Application of adaptive neuro-fuzzy inference system in diagnosing gearbox faults under non-stationary conditions

Sravan Kumar Khuntia, Amandeep Singh Ahuja

Abstract - An analysis of gearbox vibration signals is almost always the default choice when diagnosing the condition of a gearbox because of the rich information contained in the vibration signals and their ease of measurement. Gearbox vibration signals are mostly non-stationary owing to uncertainties associated with the drive and load mechanisms. The non-stationary nature of gearbox vibration signals is evident from an unequal number of samples between successive tachometer pulses. In the present work, independent angular re-sampling (IAR) technique is employed to convert non-stationary vibration signals in the time domain into quasi-stationary signals in the angular domain. The resulting angular domain signals for each gear health condition are merged and then partitioned into a number of data samples which are decomposed using wavelet packet transform. Standard deviation of wavelet packet coefficients is then computed and the distance evaluation technique employed to determine the frequency bands which have a higher distance evaluation factor. Normalized standard deviation values from the optimal frequency bands are then used to train and test an adaptive neuro-fuzzy inference system (ANFIS). Promising results are obtained when the proposed method is employed to diagnose common faults such as a cracked tooth, chipped tooth and missing tooth in a single stage spur gearbox under fluctuating speed conditions. Gearbox fault diagnosis under fluctuating speed conditions is a more realistic scenario where very limited work has been accomplished.

Index Terms - Adaptive neuro-fuzzy inference system, Distance evaluation technique, Gearbox fault diagnosis, Independent angular re-sampling technique, Wavelet packet decomposition

1 Introduction

Gearboxes are employed in a wide variety of applications and considerable effort has been directed towards fault diagnosis of gearboxes in the last two decades to reduce maintenance costs and to prevent down time of machinery and human casualties [1]. An analysis of vibration signals acquired from the gearbox under various gear health conditions is almost always the default choice when diagnosing the condition of a gearbox [2-5]. In rare cases, the sound emission signal may be analyzed to diagnose the gearbox health condition [6-8].

A gearbox operates under fluctuating load-speed conditions for most of its useful life. Research efforts directed towards gearbox fault diagnosis under fluctuating speed conditions, however, are limited. Jafarizadeh et al. [9] proposed a new noise cancelling technique based on time averaging method for asynchronous input and then implemented the complex Morlet wavelet for feature extraction and diagnosis of different kinds of local gear damages. Ahamed et al. [10] devised the multiple pulse independently re-sampled time synchronous averaging (MIR-TSA) technique to diagnose the crack propagation levels in the pinion tooth of a single stage spur gearbox under fluctuating speed conditions. Sharma and Parey [11] proposed the modified time synchronous averaging (MTSA) technique to improve the signal to noise ratio and compared various condition indicators to diagnose gearbox health conditions such as no crack, initial crack and advanced crack under fluctuating speed conditions. Singh and Parey [12] employed the independent angular re-sampling (IAR) technique to diagnose gearbox faults under fluctuating load conditions.

Most of the research works on gearbox fault diagnosis under fluctuating speed conditions so far have involved an analysis of gearbox vibration signals under the run up condition. In such works, since the angular velocity of the gearbox drive shaft increases linearly from one speed to another, the angular acceleration is assumed to remain constant. Li et al. [13] converted non-stationary signals in the time domain into stationary signals in the angular domain and employed the angular domain averaging technique for diagnosing gear crack faults during the run-up of gear drive. Meltzer and Ivanov [14, 15] proposed the time-frequency and the time-quefrency methods to recognize faults in a planetary gearbox during the start-up and run-down processes. Bafroui and Ohadi [16] converted non-stationary vibration signals collected under the speed-up process of a gear drive into quasi-stationary signals in the angular domain. Li et al. [17] combined computed order tracking, cepstrum analysis and radial basis function neural network for gear fault detection during the speed-up process.

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Recently, artificial neural networks (ANNs) have been extensively employed for fault diagnosis of gearboxes [18-31]. Further, fuzzy inference systems have attracted growing attention in gearbox fault diagnosis [32, 33]. Neuro-fuzzy systems are fuzzy systems which use ANNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way humans process information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS) which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [34, 35]. ANFIS has been successfully employed in the field of biomedical engineering [36 - 39], transmission line fault detection [40, 41] and fault diagnosis of rotating machinery. Wu et al. [42] employed discrete wavelet transform and ANFIS to identify gear fault positions and to classify various gear fault conditions. Wu and Kuo [43] employed discrete wavelet transform and ANFIS to classify and compare synthetic faults in an experimental engine platform under various engine operating conditions. Zhang et al. [44] proposed multi scale entropy (MSE) for feature extraction and ANFIS for fault recognition in electrical motor bearings fault diagnosis with three different fault categories and several levels of fault severity. Moosavian et al. [45] employed ANFIS to diagnose faults such as looseness and misalignment in a water pump. Feature vectors were extracted from the frequency domain of the acquired vibration signals. Bahrami et al. [46] proposed continuous wavelet transform and ANFIS to diagnose faults in a tractor gearbox. Ebrahimi and Mollazade [47] proposed intelligent fault classification of a tractor starter motor using vibration monitoring and adaptive neuro-fuzzy inference system.

In the present work, independent angular re-sampling (IAR) technique is employed to convert non-stationary gearbox vibration signals in the time domain into quasi-stationary signal in the angular domain. The resulting angular domain signals are merged to obtain the synchronized angular domain signal for the complete rotational period. The synchronized angular domain signal is then partitioned into a number of data samples. These data samples are decomposed with wavelet packet transform and standard deviation of wavelet packet coefficients computed for each frequency band. The distance evaluation technique is then employed to determine the frequency bands which have greater discrimination capability between the various gearbox health conditions. Normalized standard deviation values of wavelet packet coefficients from the optimal frequency bands are then employed to train and test an adaptive neuro-fuzzy inference system. A flowchart of the proposed fault diagnosis procedure is shown in Fig. 1.

The remainder of this paper is organized as follows: Section 2 briefly describes the IAR technique. The experimental set-up and data acquisition system are explained in Section 3. Section 4 describes the distance evaluation technique employed in the present work to determine the optimal frequency bands. A description of the adaptive neuro-fuzzy inference system (ANFIS) is the subject of Section 5 while the experimental results are discussed in Section 6.

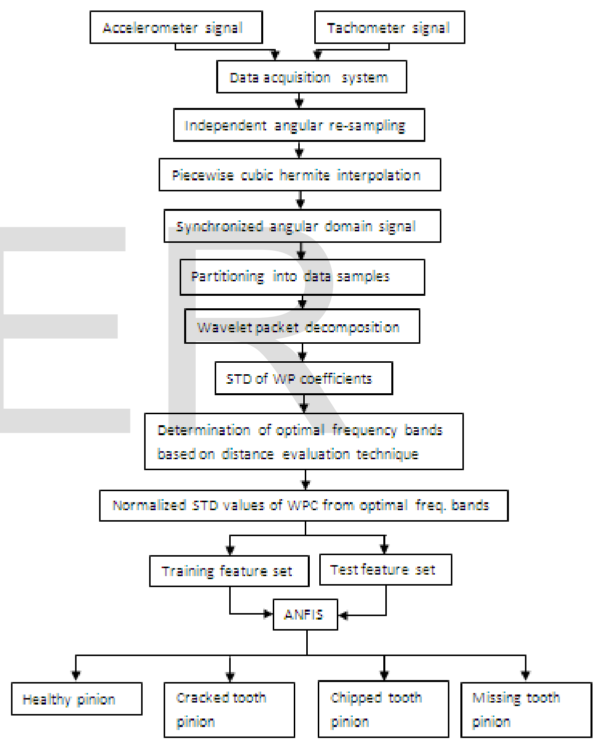


Fig. 1. *Flowchart of the proposed fault diagnosis procedure*

2 Independent angular re-sampling (IAR) technique

This section gives a brief introduction to the IAR technique, the objective of which is to convert non-stationary signals in the time domain into a number of quasi-stationary signals in the angular domain. It has been shown in [48] that a clear advantage in terms of gear fault diagnostic accuracy is attained when the time domain signal is converted into the angular domain rather than when the time domain signal is partitioned into a number of data samples prior decomposition with wavelet packet transform.

Before considering the IAR technique, it is pertinent to mention that gearbox vibration signals have a natural propensity to be non-stationary. This is evident from an unequal number of samples between successive tachometer pulses. Fig. 2 shows the time taken for 20 consecutive revolutions of the gearbox drive shaft with the healthy pinion installed. It may be noticed that the time taken for each revolution is not the same even though the vibration signal was acquired at a constant speed of 20 Hz under 0% (4 lb-in) load.

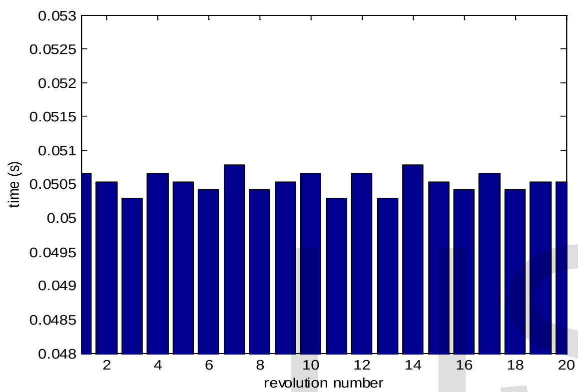


Fig. 2. *Time taken for 20 in number consecutive revolutions in case of the healthy pinion*

Since the vibration signatures acquired from the gearbox are non-stationary, techniques such as conventional time synchronous averaging (TSA) cannot be directly employed and there is a need to first synchronize the acquired signals from the revolution point of view. In the present work, the IAR technique is combined with interpolation theory to convert the non-stationary signals in the time domain into quasi-stationary signals in the angular domain. Another application of synchronizing the vibration signals from the revolution point of view is the work by Rafiee et al. [19] where the time domain vibration signals were first synchronized using piecewise cubic hermite interpolation (PCHI) before segmentation and decomposition using wavelet packet transform,

Unlike the works presented in [13, 16-17], the IAR technique assumes the angular acceleration to remain constant during each independent revolution of the gearbox drive shaft. This implies that the shaft angular velocity may increase or decrease linearly or remain constant during a given revolution. The underlying assumption of a linear variation in velocity during each revolution is based on the fact that the velocity profile of each revolution can be represented by a very small segment of the overall velocity profile and may be assumed linear.

In order to convert into the angular domain, the IAR technique demands that the instants of time at three different shaft angular positions during a revolution be known. This is accomplished experimentally by mounting an additional reflective strip on the tacho-reflector wheel at 110° from the reference strip. The resultant multiple pulse tachometer arrangement, therefore, enables determination of time instants at three different shaft angular positions during a revolution. The next revolution is assumed to commence immediately after the pulse marking the end of a revolution is generated. This is demonstrated schematically in Fig. 3 which shows a tacho-reflector wheel with 2 reflective strips displaced by 110°.

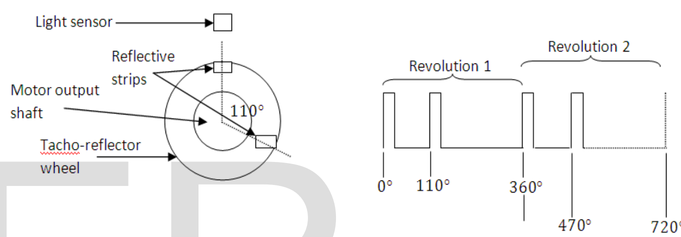


Fig. 3. *Multiple pulse tachometer arrangement*

The re-sample time instants corresponding to constant angular increments are then obtained independently for each revolution. The amplitude of vibration signals at the re-sample time instants can be obtained from interpolation theory. In the present work, piecewise cubic hermite interpolation (PCHI) [49] is employed to determine the amplitude of vibration signals at the re-sample time instants. Non-stationary vibration signals in the time domain are thus converted into a number of quasi-stationary signals in the angular domain.

3 Experimental set-up and data acquisition

The experimental set-up consists of a single stage spur gearbox that forms an integral part of the drive train diagnostic simulator (DDS) shown in Fig. 4. The DDS gearbox consists of a 32-tooth pinion in mesh with an 80-tooth gear mounted on the output shaft. The pinion is mounted on a shaft driven by a 3Φ, 3hp, 0-5000 rpm synchronous motor while the output torque produced the magnetic particle brake ranges from 4 - 220 lb-in (0% -

100%). The DDS allows both the speed profile as well as the load profile to be programmed.

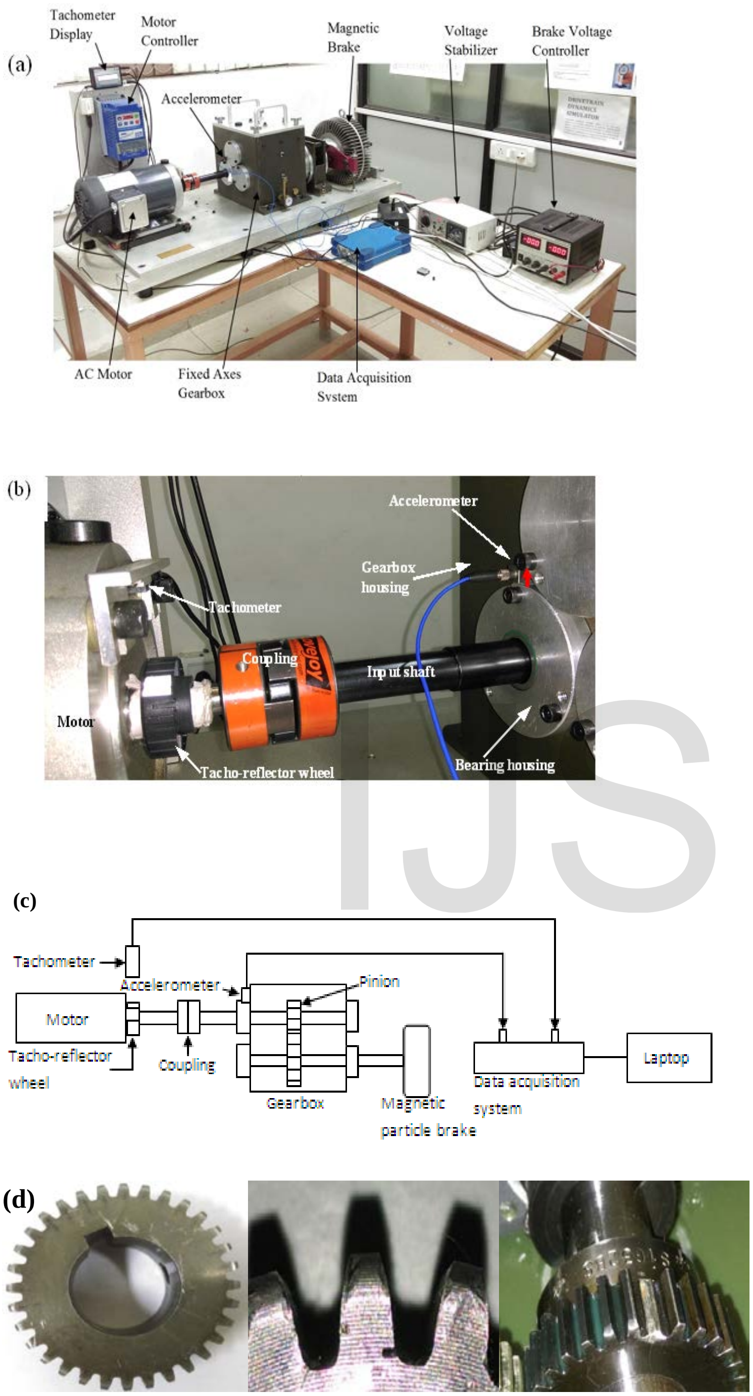
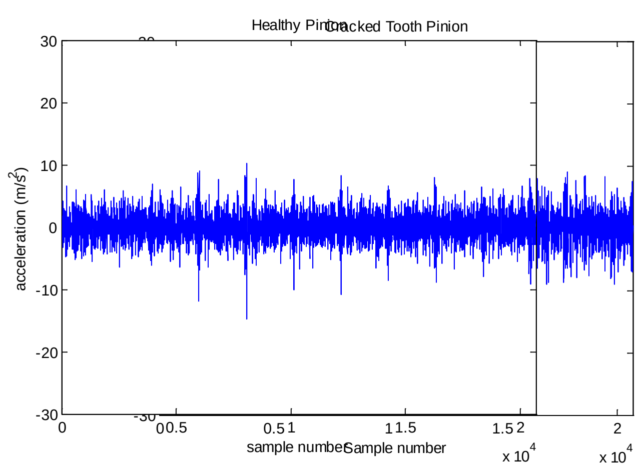


Fig. 4. *(a) Drive train diagnostic simulator (DDS), (b) sensor arrangement, (c) schematic diagram and (d) healthy pinion, cracked tooth pinion and missing tooth pinion*

The most common gear diagnosis method is to analyze the vibration signals obtained from the machinery, specifically the shafts containing the gears [10]. Therefore, the accelerometer for acquiring the vibration signal is mounted on the bearing housing of the gearbox input shaft. Since the present work involves fault diagnosis of a single stage spur gearbox, vibration signals are measured along the y-axis as indicated in Fig. 4 (b). The multiple pulse tachometer arrangement is facilitated by mounting a multiple strip tacho-reflector wheel on the motor output shaft. The accelerometer and tachometer are interfaced to a PC via a data acquisition system.

Vibration signals are acquired under four different gearbox health conditions, viz., healthy pinion, pinion with a cracked tooth, pinion with a chipped tooth and pinion with a missing tooth at a constant speed of 20 Hz at 0% load. The sampling frequency is selected as 8192 Hz and the gear wheel remains the same in each of the experiments. For simplicity, segments of vibration signals during which the gearbox drive shaft undergoes only 50 complete revolutions have been considered for analysis. Fig. 5 shows the vibration signals acquired from the gearbox under various pinion health conditions over 50 complete revolutions of the gearbox drive shaft. The number of samples corresponding to 50 revolutions is not the same in each of the four cases owing to fluctuations in speed of the gearbox drive shaft.



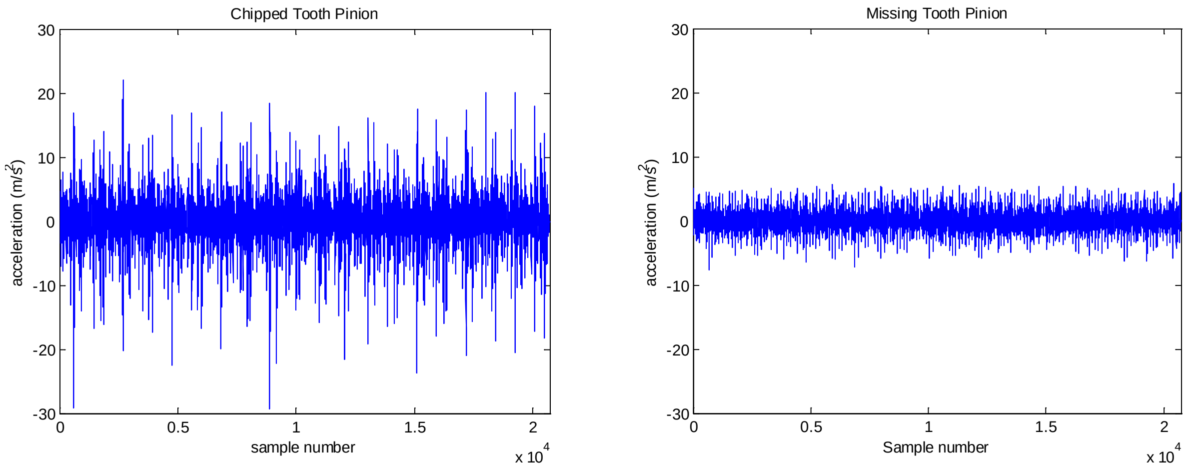
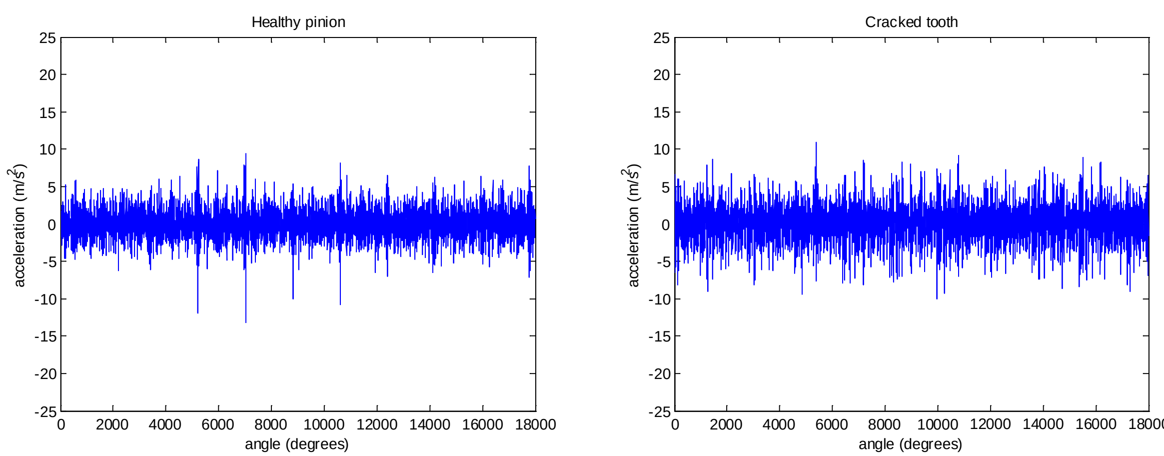


Fig. 5. *Vibration signal representing 50 complete revolutions of the gearbox drive shaft with healthy pinion, cracked tooth pinion, chipped tooth pinion and missing tooth pinion*

It can be observed from the time domain vibration signals pertaining to the various pinion health conditions that the amplitude of the vibration signal is highest for the chipped tooth pinion and least for the missing tooth pinion. The signal for the missing tooth pinion also exhibits an impulsive nature not present for the other gear health conditions. In particular, it is difficult to distinguish between the signals pertaining to the healthy pinion and cracked tooth pinion. A visual inspection of only the time domain signals to ascertain the condition of the gearbox is likely to generate error and there is a requirement of an automated method of gearbox fault diagnosis.

A clear advantage in terms of gear fault diagnostic accuracy is attained when the non-stationary time domain vibration signals are converted into the angular domain prior application of wavelet packet transform [48]. Non-stationary time domain vibration signals are converted into quasi-stationary signals in the angular domain employing the IAR technique as described in Section 2. The resulting angular domain signals, each representing one complete revolution of the gearbox drive shaft, are merged to generate the synchronized angular domain vibration signal for the complete rotational period. Fig. 6 shows the synchronized angular domain signals obtained from the proposed method. The number of samples in each of the four cases is equal and corresponds to 50 complete revolutions of the gearbox drive shaft.



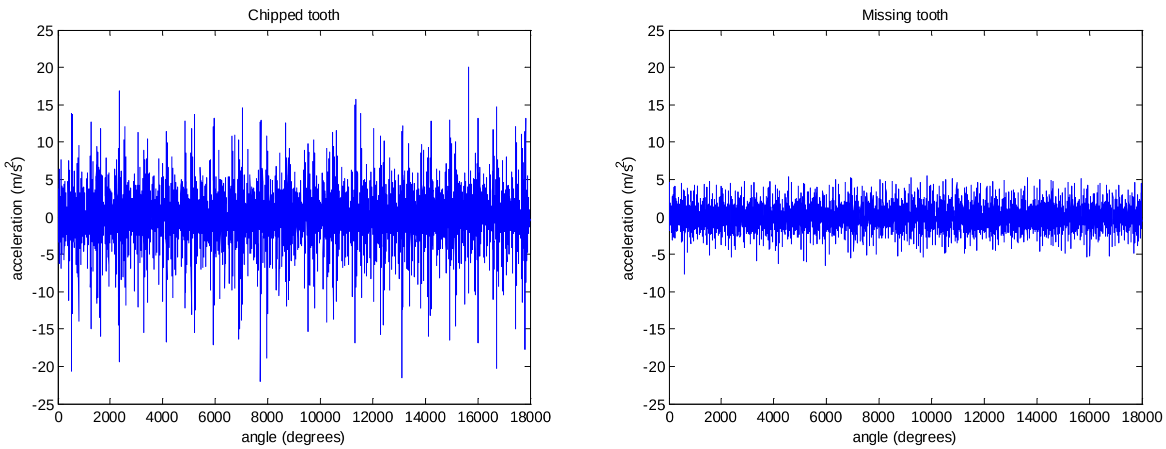


Fig. 6. *Synchronized angular domain vibration signals representing 50 complete revolutions of the gearbox drive shaft with healthy pinion, cracked tooth pinion, chipped tooth pinion and missing tooth pinion*

The present work is limited to fault diagnosis of a single stage spur gearbox which forms an integral part of the drive train diagnostic simulator (DDS) shown in Fig. 4. The vibration signatures may exhibit a different trend for another gearbox and, therefore, a visual inspection of the time domain or angular domain signals to ascertain the condition of the gearbox is likely to be erroneous. An automated method of gearbox fault diagnosis is desirable such that the condition of the gearbox can be assessed with minimum intervention of the operator.

Wavelet transform possesses good local properties in time and frequency spaces [56]. But the wavelet transform method does not split the high frequency bands where the modulation information of machine fault exists. Wavelet Packet Transform (WPT) furthers decomposition of the high frequency bands and may generate a more precise frequency-band partition over the whole analyzed frequency bands. Thus, the frequency resolution may be enhanced [57]. In the present work, the synchronized angular domain vibration signal is split into a number of data samples consisting of 512 samples. Each data sample is decomposed with WPT to the third level utilizing db4 as the mother wavelet function.

Fig. 7 shows a data sample extracted from the synchronized angular domain signal for the healthy pinion and the eight frequency bands obtained after wavelet packet decomposition. Standard deviation of wavelet packet coefficients in each of the frequency bands is then computed and the distance evaluation technique employed to identify the frequency bands which have a greater fault discrimination capability.

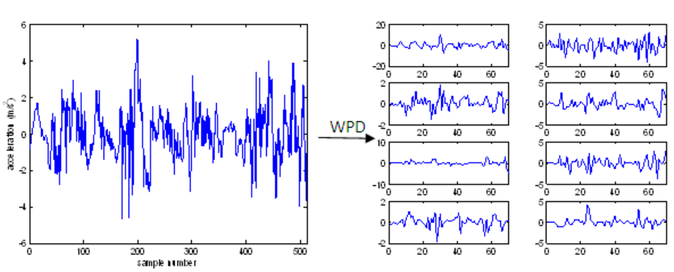


Fig. 7. *Data sample extracted from the synchronized vibration signal for the healthy pinion and the eight frequency bands obtained after wavelet packet decomposition*

4 Distance evaluation technique

The various frequency bands obtained from wavelet packet decomposition of data samples have different fault recognition capabilities. Some of the frequency bands have greater sensitivity to fault detection than the other frequency bands. Thus, it is necessary to identify those frequency

bands which have greater sensitivity to fault detection. There are a number of feature selection methods which aim at reducing the dimensionality of input feature vectors such that an intelligent classifier is fed with only those features which have greater sensitivity to fault detection. Some of the popular feature selection methods include conditional entropy [50], genetic algorithm [51, 52] and distance evaluation technique [53-55].

Owing to its simplicity, the distance evaluation technique is employed in the present work to select the sensitive frequency bands. This technique is based on the fact that the frequency bands that make the distance of feature vectors within a class shorter and the distance between classes longer is better than the others [55].

Suppose a feature set of C conditions is

$$\{q_{m,cj}, m = 1,2, \dots, M_c; c = 1,2, \dots, C; j = 1,2, \dots, J\} \quad (1)$$

where $q_{m,cj}$ is the jth feature value of the mth sample under the cth condition, M_c is the sample number of the cth condition, and J is the feature number of each condition.

Then the feature evaluation technique based on distance can be depicted as follows:

(1) Calculating the average distance of the same condition samples

$$d_{cj} = \frac{1}{M_c \times (M_c - 1)} \sum_{l,m=1}^{M_c} \left| q_{m,cj} - q_{l,cj} \right|, \quad l,m = 1,2,\dots,M_c, \quad l \neq m \tag{2}$$

(2) Getting the average distance of C conditions

$$d_j^{(w)} = \frac{1}{C} \sum_{c=1}^{C} d_{cj} \tag{3}$$

(3) Calculating the average feature value of all samples under the same condition

$$u_{cj} = \frac{1}{M_c} \sum_{m=1}^{M_c} q_{m,cj} \tag{4}$$

(4) Obtaining the average distance between different condition samples

$$d_j^{(b)} = \frac{1}{C \times (C-1)} \sum_{c,e=1}^{C} \left| u_{ej} - u_{cj} \right|, \quad c,e = 1,2,\dots,C, \quad c \neq e \tag{5}$$

(5) Calculate the ratio $d_j^{(b)}$ and $d_j^{(w)}$ and getting the distance evaluation factor

$$\alpha_j = \frac{d_j^{(b)}}{d_j^{(w)}} \tag{6}$$

Once the evaluation factors for all the frequency bands have been calculated, they are ranked in terms of their distance evaluation factors from large to small. Fig. 8 shows the distance evaluation factors for the eight frequency bands. The third, seventh and fifth frequency bands have highest distance evaluation factors and are selected for further analysis using ANFIS. The number of selected frequency bands is limited to three as an increase in the number of inputs to the ANFIS will only increase the complexity and computational burden.

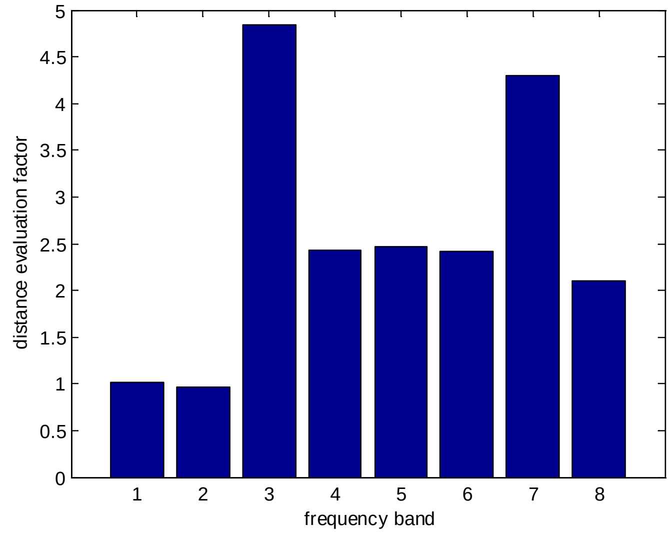


Fig. 8. *Distance evaluation factors for the eight frequency bands*

5 Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS is a fuzzy Sugeno model put in the frame work of adaptive systems to facilitate learning and adaptation [34, 35]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1: If $(x \text{ is } A_1)$ and $(y \text{ is } B_1)$ then $(f_1 = p_1 x + q_1 y + r_1)$

Rule 2: If $(x \text{ is } A_2)$ and $(y \text{ is } B_2)$ then $(f_2 = p_2 x + q_2 y + r_2)$

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule; p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 9 in which a circle indicates a fixed node whereas a square indicates an adaptive node.

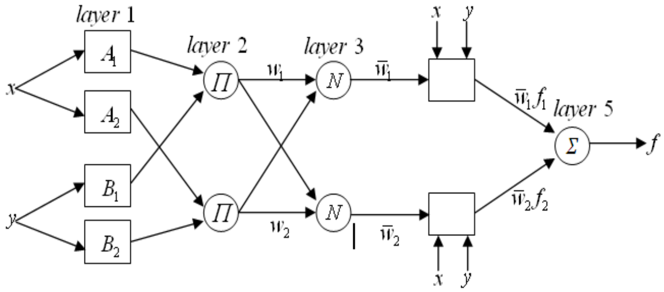


Fig. 9. ANFIS architecture [34, 35]

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by [34, 35]

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \tag{7}$$

and

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3,4 \tag{8}$$

where $\mu_{A_i}(x)$, $\mu_{B_i-2}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{A_i}(x)$ is given by [34, 35]:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{\alpha_i} \right)^2 \right\}^{b_i}} \tag{9}$$

where a_i, b_i and c_i are the parameters of the membership function governing the bell-shaped functions accordingly. In the second layer, the nodes are fixed nodes. They are labeled with Π indicating that they perform as a simple multiplier. The outputs of this layer can be represented as [34, 35]

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \tag{10}$$

which are called firing strengths of the rules.

In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as [34, 35]

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{11}$$

which called normalized firing strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Thus, the outputs of this layer are given by [34, 35]:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad i = 1,2 \tag{12}$$

In the fifth layer, there is only one single fixed node labeled with $\sum$. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by [34, 35]:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{13}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the called *premise* parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are called *consequent* parameters.

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$ to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as [34, 35]

$$f = \overline{w_1}(p_1 x + q_1 y + r_1) + \overline{w_2}(p_2 x + q_2 y + r_2) \tag{14}$$

After rearranging terms in Eq. (14), the output can be expressed as [33, 34]:

$$f = (\overline{w_1 x}) p_1 + (\overline{w_1 y}) q_1 + \overline{w_1} r_1 + (\overline{w_2 x}) p_2 + (\overline{w_2 y}) q_2 + \overline{w_2} r_2 \tag{15}$$

which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily.

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When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [34, 35].

6 Results and discussions

Normalized standard deviation values of wavelet packet coefficients from only the optimal frequency bands (as identified from the distance evaluation technique) are employed as inputs to train and test the ANFIS. Since each data sample consists of 512 samples in the angular domain, there are 35 data samples pertaining to each gear health condition. Table 1 shows that amongst the 35 data samples for each gear health condition, 20 randomly selected data samples are utilized for training the ANFIS while the remaining 15 data samples are reserved for testing.

Table 1 Division of the gearbox data set

Gear health condition	No. of training samples	No. of test samples	Label of classification
Healthy pinion	20	15	1
Cracked tooth	20	15	2
Chipped tooth	20	15	3
Missing tooth	20	15	4

There is a choice of membership functions which can be adopted while training the ANFIS. The best membership functions must be selected by trial and error. In the present work, the Gaussian membership functions are chosen for the inputs and the linear membership function for the output. There are three inputs consisting of normalized standard deviation values of wavelet packet coefficients from the three optimal frequency bands. The membership functions of each input parameter are divided into three regions, namely, small, medium and large. At the end of 30 training epochs, the network error (mean square error) convergence of the ANFIS is shown in Fig. 10. From the curve, the final convergence value is 0.0059738.

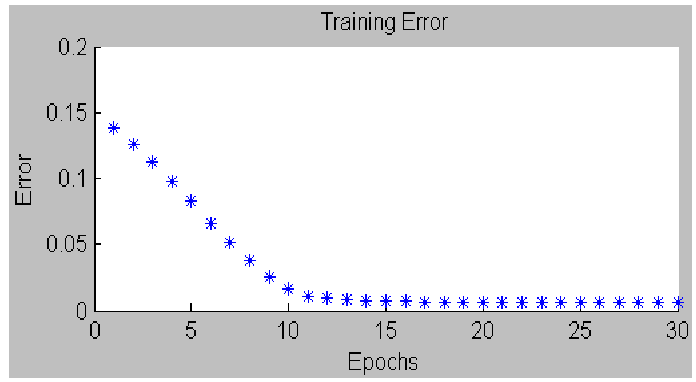
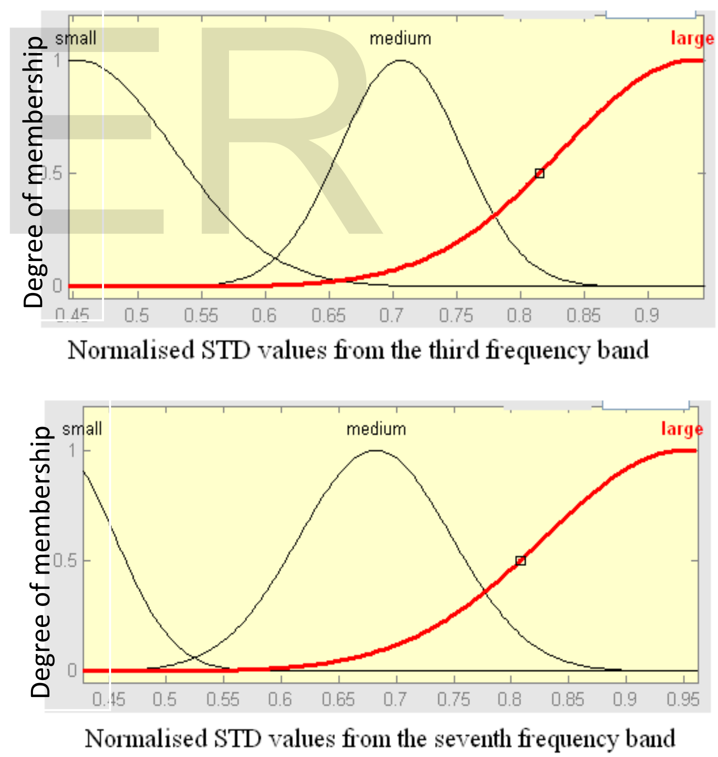


Fig. 10. ANFIS error convergence curve

The membership functions for the three inputs at the end of the training process are shown in Fig. 11.



Degree of membership

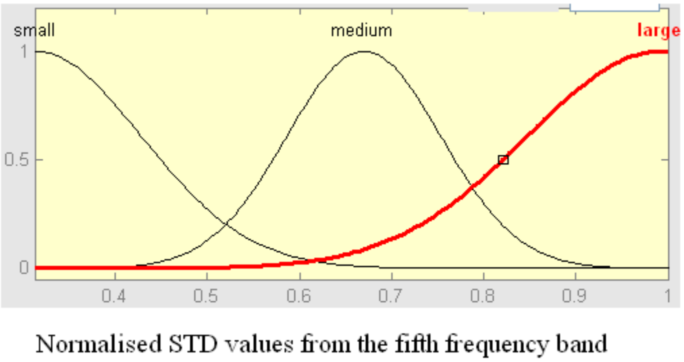


Fig. 11. *Membership functions for the three inputs at the end of the training process*

Once the ANFIS has been trained, it is tested for its classification accuracy. Fig. 12 shows the classification accuracy of the trained ANFIS when it is presented with the training data set consisting of 20 randomly selected data samples from each class. Fig. 13 shows the classification accuracy of the ANFIS when it is presented with the test data set consisting of 15 data samples from each class. It is observed that the trained ANFIS is able to correctly identify the gear health condition.

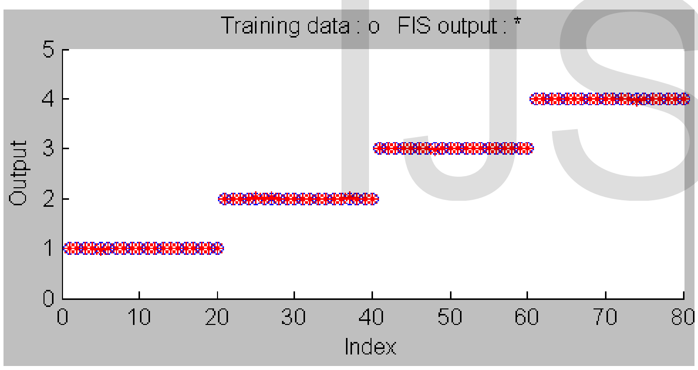


Fig. 12. *Classification results of the trained ANFIS with training data samples*

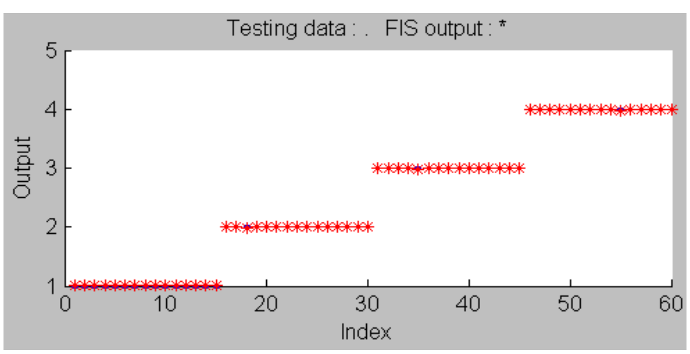


Fig.13*. Classification results of the trained ANFIS with test data samples*

8 Conclusion

Gearbox vibration signatures are mostly non-stationary owing to uncertainties associated with the drive and load mechanisms. It can be shown that even when a prime mover is designed to run at a constant speed of rotation, the time taken for each revolution of the gearbox drive shaft is not necessarily the same. Conventional time synchronous averaging to improve the signal to noise ratio cannot be then employed. The IAR technique is a simple yet powerful method to convert non-stationary signals in the time domain into quasi-stationary signals in the angular domain. It is a technique which provides an added advantage in terms of gear fault diagnostic accuracy prior decomposition of data samples with WPT. Standard deviation of wavelet packet coefficients is computed and the optimal frequency bands identified based on the distance evaluation technique. Normalized standard deviation values from the optimal frequency bands are employed as feature sets to train and test the ANFIS. Superior gear fault diagnostic results are obtained when the proposed method is employed to diagnose gearbox faults through an analysis of non-stationary vibration signals. The only requirement of implementing the proposed method in real-life applications is to train the ANFIS with data set extracted from a similar gearbox under different fault conditions (most frequent ones). Once the ANFIS has been trained on various commonly occurring faults, the system can be fed with real time data from the gearbox in-situ. This program can perform a comparative analysis and indicate any abnormality if detected. The proposed method also has the potential to diagnose gearbox faults under the realistic fluctuating speed conditions.

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