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Artificial Immune Network for Bearing Fault Detection of Induction Motor

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Abstract— **Inspired from the increasing interest of Artificial Intelligence (AI) applications, this work presents a novel approach for Bearing Fault (BF) detection in induction motor (IM) using a combination of artificial immune Network (aiNet) and Undecimated Wavelet Packet Transform (UWPT). Several studies prove that bearing defects are the main cause of the IM failure. Thus, the detection of bearing faults (BF) has become the key issue to enhance the IM reliability and to decrease its downtime. To evaluate this approach, different bearing faults were experimented and the effectiveness of the suggested approach is then verified.**

Keywords—**Induction Motor; bearing; fault detection; Wavelet Transform; Artificial Immune Network.**

I. INTRODUCTION

Managing rotating machines breakdown is the key for improving performances and reliability, decreasing downtime and therefore maintenance efficiency. Then, as being the main part of them, bearing failure detection and diagnosis have become an important issue [1]. Especially in case of the IM, bearing fault (BF) monitoring is extremely critical. Today, due to the engineering development, the interest of bearing condition monitoring (CM) automation by artificial intelligence (AI) has been increasing [2]-[3].

AI applications like, Artificial Neural Networks (ANN), Support Vector Machine (SVM) and Artificial Immune System (AIS) are still studied [4]. Comparing these methods performances, SVM had solved many issues in various fields and has proved better results and more effectiveness in failure diagnosis due to its ability to operate a greater number of input dataset using only a slight number of samples [5]-[9]. Although the SVM is a powerful tool, its best performance is obtained under a precise combination of SVM parameters used [10]. To optimize the SVM parameters, Artificial Immune System (AIS) have recently achieved an advance in this regard. AIS is chosen in this study and has proven ability to deliver a global and optimal searching parameters ability and memory function [11], [12]. Inspired from the natural immune system, previous researches explored the AIS approach [13]. Based on that principle, the AIS have been used in the field of engineering, and a set of artificial immune theory has been progressively formed. Clonal selection, negative selection and immune network are the three classic approaches existing in the artificial immune system. Corresponding algorithms have been applied in various fields [14].

Lucifredi et al. [15] and Strackeljan et al. [16] used the antibody network (AbNet) as an expert system to detect the bearing faults. Three bearing faults (rolling element fault, outer race (OR) fault and inner race (IR) fault) are used under a sampling rate of 22050 Hz. This algorithm requires binary inputs while experimental data are analog signal, therefore, a binary conversion of the data is necessary. The process of data conversion from real to binary results in the loss of a large quantity of information. Then, the analysis process of the AbNet requires several facts to achieve a balanced phenomenon. Montechiesi et al. [17] proposed a different approach, Euclidean Distance Minimization (EDM), which is helpful to keep away any intruder features. The EDM method is derived from the AbNet concept to detect the bearing defects (BD). The bearings were tested with a vibration signal. This approach requires a complex and expensive acquisition set-up. The experiments considered three bearing conditions (OR, IR and cage (C)) and amounts of 35 acquisitions under a sampling rate of 10 kHz. To prove the effectiveness of this method, it is crucial to use a large quantity of data and multiple accelerometers. These undesirable aspects are actually evaded thanks to an alternative algorithm suggested to identify bearing faults of multi-class in IM and based on an artificial immune Network (aiNet).

In this work, a new combined technique is developed for BF detection using Undecimated Wavelet Packet Transform (UWPT) and Artificial Immune Network (aiNet). In this method, the fault descriptors are optimized and the detection performance is improved. Then, A Novel algorithm for fault classification by using Artificial Immune Network (aiNet) is presented. The fault diagnosis algorithm is validated for three bearing faults under various load conditions.

The rest of this work is structured as follows: Section II represents the feature extraction technique. The artificial immune network is presented in section III. Section IV shows the experimental setup. Section V describes the fault diagnosis algorithm. Then, the classification results are reported in section VI. At last, we conclude with the highlights of this work in section VII.

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II. Features Extraction

Feature extraction is the first step for an automatic classification system. Power Spectral Density and Wavelet Transform are among the most famous techniques that are applied for signal processing. UWPT is an overview of the Discreet Wavelet Tansform (DWT), where both the approximations (A) and details (D) sub-bands are decomposed without decimation in each decomposition step [18]-[20]. Fig1. Shows the UWPT tree decomposition for two levels, where the stator current is represented by C_{00}. UWPT coefficients can be defined as:

$$C_{l+1,2n}(t) = \sqrt{2}\sum_{j} D_{l+1}(j)\cdot C_{l,n}(2t-j) \tag{1}$$

$$C_{l+1,2n}(t) = \sqrt{2}\sum_{j} A_{l+1}(j)\cdot C_{l,n}(2t-j) \tag{2}$$

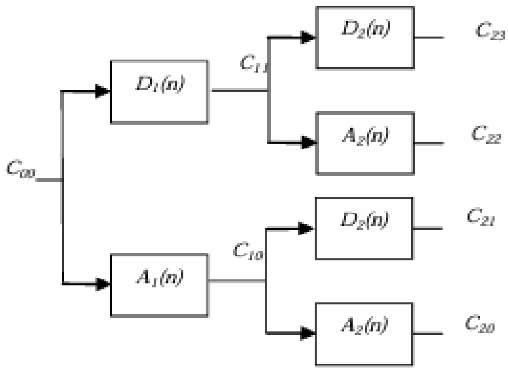

Fig.1. The structure of UWPT.

III. Artificial immune network algorithm

The aiNet is inspired from the human immunity. Its primary objective is an automatic compression and redundancy reducing of data [12]. The natural antigen (Ag) is represented in aiNet as the input dataset while the antibodies (Ab) are the output dataset. Each Ab identifies an Ag dataset. The Ag-Ab affinity determines their interaction. This interaction constitutes Networks cells. These later are similar in dimension to the input dataset. In fact, the objective of aiNet algorithm is to form a memory set that characterises the original dataset. Fig.2. summarizes the aiNet process.

IV. Experimental Setup Description

A 3KW four-pole three-phase induction motor is installed to validate the presented technique as shown in Fig.3. To variate the motor load from no load to full load condition, the motor is coupled to a DC machine. Then, 30 acquisitions of the stator current are made within a NI PCI-6221 data acquisition card for each motor condition. Four 6206 bearings are tested, a healthy bearing (HLT) and three faulty ones, with outer race fault (ORF), inner race fault (IRF) and cage fault (CF) as depicted in Fig.4, Fig.5 and Fig.6 respectively.

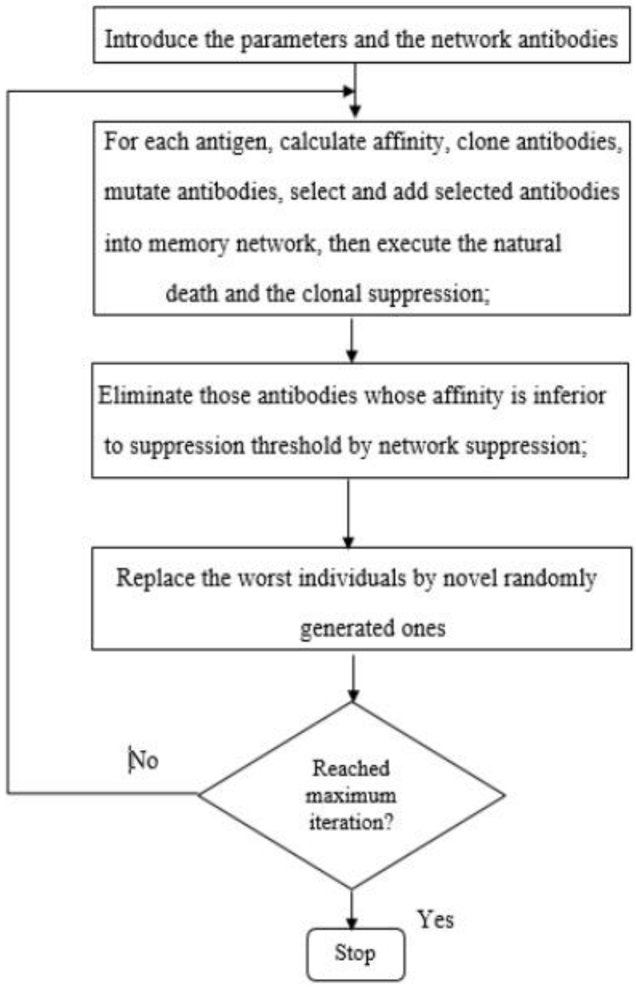

Fig.2. The procedure of aiNet algorithm.

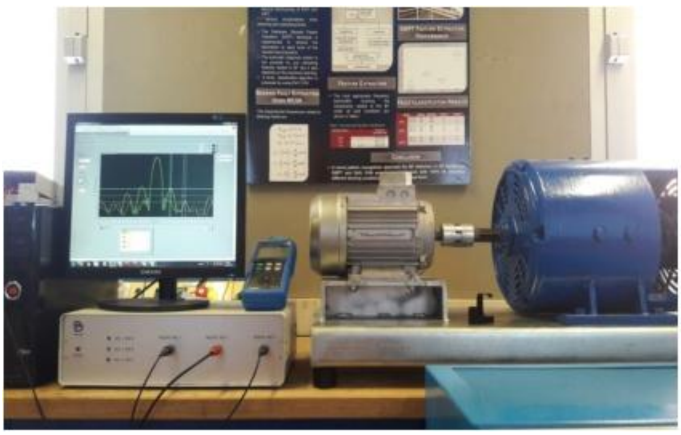

Fig.3. Experimental bench for bearing fault diagnosis.

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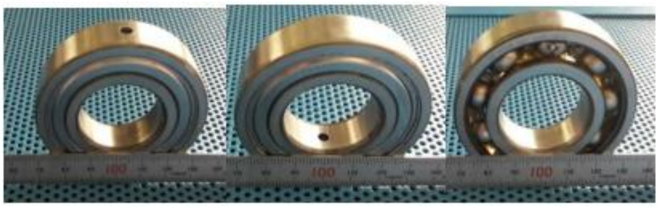

Fig.4. Outer Race Defect (ORD) Fig.5. Inner Race Defect (IRD) Fig.6. Cage Defect (CD)

V. Fault Diagnosis Algorithm

As shown in Fig.7, the fault diagnosis methodology consists of three sections: Collect data, feature extraction and training and testing process. The Undecimated Wavelet Packet Transform is used to select the relevant data to the BF. Each BF is associated to a characteristic frequency given by [21]:

$$f_{ORF} = \frac{f_r}{2} N_b \left(1 - \frac{bd}{pd} \cos\Theta \right) \tag{3}$$

$$f_{IRF} = \frac{f_r}{2} N_b \left(1 + \frac{bd}{pd} \cos\Theta \right) \tag{4}$$

$$f_{CF} = \frac{f_r}{2} \left(1 - \frac{bd}{pd} \cos\Theta \right) \tag{5}$$

f_{ORF}, f_{IRF} and f_{CF} are respectively associated to the ORF, the IRF and the CF. f_r is the motor rotational speed, N_b denotes the number of balls, bd is their diameter and pd is the cage diameter. Θ is the contact angle between a ball and the race.

In the current spectrum, the BF generates signatures given by:

$$F_{BF} = f_s \pm k \cdot f_{ORF,IRF,CF} \tag{6}$$

where f_s is the supply frequency, and k= 1,2,3….

Therefore, two UWPT coefficients are able to detect all bearing conditions. The RMS of these coefficients is then investigated as a fault descriptor.

VI. Classification Results and Discussions

The identification of the related parameters included in order to design aiNet algorithm is too critical. Thereby, these parameters settings are detailed in table I.

For the aiNet approach, 2/3 of the samples, presents the training data set, while the classifier's generalization ability is tested by the other 1/3. Table II shows the aiNet classification results (TCR). The best combination of the aiNet parameters allows finding the highest classification rate. Indeed, the eleventh combination provides the best TCR reaching 96.9%.

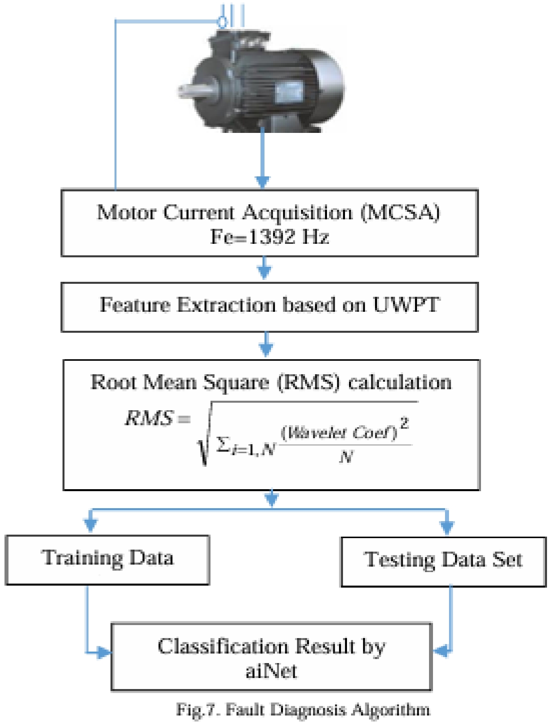

Fig.7. Fault Diagnosis Algorithm

TABLE I
THE PARAMETERS OF AINET

Parameters	Min(1)	Max(2)
gen: maximum number of generations	10	30
mi: learning (hypermutation) rate	2	8
n: no. of best-matching cells taken for each Ag	2	4
N: clone number multiplier	2	10
qi: percentile amount of clones to be Re-selected	0.1	0.3
tp: pruning threshold	0.1	1
ts: suppression threshold	0.2	0.8
N1: no. of antibodies (constructive)	10	15

VII. Conclusion

In the present study, an intelligent fault diagnosis method to detect bearing faults in induction motor has been developed based on the combination between artificial immune Network and Undecimated Wavelet Packet Transform. The experimental validation proved that this fault diagnosis algorithm permits to detect various BFs with only two descriptors which is lower than several recent studies. In the other hand, a high classification's accuracy of 96.9% is attained which enables an automatic isolation of bearings. For practical applications, these results are promising to extend this study for other IM faults with different severity levels.

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TABLE II
CLASSIFICATION RESULTS

Run	**gen**	**mi**	**n**	**N**	**Qi**	**Tp**	Ts	**N1**	**TCR (%)**
1	1	1	1	1	1	1	1	1	94.8
2	1	1	1	1	1	2	2	2	73.4
3	1	1	2	2	2	1	1	1	65.6
4	1	2	1	2	2	1	2	2	94.4
5	1	2	2	1	2	2	1	2	88.9
6	1	2	2	2	1	2	2	1	9.6
7	2	1	2	2	1	1	2	2	10.8
8	2	1	2	1	2	2	2	1	17.2
9	2	1	1	2	2	2	1	2	84.3
10	2	2	2	1	1	1	1	2	62.6
11	2	2	1	2	1	2	1	1	96.9
12	2	2	1	1	2	1	2	1	10.3

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