Gearbox Fault Diagnosis using Independent Angular Re-Sampling Technique, Wavelet Packet Decomposition and ANN

[1]Amandeep Singh Ahuja, [2]Sravan Kumar Khuntia, [3]Anand Parey

[1][2]Naval Institute of Aeronautical Technology, Naval Base, Kochi, India,

[3]IIT Indore, India

Abstract: **- The vibration signal of a gearbox carries abundant information about its condition and is widely utilized to diagnose the condition of the gearbox. Most of the research efforts in diagnosing gearbox faults, however, assume the acquired vibration signal to be stationary. This paper attempts to highlight the non-stationary nature of gearbox vibration signals owing to uncertainties of the drive and load mechanisms and to synchronize such signals from the revolution point of view. This synchronization is achieved by a simple process referred to as the independent angular re-sampling (IAR) technique. The basis of the IAR technique is the assumption of constant angular acceleration over each independent revolution of the gearbox drive shaft. Through the IAR process, non-stationary signals sampled at constant time increments are converted into quasi-stationary signals sampled at constant angular increments. The angular domain signals obtained from the IAR technique are merged to generate the synchronized angular domain vibration signal for the complete rotational period. The angular domain signal for each gear health condition is partitioned into a number of data samples which are then analyzed using wavelet packet decomposition. Standard deviation values of wavelet packet coefficients are then computed and the resulting vectors utilized as inputs to a multilayer perceptron neural network for identifying the condition of the gearbox.**

Keywords: **Gearbox fault diagnosis, independent angular re-sampling (IAR) technique, wavelet packet decomposition, multilayer perceptron neural network**

I. INTRODUCTION

The gearbox forms an integral part a vast majority of machines and great attention has been directed towards fault diagnosis of gearboxes to prevent unexpected breakdown and possible loss of life. Gearbox failure in certain critical applications such as single engine aircraft and propulsion systems of warships is unacceptable.

A gearbox is likely to transit through a run-up period during start-up of the machinery. Therefore, most of the research works on gearbox fault diagnosis under non-stationary conditions have involved an analysis of gearbox vibration signals under the run-up condition of the drive mechanism. In such works, it has been assumed that the velocity of the gearbox drive shaft increases linearly from one speed to another and hence the angular acceleration remains constant over the considered rotational period. Li et al. [1] employed the angular domain averaging technique to diagnose gear crack faults during the run-up of a gear drive and converted non-stationary signals in the time domain into stationary signals in the angular domain. Meltzer and Ivanov [2, 3] 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 [4] 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. [5] combined computed order tracking, cepstrum analysis and radial basis function neural network for gear fault detection during the speed-up process.

In practical applications, a gearbox is likely to be subjected to variable loads and speeds resulting in fluctuating speed conditions. Research efforts in diagnosing gearbox faults under fluctuating speed conditions, however, are limited. Jafarizadeh et al. [6] 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. [7] 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 [8] 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 [9] employed the independent angular re-sampling (IAR) technique to diagnose gearbox faults under fluctuating load conditions.

Recently, wavelet packet decomposition has been applied successfully in fault diagnosis of rotating machinery [10-13]. In a number of studies based on fault diagnosis with wavelet packet decomposition, the time domain vibration/ sound emission signal is split into a number of data samples consisting of 2^n sampling points. These data samples are then decomposed with wavelet packet decomposition resulting in a number of frequency bands depending on the level of decomposition. One or more statistical parameters such as standard deviation, energy, entropy etc. of wavelet coefficients is then calculated and employed in the form of input feature vectors to an artificial neural network for the purpose of fault identification.

In some cases, however, the vibration signal acquired from the gearbox is first synchronized from the revolution point of view before the data samples are analyzed with wavelet packet decomposition. Rafiee et al. [14] devised a method to experimentally recognize bearing and gear faults in a four speed motorcycle gearbox using an artificial neural network. The vibration signals acquired from the gearbox were first synchronized from the revolution point of view using piecewise cubic hermite interpolation. The synchronized vibration signals were divided into several equal partitions which were then decomposed using wavelet packet decomposition. Kang et al. [15] presented an intelligent method for gear fault diagnosis based on wavelet packet analysis and support vector machine. Raw vibration signals were segmented into the signals recorded during one complete revolution of the input shaft using tachometer information and then synchronized using cubic spline interpolation to construct sample signals with the same length.

One of the objectives of the present study is to determine if synchronization of the vibration signal from the revolution point of view has any advantage prior to decomposing the data samples with wavelet packet decomposition. Two cases are, therefore, compared in the present study:

(a) The time domain vibration signal is split into a number of equi-sized data samples which are decomposed using wavelet packet decomposition.

(b) The vibration signal is first synchronized from the revolution point of view utilizing the IAR technique and then the synchronized angular domain vibration signal is split into equi-sized data samples which are decomposed using wavelet packet decomposition.

In each of the above cases, the resulting data samples consisting of 512 sampling points are decomposed using wavelet packet decomposition to the third level utilizing db1 as the wavelet basis function. Standard deviation of wavelet packet coefficients is then computed and the resulting 8-dimensional input feature vectors employed as inputs to a back propagation neural network with the objective of identifying the gearbox health condition. A flowchart of the proposed fault diagnosis procedure is shown in Fig 1.

The remainder of this paper is organized as follows: Section 2 describes the independent angular re-sampling technique which is employed in the present work to synchronize the vibration signals acquired from the gearbox. The experimental set-up is described in Section 3. The procedure of feature extraction from the synchronized vibration signals is the subject of Section 4. Section 5 briefly describes the artificial neural network while the experimental results are discussed in Section 6.

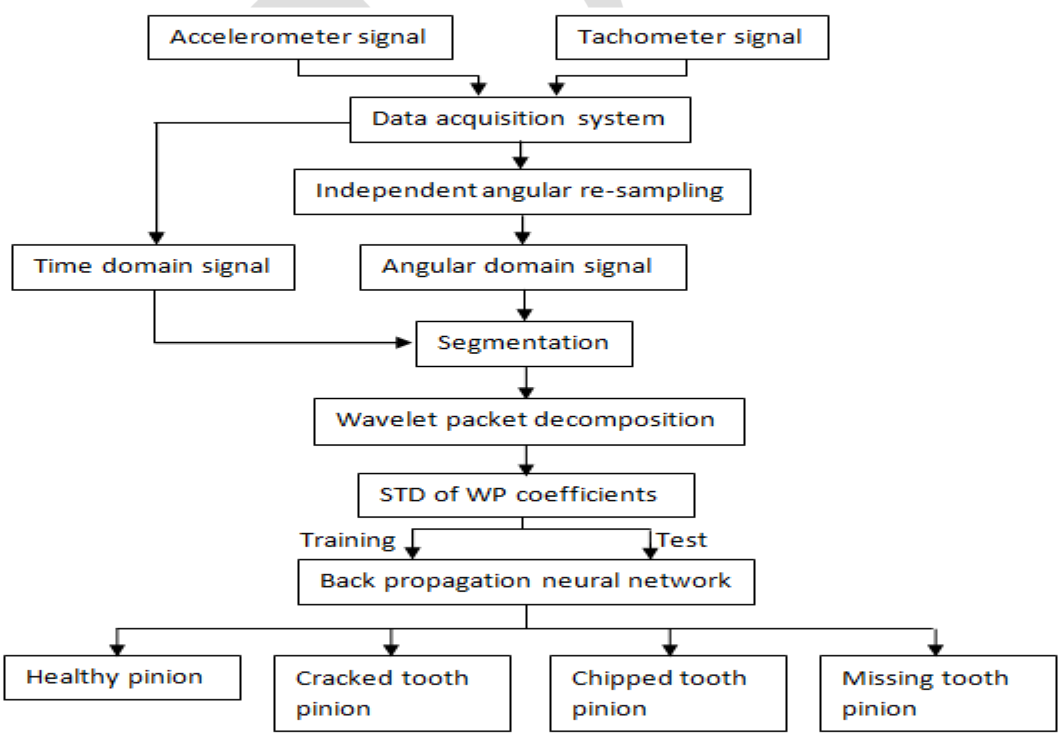

Fig. 1. Flowchart of the proposed fault diagnosis procedure

II. INDEPENDENT ANGULAR RE-SAMPLING (IAR) TECHNIQUE

A standard electrical tachometer generates a pulse once per revolution by receiving light from a single reflective strip mounted on the shaft. The output, generated in terms of pulse versus time, indicates the speed of rotation in revolutions per minute (rpm) of the shaft. The occurrence of a fault in a geared system is usually identified by comparing the vibration or sound emission signals collected under the fault and no-fault conditions. The vibration or sound emission signal acquired using the accelerometer or microphone is sampled at a pre-defined sampling frequency. A constant speed of rotation is characterized by an equal number of samples between tachometer pulses. A variation in the number of the samples between successive tachometer pulses indicates fluctuations in speed.

Most of the research works in gearbox fault diagnosis under the speed-up process assume constant angular acceleration over the complete speed-up period, the angular rotation being defined by Eq. (1) [1, 4-5].

$$\theta(t) = b_0 + b_1 t + b_2 t^2 \tag{1}$$

The first derivative of Eq. (1) gives the angular velocity which varies linearly with time; hence, the concept of fault diagnosis under the linear speed-up process in [1, 4-5]. Even when the vibration signal has been acquired at a constant speed of rotation, the actual velocity profile of the gearbox drive shaft is likely to exhibit variations from the programmed constant speed profile. However, if a very small segment of the actual velocity profile representing only one revolution of the gearbox drive shaft is taken into consideration, it may be assumed linear. In other words, the shaft angular velocity may increase or decrease linearly or remain constant with time during a given revolution. In this work, it has been assumed that the angular acceleration remains constant during each independent revolution though the value of angular acceleration may vary from one revolution to another.

In order to determine the constants b_0, b_1 and b_2 for a revolution, the instants of time at three different shaft angular positions are required. This is accomplished experimentally by mounting an additional reflective strip 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. The IAR technique is illustrated in Fig. 2.

The re-sample time instants corresponding to constant angular increments of $\Delta\varphi = 1°$ are then computed for each revolution from Eq. 2 [1, 4-5].

$$t = \frac{1}{2b_2}[\sqrt{4b_2(k\Delta\varphi - b_0) + b_1^2} - b_1] \tag{2}$$

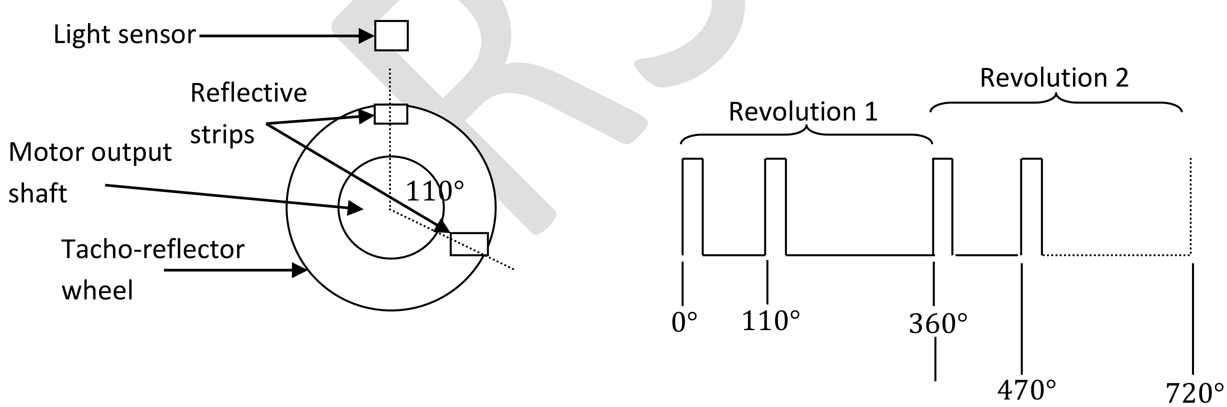

Fig. 2. Illustration of the IAR technique

The amplitude of the vibration signal at the re-sample time instants can be obtained from interpolation theory. In the present work, piecewise cubic hermite interpolation [16] is applied to determine the amplitude of vibration signals at the re-sample time instants. Thus, non-stationary signals in the time domain are converted into quasi-stationary signals in the angular domain. The angular domain signals, each representing 360 degrees of rotation of the gearbox drive shaft, are merged to generate the combined angular domain signal for the complete rotational period.

The synchronized angular domain signal for each gear health condition is partitioned into a number of data samples consisting of 512 sampling points. Each data sample is then decomposed using wavelet packet decomposition as discussed in Section 4.

III. 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. 3 (a). 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 by the magnetic particle brake ranges from 4-220 lb-in. The DDS allows both the speed profile as well as the load profile to be programmed.

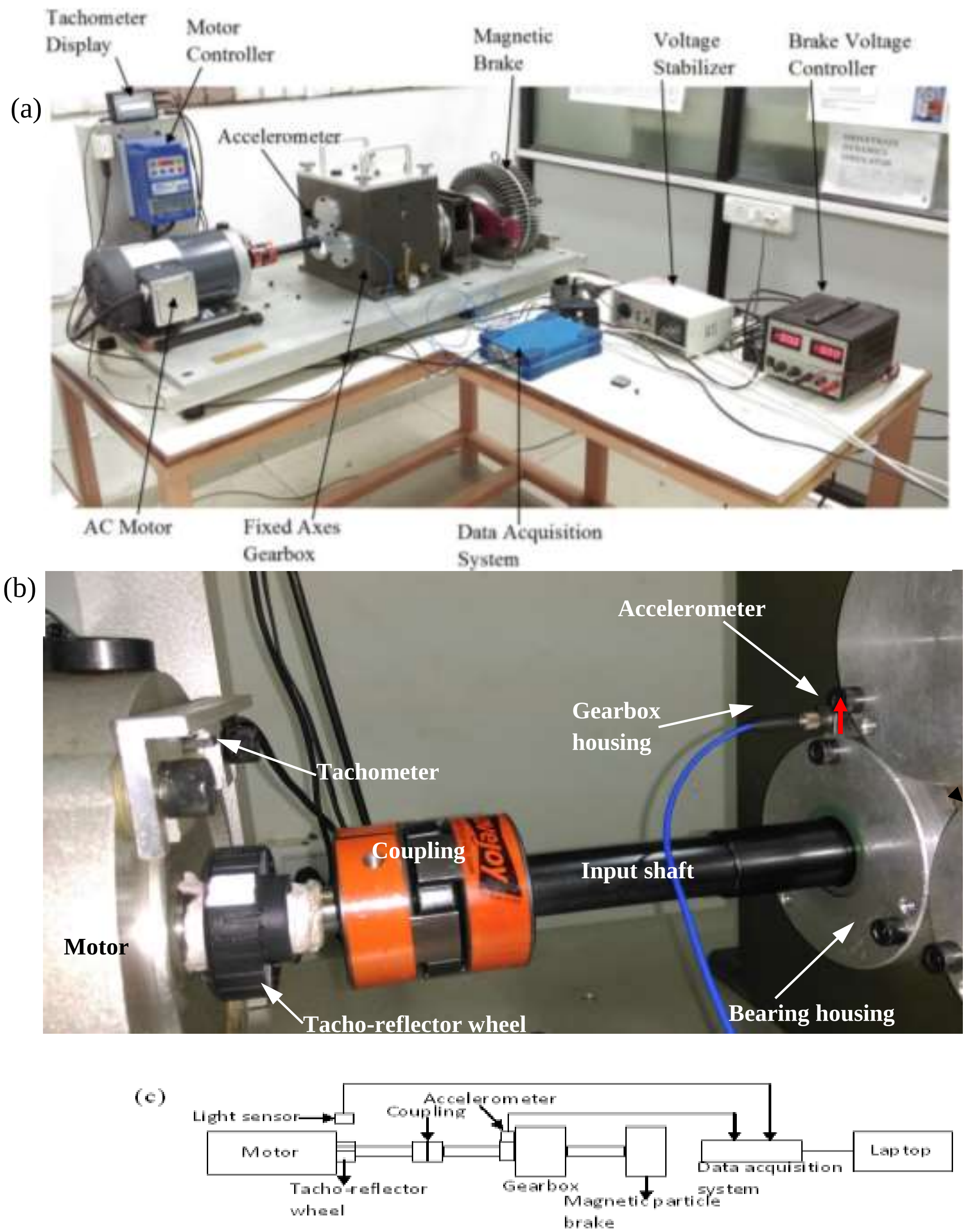

Fig. 3. (a) Drive train diagnostic simulator (b) sensor arrangement and (c) functional diagram

The uni-axial accelerometer for acquiring the vibration signal is mounted on the bearing housing of the gearbox input shaft. Vibration signatures are acquired from the gearbox in the vertical direction as indicted with a red arrow in Fig. 3(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 signatures 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 broken/ missing tooth. Various faults are introduced in the pinion wheel while the gear wheel remains undisturbed.

For simplicity as well as to keep the computational burden under control, time domain vibration signals during which the gearbox drive shaft undergoes 20 complete revolutions have been considered for analysis. Fig. 4 shows the vibration signals acquired under the four different gearbox health conditions at a constant programmed speed of 20 Hz at 0% load. The sampling frequency is selected as 8192 Hz. The number of samples corresponding to 20 complete revolutions is unequal in each of the four vibration signals owing to speed fluctuations.

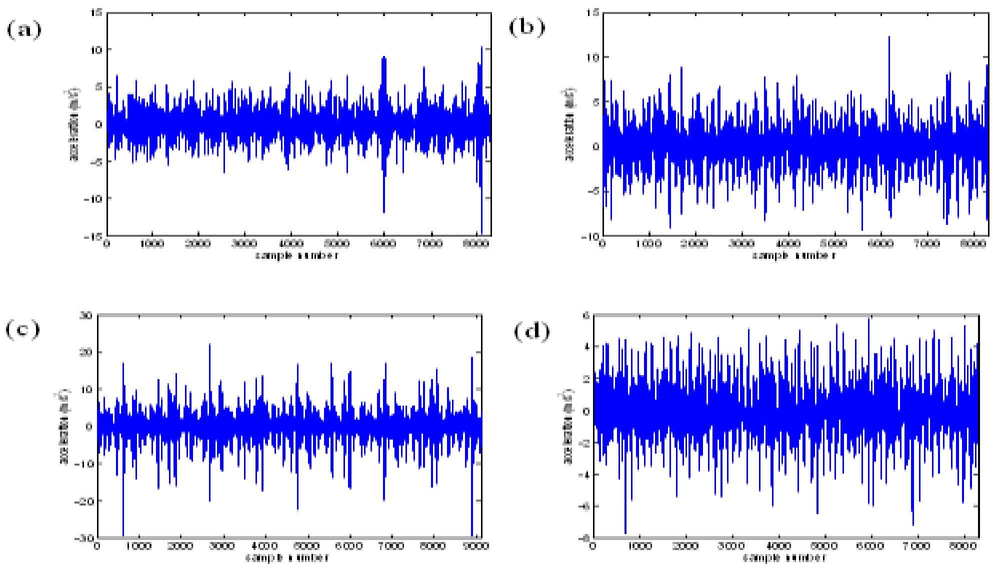

Fig. 4. Vibration signal acquired from the gearbox with (a) healthy pinion, (b) cracked tooth pinion, (c) chipped tooth pinion and (d) missing tooth pinion

Fig. 5 shows the angular domain vibration signal synchronized using the IAR technique. The number of data samples in each of the four vibration signals is equal and corresponds to 20 complete revolutions of the gearbox drive shaft.

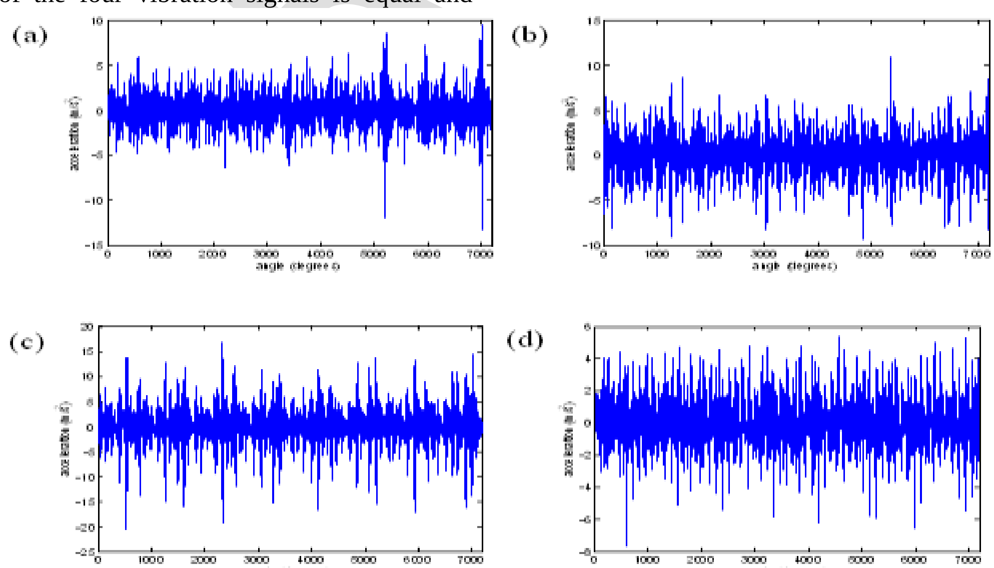

Fig. 5. Synchronized angular domain vibration signal for the gearbox with (a) healthy pinion, (b) cracked tooth pinion, (c) chipped tooth pinion and (d) missing tooth pinion

For effective fault diagnosis, useful features representing the gearbox health condition must be extracted from the acquired vibration signals.

IV. FEATURE EXTRACTION

Wavelet transform possesses good local property in both time and frequency spaces [17]. However, the high frequency bands where the modulation information of the machine fault usually exists are not split in wavelet transform. Wavelet packet transform, however, decomposes the approximations (low frequency components) as well as the details (high frequency components) resulting in 2^l frequency bands where l is the level of decomposition. In the present work, the gearbox vibration signals synchronized using the IAR technique are split into a number of data samples consisting of 512 sampling points each. Each data sample is decomposed with wavelet packet decomposition up to the third level employing db1 as the wavelet basis function. Fig. 6 shows a data sample extracted from the synchronized vibration signal for the healthy pinion along with the 8 frequency bands and the corresponding standard deviation values of wavelet packet coefficients.

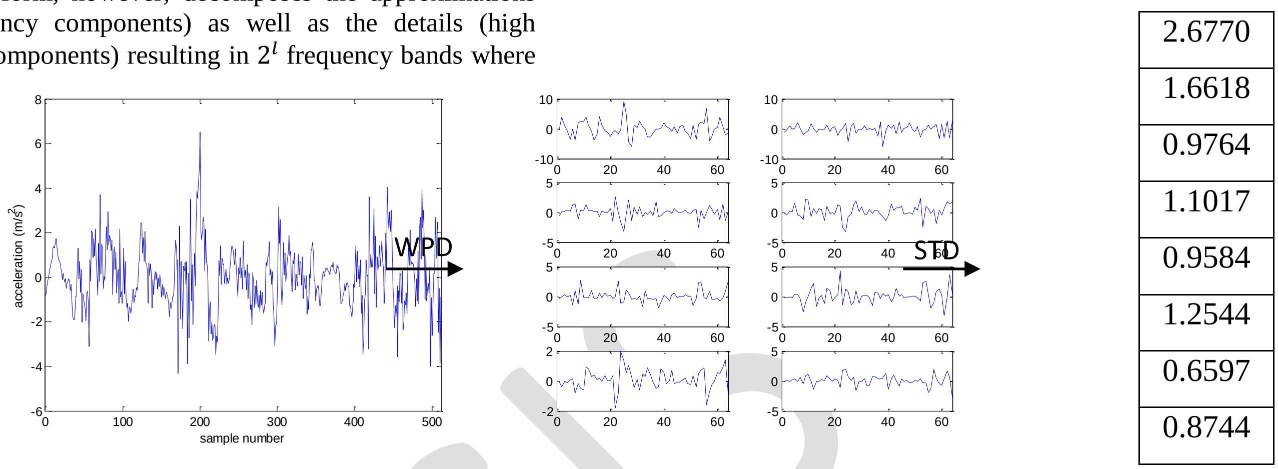

Fig. 6. A data sample from the synchronized vibration signal for the healthy pinion, the 8 frequency bands and standard deviation values of wavelet packet coefficients

Since each data sample consists of 512 sampling points in the angular domain, a maximum of 14 data samples are generated from the synchronized angular domain vibration signal pertaining to each gear health condition. Thus, 14 in number eight-dimensional input feature vectors from each of the 4 classes, consisting of standard deviation values of wavelet packet coefficients, are available to train and test the artificial neural network.

V. ARTIFICIAL NEURAL NETWORK

One of the most commonly employed forms of artificial neural networks (ANN) for fault diagnosis is the multilayer perceptron (MLP) neural network trained with the back-propagation algorithm. Such a neural network is shown in Fig. 7 and is also referred to as the back-propagation neural network. In its simplest form, a back-propagation neural network consists of an input layer, one or more hidden layers and an output layer. The neurons in the different layers are connected to each other with connecting links called synapses and each such link is associated with a synaptic weight.

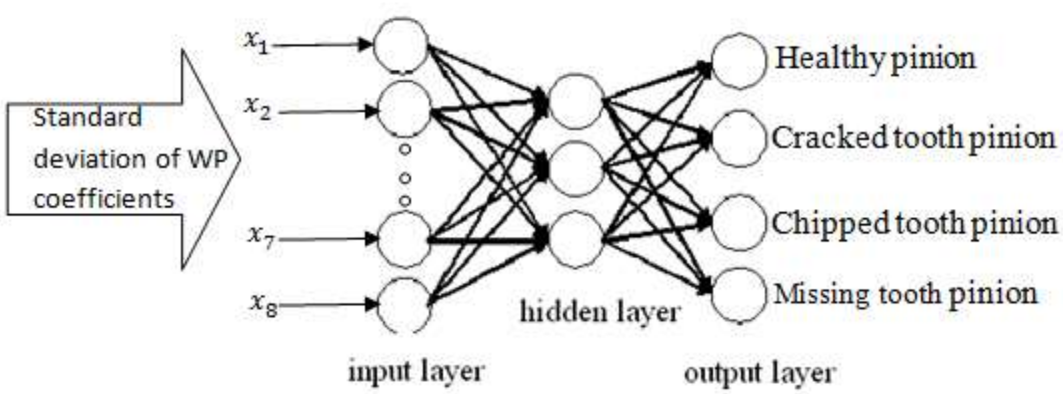

Fig. 7. Concept of multi-layer perceptron model

The number of neurons in the input layer depends upon the dimensionality of the input feature vectors and the number of output neurons depends on the number of classes into which the dataset is to be classified. The back-propagation algorithm involves two passes – a forward pass and a backward pass. In the forward pass, input features are presented to the network in the form of vectors. This information propagates in the forward direction and each neuron in the output layer computes a value which may be different from the desired output value. A mean squared error (MSE) is then computed based on the difference between the desired output and the target output. This information is propagated in the backward direction. As the network is trained, the synaptic weights are adjusted until the error reaches a pre-defined value or another termination criterion is met. Detailed information on the algorithm and other training algorithms can be found in [18, 19].

The test accuracy of a back propagation neural network consisting of 9 hidden neurons and employing the sigmoidal activation function for the hidden and output neurons is compared for two cases. In Case A, data samples consisting of 512 sampling points are extracted from the original time domain vibration signal while in Case B, data samples consisting of 512 sampling points are extracted from the synchronized angular domain vibration signal. The present work deals with a four-class gear fault identification problem and hence there are only four output neurons. 50% of the feature set in each case is used to train the neural network while the remaining 50% is utilized to test its classification accuracy.

VI. EXPERIMENTAL RESULTS AND DISCUSSIONS

In Case A, 14 data samples, each consisting of 512 sampling points, are extracted from the raw time domain vibration signal pertaining to each gearbox health condition resulting in a total of 56 data samples. In Case B, the data samples are extracted from the angular domain vibration signal synchronized using the IAR technique. Each data sample in this case consists of 512 sampling points representing 512 degrees of rotation of the gearbox drive shaft. Each of the 56 data samples is decomposed with wavelet packet decomposition up to the third level. Standard deviation of the wavelet packet coefficients is then computed and fed in the form of input feature vectors to an artificial neural network. The percentage of correctly classified instances from each class is shown in Table 1. 100% training and test accuracy is obtained when data samples from the synchronized vibration signals are employed for fault diagnosis.

Table 1 Percentage of correctly classified instances for a fixed ANN architecture

	Percentage of correctly classified test instances	
ANN Architecture	8:9:4	
Pinion	Case A	Case B
HEALTHY	85.7%	100%
CRACKED TOOTH	60%	100%
CHIPPED TOOTH	90%	100%
MISSING TOOTH	83.3%	100%

VII. CONCLUSION

Uncertainties associated with the drive and load mechanisms inevitably result in non-stationary conditions even when the drive mechanism has been programmed to be driven at a constant speed. The non-stationary vibration signals collected from a single stage spur gearbox are synchronized from the revolution point of view utilizing the independent angular re-sampling (IAR) technique. The IAR technique serves as a method to convert non-stationary signals in the time domain into quasi-stationary signals in the angular domain and demands only minor changes in hardware such as the introduction of an additional tachometer reflective strip. The classification accuracy of a back propagation neural network is compared for features sets extracted from wavelet packet decomposition of data samples in the time domain and the angular domain. Superior gear fault diagnostic accuracy is achieved when data samples extracted from the synchronized vibration signal are employed for fault diagnosis. It is concluded from this experiment that the IAR technique is a simple yet powerful method of synchronizing the vibration signal prior decomposition with wavelet packet transform. The proposed method can be employed to diagnose faults in rotating machineries under non stationary conditions with reasonably good accuracy.

REFERENCES

[1]. H. Li, Y. Zhang, H. Zheng, Angle domain average and CWT for fault detection of gear crack, in: Proceedings of the IEEE Transaction, Fifth International Conference on Fuzzy Systems and Knowledge Discovery 3, Jinan, Shandong, China, 2008, pp. 137-141.

[2]. G. Meltzer, Y. Ivanov, Fault detection in gear drives with non-stationary rotational speed - part I: the time-frequency approach, Mech. Syst. Signal Process. 17 (2003) 1033-1047.

[3]. G. Meltzer, Y. Ivanov, Fault detection in gear drives with non-stationary rotational speed - part II: the time-quefrency approach, Mech. Syst. Signal Process. 17 (2003) 273-283.

[4]. H. H. Bafroui, A Ohadi, Application of wavelet energy and Shannon entropy for feature extraction in gearbox fault detection under varying speed conditions, Neurocomputing 133(2014) 437-445.

[5]. H. Li, Y. Zhang, Gear fault detection and diagnosis under speed-up condition based on order cepstrum and radial basis function neural network, J. Mech. Sci. Technol. 23 (2009) 2780-2789.

[6]. M.A. Jafarizadeh, R. Hasannejad, M.M. Ettefagh, S. Chitsaz, Asynchronous input gear damage diagnosis using time averaging and wavelet filtering, Mech. Syst. Signal Process, 22 (2008) 172–201.

[7]. N. Ahamed, Yogesh Pandya, A Parey, Spur gear tooth root crack detection using time synchronous averaging under fluctuating speed, Measurement 52 (2014) 1-11.

[8]. V. Sharma & A. Parey, Gear crack detection using modified TSA and proposed fault indicators for fluctuating speed conditions, Measurement, 90 (2016), 560–575.

[9]. A. Singh & A. Parey, Gearbox fault diagnosis under fluctuating load conditions with independent angular re-sampling technique, continuous wavelet transform and multilayer perceptron neural network, I. E. T. Science, Measurement and Technology, 2016.
[10]. Jian-Da Wu, Chiu-Hong Liu, An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network, Expert Systems with Applications 36 (2009) 4278-4286.
[11]. Yaguo Lei, Zhengjia He, Yanyang Zi, Application of an intelligent classification method to mechanical fault diagnosis, Expert Systems with Applications 36 (2009) 9941-9948.
[12]. Yaguo Lei, Ming J. Zuo, Zhengjia He, Yanyang Zi, A multidimensional hybrid intelligent method for gear fault diagnosis, Expert Systems with Applications 37 (2010) 1419-1430.
[13]. Jian-Da Wu, Jian-Ji Chan, Faulted gear identification of a rotating machinery based on wavelet transform and artificial neural network, Expert Systems with Applications 36 (2009) 8862-8875.
[14]. J. Rafiee, F. Arvani, A. Harifi, M.H. Sadeghi, Intelligent condition monitoring of a gearbox using artificial neural network, Mech. Syst. Signal Process 21 (2007) 1746-1754.
[15]. J. Kang, X. Zhang, J. Zhao, H. Teng, D. Cao, Gearbox fault diagnosis method based on wavelet packet analysis and support vector machine, IEEE Conference on Prognostics and System Health Management (PHM), 2012.
[16]. F.N. Fritsch, R.E. Carlson, Monotone piecewise cubic interpolation, SIAM Journal of Numerical Analysis 14 (1980) 238-246.
[17]. Z. K. Peng, F. L. Chu, Application of wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography, Mech. Syst. Signal Process 18 (2003) 199-221.
[18]. B. Samanta, Gear fault detection using artificial neural networks and support vector machines with genetic algorithms, Mech. Syst. Signal Process 18 (2004) 625-644.
[19]. S. Haykin, “Neural Networks: A Comprehensive Foundation”, second edition, Pearson Education, 1998.