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An Artificial Immune System Approach for the Fault Detection and Diagnosis of a DC Machine

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Abstract:
In this paper, an artificial immune system approach for the detection and diagnosis of faults in the dc machines is presented. The proposed technique requires the measurement of two output variables to compute their representation before and after a fault condition. A pattern recognition algorithm inspired by how the immune system operates throughout the body is proposed to identify and classify the fault condition. According to the proposed methodology, there is no need to know the details of machine operation in a certain regime and all phenomena and effects resulting from the machine operating in this regime are taken into account. Experimental results obtained on 5HP 240V 1750RPM dc machine is presented and discussed to validate the methodology, verifying its good performance in preventive fault detection.

Key words: *Artificial Immune System, DC Machines, Fault detection, Pattern recognition*

1. Introduction

Electrical testing of Direct Current (DC) electric motors is a challenge within industry, manufacturing and repair centers alike. Unpredictable faults in machines and its consequent economic and security implications justify the need for fault detection techniques adapted to preventive maintenance. Most of the faults in a machine occur at the stator and rotor level, being caused by a combination of mechanisms that are associated with the windings and rotor bars. These are subjected to the pernicious action of many stress mechanisms such as thermal, electrical, mechanical and environmental effects. As a result, various faults may occur, including winding inter-turn short-circuits, short-circuits between phases, broken rotor bars, broken rotor windings, etc. These unbalanced situations are responsible for the injection of negative sequence currents in the machine. Thus, fault detection in dc machines can be carried out during qualification and quantification tests by looking for a negative current sequence superimposed on the stator currents. Most research developed for fault detection looks for solutions requiring the understanding of how the machine operates in certain fault regimes using detailed and/or simplified mathematical models [1-3]. Other fault detection approaches use techniques based on pattern recognition methodologies that are, in general, a means of automating fault diagnosis without the presence of an operator which were performed on induction machines [4-5].

In this work, a new artificial immune system for detecting faults in machines by constructing a “characteristic image” of its operation is proposed [6]. The strategy is based on comparing the machines dynamics when in a normal operating condition with its dynamics in an unbalanced state.

According to the proposed strategy, there is no need to know the details of machine operation in a certain regime and all phenomena and effects which result from the machine operating in a given fault condition are taken into account. Using the outputs armature current (Ia) and speed (w) as variables, they exhibit different patterns, which allow creating a characteristic pattern of the operating regime of the dc machine. Besides, according to the proposed strategy, it is not necessary to know the operating details corresponding to a certain regime, and all phenomena and effects which result from the dc machine operating in this regime are taken into account.

In the following section, the patterns shown by the stator currents due to the fault condition are analyzed through simulation results. The proposed fault detection algorithm inspired by the operating principles of the immune system is presented. The proposed fault detection strategy is tested under different fault operating conditions and is presented and analyzed in while conclusions are drawn.

2. Proposed Scheme

The first step in the proposed fault detection algorithm which flowchart is shown in Figure 1 is its codification mechanism. This consists of two parts: eccentricity and scattering codification as explained next.

2.1. Eccentricity codification

The procedure to codify the trajectory eccentricity of the (Ia, ω) components includes the following steps:

- Obtain the set of values of armature current and speed (Ia, ω) from a dc machine.
- Calculate the principal components of the registered data set (Ia, ω) to obtain the main directions of the geometric pattern corresponding to the data distribution [A]. Notice that the principal components are computed each time it was effectuated the data acquisition from the recorded values. Therefore, the system has to be programmed to acquire from time to time a certain data set, record the values((Ia, ω) and follow calculating the principal components. In Appendix A, a brief explanation about the principal component analysis technique is given.
- Using the first eigenvector z1 obtained in step 2 from the principal component analysis, which gives the direction where data has its highest distribution, and calculating the vector normal to z1, calculate the size of the two lines that are delimited between the origin and the

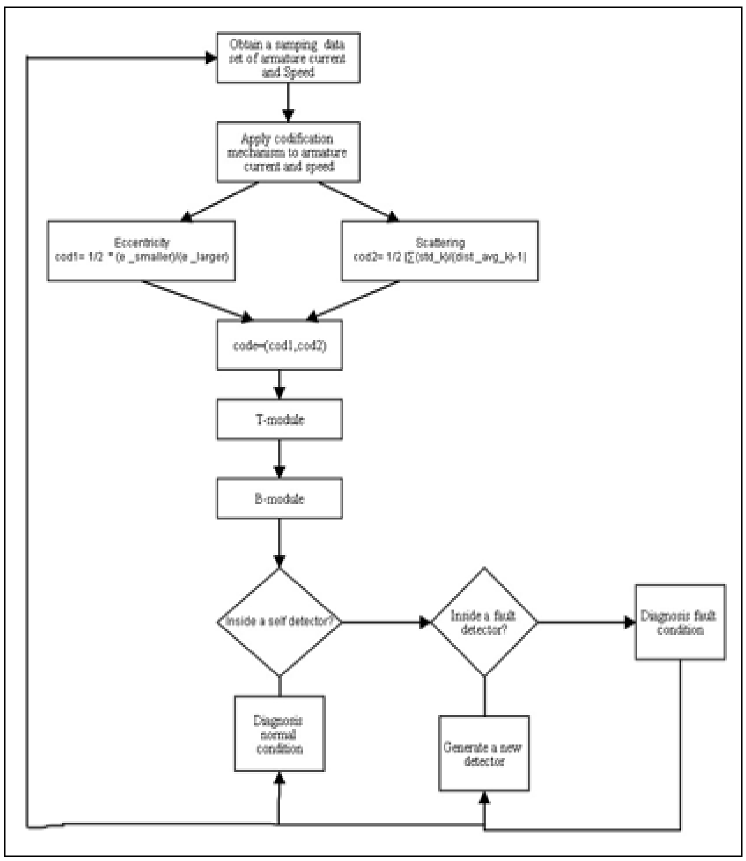

Figure 1: Flowchart of the proposed fault detection algorithm

Further data point situated nearest the line. The values associated with each line size are related with larger and smaller data dispersion and are denoted as e_larger and e_smaller, respectively.

- Calculate the ratio between e_larger and e_smaller as in (1) to obtain the first code named cod1. The code will have a numerical value between zero and 0.5 (in this case a perfect circle since the two axes have equal magnitude). Notice that cod1 will codify situations of major or minor normality of the dc machine operation concerning the stator circuits' integrity.

$$cod1 = \frac{1}{2}\frac{e\_smaller}{e\_larger} \quad (1)$$

2.2. Scattering Codification

Scattering of the (Ia, ω) usually happens due to the low frequency harmonics occurring in the stator currents and caused by a fault in the rotor circuits. The scattering codification procedure is now explained which shows an example of the effect that data scattering has on the resulting pattern. The scattering codification consists now of the following steps:

- Figure 2 shows that the two axes associated with the principal components establish four narrow sectors that are delimited by four straight lines, eg, bd, fh and ac.
- The data set belonging to each sector is used to obtain the magnitude of the respective middle axis using Eq. (2). The computation consists of the average value of the distances of each sector point (xpi, ypi) to the origin, where np is the number of total points in sector p.

dist_avg= $1/n_p \sum_{i=1}^{n_p} dis(x_{pi}, y_{pi})$ $dis(x_{pi}, y_{pi}) = \sqrt{x_{pi}^2 - y_{pi}^2}$ (2)

- For each sector, also find the standard deviation (3) of data formed by the set of the distances from step 2.

$Std_p = \sqrt{1/n_p \sum_{i=1}^{n_p} (dis(x_{pi}, y_{pi}) - dist\_avg\_p)^2}$, p=1, 2, 3, 4 (3)

- The four std values obtained in step 3 are now used to codify the scattering data feature in the pattern of the current using Eq. (4).

$cod2 = \frac{1}{2}\left|\sum_{k=1}^{4} \frac{std_k}{dist\_avg\_k} - 1\right|$ (4)

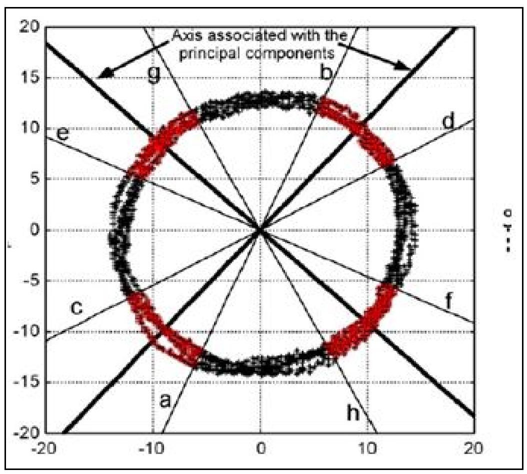

Figure 2: Ring pattern and the formation of sectors by principal component analysis

The eccentricity and scattering characteristics were codified by variables *cod1* and *cod2*, respectively, which are given by equations (1) and (4).

3. Simulation Studies of DC Motor

The simulation studies of the dc motor are carried out by connecting a dc supply to the 5HP 240V DC motor by using Simulink software. In the balanced condition of the motor, no parameter is adjusted in the circuit. The output values of speed (w) and armature current are observed in the scope and recorded.

In the unbalanced condition of the motor, the armature resistance of the motor is decreased by 80% by adjusting the parameters in the dc motor block and the output values of speed (w) and armature current are observed in the scope and recorded.

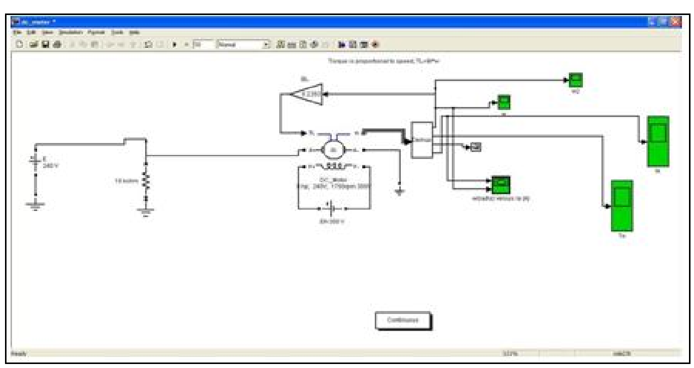

Figure 3: MATLAB model of DC Motor

4. Artificial Immune Systems

Artificial Immune Systems (AIS) are computational paradigms that belong to the computational intelligence family and are inspired by the biological immune system. The primary function of a biological immune system is to protect the body from foreign molecules known as antigens. It has great pattern recognition capability that may be used to distinguish between foreign cells entering the body (non-self or antigen) and the body cells (self). Immune systems have many characteristics such as uniqueness, autonomous, recognition of foreigners, distributed detection, and noise tolerance [7].

The Negative Selection is one of the mechanisms of the natural immune system that has inspired the developments of most of the existing Artificial Immune systems. In the T-cell maturation process of the immune system, if a T- cell in thymus recognizes any self cell, it is eliminated before deploying for immune functionality. Similarly, the negative selection algorithm generates detector set by eliminating any detector candidate that match elements from a group of self samples.

Negative selection based algorithms have been used in different applications areas, such as anomaly detection. Forrest (1994) proposed a negative selection algorithm. The main idea of his algorithm is to generate a set of detectors by first randomly making candidates and then discarding those that recognize training self-data, and then these detectors can later be used to detect anomaly.

5. Application to DC Machine Fault Detection and Diagnosis

5.1. Normal Operating Condition of DC Machine

A constant dc supply is fed to the DC machine in its normal operating condition. The values of armature current (Ia) and speed (w) obtained are used for the calculations. Figure 4 shows the waveforms of Armature current and speed of dc machine Figure 5 shows the pattern generated in the normal operating condition of code with coordinates (cod1, cod2) = (0.4882, 0.4794) along with eigen vectors for the values from no-load to full-load of the machine.

Figure 4: Waveforms of Armature current and speed of dc machine

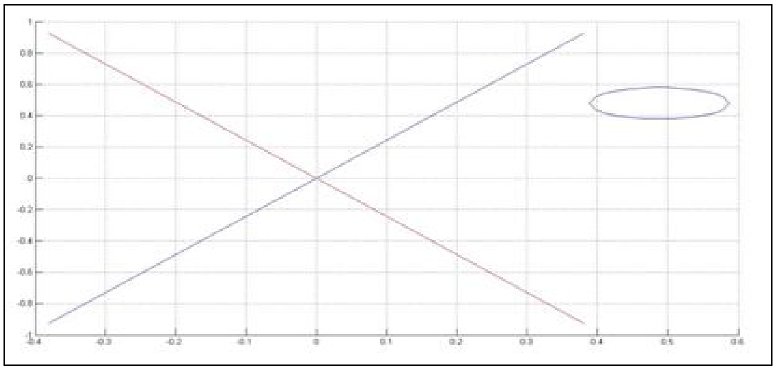

Figure 5: Pattern generated when the DC machine is normal operating condition

5.2 Fault Condition in DC Machines

The unbalance in the DC machine is created by decreasing the armature resistance to represent as a broken or cracked armature winding. In this way, an asymmetry was created in the rotor side of DC machine, being similar to a possible failure in the circuits. The values of armature current (Ia) and speed (w) in radians are used for the calculations are same compared to Figure 4 The pattern generated for the faulted condition of code is (cod1, cod2) = (0.735, 0.3767) shown in fig 6 along with its eigen vectors for the value from no-load to full load conditions of the machine. As code values are obtained from the machine, they are sent to the B-module shown in fig. 7. The B-module has initial detectors and as the codes are arriving, a cluster is created according to the defined values when the codes arrive. This arriving code is indicated by '*' also shown are the "self" codes and the fault detectors that are distributed by the operating domain.

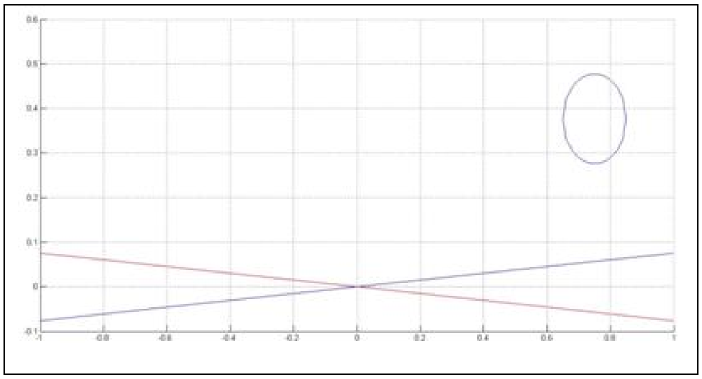

Figure 6: Pattern generated when the DC machine is in faulted condition along with its eigen vectors

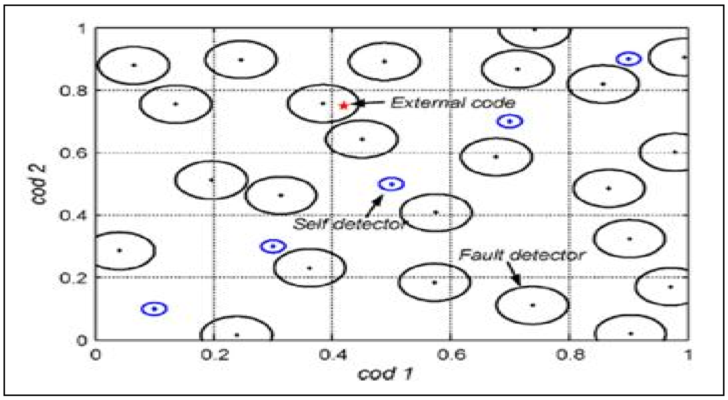

Figure 7: Indication of arrival of external code

6. Conclusion

Restricting the study to unbalance in the supply, it became clear that these cases produce unbalanced operating regimes. The proposed artificial immune system for detecting faults in dc machines is based on the detection of changes in pattern away from the operating situation considered normal. So it has to be tried to avoid the use of models that are complex to use. To characterize the operation of the dc machine, the proposed method monitors two of output values. However, please note that this approach is not restrictive and the proposed methodology may include monitoring of other influences beyond the stator currents, possibly to identify other types of fault.

The operation of the machines is characterized by parameters that somehow measure the effects on the stator currents of an unbalanced component. The loci of values of these parameters in normal operation form an image feature, or standard image whose change indicates the existence of a malfunction. This representation has an analogy with what happens in the immune system of the human body. Consequently, a new technique was developed for detecting faults in dc machines based on a comparison of characteristic patterns.

Therefore, the dc machines with different rated powers can be analyzed by the proposed methodology in a direct way, even if the machine has different electromechanical parameters.

6.1. Principal Component Analysis (PCA)

The method of principal components creates from a data set of available variables, which may have been obtained experimentally or not, a new set of variables called principal components. The principal components are orthogonal, which assures us that there is no redundant data and each new PCA variable is a linear combination of original variables.

Assuming that there is a set of p variables, the PCA technique transforms the set of system variables in p dimensional space into a new set whose variables are not correlated.

Using the available data set, the correlation matrix S described in (A.1) is computed for the problem of p variables. In the correlation matrix, the term s2 ii is the value of the variance of the variable xi calculated by Eq. (A.2), and the term sij is the value of the correlation between xi and xj obtained by Eq. (A.3). The parameter n in (A.2) and (A.3) is the total number of data used to calculate the correlation matrix

$$S = \begin{bmatrix} s_{11}^2 & s_{12} & \cdots & s_{1p} \\ s_{12} & s_{22}^2 & \cdots & s_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1p} & s_{2p} & \cdots & s_{pp}^2 \end{bmatrix} \qquad (A.1)$$

.

$$s_{ii}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x}_i)^2 \qquad \text{(A.2)}$$

$$s_{ij} = \frac{1}{n-1}\sum_{j=1}^{n}(x_i - \bar{x}_i)(x_j - \bar{x}_j) \qquad \text{(A.3)}$$

The PCA algorithm generally converts the p original variables, represented by the vector $\vec{x}$ = (x1, x2, . . . , xp), in a new set of coordinates formed by p variables uncorrelated with each other and designated by the vector $\vec{z}$ = (z1, z2, . . . , zp).
The new set of coordinates, called principal components, is formed by the linear combination of original variables and is obtained so that the first principal component z1 indicates the direction in which there is greater data distribution, therefore a higher variance.

The new coordinate system is described by i eigenvectors calculated from the correlation matrix S and called $\vec{u}$ i. Each eigenvector defines a direction on which the data set used is distributed. The set of eigenvectors provide a transformation matrix U that is used in the change of coordinates of $\vec{x}$ to the main components $\vec{z}$ according to (A.4).

$\vec{z}$ = UT $\vec{x}$

Each principal component zi shows a zero mean value and a variance value of λi corresponding to the eigen value of vector $\vec{u}$ I The eigen value λi will give a certain weight to each eigenvector Representing how the data set collected is distributed in this direction.
Each principal component zi is calculated according to Eq. (A.5) by linear combination between their eigenvector and the vector $\vec{u}$ I composed of the original variables, $\vec{x}$

zi = $\vec{u}$ iT $\vec{x}$ (A.5)

The analysis of the eigenvectors will indicate whether any of the original variables are strongly correlated, and if it happens only one is a significant variable for the system.

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