinery with normal and defective bearings have been used by (Samanta and Al-Balushi, 2003) as input vectors to the MLP-ANN. The input layer consists of 15 nodes for time domain vibration signal (RMS, variance, skewness, kurtosis, normalizes sixth central moment). The output layer consists of 2 binary nodes indicating the status of the machine (normal or defective bearings). Two hidden layers with different number of neurons are investigated. The effect of some pre-processing techniques) high pass, band pass filters, envelope detection, and wavelet transform prior to feature extraction are also evaluated. The reduced number of inputs leads to faster training requiring less iteration making the procedure suitable for on-line machines condition monitoring and diagnosis. The statistical parameters which include variance, skewness and normalized moment of sixth order generated of a 100% fault classification success rate. The uses of central moments higher than sixth order have not produce any significant effect on the diagnosis results. The training and test success rates are improved with the application of the high and band pass filter for the acquired signals. The DWT with Db4 as a base function produced 100 % training success in all cases and the ANN test success rate varied from 100% to 83.33%. The features extracted from high frequency signal (second and third WT level) produced high success rates. However, the DWT has not offered any substantial advantage over that of simple high pass or band pass filtrations. The signal envelope analysis using Hilbert transform gave training success rate of 100%.

The Genetic Algorithm (GA) is used by (Jack and Nandi, 2002) to automatically determine the features which provide the most significant information to the NN classifiers, whilst reducing the number of inputs required. The extracted features are 18 different moments and cumulate from the resultant of two dimensional vibration data and high order spectra. The ANN performance is measured in terms of the network's classification success on unseen data in the test set. Fitness function of GA returns the number of correct classifications mode over the training and validation features sets. ANN achieves a success rate of 98.9% on the training set and 97.6% on the test set, and SVM achieves only 81.8 on the training set and 80.4 % on the test set without application of GA feature selection. With GA feature selection, the success rates are increased for both ANN and SVM with less numbers of input features. The ANN with GA gave a success rate of 99.8% and 100% on the training and test sets, respectively, with 12 inputs out of the possible 90 in the feature set. While the SVM with GA feature selection produced 99.5% and 98.1 % success rates on the training and test sets, respectively, with 6 input features. The results show that the ANN is faster to train and slightly more robust than SVM.

A modified Morlet Wavelet combined with Neural Networks (WNNs) is presented by (Guo et al., 2005) for rolling bearing fault detection. The modified Morlet wavelet function is used as activation functions of the wavelet nodes in the hidden layer. Time-frequency spectrum of data is computed and fed into a training stage, in which 6 faults and 7 frequency bands are selected to form a feature vector. The WNN approaches were tested on the rotating machinery and compared with BP techniques. The test results show that the proposed modified Morlet WNN approach needs much less training epochs and has higher convergence rate and diagnosis accuracy than the BP method.

The performance of three approaches of neural network classifiers namely, MLP, Radial Basis Function (RBF), and parabolistics (PNN) for bearing fault detection are investigated by (Samanta et *al.*, 2006). The input features are extracted from time domain vibration signals, without and with pre-processing. The extracted features are used as inputs to all three ANN classifiers for two classes (normal / faulty) recognition. GA has been used to select the characteristic parameters of the classifier and the NN input features. The RBF with one hidden node of non-linear Gaussian activation function is faster training than a MLP of similar structure. The major drawback of PNN which used a pattern layer, was the more computation cost for the potentially large number of hidden layers which might be equal to the input nodes number. The use of GAs with only three selected features produced approximately 100% success rate with MLPs and PNNs for most of the test cases. The use of six selected features with MLPs and PNNs resulted in 100% test success whereas with RBF, test success was 99.31% for eight features. The training time with feature selection is quite reasonable for PNNs compared to the other two approaches. The results show the potential application of GAs for selection of input features and classifier parameters in ANN based condition monitoring systems.

In this paper, the Laplace wavelet has been used as a wavelet-based function. The most dominant Laplace-wavelet transform coefficients based on scale-kurtosis level, which represent the most correlated features to the bearing condition, are selected for feature extraction. The extracted features in time and frequency domain are used as input vectors to the ANN classifiers for the rolling bearing condition classification. The performance of three different NN classification approaches is investigated for rolling bearing fault identification.

2 Wavelet Transform (WT)

2.1 Laplace Wavelet Function

The Laplace wavelet is a complex, analytical and single-sided damped exponential, and it is given by,

$$\begin{aligned} \Psi(t) &= A \quad e^{-\left(\frac{\beta}{\sqrt{1-\beta^2}}+j\right)\omega_c t} && \textit{when} \quad t \geq 0 \\ \Psi(t) &= 0 && \textit{when} \quad t < 0 \end{aligned} \qquad (1)$$

Where β is the damping factor that controls the decay rate of the exponential envelope in the time domain and hence regulates the resolution of the wavelet, and it simultaneously corresponds to the frequency bandwidth of the wavelet in the frequency domain. The frequency ω_c determines the number of significant oscillations of the wavelet in the time domain and corresponds to the wavelet centre frequency in the frequency domain, and A is an arbitrary scaling factor. Figure 1 shows the Laplace wavelet, its real part, imaginary part, and spectrum.

It is possible to find optimal values of β and ω_c for a given vibration signal by adjusting the time-frequency resolution of the Laplace wavelet to the decay rate and frequency of impulses to be extracted. Kurtosis is an indicator that reflects the "peakiness" of a signal, which is a property of the impulses and also it measures the divergence from a fundamental Gaussian distribution. A high kurtosis value indicates a high impulsive content of the signal with more sharpness in the signal intensity distribution.

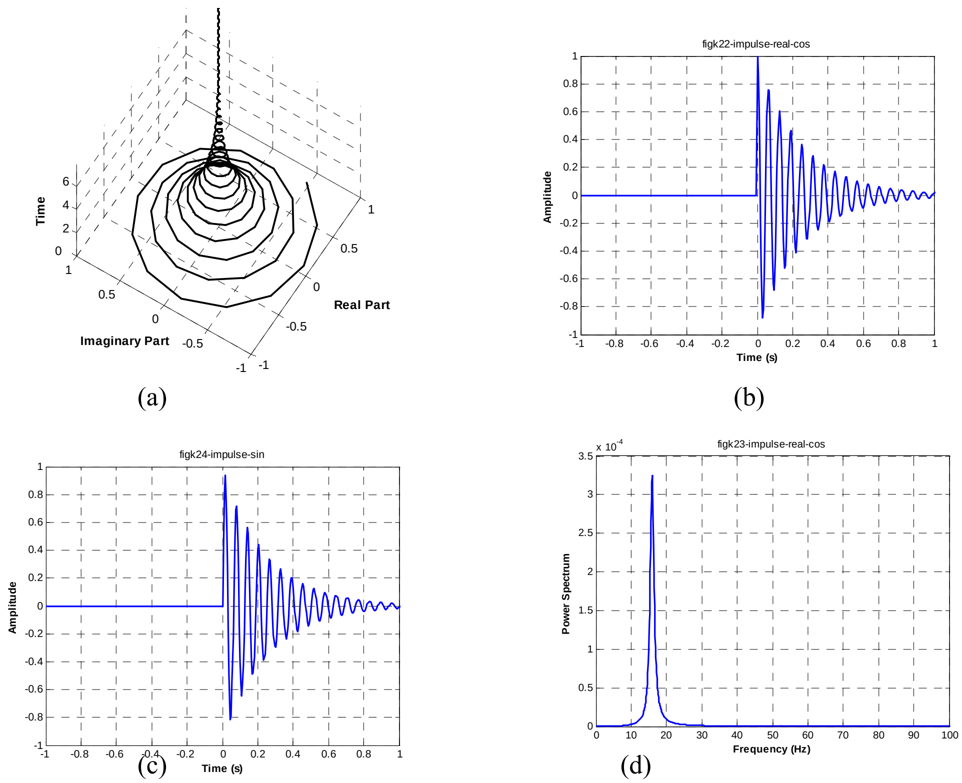


Figure 1 (a) the complex Laplace wavelet, (b) real part, (c) imaginary part, and (d) its FFT spectrum.

Let *x (t)* be a real discrete time random process, and *WT* its Laplace wavelet transform. The objective of the Laplace wavelet shape optimization process is to identify the wavelet shape parameters (β and ω_c) which maximize the kurtosis of the wavelet transform output which can be given by:

$$Optimal(\beta,\omega_c) = \max.\left[\frac{\sum_{n=1}^{N} WT^4(x(t),\psi_{\beta,\omega_c}(t))}{\left[\sum_{n=1}^{N} WT^2(x(t),\psi_{\beta,\omega_c}(t))\right]^2}\right] \tag{2}$$

2.2 Envelope Wavelet Power Spectrum

The vibration signal of a faulty rolling bearing can be viewed as a carrier signal at a resonant frequency of the bearing housing (high frequency) modulated by the decaying envelope. The frequency of interest in the detection of bearing defects is the modulating frequency (low frequency). The goal of the enveloping approach is to replace the oscillation caused by each impact with a single pulse over the entire period of the impact.

The wavelet transform (WT) of a finite energy signal x(t), with the mother wavelet $\psi(t)$, is the inner product of *x(t)* with a scaled and conjugate wavelet $\psi^*_{a,b}$, since the analytical and complex wavelet is employed to calculate the wavelet transform. The result of the WT is also an analytical signal,

$$WT\{x(t),a,b\} = \langle x(t),\, \psi_{a,b}(t) \rangle = \frac{1}{\sqrt{a}} \int x(t)\ \Psi^*_{a,b}(t)\ dt$$

$$= \mathrm{Re}[WT(a,b)] + j\,\mathrm{Im}[WT(a,b)] = A(t)e^{i\,\theta(t)} \tag{3}$$

Where $\psi_{a,b}$ is a family of daughter wavelets, defined by the dilation parameter a and the translation parameter *b*, the factor $1/\sqrt{a}$ is used to ensure energy preservation. The time-varying function *A(t)* is the instantaneous envelope of the resulting wavelet transform (EWT) which extracts the slow time variation of the signal, and is given by,

For each wavelet, the inner product results in a series of coefficients which indicate how close the signal is to that particular wavelet. To extract the frequency content of the enveloped correlation coefficients, the Wavelet-scale Power Spectrum (WPS) (energy per unit scale) is given by,

$$A(t) = EWT(a,b) = \sqrt{\{\mathrm{Re}[WT\ (a,b)]\}^2 + \{\mathrm{Im}[WT\ (a,b)]\}^2} \tag{4}$$

$$WPS(a,\omega) = \int_{-\infty}^{\infty} \left|SEWT(a,\omega)\right|^2 \, d\omega \tag{5}$$

where SEWT (a, ω) is the Fourier Transform of EWT(a,b) .

2.3 Feature Extraction Using Laplace Wavelet Analysis

The predominant Laplace wavelet transform scales (most informative levels) based on the scale-kurtosis value have been selected for features extraction. Figure 2 shows the scale-kurtosis distribution for different bearing conditions with the corresponding wavelet scale threshold. By using the maximum kurtosis for normal bearing as a threshold level (the dotted line in Figure 2) for the wavelet scales, it could be seen that the scales range of 15-20 are the mostly dominant scales , which can reveal the rolling bearing condition sufficiently. The extracted features for the dominant scales are: Root Mean Square RMS, Standard Deviation (SD), Kurtosis in the time domain and, the (WPS) peak frequency to the shaft rotational frequency, (WPS) maximum amplitude to the overall amplitude ratio in the frequency domain. The extracted features were linearly normalized in between [0, 1], and used as input vectors to the neural network.

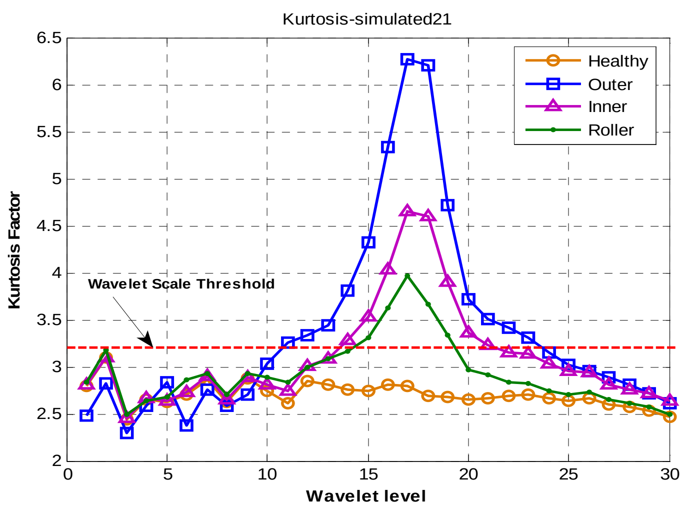


Figure (2): The Laplace Wavelet Kurtosis (LWK) for simulated vibration signals of bearing with different fault condition.

3. The ANN Scheme for Rolling Bearing Fault Classification

A feed-forward multi-layer perceptron (MLP), Radial Base Function (RBN) and Probabilistic Neural Networks have been developed for rolling bearing fault classification as follows:

3.1 BP-ANN

A feed-forward multi-layer perceptron (MLP) which consists of three layers. The input layer of five source nodes represents the normalized features extracted from the predominant Laplace wavelet transform scales. A hidden layer with four computation nodes has been used, Figure 3. The number of the hidden nodes is optimized using a genetic algorithm with parameters shown in Table 1, with minimization of Mean Square Error (MSE) between the actual network outputs and the corresponding target values as evaluation function. The output layer with four nodes which represent the different bearing working conditions to be identified by the neural network has been developed.

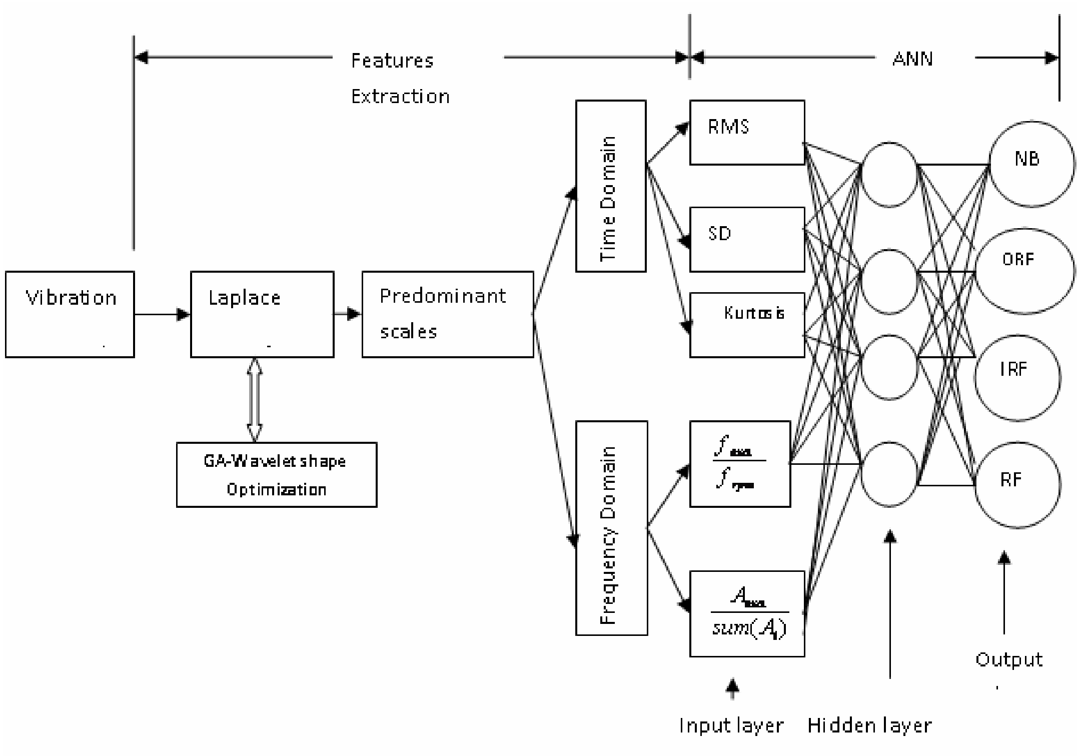


Figure 3: the applied diagnosis system.

Table 1 the applied GA parameters

Population size	10
Number of generation	20
Termination function	Maximum generation
Selection function	Roulette wheel
Cross-over function	Arith-crossover
Mutation function	Uniform mutation

The four-digit output target nodes that need to be mapped by the ANN are distinguished as: (1, 0, 0, 0) for a new bearing (NB), (0, 1, 0, 0) for a bearing with outer race fault (ORF), (0, 0, 1, 0) for an inner race fault (IRF), and (0, 0, 0, 1) for a rolling element fault (REF). Figure 4a depicts the overall architecture of the proposed diagnostic system. The training sample vector comprises the extracted features and the ideal target outputs expressed by $[x_1, x_2, x_3, x_4, x_5, T]^T$, where x_1-x_5 represent the input extracted features, and T is the four-digit target output. The input vector is transformed to an intermediate vector of hidden variables h using the activation function φ_1. The output hj of the jth node in the hidden layer is obtained as follows

$$h_j = \varphi_1 \left(\sum_{i=1}^{N=5} w_{i,j}\, x_i + b_j\right) \qquad (6)$$

Where b_j and $w_{i,j}$ represent the bias and the weight of the connection between the j^{th} node in the hidden layer and the i^{th} input node respectively.

The output vector $O = (o_1\, o_2 \ldots o_M)$ of the network is obtained from the vector of the intermediate variable h through a similar transformation using activation function φ2 at the output layer. For example, the output of neuron k can be expressed as follows:

$$O_k = \varphi_2 \left(\sum_{l=1}^{M=4} w_{l,k}\, u_l + b_k\right) \qquad (7)$$

The training of an MLP network is achieved by modifying the connection weights and biases iteratively to optimize a performance criterion. One of the widely used performance criterion is the minimization of the mean square error (MSE) between the actual network output (O_k) and the corresponding target values (T) in the training set. The most commonly used training algorithms for MLP are based on back-propagation (BP). The BP adapts a gradient-descent approach by adjusting the ANN connection weights. The MSE is propagated backward through the network and is used to adjust the connection weights between the layers, thus improving the network classification performance. The process is repeated until the overall MSE value drops below some pre-determined threshold (stopping criterion). After the training process, the ANN weights are fixed and the system is deployed to solve the bearing condition identification problem using unseen vibration data. The ANN was created, trained and tested using Matlab Neural Network Toolbox with Levenberg-Marquarat Back-propagation (LMBP) training algorithm. In this work, A MSE of 10E-15, a minimum gradient of 10E-10 and maximum iteration (epochs) of 1000 were used. The training process would stop if any of these conditions were met. The initial weights and biases of the network were generated automatically by the program.

3.2 Radial Basis Function (RBF) Networks

The RBF uses local hyper-sphere surfaces (non –linear mapping) to separate the classes in the input space as a response to cluster, rather than the global hyper-planes (lines) used in MLP networks. RBF networks typically have three layers: an input, a single hidden layer with Gaussian activation function and a linear output layer. The activation function $\varphi(x)$ of the hidden layer is Gaussian spheroid function as follows:

$$\varphi(x) = \exp\left(-\frac{(x - c_i)}{2\sigma^2}\right) \tag{8}$$

During the learning process the RBF networks parameters are adjusted based on the distribution of input features, x_i in the input space, in two steps. In first step the non-linearity weights of the hidden layer represent by the centre of Gaussian (cluster) c_i , and the width (spread) of Gaussian function σ with the number of the hidden nodes are manipulated. While, in the second step the linearly trained output layer weights are updated. The RBFs were created, trained, and tested using Matlab through a simple iterative algorithm of adding more neurons in the hidden layer till the performance goal is reached. This procedure could produce a larger number of hidden neurons accompanied with longer computation time.

3.3 Probabilistic Neural Networks (PNN)

Probabilistic neural networks are a special type of radial basis network suitable for classification problems. When input features are presented, the first layer (pattern layer) computes the Gaussians for each class in the input space. The second layer (category layer) computes the approximation of the class probability function through combination. Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes.

4. Implementation of WPS –ANN for Bearing Fault Classification

The bearing vibration data for rolling bearing with different faults were obtained from the Case Western Reserve University (CWRU, Bearing Data Center). The experiments were conducted using a 3 HP electric motor and the acceleration data was collected at locations near to and remote from the motor bearings The deep groove ball bearing faults were created using Electric Discharge Machining (EDM). The faults ranging from 0.007 inches to 0.40 inches in diameter and 0.011 inches in depth were introduced separately at the outer-raceway (with centered position @ 6:00 relative to the load zone), inner-raceway, and the rolling element. The vibration data have been collected using an accelerometer mounted on the bearing housing with a sampling rate of 12 KHz and 10 seconds duration. The smallest fault diameter has been selected for this study with shaft rotational speed of 1797 rpm (with no motor load condition) for training data, and rotational speed of 1772 (with 1 HP motor load) for the test data.

The neural network input feature vectors consists of five groups represent the different bearing conditions, a total of 3856 segments of 1000 sample each. The data sets were split in training and test (unseen) sets of size 1928 samples each. The distribution of the extracted features using the most dominant scales of the Laplace wavelet transform for different rolling bearing fault conditions is shown in Figure 4.

4.1 MLP-BP Neural Network

The result of the learning process of the proposed MLP-BP neural network and the classification MSE, are depicted in Figure 5a and 5b, respectively, which shows that the training with 45 epochs met the MSE stopping criteria (MSE less than 10E-15) with training time of 3.4 sec. The NN test process for unseen vibration data of the trained ANN combined with the ideal output target values are presented in Figure 5c, which indicates the high success rate of 100% for rolling bearing fault classification. The success rate is equal to the percentage ratio of the total numbers of input data to NN to the number of success classification of the NN output.

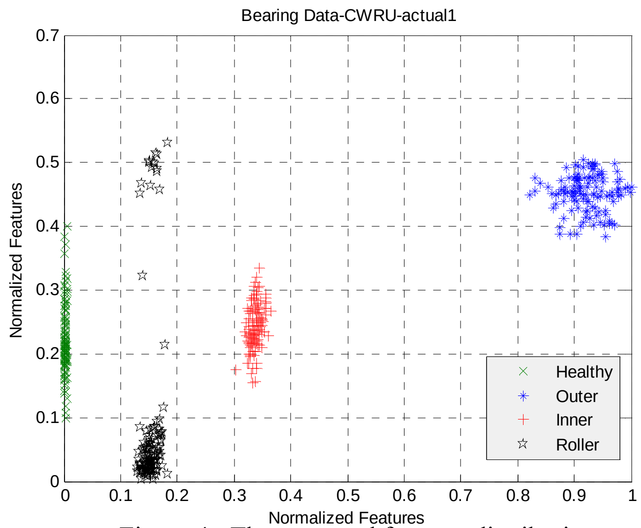


Figure 4: The extracted features distribution

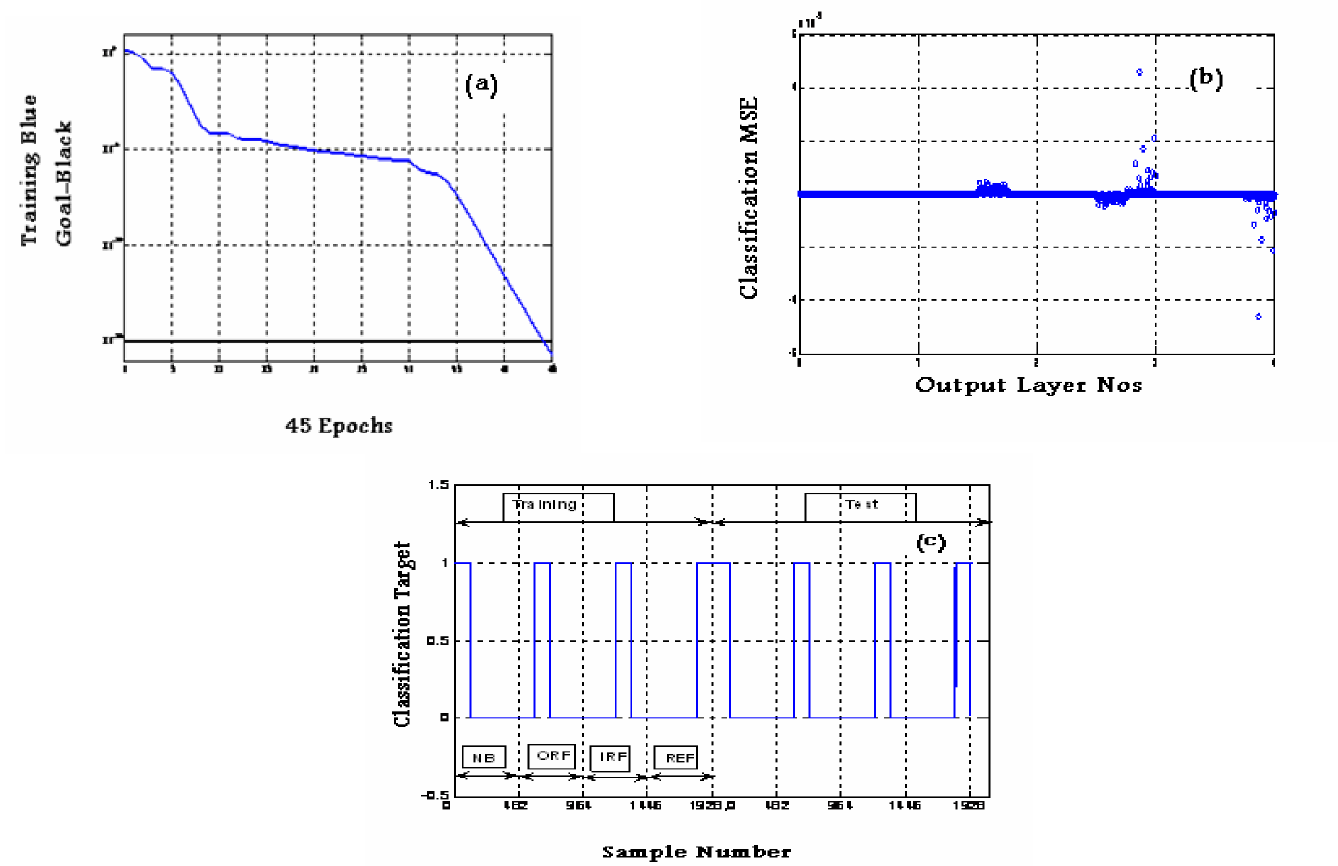
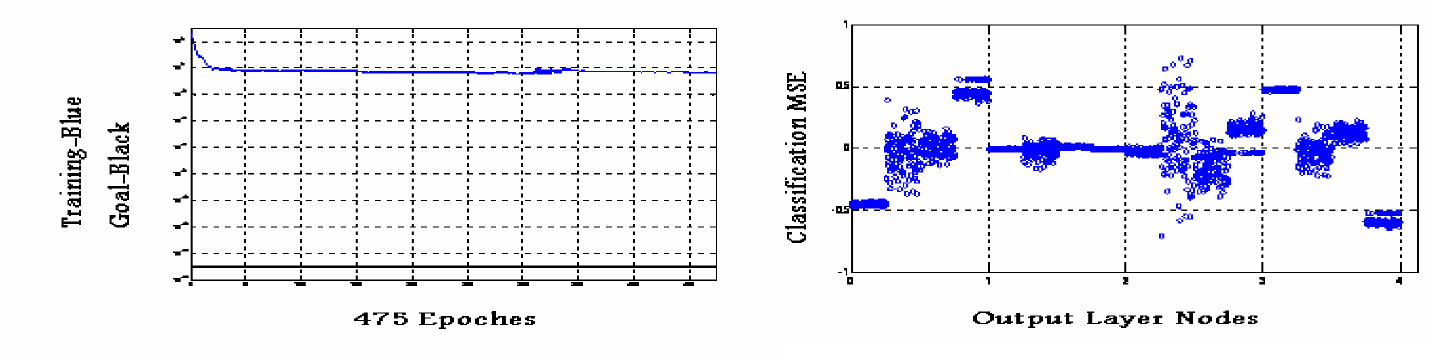


Figure 5: (a) The Training process of the proposed MLP-NN, (b) the MSE of the NN test, (c) the NN training and test results.

4.2 RBF Neural Network

The result of the learning process and classification MSE of the RBF NN is depicted in Figure 6a and the classification MS error is shown in Fig.6b, which shows that the training with 475 epochs with training time of 121.2 sec met the training stopping criteria. The NN test process for unseen vibration data of the trained RBFNN combined with the ideal output target values are presented in Figure 7, which indicates the success rate of 72.1% for rolling bearing fault detection and classification. The first column in Fig.7 shows the training patterns which are 1000 for healthy, 0100 for outer race fault, 0010 for inner race fault and 0001 for rolling element fault, and the second column shows the NN classification outputs.



(a) (b)

Figure 6: (a) The Training process of the proposed RBF-NN, (b) the MSE of the NN test.

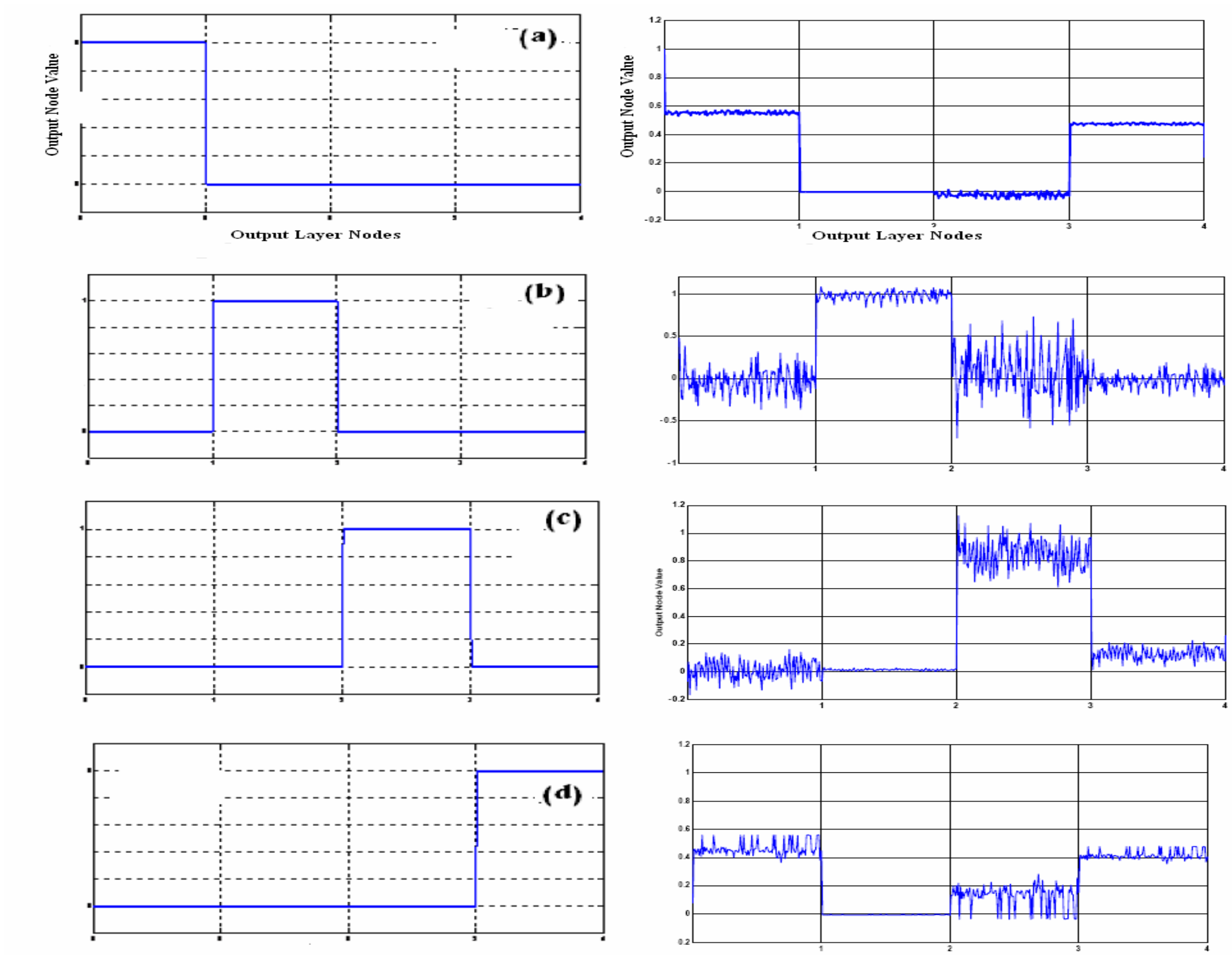


Figure 7: The training and testing pattern for RBF-NN for different bearing condition classes: (a) Healthy, (b) Outer race fault, (c) Inner-race fault, and (d) Rolling element fault.

4.3 Probabilistic Neural Network

The results of the learning process and the classification MSE of the PNN are with the training time of 0.5 sec to meet the MSE stopping criteria (MSE less than 10E-15), the training MSE is shown in Fig. 8. The NN test process for unseen vibration data of the trained PNN combined with the ideal output target values are presented in Figure 8, which indicates the high success rate of 97.5% and training time of 0.5 sec, for rolling bearing fault detection and classification. Table 2 shows the NN classification success rate and the required training time for the three different applied NNs.

Table 2: The success rate and training time for different neural networks

NN type	Success Rate	Training Time (sec)
MLP- BP with LM algorithm	100%	3.4 (45 epochs)
PNN	97.5%	0.5
RBF	72.1%	121.2 (475 epochs)

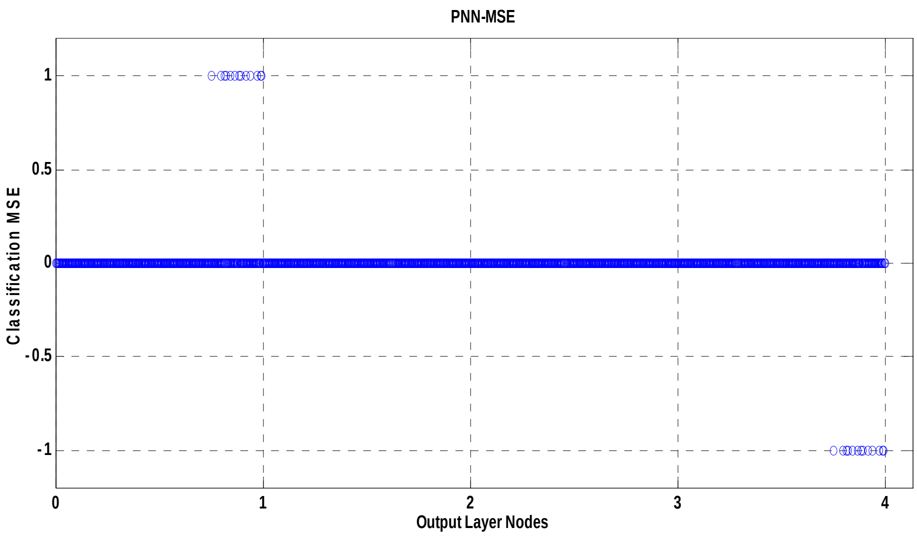


Figure 8: the MSE for PNN classification.

5. Conclusions

Based on the obtained results, the following conclusions can be extracted:

- The RBF NN is not suitable for multi-classes classification problem, as the number of hidden nodes would be more and the computation time is high. Moreover, the success rate is less compared with BP and PNN approaches.
- The training time of PNN is less compare with BP and RBN networks with high classification success rate. However, more classification error can be seen for rolling element fault identification, as the extracted features are with low magnitude compared with the outer and inner race fault conditions.
- The BP network generates a classification success rate of 100% for all the bearing fault conditions but with more training time than PNN.

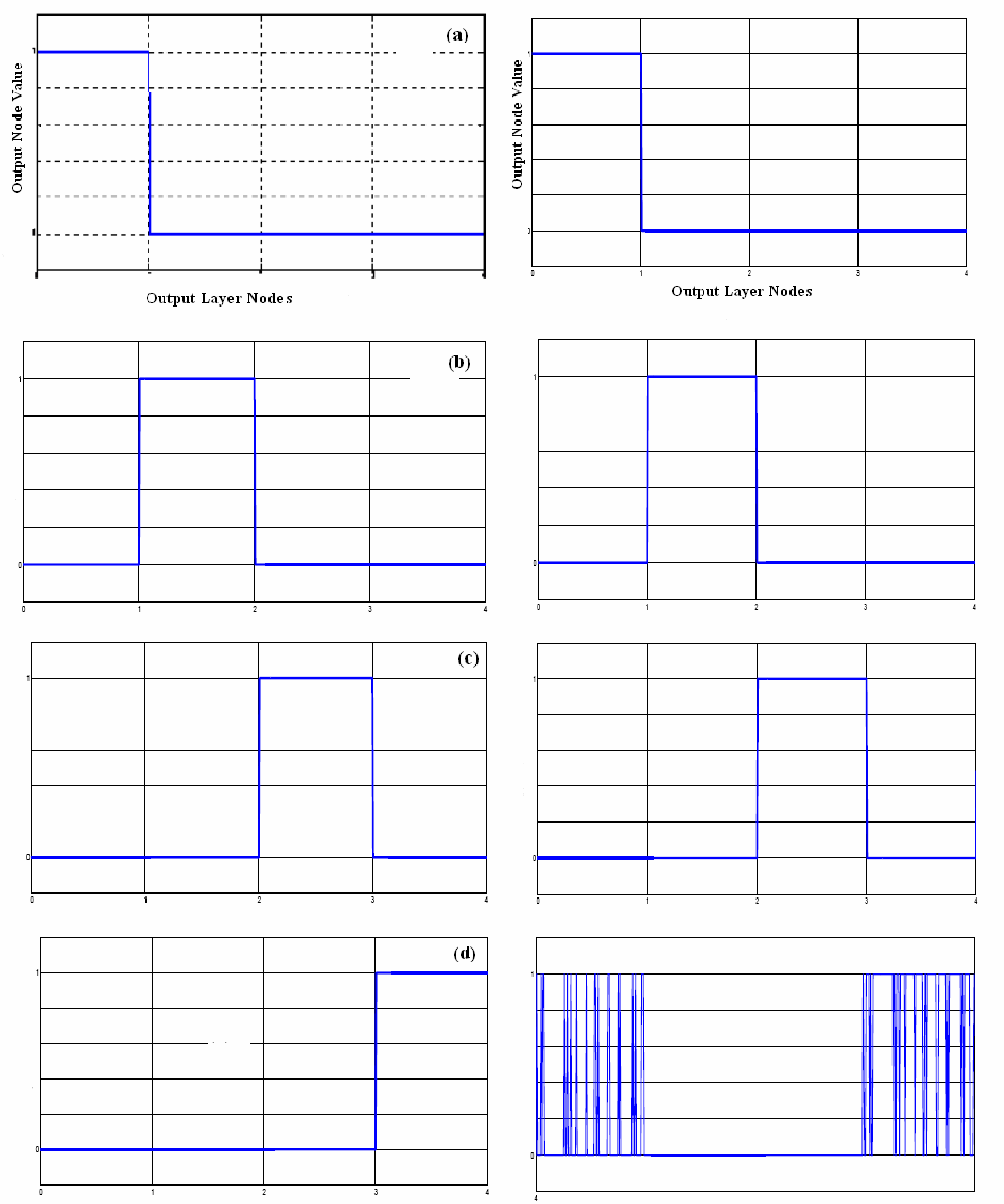


Figure 9: The training and testing pattern for PNN for different bearing condition classes: : (a) Healthy, (b) Outer race fault, (c) Inner-race fault, and (d) Rolling element fault.

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