Fault Detection of Linear Bearing in Auto Core Adhesion Mounting Machine Using Artificial Neural Network

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Abstract: Nowadays, the major competition of Hard Disk Drive (HDD) industry is to reduce the cost of manufacturing process via increasing the rate of productivity and reliability of the automation machine. This study aims to increase the efficacy of Condition-Based Maintenance (CBM) of linear bearing in Auto Core Adhesion Mounting machine (ACAM). The linear bearing faults were considered in six fault conditions. The Fast Fourier Transform spectrum (FFT spectrum), motor current and crest factor can be detected for linear bearing faults. The Artificial Neural Network (ANN) method was used to analyze and classify the cause of linear bearing faults into operational condition. The experimental results showed the application of ANN as Fault Detection and Isolation (FDI) tool for linear bearing fault detection performance. The accuracy and decision making of ANN are enough to develop the diagnostic method for automation machine in operational condition.

Key-Words: Fault detection and isolation, Linear bearing, Artificial neural network, Fast Fourier transform spectrum, Condition-Based Maintenance.

1 Introduction

Hard Disk Drive (HDD) industry has a competition of product price and capacity of data storage. The cost of manufacturing process and reliability of the automation machine play an important role in profit margin of a production. Head Gimbal Assembly (HGA) is used for reading and writing data in HDD [1]. HGA assembly process used Auto Core Adhesion Mounting machine (ACAM) (Fig.1) to adhesive glue and attach the slider to suspension requiring short cycle time and high accuracy in submicrometer. The ACAM machine was drive HGA clamping unit by motor with link together with linear bearing to transfer work pieces to decide position then processing. The machine was run continuously with high-speed condition. The deterioration of linear bearing shows trend to early fault and causes unplanned downtime of machine. The minor reliability of linear bearing can severely decrease machine performance and reliability. Hence, the preliminary damage of the linear bearing must be detected before the machine breaks down. Thus, the Condition-Based Maintenance (CBM) of the linear bearing condition is necessary. In order to detect faults of rolling element bearings, faulty diagnoses are used. For automatic condition, monitoring system provides by using empirical mode decomposition to extract the vibration signal. Artificial Neural Network (ANN) was applied to classify bearing defects. The result indicates that the classifier is promising for high accuracy of fault bearing detection [2]. Fault diagnostics of ball bearing Adaptive Neuro Fuzzy Inference Systems (ANFIS) is used for automatically identifying and classifying of bearing fault. It reveals the accurate classification of 99.83% [3]. The artificial neural network (ANN) is used to diagnosis of big-end bearing knock faults in IC engines. The experiment investigates on normal bearing clearances and different oversize bearing clearances. The envelope of vibration signal is the data for training the model. It was demonstrated that the model could successfully detect different bearing knock faults in actual tests, and classify the faults location [4].The paper on fault diagnosis of rolling bearings with recurrent neural network based auto encoders describes the effect of ambient noise to extract the diagnostic result, therefore multiple sensors were used. Recurrent Neural Network (RNN) is used to a rotary machine for classifying fault. The model for predicting using Gated Recurrent Unit (GRU) based on this advantage utilizes information from multiple sensors [5]. Zhiqiang Chen provided a deep neural network to rolling bearing fault diagnosis. Vibration signal of seven fault patterns in terms of time and frequency domain was use for data training in three deep learning models, which consist of Stacked Auto-Encoders (SAE), Deep Boltzmann Machines (DBM) and Deep Belief Networks (DBN) all models are efficient to classify. The accuracy achieved more than 99% [6]. In addition, the model of linear bearing is employ to detect fault form vibration signal. Statistical analysis is an extension method to analyze vibration. Moreover, in order to detect the fault of linear bearing, the vibration model is important [7]. Convolution neural network was provided due to fault classification of the rolling bearing by using vibration signal data. The training structure defines the hierarchical and back propagation process to classify the result indicating that the training sample affect to accuracy, which is more sample the accuracy, can be achieved [8]. Fault identification in the paper on sparse classification is based on dictionary learning for planet bearing fault identification. Four conditions (sun gear, planet gear, ring gear, and rolling gear) of fault were investigated. Chuan Zhao discusses spare method based on dictionary learning that it has a merit of tackling raw inputs. On the other hand, the vibration signal cannot be optimized inasmuch, mapped to transform the signal vector to a matrix form which retains the intrinsic fault feature information [9].To analyze nonlinear vibration signal of rotating electrical machine three intelligence approaches: the artificial neural network, genetic algorithms and active-set methods were proposed [10]. The Singular Spectral Analysis (SSA) is a time domain analysis technique. This shows the complex feature extraction. Roller element of bearing fault was detected by the applied neural network on singular spectral and evaluation using two experimental datasets. The result revealed that bearing fault diagnosis was simple, noise tolerant and efficient [11]. Compound dies are widely used in stamping industrial. The stripper is the main component in compound die, which was used for producing more accurate sheet metal parts without any internal or external defects. However, the study on fatigue life of strippers was spread. Salunkhe, S presented the method for life cycle prediction of stripper by comparing two approaches: artificial neural network (ANN) and adaptive neuro fuzzy inference (ANFIS) in the process of training. This training used four input for creating the model including maximum principle stress, minimum principle stress, amplitude stress, and mean stress. The desire output of prediction is life cycle of stripper. The result revealed that the ANFIS is a suitable method for predicting a life cycle because it showed higher predictability than ANN[12]. Bettine, F provided the novel approach for predicting kinematic errors of trochoidal machining by using artificial neural network (ANN). The model of ANN was proposed in multilayer perceptron (MLP) to find the inverse kinematics solution for a five-axis machine. For the training data set, 1042 sample were used for each axis. The result of training obtains less than 1 second. The result of validation displayed the model performance with nearly zero error [13]. The model based on machine learning was apply for fault diagnosis of injection machine. The experiment revealed that it was possible to create a machine-learning-base fault diagnostics model that was train on process data [14]. The paper on Condition monitoring and fault diagnostics for hydropower plants describes a fault diagnosis and classification of data using the support vector machine. This work investigates the hydropower plants under varying speed conditions, by using the envelope order tracking analysis scheme [15].

Fig.1 Auto Core Adhesion Mounting machine (ACAM)

This study aims to increase the efficacy of condition-based maintenance of linear bearing in ACAM machine by using fault detection and isolation technique. The mechanical failure of linear bearing can be classified into six causes such as healthy bearing, one ball bearing damage, one ball bearing loss, starved lubricant bearing, one ball bearing damage with starved lubricant, and one ball bearing loss with starved lubricant. The three signal processing techniques were used for data collecting as FFT spectrum, time waveform and motor current. This research proposes Artificial Neural Network (ANN) methodology to be used for analyzing the root causes of the linear bearing fault in operational condition.

2 Theoretical Background

The analysis method can be analysed the linear bearing fault of the automation machine such as frequency of fault ball bearing and frequency of the loss ball bearing using Fast Fourier Transform (FFT) spectrum. The artificial neural network (ANN) can be correctly identified linear bearing fault condition.

2.1 Linear ball bearing model

The linear bearing with recirculating ball bearings was designed to use for moving heavy loads along the precision linear path. The linear bearing consists of two major components with moving carriage and precision linear rail as shown in Fig.2. The ball bearing is used for movement between the carriage and linear rail with frictionless during translation.

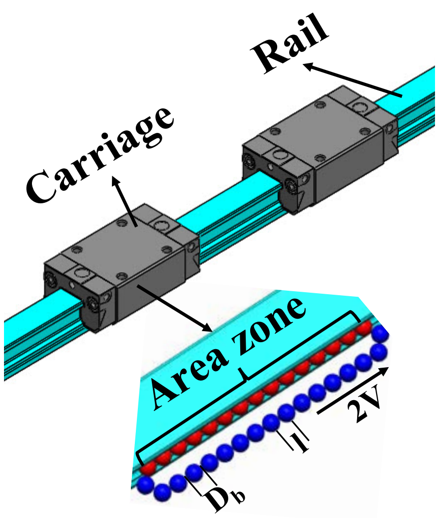

Fig.2 Elements of the linear bearing.

2.1.1 Fault on ball bearing damage

The fault characteristic frequency of the ball bearing was caused by the contact between the ball bearing to rail and carriage on each time when completing one cycle. The characteristic frequency of fault ball bearing is described as Eq. (1)

$$f_{ball} = \frac{2V_{ball}}{\pi D_b} \quad (1)$$

where f_{ball} is the characteristic frequency of ball bearing, V_{ball} is the velocity of the ball bearing, D_b is the diameter of the ball bearing and l is the central distance of two balls bearing.

2.1.2 Fault on one ball bearing loss

The characteristic frequency of the loss of ball bearing in carriage is defined as Eq. (2)

$$f_{loss} = \frac{V_{ball}}{l} \quad (2)$$

2.2 Fault detection and isolation (FDI)

Fault detection and isolation technique is used to detect and isolate the system condition. Then diagnostic and feedback information is applied to reconfigure the appropriate controller mechanism or parameter to minimize the impact of the overall system.

2.3 Artificial Neural Network (ANN)

The Artificial Neural Network uses the principle of neural simulation. Each of the neural communicates with each other through electrical stimulation. The ANN can be classified into feed forward perceptron and backpropagation.

2.3.1 Feed forward perceptron

The feedforward perceptron is the simplest type of artificial neural network. The algorithm of this network is the information moves from the input node to the output node in only one direction by through the hidden mode and there are no cycles in the network. The feedforward neural network divided into two methods first is the single layer perceptron and another is a multi-layer perceptron(MLP). The single layer perceptron consists of a hidden node only one layer that a capable of learning linearly separable patterns, on the other hand, the multi-layer perceptron can be used several hidden layers that is the variety of learning techniques as shown in Fig. 3.

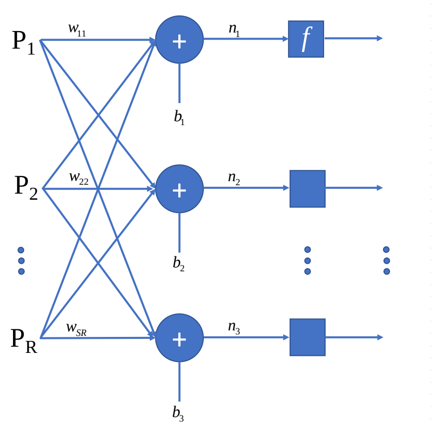

Fig.3 Schematic of multi-layer perceptron.

The output function can be expressed in terms of the matrix as Eq. (3):

$$y = f\left(Wp + b\right) \tag{3}$$

where: $p^T = \begin{bmatrix} p_1 & p_2 & \cdots & p_S \end{bmatrix}$ is the input of MLP. $b^T = \begin{bmatrix} b_1 & b_2 & \cdots & b_R \end{bmatrix}$ is the bias of MLP and $W = \begin{pmatrix} W_{11} & \cdots & W_{1R} \\ \vdots & \ddots & \vdots \\ W_{S1} & \cdots & W_{SR} \end{pmatrix}$ is the weight of MLP.

2.3.2 Backpropagation

The backpropagation is the training method of an artificial neural network. The algorithm uses gradient descent to optimize the error function by return the error value of the output in each hidden layer. When the data entering each input layer into the network output layer will be compared to the target as shown in Fig. 4. The algorithm will adjust the weight and bias of the network to minimize the average square error of the output layer and target.

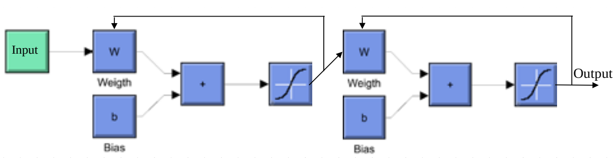

Fig.4 Schematic backpropagation

$$F(x) = E[(t-y)^2] \tag{4}$$

In case of more than one output

$$F(x) = E[(t-y)^T (t-y)] \tag{5}$$

Where: x is the matrix of weight and bias, t is the matrix of the target, and y is the matrix of the output.

2.4 Fast Fourier transform (FFT) spectrum

The Fast Fourier Transform (FFT) is a signal processing method, it is used to converse the time waveform to spectrum referred to as the frequency domain. The mathematical of FFT is used to arrange the complex waveform into its harmonic component shown as Eq. (6).

$$X(k) = \sum_{n-1}^{N-1} x(k)\cos\frac{2\pi kn}{N} - j\sum_{n-1}^{N-1} x(k)\sin\frac{2\pi kn}{N} \tag{6}$$

The waveform contains N samples. The two components included cosine and sine function, j is represent for the phase of signal. The spectrum is illustrated as frequency and amplitude referring to Eq. (6). Only vibration spectrum is considered.

2.5 Crest factor

The analysis of vibration sometime can be explained by crest factor, which is the ratio of the peak value to the root mean square(RMS) value as Eq. (7).

$$Crest\ factor = \frac{Peak}{RMS} \tag{7}$$

The principle of this method shows impacts in the waveform. If the amplitude of waveform is sinusoidal, the crest factor will be close to 1.4 as shown in Fig.5. On the other hand, if the machine with a bearing fault has more spiky waveform, the crest factor will be higher as illustrated in Fig.6.

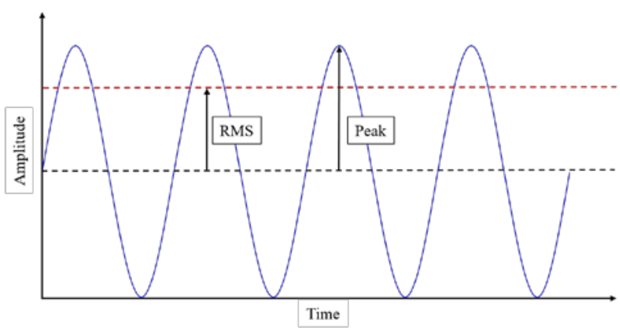

Fig.5 Crest factor of sinusoidal waveform

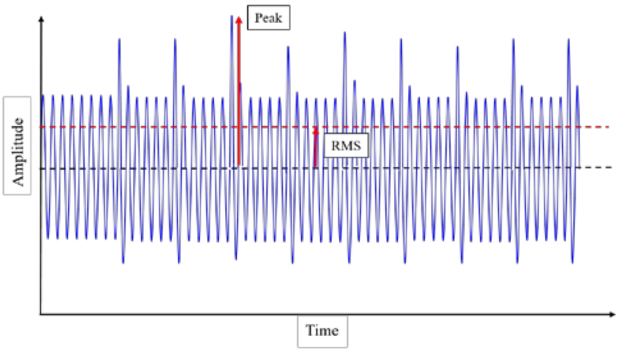

Fig.6 Crest factor of waveform with bearing fault

3 Experiment Setup and Procedure

This experimental setup contains an actuator as linear DC motor, sensor and analyzer. The procedure presents fault condition of linear bearing in possible terms and operating speed of ACAM machine related to operational condition.

3.1 Experiment setup

In this research, the experimental setup was performed by using the linear DC Motor (SGL 100-AUM3-PS4J model). The clamping unit installing with load 7 kg on top of linear DC motor. The 3-axes acceleration sensor of PCB Piezotronics model 356A32 was used for vibration measurement. The sensor was placed follow by X-axis parallel to the motor direction and Z-axis perpendicular to the machine base. The sensitivity of the acceleration sensor was setup for all 3 axes as 99.2 mV/g, 98.1 mV/g and 101.1 mV/g for X, Y and Z axis respectively. The sampling rate frequency was set at 4000 Hz for data acquisition via IOtech and EZ analyzer software was used for analyze.The operation condition of the linear motor was setup referring to actual setting in production with acceleration 1.00 m/s^2, velocity of 0.5 m/s and clamping unit translation distance equal to 400 mm. The experimental setup is shown in Fig. 7.

3.2 Fault condition of linear bearing

This study considered the mechanical failure of linear bearing into six causes such as healthy bearing, one ball bearing damage, one ball bearing loss, starved lubricant bearing, one ball bearing damage with starved lubricant, and one ball bearing loss with starved lubricant.

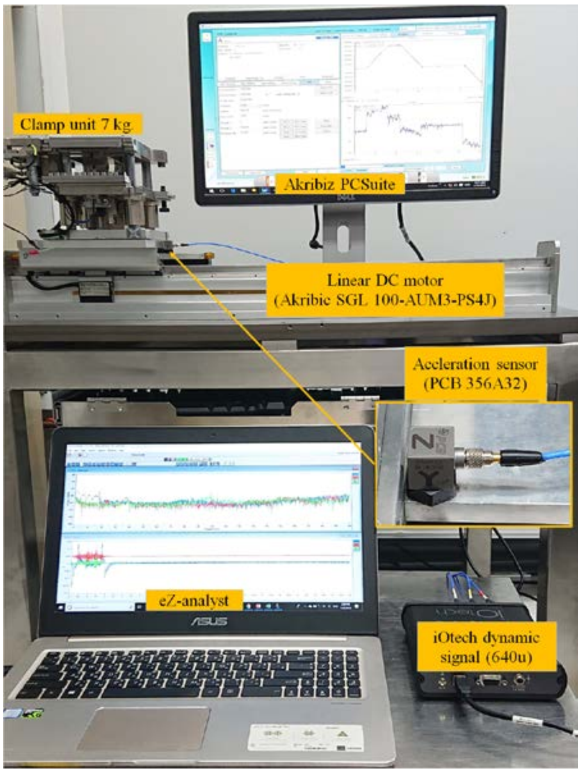

Fig.7 Experiment setup

3.2.1 Healthy bearing

The healthy bearing is the perfect condition of linear bearing with proper lubricant and healthy ball bearing as shown in Fig.8.

3.2.2 One ball bearing damage

The ball bearing damage was performed by the grinding surface of the ball bearing with area 2.565 mm^2 as depicted in Fig. 9.

3.2.3 One ball bearing loss

The ball bearing loss condition was conducted by removing ball bearing from carriage cage to vary the distance randomly. This spectacle leads to random fluctuations of the time distribution of impacts depicted in Fig. 10.

3.2.4 Starved lubricant bearing

The lubricant was used for friction reduction and corrosion protection. The experiment was setup to remove lubricant from bearing by using isopropyl alcohol (IPA) cleaner with BRANSON (2510 model) digital ultrasonic cleaning machine as shown in Fig. 11.

3.2.5 One ball bearing damage with starved lubricant

This combined fault condition was conducted by removing lubricant of ball bearing damaged condition by ultrasonic cleaning as depicted in Fig. 12.

3.2.6 One ball bearing loss with starved lubricant

The ball bearing loss with starved lubricant was conducted by remove lubricant with ultrasonic cleaning machine as depicted in Fig. 13.

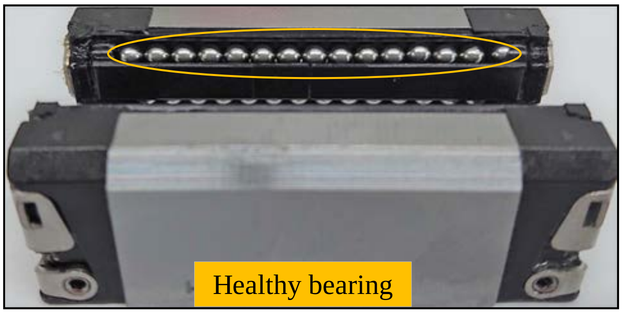

Fig.8 Healthy bearing

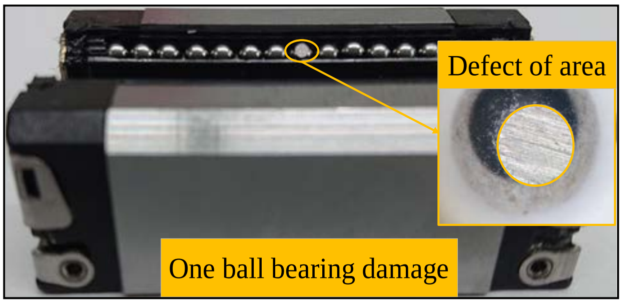

Fig.9 One ball bearing damage

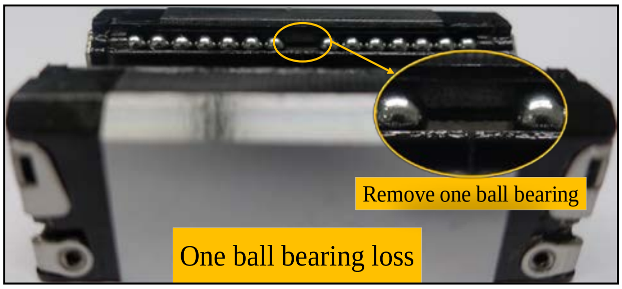

Fig.10 One ball bearing loss

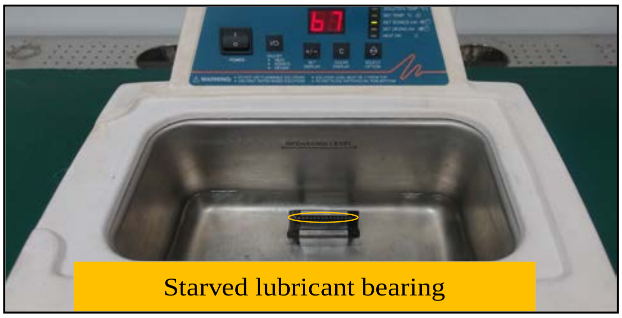

Fig.11 Lubricant removal from bearing using ultrasonic cleaning

Fig.12 Ball bearing damage in ultrasonic cleaning machine

Fig.13 One ball bearing loss in ultrasonic cleaning

3.3 Data acquisition procedure

Data acquisition by measuring vibration signal with FFT spectrum (dB), crest factor from time waveform and motor current (mA) as setting. 50 data samples were collected for each condition per statistical requirement as shown in Fig. 14.

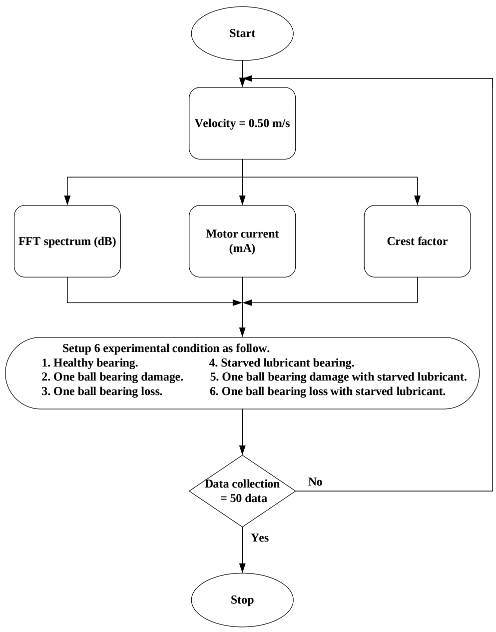

Fig.14 Schematic of data collection

3.4 Classification of artificial neural network

ANN technique was used to classify root cause of linear bearing fault condition. Three types of input signals included FFT spectrum, motor current and crest factor. The ANN programs consisted of the three group of input parameter such as single, double and triple input parameter. The propose of this experiment was conducted to compare accuracy of the ANN program as shown in Fig.15, Fig.16, and Fig.17 respectively. The experiment is simplifying procedure of all three program with the total 300 sample data sets of six conditions. ANN program classified linear motor fault conditions as follow by single, double, and triple parameter into input layers, 1 hidden layer 10 nodes and 6 output are showed as Fig. 18. The ANN training used the scaled conjugate gradient algorithm by dividing the data set by 70% for training, 15% for validating and 15% for testing.

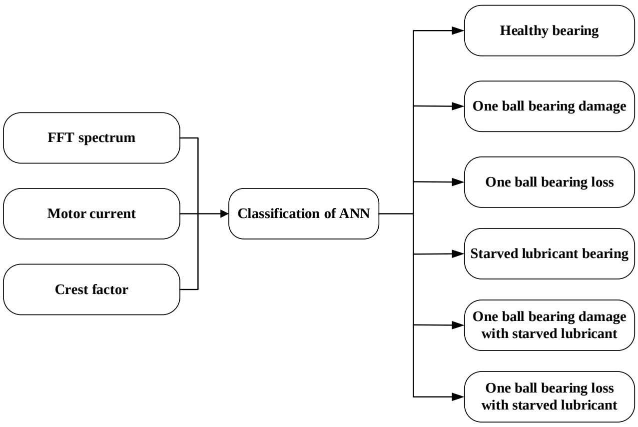

Fig.15 Schematic of single parameter ANN program

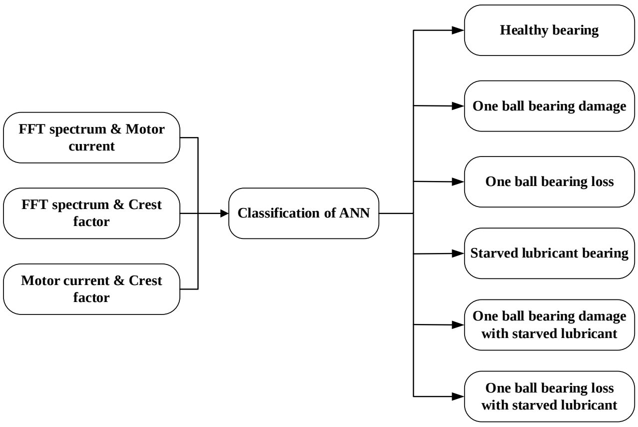

Fig.16 Schematic of double parameters ANN program

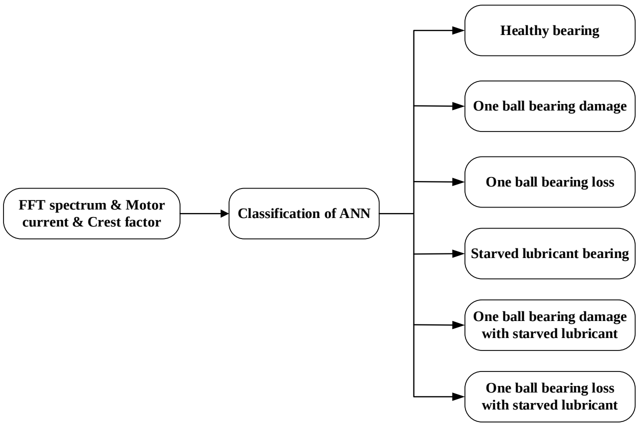

Fig.17 Schematic of triple parameters ANN program

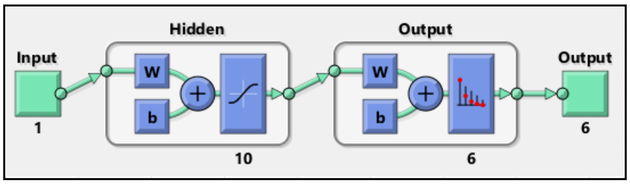

Fig.18 Schematic of Artificial Neural Network

4 Result and Discussion

The results of ANN program analyzed based on all three types of input parameter.

4.1 Data acquisition procedure

4.1.1 FFT spectrum analysis

The amplitude of FFT spectrum comparison for six conditions depicted as Fig.19, result can be divided into two groups of data. First group includes healthy and starved lubricant condition shown significant different from the second group which includes four conditions. All four conditions show comparable vibration amplitude with 95% confidence interval (Table 1).

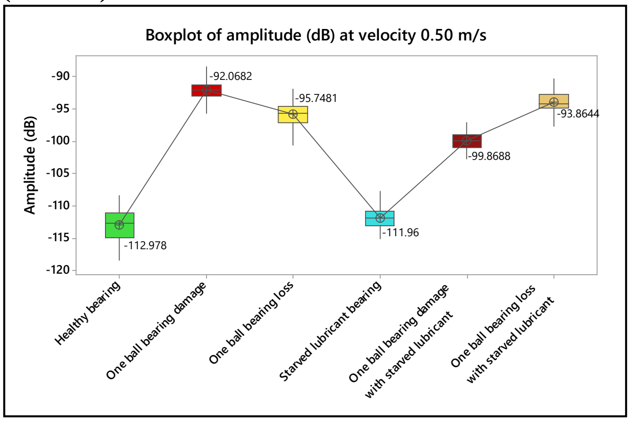

Fig.19 Boxplot of FFT spectrum

Table 1. 95% confidence interval of spectrum

Type	Condition	FFT spectrum (dB) of 95% Confidence Interval
single	Healthy bearing	-113.493 to -112.463
single	One ball bearing damage	-92.583 to -91.553
single	One ball bearing loss	-98.959 to -97.929
single	Starved lubricant bearing	-112.475 to -111.445
Combine	One ball bearing damage with starved lubricant	-100.384 to -99.354
Combine	One ball bearing loss with starved lubricant	-99.358 to -98.329

Table 2. Spectrum comparison with healthy bearing

Target	Fault bearing conditions	Delta	%
Healthy bearing	One ball bearing damage	20.909	18.51
Healthy bearing	One ball bearing loss	17.230	12.86
Healthy bearing	Starved lubricant bearing	1.018	0.90
Healthy bearing	One ball bearing damage with starved lubricant	13.109	11.60
Healthy bearing	One ball bearing loss with starved lubricant	19.113	12.51

The FFT spectum compared between bearing fault conditions with healty condition. One ball bearing damage showed 18.51% higher than healthy condition, while starved lubricant condition showed 0.9% delta compared to healthy bearing.

4.1.2 Motor current (mA) analysis

Motor current of six conditions was shown using boxplot in Fig.20. Moreover, the highest motor current value of 1286 mA or 21% higher than healthy bearing condition is one ball bearing loss with starved lubricant condition as shown in Table and Table 4. The bearing fault condition with starved lubricant showed raising up trend of motor current, while other 2 fault conditions (ball bearing loss and damage) showed motor current value slightly higher than healthy bearing condition.

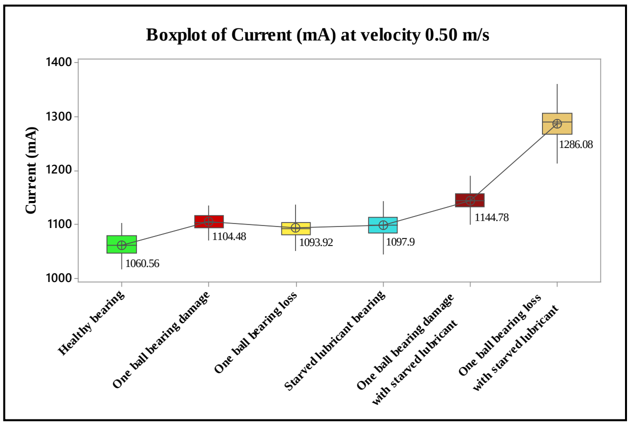

Fig.20 Boxplot of current (mA)

Table 3. Motor current of 95% confident interval

Type	Condition	Motor current (mA) of 95% Confidence Interval
single	Healthy bearing	1054.60 to 1066.52
single	One ball bearing damage	1098.52 to 1110.44
single	One ball bearing loss	1087.96 to 1099.88
single	Starved lubricant bearing	1091.94 to 1103.86
Combine	One ball bearing damage with starved lubricant	1138.82 to 1150.74
Combine	One ball bearing loss with starved lubricant	1280.12 to 1292.04

Table 4. Motor current (mA) comparison with healthy bearing

Target	Fault bearing conditions	Delta	%
Healthy bearing	One ball bearing damage	43.920	4.14
Healthy bearing	One ball bearing loss	33.360	3.15
Healthy bearing	Starved lubricant bearing	37.340	3.52
Healthy bearing	One ball bearing damage with starved lubricant	84.220	7.94
Healthy bearing	One ball bearing loss with starved lubricant	225.520	21.26

4.1.3 Crest factor analysis

The crest factor comparison using boxplot as Fig.21 demonstrate that both ball bearing loss and ball bearing loss with starved lubricated showed low crest factor value or 9.67% and 12.11% respectively compared to healthy condition.

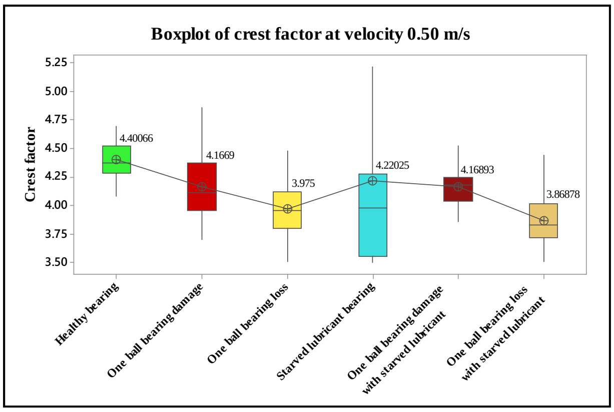

Fig.21 Boxplot of crest factor

Table 5. Crest factor of 95% confidence interval

Type	Condition	The crest factor of 95% Confidence Interval
single	Healthy bearing	4.3017 to 4.4996
single	One ball bearing damage	4.0680 to 4.2658
single	One ball bearing loss	3.8761 to 4.0739
single	Starved lubricant bearing	4.1213 to 4.3192
Combine	One ball bearing damage with starved lubricant	4.0700 to 4.2678
Combine	One ball bearing loss with starved lubricant	3.7699 to 3.9677

Table 6. Crest factor comparison with healthy bearing

Target	Fault bearing conditions	Delta	%
Healthy bearing	One ball bearing damage	0.234	5.31
Healthy bearing	One ball bearing loss	0.426	9.67
Healthy bearing	Starved lubricant bearing	0.180	4.10
Healthy bearing	One ball bearing damage with starved lubricant	0.232	5.27
Healthy bearing	One ball bearing loss with starved lubricant	0.533	12.11

4.2 Classification fault condition by Artificial Neural Network

4.2.1 Single parameter program

The ANN program of single parameter using confusion matrix is shown in Fig.22, Fig.23 and Fig.24. The accuracy of the model 58.7% ,54.7% and 43.3% for FFT spectrum, motor current and crest factor parameter respectively. The single parameter input program is not satify for predictive fault of linear bearing.

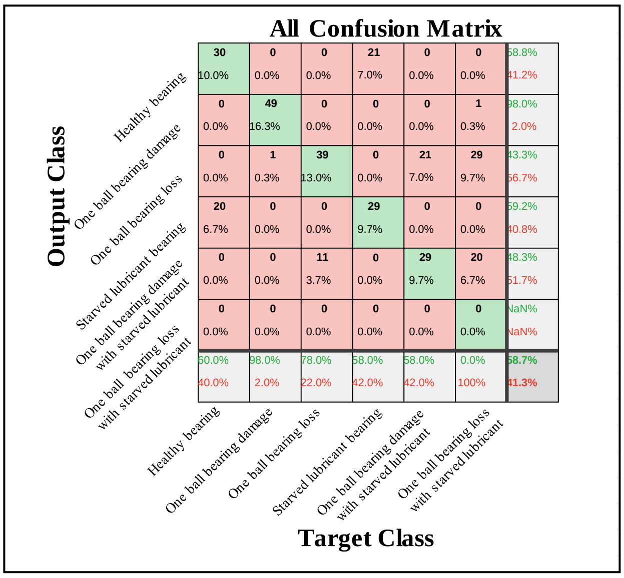

Fig.22 Confusion matrix of FFT spectrum

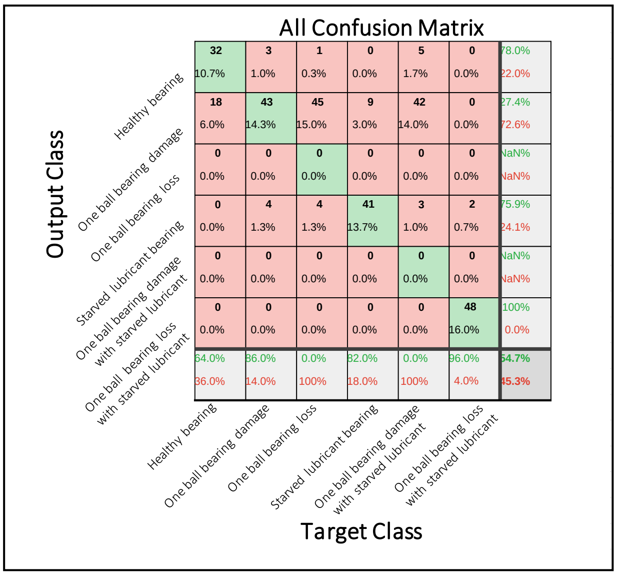

Fig.23 Confusion matrix of motor current

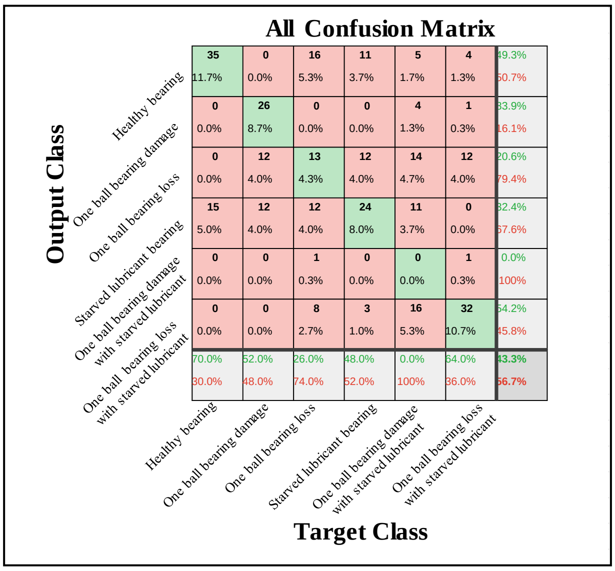

Fig.24 Confusion matrix of crest factor

4.2.2 Double parameters program

The double input parameters program was setup by combining two input parameters. As follow by FFT spectrum plus motor current, FFT spectrum plus crest factor and the motor current plus crest factor showed as Fig.25, Fig.26, and Fig.27 respectively. The results of model accuracy are showed 89.7% for FFT spectrum with motor current. While FFT spectrum and crest factor showed 73.3%. And motor current with crest factor showed 68.0%. All result of double parameters program showed more accurate compared to single parameter program.

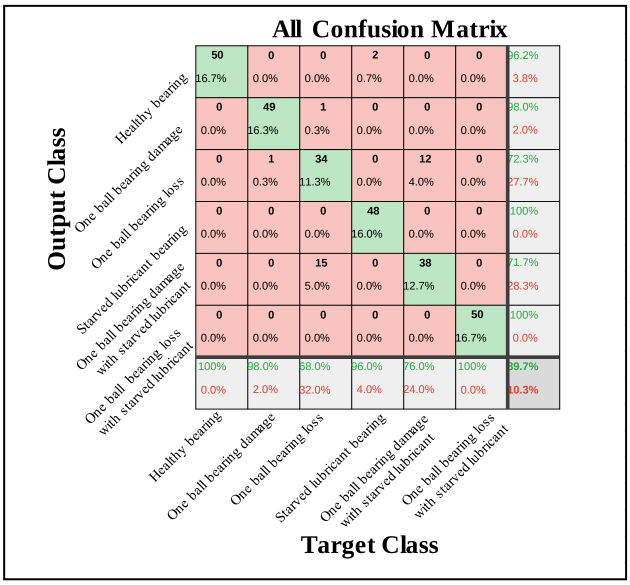

Fig.25 Confusion matrix of FFT spectrum and motor current

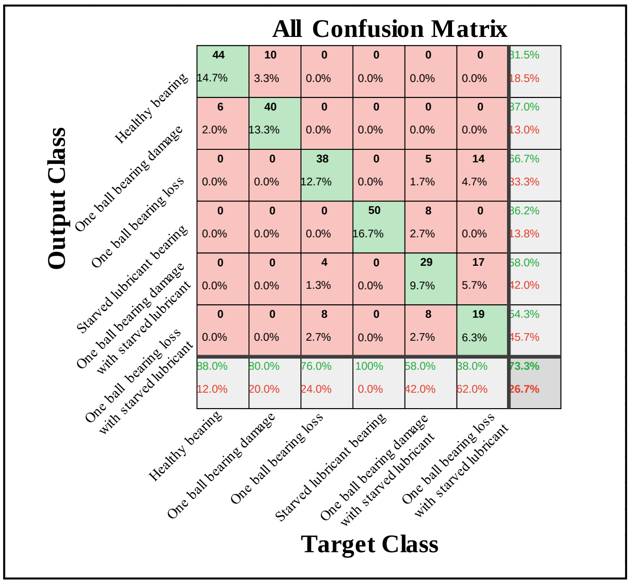

Fig.26 Confusion matrix of FFT spectrum and crest factor

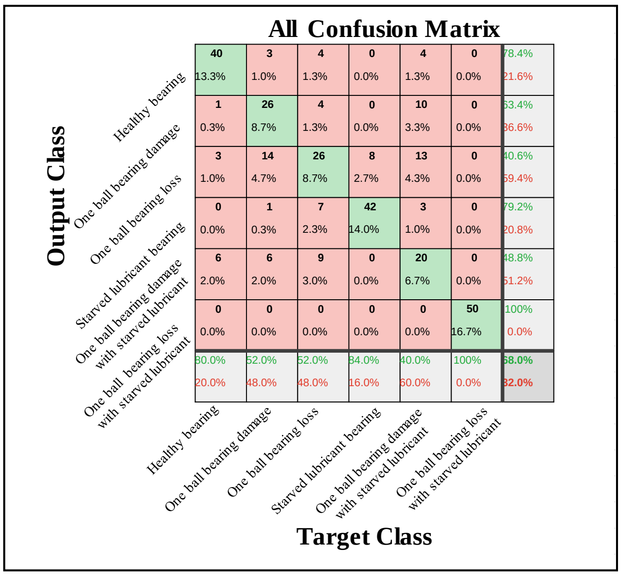

Fig.27 Confusion matrix of motor current and crest factor

4.2.3 Triple parameters program

Triple parameters (FFT spectrum, motor current and crest facture) were used for ANN program. The confusion matrix as Fig.28 showed result of the triple parameters program with accuracy equal to 93%, compared to single and double parameters program. Therefor the prediction by triple input parameters ensures the fault detection of linear bearing.

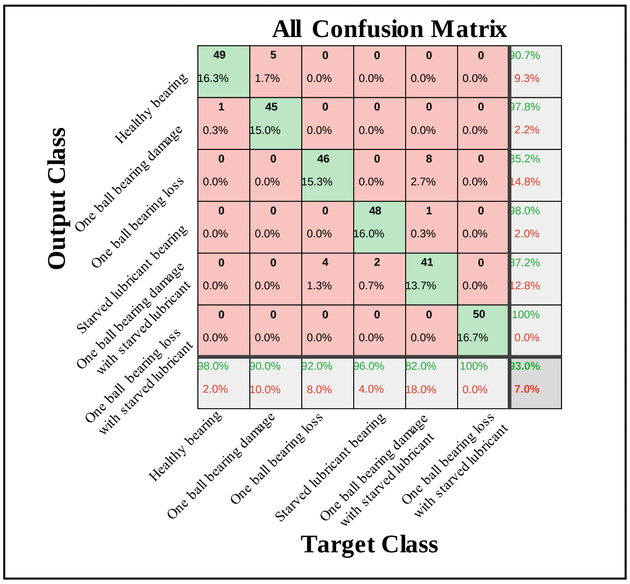

Fig.28 Confusion matrix of FFT spectrum, motor current and crest factor

Table 8. Summary of confusion matrices

1st Parameter	2nd Parameter	3rd Parameter	%
FFT Spectrum	-	-	58.7%
Motor current	-	-	54.7%
Crest factor	-	-	43.3%
FFT Spectrum	Motor current	-	89.7%
Motor current	Crest factor	-	73.3%
Crest factor	Motor current	-	68.0%
FFT Spectrum	Crest factor	Motor current	93.0%

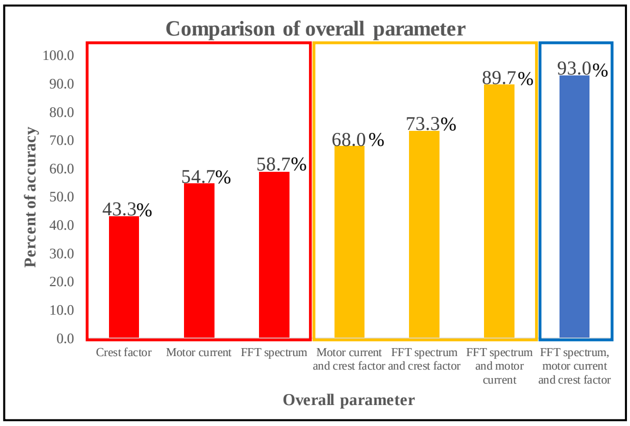

Fig.29 Comparison of the accuracy of ANN model

5 Conclusion

FDI method can be used for reliability improvement of the automation machine. The primary mechanical failure detection of the automation machine is very important in operational condition before the machine breaks down. This paper presents linear motor fault detection using FFT spectrum, motor current, and crest factor as input signal to detect the linear bearing condition. ANN was used to classify the linear bearing condition resulted from experiment shown increased parameter from single to tripple. The accuracy of model increased raise up to 93.0% as shown in Fig.29. The linear bearing fault can be correctly identified by the decision of ANN. The experimental results showed potential application of ANN as FDI tool for linear bearing fault detection performance.

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