Vibration analysis of bearing for fault detection using time domain features and neural network

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Abstract—*Ball bearings are among the most important and frequently encountered components in the vast majority of rotating machines, their carrying capacity and reliability being prominent for the overall machine performance. Fault detection and diagnosis in the early stages of damage is necessary to prevent their malfunctioning and failure during operation. This paper presents fault detection of ball bearing using time domain features of vibration signals. The vibration signals are recorded at bearing housing of 5hp squirrel cage induction motor. These extracted features are used to train and test the neural network for four bearing conditions namely: Healthy, defective Outer race, defective Inner race and defective ball fault condition. The experimental observation shows that the proposed method is able to detect the faulty condition with high accuracy*.

Keywords- *Vibration monitoring; ball bearing; fault diagnosis; time domain features, bearing fault; artificial neural network (ANN).*

I.

II.   INTRODUCTION

Vibration monitoring is the most widely used and cost effective monitoring technique to detect, locate and distinguish faults in ball bearings. The vibration signal contains huge information, which can be applied for condition monitoring without interfering with machinery operation. When a localized fault in a bearing surface strikes another surface, impact vibrations are generated. Condition monitoring is performed by analyzing the changes in the vibration signature due to the presence of these impulses. Fault diagnosis helps to identify the location of the fault so that corrective action can be taken and maintenance can be planned accordingly.

At the heart of fault diagnosis lays the model based approach, whereby as many variables and system parameters are taken into account as possible in order to construct a detailed mathematical model of the system under observation. Once the dynamic behavior of the system has been modeled, it should be possible to detect faults via analysis of changes of input parameters to the model. However, when these models are tested in practice, they often fail due to their inability to cope with some unexpected or uncertain parameter(s). A relatively new approach to system modeling is the use high precision computer controlled monitoring system based on-line modeling.

In this system, the machine parameters are recorded on-line and, on continuous basis. The important features such as rms value, peak value etc is then obtained from the fixed length signal. These features are then given to the trained artificial neural network to know the machine health status at that time. So, by use of artificial intelligence, an adaptive modeling of the machine is achieved. In this work, the laboratory investigations are carried out on 5 hp, induction motor. The faults in bearing are introduced intentionally and signals are recorded by the developed health monitoring system. To ascertain consistency in the obtained results, the recording for each fault condition is done number of time and is saved in computers memory. The obtained signals are analyzed and features are extracted. Theses extracted features are used to train and test the neural network.

III.   INDUCTION MOTOR FAULTS

Induction motors are a frequently used due their simplicity of construction robustness and high efficiency. The motor faults can be categorized into two types: electrical faults and mechanical faults. Single phasing, unbalanced supply voltage, ground fault, over-voltage and under-voltage etc. are the electrical type of faults, which may occur in induction motor. Eccentricity and misalignment and bearing failure are the major type of mechanical faults to which the rotor of the machine subjected to, while stator eccentricity and core shrinkage are the main types of mechanical faults in the stator.

A.   Bearing faults

Bearing is an essential component of any electrical motor. The function of different types of bearing is to provide slipping of the rotor inside the stator maintaining uniform air gap. The bearing consists mainly of the outer-race; inner-race, balls and the cage which assures equidistance between the balls .Bearing faults can take place due to fatigue even under normal balanced operation with good shaft alignment and can also be caused by improper lubrication, installation errors and contamination. One of the results of bearings failures are increased level of vibration and noise. In single point defect are localized and can be classified according to the affected element, outer raceways defect, inner race

ways defect, ball defect and cage defect. Each bearing element has its own characteristic frequency of defect. All of these frequencies can be calculated from the kinematic relations, that is the geometry of the bearing and its rotating speed.

IV. FEATURE EXTRACTION AND SELECTION

For on-line monitoring purposes, it is always desirable to reduce the large amount of information contained in the on-line vibration signal to a single index or small number of features that reflects the overall characteristics of the signal. This procedure, known as signal feature extraction.

A. Time-domain features

The time-domain features are extracted from the raw vibration signal through the stastical parameters. The stastical parameters are used: Peak value (P_V), Root mean square (RMS); Crest factor (C_{rf}), Kurtosis (K_v), Skewness (S_w), Clearance factor (C_{lf}).Impulse factor (I_{mf}), shape factor(S_{hf}), standard deviation(std), normal negative log-likelihood value (Nnl), Weibull negative log-likelihood value (Wnl), Entropy (E), histogram upper bound(UB), histogram lower bound (LB).The expression is show below:

$$P_V = max(X_i)$$

(1)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$$

(2)

$$K_v = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i - \bar{X}}{RMS}\right)^4$$

(3)

$$C_{rf} = \frac{Peak\ value}{RMS\ value}$$

(4)

$$S_w = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_i - \bar{X}}{RMS}\right)^3$$

(5)

$$Std = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})^2}$$

(6)

$$C_{lf} = \frac{Peak\ value}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{|X_i|}\right)^2}$$

(7)

$$I_{mf} = \frac{Peak\ value}{\frac{1}{N}\sum_{i=1}^{N}|X_i|}$$

(8)

$$S_{hf} = \frac{RMS\ value}{\frac{1}{N}\sum_{i=1}^{N}|X_i|}$$

(9)

$$UB = max(X_i) + 0.5 * \left(\frac{max(X_i) - min(X_i)}{N-1}\right)$$

(10)

$$LB = min(X_i) - 0.5 * \left(\frac{max(X_i) - min(X_i)}{N-1}\right)$$

(11)

Where X_i the amplitude at sampling point and N is the numbers of sampling point.

Entropy is usually known as a measure of uncertainty of a process. For a set of events with probability density function (pdf) of {Xi, i=1, 2……..N} the Shannon entropy is defined as

$$E(P) = -\sum_{i=1}^{N}P_i\ log P_i$$

(12)

Where Pi are the probabilities computed from distribution Xi.

Weibull negative log-likelihood value was used recently for feature extraction from vibration signals. The Weibull negative log-likelihood value (Wnl) and the normal negative log-likelihood value (Nnl) of the time domain vibration signals are used as input features along with the other features defined above in this study. The negative log-likelihood function is defined as

$$-L(\alpha) = -\sum_{i=1}^{N}log\{f(X_i\mid\theta_1,\theta_2)\}$$

(13)

Where f *(xi; θ1, θ2)* is the probability density function (pdf). For Weibull negative log-likelihood function and normal negative log-likelihood function, the pdfs are computed as follows

$$Weibull\ pdf, f(X_i\mid\beta,\alpha) = \beta\alpha^{-\beta}|X_i|^{\beta-1}exp^{-\left(\frac{|X_i|}{\alpha}\right)^\beta}$$

(14)

Where β and α are the shape and the scale parameters respectively.

$$Normal\ pdf(X_i\mid\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}exp^{\left(-\left(\frac{|X_i|-\mu^2}{2\sigma^2}\right)\right)}$$

(15)

Where μ and σ are the mean and standard deviation respectively.

B. Data normalization

All extracted features are normalized before applied the neural network. In this paper data is normalized between slightly offset values such as 0.1 and 0.9 rather then between 0 and 1 to avoid the

sigmoid function leading to slow or no learning. The normalization equation is show below:

$$X_i = 0.8 \frac{(X_i^{old} - min(X_i^{old}))}{(max(X_i^{old}) - min(X_i^{old}))} + 0.1$$

(16)

Where, x_i^{old} is actual data, max (x_i^{old}) and min (x_i^{old}) are the maximum and minimum value of the data and X_i is the normalized data.

V.   NEURAL NETWORK BASED FAULT DIAGNOSIS

Artificial neural networks have been very useful for data handling and information processing. Neural networks possess the high level of adaptability that cannot be obtained from other completely analytical or numerical procedures and further, they provide a data based heuristic approach to condition monitoring and diagnostics of production systems and service machinery. A neural network can automatically store knowledge about the faults or malfunctions in the machinery system being monitored by learning from the historical data and possesses the characteristics of associative memory. These associative diagnostic capabilities make neural networks suitable for machinery fault diagnostics. The choice of the network type depends on the nature of the problem to be solved. In this proposed method multilayer feed forward neural networks trained by back propagation algorithms (MLFFBPN).

A.   Multi-layer feed forward neuralnetwork.

The most popular neural network architecture is the multilayer perception. The network consists of an input layer, a hidden layer and an output layer. The hidden layer is used to process and connect the information from input layer to the output layer only forward direction. The hidden layer performs feature extraction on the input data. Each neuron in the hidden layer sums up its signals after weighting them with the strengths of the respective connection and computes an output as a function of the sum.

In this work three layer feed forward networks are modeled with the MATLAB neural network toolbox. The networks are trained using a Levenberg–Marquardt algorithm. The activation function at the hidden layer and the output layer are sigmoid function. The initial values of the weights and offsets are randomly assigned. For training, a target mean square error (MSE) of 10^{-8}, a minimum gradient of 10^{-7} and maximum iteration number (epoch) of 500 are used. The training process would stop if any of these conditions is met.

VI.   EXPERIMENTAL SETUP

The vibration data from bearing were collected using test bench. The vibration monitoring is two step processes first collecting the vibration data and second is fault diagnosis.

(a)

(b)
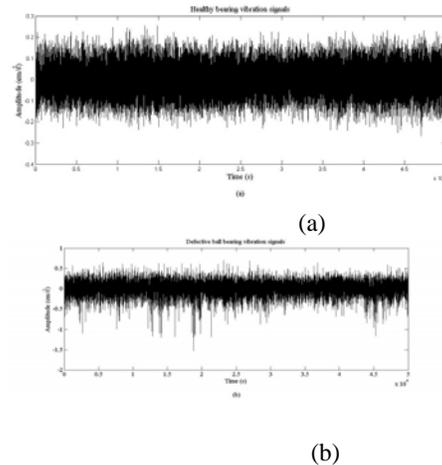
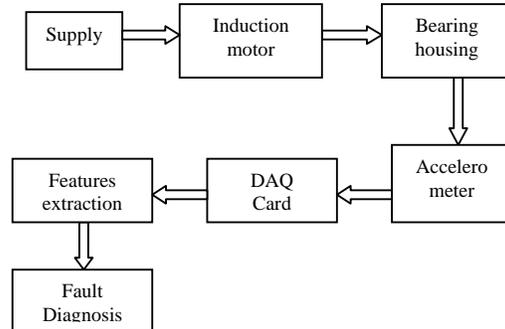The block diagram of vibration monitoring system is shown   in Figure1.

Figure 1. Block diagram of vibration monitoring system

The motor is a 3-phase induction motor 5hp, 3.7kw, 50Hz, 414v, 1440rpm, and 4-pole-pair. Single point faults are introduced into the bearings using electric discharge machining with a fault diameter 0.15mm and a depth of 0.25mm. Vibration data is acquired using accelerometer sensor, which are attached to the housing with magnetic bases. The Signals from accelerometer were transmitted to an Advantech USB-4711A PC-Lab card and sample at a rate of 1500 samples/sec. ZKL 1207EK series ball bearings are used for analysis. The specifications of bearing

are: ball diameter=15.08mm; pitch diameter=65mm; number of balls= 9; and angle of contact = 0.

The time domain vibration signals considered for analysis are collected for four different conditions of the bearing: Healthy (H); defective ball (DB); defective outer race (DOR); defective inner race (DIR) is shown in Figure 2.

(c)

(d)

(d)

(d)
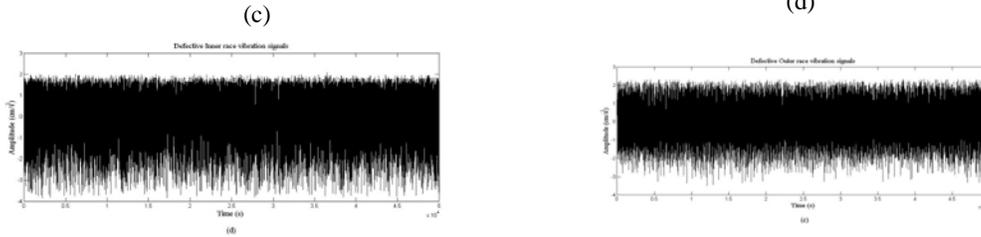
The vibration data for each condition 50000 samples is used in this work for fault diagnosis. The 15 vibration signals for each condition were used for feature extraction in time domain parameter. All vibration data used for fault diagnosis is implemented for four conditions, healthy (H), defective ball (DB), defective inner race (DIR) defective outer race (DOR).

A. Analysis of time domain feature

The time-domain features are extracted from the raw vibration signals for bearing fault diagnosis. The extracted features values are show in Table 1. These are Peak value (P_V), Root mean square (RMS); Crest factor (C_{rf}), Kurtosis (K_v), Skewness (S_w), Clearance factor (C_{lf}).Impulse factor (I_{mf}), shape factor(S_{hf}), standard deviation(std),normal negative log-

S.N	Extracted features	Bearing Conditions			
		H	DB	DIR	DOR
1	P_v	0.25	0.68	2.09	2.34
2	RMS	0.06	0.17	1.17	0.92
3	C_{rf}	3.74	3.91	1.78	2.53
4	K_v	2.90	4.70	2.60	2.69
5	S_w	0.01	-0.50	-0.53	-0.01
6	C_{lf}	5.52	6.04	2.46	3.65
7	I_{mf}	4.68	5.06	2.14	3.12
8	S_{hf}	0.31	0.52	1.27	1.15
9	Std	0.06	0.17	1.17	0.92
10	Nnl	4.75	5.88	9.87	1.32
11	Wnl	-9.75	-5.11	4.48	3.31
12	E	3.48	4.26	3.84	4.09
13	UB	0.25	0.68	2.09	2.34
14	LB	-0.26	-1.52	-3.84	-3.50

likelihood value (Nnl), Weibull negative log-likelihood value (Wnl), Entropy (E), histogram upper bound(UB), histogram lower bound (LB).

From Table 1, following are observations, which

can be made: RMS level is the consistent parameter, which increases with increase in fault severity level. For low level fault, peak level is good indicator; however for increased fault level it can not be useful. The clearance factor has highest separation ability for defective ball (DB) and followed by impulse factor,

kurtosis, entropy, crest factor. For defective outer race (DOR), peak value, histogram upper bound and, along with entropy is good choice. The normal negative log-likelihood has the highest separation ability for defective inner race (DIR) and followed weibull negative log-likelihood function, entropy.

Table 1 Mean value of Time Domain Parameters from Vibration Signal

B. Neural network based training and test

The neural networks tested in this work were trained with the 50000 samples data. The 40000 samples are used for training purpose and 10000 samples are used for testing purpose successfully. The 15 vibration signals for each condition were used for feature extraction in time domain parameter and normalized data is used for neural network input to output layer, difference is checked with the target output as shown in Table 2. And error is back propagated to adjust synaptic weight between output to hidden layer and input to hidden layer. Process is repeated till mean square error become less than 0.1.

The 14-30-4 neural network architecture is implemented to show the performance of the bearing fault condition. The 14 time domain feature are used as input layer, 30 hidden layers and four output layer

which show the bearing condition. The Table 3 shows the performance result: healthy; defective ball (DB); defective outer race (DOR); defective inner race (DIR).

The accuracy rate for time domain parameters for healthy that is incipient fault, the results are encouraging that is both testing and training the results are 100%. However for other cases the training accuracy varies from 93-97%, whereas testing accuracy varies from 90-93%. It can be concluded that for incipient fault detection, the time domain method is more accurate.

Table 2. Target vector for output layer nodes

S.N	Bearing defect	Target			
		Node 1	Node 2	Node 3	Node 4
1	Healthy	0.9	0.1	0.1	0.1
2	DB	0.1	0.9	0.1	0.1
3	DIR	0.1	0.1	0.9	0.1
4	DOR	0.1	0.1	0.1	0.9

Table 3 Performance result of training and testing

S.N	Bearing condition	Diagnosis result	
		Training accuracy (%)	Testing accuracy (%)
1	Healthy	100	100
2	DB	96.66	90.00
3	DOR	93.33	90.00
4	DIR	96.66	92.50

VIII. CONCLUSION

The developed monitoring system has successfully recorded the signal under different bearing fault condition. The important features which contain maximum fault information are selected and extracted for fault categorization. For fault categorization, A MLP neural network model, trained with back propagation algorithm is used. Fourteen features in time domain. Neural networks are trained independently. Input to neural network consists of time domain parameters. The architecture is trained successfully for all bearing case considered in this study. Neural network architecture gives it optimum performance for classification between Normal and incipient fault condition (100% testing accuracy).

However, final decision is based on the output of networks which improves fault detection ability of the system.

REFERENCES

[1] Boving K. G., "NDE Handbook for Condition Monitoring", Butterworth's, Denmark 1989.
[2] Chow M. Y., Sharpe R. N. and Hung J. C., "On the Application and Design of Artificial Neural Networks for Motor Fault Detection -Part I", IEEE Trans. on Industrial Electronics, Vol. 40(2), pp. 181-188, April 1993.

[3] H.B Demath, M. Beale, "Neural network toolbox for use with MATLAB" User's guide, The math works Inc. Natick M.A, USA,2004 .
[4] Y. Lei, Z. He, Y. Zi, Q Hu, "Fault diagnosis of rotating machinery based on a new hybrid clustering algorithm," International J of Advanced Manufacturing Technology, vol. 35, 2008, pp. 968-977.
[5] B. Sam anta, K. R. Al-balushi, "Artificial neural network based fault diagnostics of rolling element bearings using time-domain features," Mechanical Systems and Signal Processing, vol. 17(2), 2003, pp. 317-328.
[6] B. Li, G. Goddu, M. Chow, "Detection of common bearing faults using frequency-domain vibration signals and a neural network based .approach," Proceedings of the American Control Conference, Philadelphia, Pennsylvania, June 1998, pp. 2032-2036.
[7] D. M. Yang, A. F. Stronach, P. Mac Connell, "Third-order spectral techniques for the diagnosis of motor bearing condition using artificial neural networks," Mechanical Systems and Signal Processing, vol.16(23), 2002, pp. 391-411.
[8] B. S. Yang, T. Han, J. L. An, "ART-KOHONEN neural network for fault diagnosis of rotating machinery," Mechanical Systems and Signal Processing, vol. 18, 2004, pp. 645-657.
[9] S. Abbasion, A. Rafsanjani, A. Farshidianfar, N. Irani, "Rolling element bearings multi-fault classification based on the wavelet denoising and support vector machine," Mechanical Systems and Signal Processing, vol. 21, 2007, pp. 2933-2945.
[10] C. Bishop, Neural networks for pattern recognition, Oxford University Press, New York, 1995.
[11] M.R. Rafimanzelat, B.N, Arabbi, and E. Khosroshabi, "Induction machine broken bar detection using neural network based classification," in Proc. IEEE conf. Cybern. Intell. Syst., 2004,vol. 2,pp. 1362-1367
[12] S. Nandi and H.A. Toliyat, "condition monitoring and fault diagnosis of electrical machines –A review, in Proc. IEEE conf. Ind, Appl., vol. 1, pp.197-204
[13] Alguindigue I.E., wicz-Buzak, A.E., and Uhrig R.E."Monitoring and diagnosis of rolling element bearing wring Artificial neural network." in Proc. IEEE Trans. on Ind, Electronics, vol. 40, 1993, pp.209-217.
[14] Norton M.P and Karcuzb D.G., " Fundamentals of noise and vibration analysis for engineers" Cambridge university press, UK,2003
[15] T. I. Laine, K. W. Bauer, "Feature selection assessment and comparison using two saliency measures in an Elman recurrent neural network, "Proceedings of the

International Joint Conference on Neural Networks, IEEE Press, vol. 4, July 2003, pp. 2807- 2812.

[16] *R. J. Alfred son and J. Mathew, "Time Domain Methods for Monitoring the Condition of Rolling Element Bearings, "presented at Mechanical Engineering Transactions, 1985.*

[17] *N. Arthur and J. Penman, "Induction Machine Condition Monitoring with Higher Order Spectra," IEEE Trans. on Ind. Electronics, vol. 47, no. 5, Oct. 2000, pp.1031-1041.*

[18] *P. Vas, "Parameter Estimation, Condition Monitoring, And Diagnosis of Electrical Machines," Clarendon Press, Oxford,1993.*

[19] *W.R. Finley, M.M. Hodowanec and W.G. Holter, "An Analytical Approach to Solving Motor Vibration Problems," IEEE Trans. on Ind. Appl., vol. 36, no. 5, Sep. /Oct. 2000, pp. 1467-1480.*

[20] *F.C. Trutt, J Sottile and J.L. Kohler, "On-Line Condition Monitoring of Induction Motors," IEEE Ind. Appl. Society Annual Meeting,2001.*