

MONITORING AND PREDICTION OF BEARING FAILURE BY ACOUSTIC
EMISSION AND NEURAL NETWORK

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ABSTRACT

The purpose of this research is to develop an appropriate ANN model of bearing failure prediction. Acoustic emission (AE) represented the technique of collecting the data that was collected from the bearing and this data were measured in term of decibel (dB) and Distress level. The data was then used to develop the model using ANN for bearing fault prediction model. An experimental rig was setup to collect data on bearing by using Machine Health Checker (MHC) Memo assist with MHC Analysis software. In the development of ANN modeling, the result obtained shows that the optimum model was Elman network with training algorithm, Levenberg-Marquardt Back-propagation and the suitable transfer function for hidden node and output node was logsig/purelin combination. Four models were built in this research for multiple step ahead prediction, that were one day ahead model (Model 1), seven days ahead model (Model 2), fourteen days ahead (Model 3) and thirty days ahead model (Model 4). In the application part, a computer program was written on bearing failure prediction. This program was implemented using graphical user interface (GUI) features that can be implemented by using a MATLAB GUI. In the end, the user was able to use this program as a tool to operate or simulate bearing failure prediction.

ABSTRAK

Tujuan penyelidikan ini adalah untuk membangunkan model ANN yang bersesuaian bagi meramal kegagalan gelas. Pancaran akustik mewakili teknik pengambilan data yang diambil daripada gelas dan data tersebut diukur dalam ukuran paras desibel (dB) and paras Cemas. Data tersebut kemudiannya digunakan dalam pembangunan model menggunakan rangkaian neural tiruan untuk pemodelan peramalan kegagalan gelas. Rig ujikaji dibina untuk mengumpul data pada gelas dengan menggunakan Machine Health Checker (MHC) Memo dengan perisian MHC Analysis. Dalam pembangunan pemodelan ANN, keputusan yang diperolehi menunjukkan pemodelan optima ialah menggunakan rangkaian Elman dengan algoritma pembelajaran Perambatan-balik Levenberg- Marquardt dan fungsi pindahan yang sesuai untuk nod terselindung dan nod keluaran adalah kombinasi logsig/purelin. Empat model telah dibina dalam penyelidikan ini bagi ramalan pelbagai langkah ke hadapan, iaitu pemodelan satu hari ke hadapan (Model 1), tujuh hari ke hadapan (Model 2), empat belas hari ke hadapan (Model 3) dan tiga puluh hari ke hadapan (Model 4). Dalam bahagian aplikasi satu aturcara komputer untuk meramal kegagalan gelas telah dibangunkan. Aturcara ini dilaksanakan dengan antaramuka pengguna grafik (GUI) yang menggunakan MATLAB GUI. Pada akhirnya pengguna boleh menggunakan aturcara ini sebagai perkakasan untuk membuat atau menyelaku ramalan kegagalan gelas.

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PTTA UTHM
PERPUSTAKAAN TUNKU TUN AMINAH

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LIST OF SYMBOLS

%	-	Percentage
φ	-	Transfer function
α	-	Contact angle
Σ	-	Summation
a_i	-	Actual value
a_1	-	Reliability adjustment factor.
a_2	-	Material/construction adjustment factor.
a_3	-	Operating condition adjustment factor.
B	-	Connection matrix from the input layer to the hidden layer
b_h, b_o	-	Bias vector
C	-	Connection matrix (matrix of weight) from the hidden layer to the output layer
C_r	-	Basic dynamic radial rated load (Newtons).
C_T	-	Dynamic load rating
D	-	Ball diameter
d_i	-	Bore diameter
d_m	-	Pitch diameter
d_o	-	Outside diameter
e_i	-	Error
$f(\cdot)$	-	Nonlinear mapping
f_i	-	Ball Pass Frequency, Inner race
f_o	-	Ball Pass Frequency, Outer race
f_r	-	Ball Spin Frequency

h	-	Function argument
kHz	-	Kilo Hertz
L_{10}	-	Basic rated life in 10^6 revolutions.
L_{10h}	-	Basic rated life in hours.
L_{na}	-	adjusted life rating in hours; adjusted for reliability, material and operating condition
MHz	-	Mega Hertz
N	-	Number of data
N_r	-	Rotational speed (rpm).
p	-	3 (constant value for ball bearing).
P_r	-	Equivalent radial load (Newtons).
r_i	-	Inner groove radius
r_o	-	Outer groove radius
S	-	Shaft rotation rate in hertz
$s(k)$	-	Intermediate variable
T	-	Time
t_i	-	Desired value
u_i	-	Input vector
$u(t)$	-	dB value of day t
V	-	Voltage
V_c	-	Velocity of cage bearing
V_i	-	Velocity of inner race
V_N	-	Noise level
V_o	-	Velocity of outer race
V_s	-	Signal level
w_{ij}	-	Weight
X	-	Actual input
X_{\max}	-	Actual inputs at their maximum
X_{\min}	-	Actual inputs at their minimum
X_s	-	Scaled input
y_i	-	Output vector
$y(t)$	-	Distress value of day t

z^{-1}	-	Time delay
Z	-	Number of ball



LIST OF ABBREVIATIONS

AE	-	Acoustic emission
ALE	-	Adaptive line enhancer
ANN	-	Artificial neural network
BSF	-	Ball spin frequency
C	-	Coupling
dB	-	Decibel
DWPA	-	Discrete wavelet packet analysis
DWT	-	Discrete wavelet transform
ERN	-	Externally Recurrent Networks
FFNN	-	Multilayer feedforward neural network
FFT	-	Fast Fourier Transform
GUI	-	Graphical user interface
HFRT	-	High frequency resonance technique
IRN	-	Internally Recurrent Network
kgf	-	Kilo gram force
lbs	-	Pounds
M	-	Three phase motor
m	-	Meter
MHC	-	Machine Health Checker
MLP	-	Multilayer Perceptron.
MSE	-	Mean square error
NDT	-	Non-destructive testing
NN	-	Neural Network
NNPCA	-	Neural Network PCA
OSA	-	One Step Ahead

P	-	Applied load
PC	-	Personal computer
PCA	-	Principal component analysis
RMS	-	Root mean squared
RNN	-	Recurrent Neural Networks
rpm	-	Rotation per minute
RUL	-	Remaining useful life
S1, S3	-	Support bearings and housing
S2	-	Tested bearing
SNR	-	Signal to noise ratio
SVM	-	Support vector machines



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CHAPTER I

INTRODUCTION

1.1 Background

In industries, bearings are important components and regularly being used. There are various types of bearings damage, which can be due to fatigue, cracks, deformation, wear and corrosion which can slow down the maintenance time in industries and sometimes can threaten the safety of operators.

The detection of bearings damage is conventionally performed by experts, for instance by supervisors or engineers that have the knowledge on the operating characteristics of a specific bearings that could be determined through the sense of touch, sight or noise as compared from the normal bearing performance. These approaches are susceptible to human errors and varies according to experience and individual skill which could contribute to the inaccuracies and can consume a lot of time.

Recent surveys on several industries show that maintenance costs of rotating machinery especially on bearings were between 15 to 30 percent from the costs of

goods produced. For example in food related industries, the average maintenance cost were about 15 percent of the cost of goods produced, while in textiles and other heavy industries the maintenance can reach up to 30 percent of the total production costs (Keith, 2001). In the United States some industries spend more than \$200 billion dollars each year just on the maintenance of plant equipments and facilities. Thus, the impact of productivity and profit that is represented by the maintenance operation becomes very significant (Keith, 2001).

Therefore, the industries should have a systematic process that can monitor this problem. In the past decade, maintenance practices have evolved as a result of several technology advancements. Industries no longer choose for manual scheduling methods to prevent bearing failure. For example bearings need to be changed at least every year or every 6 months, even though they are still in a good condition and can still be used within certain time frame. This method of manual scheduling is inefficient and wasteful because not all bearings will fail within the stipulated time.

The approach taken to predict or detect the failure of bearings was by modeling a rig to monitor bearings life based on Distress reading through acoustic emission (AE) from noise emitted by faulty bearing. AE technique is concerned with the detection of structure-borne ultrasonic activity that is naturally generated during the operation of all structures, machinery and processes (Holroyd, 2002).

Several method of determining bearing failure by using machine vibration have been developed by Billington, *et.al*, (1997), Da. & James (2000), Blair & Shirkhodaie (2001), Mcfadden and Toozhy (2000), B. Samanta *et al* (2003) and McNerny & Dai (2003) but AE's method is highly promising for bearing health monitoring. This method can be used in industries such as textile industry that operates 24 hours a day to monitor their bearings and avoid sudden bearing failure. All operations are monitored by using artificial neural network (ANN) and will be alerted when bearings approach failure stage.

1.2 Problem Statement

The root cause of bearing failures are normally attributed to improper installations, poor lubrication practices, excessive balance and alignment tolerances, poor storage and handling techniques. Monitoring the above failures are very important for early warning sign before those bearings approach failure stage. This will avoid serious damage which might lead to potentially hazardous situation.

Today, various method are available to detect and monitor such failure which include vibration monitoring and acoustic emission but in this research the acoustic emission will be used to monitor sound defects from bearing. Vibration monitoring is typically insensitive to more subtle effects such as the early signs of bearing wear. To overcome this, vibration analysis has to be carried out in which the vibration signal is pre-processed by using subjectively set filter and analysed in the frequency domain with Fast Fourier Transform (FFT) to provide a frequency spectrum. To interpret the vibration frequency spectrum, it is necessary to calculate possible defects within these frequencies range. This is quite tedious and time consuming.

On the contrary, AE technique has the ability to detect the high frequency of the elastic waves being generated by rotating bearings. The AE signal captures noise emitted by faulty bearing and is not sensitive to noise on normal bearings. Due to this criterion, it is possible to analyse the overall AE signal in order to provide a clear indication of the presence of faults.

The selection of ANN for modeling process in this research is due to its wide application in many situations. Its potential is not only on their capability to learn from experience, but also on their ability to recognize and learn the relationship of non-linearity process. Therefore, ANN has been chosen as the technique to model bearing failure prediction due to the non-linearity of data from bearing failure.

1.3 Objective:

The objectives of this research and general approaches taken are as follows:

1. To identify critical warning level of bearings.
2. To develop suitable ANN modeling for process prediction by using neural network toolbox in MATLAB 6.5.
3. To implement the proposed ANN model to predict bearings failure.

1.4 Project scope:

1. Study on literatures regarding AE technique, condition monitoring technique and Artificial Neural Network (ANN).
2. Collect data from one ball bearing beginning from bearing operates at normal condition until failure from test rig.
3. Build suitable ANN model using collected data.
4. Test run ANN model to predict bearing failure with new data.

1.5 Thesis Organization

The next chapter will focus on literature study and theoretical background of different approaches to predict bearing failure problem. It also includes theories of AE, condition monitoring, bearing analysis and ANN. Chapter 3 will discuss on methodology which were used in this research. Instruments, data collection

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