ABSTRACT

In this Paper, surveys, application, and comparison of three types of artificial intelligence in machinery fault diagnosis: Neural Network, Support Vector Machines, and Artificial Immune Recognition System have been introduced.

Selecting the correct features is the most important thing in training and diagnosis field and it is the core issue of this field, in this thesis, a trial is made to improve the accuracies of the three proposed methods by trying to select the proper features from time domain. The training is done by using the data collected from two-channel, horizontal and vertical in three cases first, both time and frequency domains are used as features input to the three proposed methods, secondly, using frequency domain only or thirdly, using part of the time domain features with frequency domain features; for two speed. All the three methods show excellent accuracy when training and diagnosis at same specific speed especially SVM, while the accuracy is low when diagnosis at a speed that differs from training speed. Also all the three methods give excellent diagnosis results when the applied load at the same speed of training speed.

Keywords: Artificial immune Recognition System, Artificial Neural Networks, Support Vector Machines, Intelligent Fault Diagnosis, Rotating Machines

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Surveys For Artificial Immune Recognition System and Comparison with Artificial Neural Networks and Support Vector Machines in Intelligent Fault Diagnosis of Rotating Machines

NOMENCLATURES

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>SI Units</th>
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<tbody>
<tr>
<td>$x(i), x[n]$</td>
<td>Time signal (original signal)</td>
<td>mm/s</td>
</tr>
<tr>
<td>$\bar{x}$</td>
<td>Mean Value</td>
<td>mm/s</td>
</tr>
<tr>
<td>$t$</td>
<td>Time</td>
<td>sec</td>
</tr>
<tr>
<td>$X(k)$</td>
<td>Frequency of each vibration signal component</td>
<td>Hz</td>
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Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AI</td>
<td>Artificial Intelligent</td>
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<tr>
<td>AIRS</td>
<td>Artificial Immune Recognition System</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>ARB</td>
<td>Artificial Recognition Ball</td>
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<tr>
<td>AT</td>
<td>Affinity Threshold</td>
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<tr>
<td>B</td>
<td>Bearing</td>
</tr>
<tr>
<td>BPFI</td>
<td>Ball-Pass Frequency Inner race</td>
</tr>
<tr>
<td>BPFO</td>
<td>Ball-Pass Frequency Outer race</td>
</tr>
<tr>
<td>BSF</td>
<td>Ball Spin Frequency</td>
</tr>
<tr>
<td>CrF</td>
<td>Crest Factor</td>
</tr>
<tr>
<td>dist</td>
<td>Distance</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
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<tr>
<td>FTF</td>
<td>Fundamental Train Frequency</td>
</tr>
<tr>
<td>GUI</td>
<td>Graphical User Interface</td>
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<tr>
<td>K-NN</td>
<td>K-Nearest Neighbor</td>
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</table>
1. INTRODUCTION
One of the most world classifications for the causes of mechanical defects is Vibration. Vibration is the oscillatory motion produced in mechanical systems due to exciting forces. Examples of mechanical systems are rotors, bearings, gears, impellers, pipes, and structures. When the machine is new, everything is balanced, shafts are properly aligned, tolerances are small and everything should be fine. As the machine begins to deteriorate, exciting forces start to appear such as forces due to unbalance, misalignment, eccentricity and bent shafts. Bearings problems such as pitting, wear, irregularities and scratches will cause noisy operation and high vibration level. Structural problems such as settlement can cause distortion to the machine structure resulting in high vibration level such as in soft foot condition. It is important to diagnose the fault before catastrophic failure occurs, to save human lives and time and to reduce the cost as much as possible. The challenge is to predict the fault and fix or replace the damaged part before the total failure happens. Recently, with developing of Artificial intelligent and using it in Vibration, diagnosis become more accurate and easier to monitor. Vibration measurement and analysis systems can be divided into two main categories, online and offline systems. The Artificial intelligent can be applied for both systems and can provide a warning in addition to the type of faults if it bearing fault types, misalignment, unbalance, looseness, etc…
The normal immune system is a highly complicated system with many efficient mechanisms. The specific (acquired) and nonspecific (innate) immune mechanisms occupations a multilevel defense against attackers. The main part of the immune system is to classify those cells as self or non-self and distinguish all cells (or particles) within the body. Further classified for non-self-cells in order to motivate a suitable kind of protective mechanism. The immune system acquires over development to recognize among external antigens (e.g., viruses, bacteria, etc.) and the body's private molecules or cells.

The human immune system is responsible for defends our bodies from the harm element that attack and live inside the body such as bacteria, fungi, viruses, and other harms elements. The Innate and adaptive are the two types of immunity. Innate immunity work against any pathogens that go into the body and not focused in any way towards specific attackers. It is said to be nonspecific and is mostly not changed by repeated exposure. Adaptive immunity is said to have immunological memory because it focused against specific attackers and is adapted by exposure to such attackers. The adaptive immune system is constructed of lymphocytes which are white blood cells, more specifically B and T cells. The cells are fit to specific antigens and perform identification or matching in shape-space, which is the features elements of the antigen. Distinguishing and terminating process for specific elements with help of these cells. Antigen or immunogenic is an element that is able to generate such response from the lymphocytes. Antigens are not attacking microorganisms themselves; they are elements such as enzymes, toxins in the microorganisms that the immune system which considers foreign. The antigen is motivated the Immune responses directed against and is considered to be antigen-specific. The ability of the adaptive immune system to put a more effective immune response against an antigen after its earliest facing is called the memory of the immunological system, this will leave the body in a better ability to resist in the future. [1]

There is two response in AIS, the Main response is started when facing an antigen for the first time which motivated by the immune system. Immune system might create a big number of antibodies in reaction to the infection that will help to remove the antigen from the body. A part of these antibodies will stay and act as the role of the secondary immune response after the infection has been cleared. The cells that are left designed to attack as it effectively remembers the antigen, this means when the re-infection occurs the body is prepared. Quick and more abundant production of the antibody characterized the secondary response. The established memory from secondary response which can be elicited from an antigen that is similar, although not identical, to the original one.

The artificial immune recognition system algorithm was proposed in the 2000s. Jon Timmis et al, 2000, [1] concluded that the networks produced by the artificial immune system presented here are effective classification tool.


Donald E. Goodman et al, 2003, [3] investigated for the base of the power of AIRS. They conclude that when Memory cell replaced the candidate generation part of the AIRS algorithm; the performance has no significant difference. They approved that what gives this algorithm the strength of this classifier is in its approach to adding and substituting memory cells in the memory cell population.

Watkins et al. 2004 [4], introduced AIS which is one of the larg commonly applied supervised learning methods. AIRS showed to competitive with most famous classifiers such as naive Bayes networks, artificial neural networks, decision trees, etc.


Jens Strackeljan et al, 2008 [7] presented one of the few works on Fault identification in Rotating Machinery by using Artificial Immune System. They found that there are still issues and misidentification with some fault classes like misalignment, bent shaft and unbalance because features of these faults are similar. These fault classes cannot be identified without better and wider measurements.

Halife Kodazin, 2009 [8] applied the AIRS to the medical application. First, prepare the data information values and then applied these values to AIRS with the information gain depending on Euclidean distance. He has reached 95.90% classification accuracy.

Bo Chen and Chuanzhi Zang, 2009 [9] worked on Artificial immune pattern recognition where they used it for structure damage classification. The training procedure is considered based on the clonal selection standard in the immune system. The damage patterns are characterized by feature vectors that are pulled out from the measurements of the structure’s dynamic response. The adaptive and selected features of the clonal selection let the classifier to produce recognition feature vectors that are capable to match the training data.

N.R. Sakthivel et al, 2011, [10] proposed classification system depending on artificial immunity recognition for fault identification for the centrifugal pump and compare it with hybrid systems such as PCA-Naive Bayes, and PCA-Bayes Net. They got 99.6% accuracy from AIRS and 98.2% from PCA-Naive Bayes and 99.4 from PCA-Bayes Net.

Grzegorz Dudek, 2012 in [11] proposed a new classification with multiclass depending on immune system principles. He uses the embedded property of local feature selection as a unique feature of this classifier.


Slaheddine Zgarni et al, 2017 [13] presented a new approach for Bearing Fault identification in induction motor using a combination of artificial immune Network and Undecimated Wavelet Packet Transform (UWPT) and they got accuracy of 96.9%.

2. TIME AND FREQUENCY FEATURES

2.1. Maximum Value

$$Maximum = Max(x(i))$$

Where $$x(i)$$ is the time domain series sequence, for $$i = 1, 2,...,N$$ where N is the number of the data points.

2.2. Minimum Value

$$Minimum = Min(x(i))$$
2.3. Mean Value

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x(i)
\]  
(1)

2.4. Root Mean Square (RMS)

\[
RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x(i)^2}
\]  
(2)

2.5. Standard Deviation (\(\sigma\))

\[
\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x(i) - \bar{x})^2}
\]  
(3)

2.6. Kurtosis factor

\[
Kurtosis (Kur) = \frac{1}{N} \sum_{i=1}^{N} (x(i) - \bar{x})^4 / \sigma^4
\]  
(4)

2.7. Skewness

\[
Skewness(SK) = \frac{1}{N} \sum_{i=1}^{N} (x(i) - \bar{x})^3 / \sigma^3
\]  
(5)

2.8. Peak Value

\[
Peak Value = \frac{1}{2} [\text{Max}(x(i)) - \text{Min}(x(i))]
\]  
(6)

2.9. Crest Factor (CrF)

\[
CrF = \frac{\text{Peak}}{RMS}
\]  
(7)

2.10. Fast Fourier Transform (FFT)

FFT is a powerful technique to process the time domain of vibration signal into frequency domain.

\[
X(k) = \sum_{n=0}^{N-1} x[n]e^{-\frac{i2\pi kn}{N}}
\]  
(8)

where \(X(k)\) is the \(k^{th}\) harmonic \((k = 0 ... N - 1)\)
Each component in the FFT spectrum has its own frequency and amplitude. The order of the component is its frequency divided by the shaft rotational frequency.

\[ \text{Order} = \frac{\text{actual frequency}}{\text{rotational frequency}} \]  

(9)

The features at the orders that have been taken in this work are (0.38, 0.5, 1, 1.5, 1.99, 2, 2.5, 3, 3.5, 4, 4.5, 4.95, 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, 9, 9.5, 10, 10.5) RPM

3. THEORY OF AIRS

The AIRS algorithm is based on several principles of AIS research. The immune system is an organ which is mission is identify pathogens (substances or antigens that may be harmful) and respond by defensive the organism from that substance. The system can be able to improve the identification of the harmful element through time because it is adaptable. With several antigens having similar properties, the system becomes more effective when the antigen is identified and thus responded to. Neutralizes pathogenic material when an antibody response in the form of an antibody. The adaptive immune system is constructed of lymphocytes which are white blood cells, more specifically B and T cells. The cells are fit to specific antigens and perform identification or matching in shape-space, which is the features elements of the antigen.[2]

3.1. Meaning Terms of AIRS

- **Affinity** refer to the degree of similarity between the antigen and the identification cell.
- **Affinity maturation** is a process of the adaptive ability of the immune system.
- **clonal expansion** it perform by recognition cell, and means it will breed many clones of itself in an attempt to gain a better match next time the antigen is seen, during an immune response
- **Somatic hypermutation** process mutates the generated clones in proportion to the affinity between the recognition cell and the antigen.
- **Clonal selection** process of selecting cells among the resulting cloning which maintained only to those cells that have a greater affinity.
- **Memory Cell** over the interface with antigens in the past, AIRS is able to remember what is represented by the pathogen. And can better defend the organism in the future.[43]

3.2. The Theory of the Algorithm

The lifecycle of the AIRS system is presented in Figure (3.6). The role of the AIRS algorithm is to make a pool of recognition or memory cells (data exemplars) which are agents of the training data. The model is exposed to, is suitable for classifying new data.
3.2.1. Initialization

The first part of the algorithm is to prepare the data for system variables and the training process. Before using the training data, it should be normalized to ensure the numeric range between (0, 1) at each attribute. Through the training process an affinity measure by using the inverted Euclidean distance. The maximum distance measured should be in range of (0, 1) between any two recognition cells or antigen and recognition cell, which can be done by adding the following step to the data normalization process:

\[ \text{normalizedValue} = \text{normalizedValue} \cdot \frac{1}{n} \]

(10)

Where the \( \text{normalizedValue} \) is the data attribute in the range of (0, 1), and \( n \) is the number of features used to evaluate the distance. Second method to confirming the resultant distance values are in the range of (0, 1), without need to the data to be normalized is to simply divide the calculated Euclidean distance by the maximum distance between any two vectors. The below equation shows Euclidean distance, where \( v1 \) and \( v2 \) represent two elements that affinity is measured between and \( n \) is the number of features.

\[ \text{dist} = \sqrt{\sum_{i=1}^{n} (v1_i - v2_i)^2} \]

(11)

Equation (3.49) shows the maximum distance between any two data vectors, where \( r \) is the known data range for feature \( i \).

\[ \text{max Dist} = \sqrt{\sum_{i=1}^{n} r_i^2} \]

(12)

Affinity is a similarity value, this means that the smaller the affinity value the higher the affinity is said to be (the closer the vectors are to each other).
\[ affinity = \left( \frac{\text{dist}}{\text{maxDist}} \right) \] (13)

Euclidean distance works well for numerical features but breaks down for nominal features. This can be overcome by assuming that the difference between nominal attributes is binary (match or no match) and the attribute range is one. The next step is to seed the memory cell pool. The memory cell pool is the collection of recognition elements that make up the classifier produced at the end of the training scheme. Seeding the memory pool is an optional step and involves randomly selecting a number of antigens to become memory cells.

Affinity threshold (AT) is the final step during the initialization which it prepared the affinity threshold system variable. The mean affinity between antigens in the training dataset is affinity threshold. Either it can be calculated from a sample of the training set or the entire training set. This calculated value is then used later during the training scheme to determine whether candidate memory cells that are prepared, can replace existing memory cells in the classifier.

3.2.2. Training of the Antigen
The AIRS algorithm is deliver only one pass over the training data is required to prepare a classifier. Every antigen is exposed to the memory pool one at a time. The recognition cells in the memory pool are stimulated by the antigen and each cell is allocated a stimulation value (inverted affinity). The memory cell with the greatest stimulation is then selected as the best match memory cell for use in the affinity maturation process.

\[ \text{stim} = 1 - \text{affinity} \] (14)

A number of mutated clones are then created from the selected memory cell and added to the ARB pool. An ARB (Artificial Recognition Ball) is an abstract concept and represents a number similar or identical recognition cells. The ARB pool is a work area where the AIRS system refines mutated clones of the best match memory cell for a specific antigen. The number of mutated clones created of the best match is calculated as follows:

\[ \text{numClones} = \text{stim}.\text{clonalRate}.\text{hypermutationRate} \] (15)

where the \text{stim} is the stimulation between the best match memory cell and the antigen. Both the \text{clonal rate} and the \text{hypermutation rate} are user-defined parameters.

3.2.3. Competition for Limited Resources
The process of ARB generation and competition begins, after number of mutated clones of the best matching memory cell are added to the ARB pool. This process can be described in the below figure.
To control the size of the ARB pool and renew those ARBs with greater stimulation (and thus affinity) to the antigen being trained a Competition for limited resources is used. The stop condition in the middle of the loop allows the final step of clone generation to be avoided when the ARB pool reaches a desirable condition. In this process only ARBs of the same class as the antigen are considered, meaning that the class of an ARB is never adjusted in the mutation process. The final step sees each ARB in the pool have mutated clones generated using the same clonal expansion and somatic hypermutation steps used previously to generate mutated clones of the best match from the memory cell. Here the number of clones generated for each ARB in the pool is calculated as the following:

$$\text{numClones} = \text{stim} \times \text{clonalRate}$$  \hspace{1cm} (16)

In the resource allocation process, the amount of resources allocated to each ARB is as follows:

$$\text{resource} = \text{normStim} \times \text{clonalRate}$$  \hspace{1cm} (17)

Where the resources are defined that specified that maximum number of resources that can be allocated. The total resources is allocated during the resource allocation process, which is determined and compared against the maximum total resources. When the allocated resources are determined the ARB pool is then rearranged by allocated resources and resources are deleted from ARBs starting from the end of the list until the total allocated resources are below the total resources allowed. At the final, those ARBs with zero resources are removed from the pool. The stop condition for this process of ARB refinement occurs when the mean normalized stimulation is more than the user-defined stimulation threshold.

3.2.4. Memory Cell Selection

Memory cell candidate is selected by the ARB with the greatest normalized stimulation value when the stop condition for the ARB modification process is completed. If the new stimulation value for the candidate is better than that of the original best matching memory cell, the ARB is copied into the memory cell. A test is done to define if the early best matching memory cell must be replace. This done when the affinity is less than a cut-off, between the candidate memory cell and the best matching cell. This memory cell replacement cut-off is defined as:
where the affinity threshold scalar is a user-defined parameter and the affinity threshold is the system variable prepared during the initialization process.

3.2.5. Classification

After the training process is completed, the memory cell pool recognition cells becomes the essential role of the AIRS classifier. Classification is done using a k-Nearest Neighbor method where the $k$ best similarity to a data instances are located and the class is chosen through common vote.

4. EXPERIMENTAL WORK

The device that is used to generate vibration signals for different types of faults is machinery fault simulator (MSF) as shown in Figure (4.1), which consist of 1HP & 60HZ electric motor with an AC-motor controller to control the speed of the motor, steel shaft of (1/2”) diameter with a disc with diameter (12cm), mounted in the middle of the shaft that are used for applying loads and for unbalance faults simulation, two bearing holding the shaft and a coupling joint to connect the motor with the shaft. Two accelerometer type (B&K 4338) of a serial No. (442068) & (B&K 4338) of serial No. (540553) were mounted on the housing of the bearing, in the horizontal and vertical to collect and monitor the raw vibrations signals as shown in Figure (4.2). Data acquisition (IDAC-6C) device is shown in Figure (4.3) which is used to transfer the vibrations signal from the accelerometer to a computer as vibrations data for analysis.

Figure (4.1) is showing:

1. Ac-motor controller
2. Tachometer
3. The Motor
4. Flexible coupling
5. Experimental bearing
6. Disc
7. Accelerometer
8. Faulty Gears
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Figure (3) MSF components

Figure (4) Accelerometers
4.1. Experiment procedure

Laboratory workflow diagram is shown in Figure (4.4). IDAC-6C is used to collect the raw vibration signal generated by (MSF-4) at a different speed for training, also take new data for diagnosis. The features are trained using the data collected from the horizontal channel only or vertical channel or both. The training process is done by training the features at a specific speed and diagnosis at the same and different speed for the three methods.
Specify the setting operation of IDAC-6C software interface

save the raw Data

set a fault

Read the Vibration data from the Software

set speed required from AC-controller

start the motor

**Figure (6) Experimental in Lap Procedures**

The setting operation for IDAC-6c software interface for the three speeds are

- for speed 12.5 Hz (750 rpm) the sample rate is 1024 and the number of samples is 8192 and the low-pass filter is 400 and high-pass filter is 0.3
- for speed 25 Hz (1500 rpm) the sample rate is 2048 and the number of samples is 8192 and the low-pass filter is 800 and high-pass filter is 0.3
By using feature extraction equations that explained in Chapter three in both time domain and frequency domain in MATLAB (for more information about programming see Appendix B)

The steps that have been followed are:
1. Specify the setting for specific speed
2. Browse (*.txt) file to collect raw vibration data to MATLAB
3. Save the features data in one Excel file

Training of the features data is used in one dimension and two dimensions in the three proposed methods which programmed by MATLAB (see Appendix B)

a) Neural Network: by using the features extracted from the vibration signal as input data and the output data showed in Appendix C. KNN with K=1 is used at the final step to classify the classified data by ANN

b) SVM: with the same features but add the type of fault in front of each set class, thus no need to KNN for further classifying. Using different Kernel Methods and select higher accuracy.

c) AIRS: using the same data features to train the AIRS but it needs KNN for further classifying.

Saving each trained methods and loaded by the standalone software to diagnosis with new data at same or different speed.

4.2. Software

By using the MATLAB which is one of the best applications available for providing both the computational capabilities of generating and displaying data in a variety of graphical representations.

A standalone software program that has been made for Vibration analysis and for faults diagnosis for the three proposed methods by using MATLAB GUI, the main view of the software is shown in Figure (8) have two buttons, one for vibration diagnosis and the other one is for
vibration analysis which plots the time domain and FFT, which is very useful if the user is an expert person

![Main software view](http://www.iaeme.com/IJMET/index.asp)

**Figure (8)** main software view

Figure (9) shows a vibration diagnosis view which contains diagnosis for the three methods at a specific speed

![Diagnosis software view](http://www.iaeme.com/IJMET/index.asp)

**Figure (9)** example on diagnosis fault type ‘misalignment’ by three methods at speed (12.5 Hz) in software diagnosis view

When pressing “AIRS” or “SVM” or “Neural network”, the software will ask about (*.txt) file, the new data that wanted to diagnosis, the software will calculate the features and give the output result immediately.

**Figure (10)** shows vibration analysis for two channels as specific speed by browsing
4.3. Overview of the type of Faults
Overview for Faults that provided by the manufacturer and how can be applied in Lap.

4.3.1. Bearing Faults
The faulty bearings are provided by the manufacture of MSF as shown in Figure (11). Bearing localize defects are made by the manufacturer with bearing construction:

- Outer race fault (alias ball pass frequency outer or BPFO)
- Inner race fault (alias ball pass frequency or BPFI)
- Rolling element fault (alias ball spin frequency or BSF)
- Cage fault

The major fault frequencies BPFO, BPFI, BSF, and FTF are calculated by the following:
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\[ BPFO = \frac{N_b}{2} S \left( 1 - \frac{B_d}{P_d} \cos \theta \right) \]  \hspace{1cm} (19)

\[ BPFI = \frac{N_b}{2} S (1 + \frac{B_d}{P_d} \cos \theta) \]  \hspace{1cm} (20)

\[ FTF = \frac{S}{2} (1 - \frac{B_d}{P_d} \cos \theta) \]  \hspace{1cm} (21)

\[ BPFI = \frac{P_d}{2B_d} S \left[ 1 - \left( \frac{P_d}{P_d} \right)^2 \right] \]  \hspace{1cm} (22)

Where: \( B_d \) is ball diameter, \( N_b \) is the number of the balls, \( P_d \) is pitch diameter, \( S \) is rotational speed and \( \theta \) is contact angle.

Table 4.1 specification rotor bearing

<table>
<thead>
<tr>
<th>Component</th>
<th>FTF</th>
<th>BSF</th>
<th>BPFI</th>
<th>BPFO</th>
</tr>
</thead>
<tbody>
<tr>
<td>½” RB</td>
<td>0.378</td>
<td>1.992</td>
<td>4.95</td>
<td>3.048</td>
</tr>
<tr>
<td>¾” RB</td>
<td>0.378</td>
<td>1.992</td>
<td>4.95</td>
<td>3.048</td>
</tr>
<tr>
<td>⅛” RB</td>
<td>0.378</td>
<td>1.992</td>
<td>4.95</td>
<td>3.048</td>
</tr>
<tr>
<td>1” RB</td>
<td>0.402</td>
<td>2.322</td>
<td>5.43</td>
<td>3.572</td>
</tr>
</tbody>
</table>

4.3.2. Unbalance
The unbalance is the centrifugal forces that generate from an excess mass or unequal distribution of masses with the centerline of rotation. Experimental unbalance is shown in Figure (4.9)

\[ F = m \omega^2 r \]  \hspace{1cm} (23)

Where \( m = 9.78 \) gram and radius is 6 cm when the frequency (\( \omega \)) is 12.5 Hz (750 rpm) the harmonic force generated is:

\[ F = \frac{9.78}{1000} \times 78.539^2 \times 0.06 = 3.6196 \text{ N} \]
4.3.3. Misalignment

Misalignment is the vertically or angularly offsetting in centerline between the driving shaft and the driven machine. There are two types of misalignment depending on the type of the offsetting, parallel and angular misalignment or combined. Figure (13) shows angular misalignment if offset one side and parallel misalignment if offset two sides.

4.3.4. Mechanical looseness or Soft Foot

Mechanical looseness is the presence of a gap or large tolerance in the assembled mechanical parts. It generates impacts as the vibrating part is moving forth and back and strikes the loosed adjacent parts. Figure (14) shows mechanical looseness from untighten bolts.
4.3.5. Applied load
The load of 77.4 gram is applied for each fault by tighten 18 bolts of weight 4.3 gram for each as shown below

5. RESULT AND DISCUSSION
The results of the accuracies of resultant diagnosis are shown below.

5.1. Training at 12.5Hz using all time and frequency domain features
The accuracies of training with 15% validation in each method are 100% for ANN and 100% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 12.5 Hz (750 RPM) with using all time and frequency domain features are shown in the table below.
Table (1) the accuracies of diagnosis after training at 12.5 Hz using all frequency and time domain features

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis with the same training data (12.5 Hz)</td>
<td>98.88 100 91.11</td>
</tr>
<tr>
<td>Diagnosis of new data at the same speed (12.5 Hz)</td>
<td>95.55 100 95.55</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (12.5 Hz)</td>
<td>95.55 100 95.55</td>
</tr>
</tbody>
</table>

5.2. Training at 25Hz with using all time and frequency domain features
The accuracies of training with 15% validation in each method are 100% for ANN and 100% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 25 Hz (1500 RPM) with using all time and frequency domain features are shown in the table below.

Table (2) the accuracies of diagnosis after training at 25 Hz with using all frequency and time domain features

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis with the same training data (25 Hz)</td>
<td>100 100 97.78</td>
</tr>
<tr>
<td>Diagnosis for new data at the same speed (25 Hz)</td>
<td>100 100 100</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (25 Hz)</td>
<td>96.66 100 95.55</td>
</tr>
</tbody>
</table>

5.3. Training at 12.5Hz with using frequency domain features only
The accuracies of training 15% validation in each method are 98.38% for ANN and 92.4% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 12.5 Hz (750 RPM) are shown in the table below:

Table (3) the accuracies of diagnosis after training at 12.5 Hz with using all frequency domain features only

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis with the same training data (12.5 Hz)</td>
<td>96.66 98.88 94.44</td>
</tr>
<tr>
<td>Diagnosis for new data at the same speed (12.5 Hz)</td>
<td>97.77 100 97.77</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (12.5 Hz)</td>
<td>96.66 94.44 95.55</td>
</tr>
</tbody>
</table>

5.4. Training at 25Hz with using frequency domain features only
The accuracies of training 15% validation in each method are 92.83% for ANN and 96.7% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 25 Hz (1500 RPM) are shown in the table below:
Surveys For Artificial Immune Recognition System and Comparison with Artificial Neural Networks and Support Vector Machines in Intelligent Fault Diagnosis of Rotating Machines

Table (4) the accuracies of diagnosis after training at 12.5 Hz with using all frequency domain features only.

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANN</td>
</tr>
<tr>
<td>Diagnosis with the same training data (12.5 Hz)</td>
<td>98.88</td>
</tr>
<tr>
<td>Diagnosis for new data at the same speed (12.5 Hz)</td>
<td>94.44</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (12.5 Hz)</td>
<td>92.22</td>
</tr>
</tbody>
</table>

5.5. Training at 12.5Hz with using (RMS, σ,Kur, SK and CrF) from time domain and all frequency domain features

The accuracies of training with 15% validation in each method are 100% for ANN and 100% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 12.5 Hz (750 RPM) are shown in the table below.

Table (5) the accuracies of diagnosis after training at 12.5 Hz with using some of time domain features and frequency domain features.

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANN</td>
</tr>
<tr>
<td>Diagnosis with the same training data (12.5 Hz)</td>
<td>100</td>
</tr>
<tr>
<td>Diagnosis for new data at the same speed (12.5 Hz)</td>
<td>100</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (12.5 Hz)</td>
<td>97.77</td>
</tr>
</tbody>
</table>

5.6. Training at 25Hz with using (RMS, σ,Kur, SK and CrF) from time domain and frequency domain features

The accuracies of training 15% validation in each method are 100% for ANN and 100% for SVM and 88.89% for AIRS and the accuracies of diagnosis after training at 25 Hz (1500 RPM) are shown in the table below.

Table (6) the accuracies of diagnosis after training at 25 Hz with using some of time domain features and frequency domain features.

<table>
<thead>
<tr>
<th>Type &amp; Speed</th>
<th>Accuracies %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANN</td>
</tr>
<tr>
<td>Diagnosis with the same training data at (25 Hz)</td>
<td>100</td>
</tr>
<tr>
<td>Diagnosis of new data at the same speed (25 Hz)</td>
<td>100</td>
</tr>
<tr>
<td>Diagnosis for a new data with load at the same speed (25 Hz)</td>
<td>98.88</td>
</tr>
</tbody>
</table>

From the table (1) the three methods showing good accuracies when diagnosis at same speed especially SVM. AIRS shows is better than ANN and SVM in diagnosis at 12.5 Hz when using all time and frequency domains features, because of the noise at low speed that may intervene with features pattern; this effect of the weights of the ANN and normalization for AIRS, while SVM while comparing the new data with it hyperplane and small change in its characteristic will not effect on it classification.

From table (2) showing very good results for the three methods and the accuracy of diagnosis at a different speed is increased for these methods because of the low effect of the intervening of the noise with the signal of the noise.
From table (3) and table (4) the accuracies are decreased from before because using frequency domain features only is not enough as data input.

From the table (5) showing excellent accuracies for the three methods, because some of time domain features may go randomly and it has same or close values to each different type of fault, like maximum, minimum, peak and means as shown in the table (5.1).

From table (6) all the three methods show excellent accuracy when diagnosis at the same speed because of the low effectiveness of the noise with good features selected.

5.7 Case Study Diagnosis at a different speed
Using the four of time domain and all frequency domain features to diagnosis at different speed; firstly, for the training at 12.5Hz and diagnosis at 25 Hz, the accuracies are for ANN is 38.88% and SVM is 12.22% and AIRS is 37.77%, secondly, for the training at 25Hz and diagnosis at 12.5Hz, the accuracies are for ANN is 56.66% and SVM is 34.44% and AIRS is 38.88%.

From the above results showing low accuracy when diagnosis at different speed from the training speed; this because the features characteristic will change at different speed and became unknown for the same class that trained for, however, training at specific speed and diagnosis at lower than training speed gives better results than diagnosis at higher speed from training one. ANN gives the best accuracy result between the three because it depends on the weights of the fault, while SVM gives the lowest accuracy because it will compare the unknown fault with the same hyperplane that done by training at different speed, while AIRS will compare the new fault with it memory which it will difficult to find the fault matching.

6. CONCLUSION
The most important conclusions from the current study are:

1. All the methods are very good in diagnosis at same speed of training especially SVM which gives 100% accuracy in most cases.
2. All the three methods gives excellent diagnosis results when applied to diagnose faults with loading at same speed of training speed.
3. Using FFT only is not enough as features input since the accuracy of diagnosis decreased as compared to cases where all or some of the time domain features are considered.
4. Some of time domain features gives random values or close to each other in different faults like maximum, minimum, mean and peak
5. To have high accuracy results of diagnosis it is better to train and diagnosis at same specific speed
6. SVM gives the lowest accuracy when diagnosis at different speed and best accuracy when diagnosis at same training speed.
7. Angular misalignment fault is more sensitive to time domain features while other faults are less or not sensitive to the time domain features.

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