Bearing faults and broken bars simulation in an induction motor using an engineering tool

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Abstract. Industrial processes require reliable, safe, and continuous operation of electric motors. However, unexpected failures result in production losses, high emergency maintenance costs, damage to other related machines and prolonged shutdowns. Therefore, the development of failure analysis, detection and prevention systems is of high importance for the industrial sector. The following paper proposes the generation of a model of a squirrel cage induction motor in the software tool Simulink capable of simulating: i) broken bars and broken rotor rings, and ii) failures in the bearings of the motor, based on the Motor Current Signature Analysis (MCSA) technique which is a non-invasive method. Moreover, the Fast Fourier Transform (FFT) analysis is used to perform spectral investigation on the current to detect specific components that characterize faults in these conditions.

1. Introduction
The induction motor is the most widely used electric motor in the industry. The squirrel-cage variant has the great advantage of being a simple, robust, low-cost construction engine that requires much less maintenance than any other rotary machine with no brushes, ring collector or delta collector. Due to the induction method of energy production, they are easy to operate. As a result, these engines are quite suitable for large applications as in the oil extraction industry [1]. Although these motors are robust and have good reliability, they are not exempt from suffering faults during their use. One of the main reasons of these failures is the application of strong forces in: the magnetic cores, bearings, shaft, stator and cage windings.

A component failure is usually defined as a condition of capacity reduction related to minimum specification requirements. It is the result of normal wear, poor design or poor specification, incorrect assembly, misuse, or a combination of the aforementioned. If a failure is not detected in time or if it is allowed to develop further it can lead to the collapse of the machine [2]. Nowadays, it is important to consider the implementation of online fault diagnosis strategies to increase the useful life of machine components, thus increasing their availability and the productivity of the plant.
The detection and diagnosis of electrical or mechanical faults in an induction motor involve, in many cases, the interpretation of the frequency spectrum of its: current, power, Park vector, among others [3]. This requires an expert to perform the task, based on the information obtained from the processed signals. In the current days, the techniques of Machine-learning based Artificial Intelligences, have taken great importance. Some of the reasons is that they require a minimal interpretation of the studied system and greatly simplifying the diagnostic task [4, 5]. Machine-learning based fault diagnosis techniques have been widely studied and have succeeded in many applications of electrical machines and drives. However, these type of solutions require a great amount of data to generate models capable of identifying specific features.

The main investigation line related to the following work aims to generate an online data analysis system based on machine learning for failure detection in the inductive motors of an oil extraction station. One of the main limitations while developing this artificial intelligence, is the amount of data available to train the model. However, with the help of the software tool Simulink, a reconfigurable model of an inductive motor can be generated. With the right understanding of the effects that some of the most common failures have in the operation of this type of motors, the classic model of the induction motor can be modified to also simulate: broken bars, broken rotor rings, short-circuits between copper winds and bearing failures. The following work describes some of the advances done in the generation of the proposed simulation model.

This paper is structured as follows: Section 2 shows some related works that have been used as the starting point for this research. Section 3 describes de modeling of a squirrel cage induction motor using finite element method (FEM). Section 4 summarizes some of the most common failures in induction motors and their effects. Section 5 shows the analysis of results and finally, in Section 6 some conclusions and ongoing work are given.

2. Literature review
The aim of this section is to show how other researches deal with predicting the electric motor damage using fault detection system based on the simulation or implementation of Motor Current Signature Analysis (MCSA) technique. In this sense, a set of related works are presented, and paradigms and technology developments, which provide the use of this technique at the industrial level, are also discussed.

The classical technique for the valuation of the rotor condition in electric induction motors is the Motor Current Signature Analysis (MCSA) [6-9], that relies on acquiring the waveform of the current demanded by the motor during steady-state operation and analyzing this signal using the Fast Fourier Transform (FFT). Evaluating the amplitude of components and harmonics that are amplified by the rotor fault. This approach has given excellent results for various range of industrial applications, where the operation regime is rather stable [10, 11].

In this sense, an approach, based on combined application of advanced signal processing tools adapted to a transient analysis (ATCSA), to detect the electrical rotor asymmetries in real mining field cases, in which the MCSA method was not reliable, is showed in [12]. This paper combines the application of sophisticated continuous transforms for obtaining the characteristic patterns created by the fault components, with discrete transforms to compute the fault severity indicators. The results prove the reliability of this advanced methodology for diagnosing the rotor condition, even in adverse situations, such as motors operating under variable speed regimes.

In this paper, the integration of simulating techniques of the electric motor model and different failures are addressed. Furthermore, this paper develops a new software tool based on Simulink, enabling an easy and fast building of this kind of electric systems.

3. The finite element method (FEM) for modelling electric machines faults
The finite element method (FEM) is a numerical method for solving problems of engineering. Once the finite element method is applied, the partial differential equations that shape physical systems with an infinite number of degrees of freedom are reduced to systems of algebraic equations.
The method approximates the unknown function over the domain. The basic idea of this method is that if the studied structure is divided into several parts, called finite elements, for each of these calculation theories can be applied corresponding to the scheme adopted. The character of generality of this method gives the advantage to adjust the most complex and varied problems, with simple modifications.

The FEM provides detailed information about the machine's nonlinear effects. This modeling approach is capable of obtaining an accurate and complete description of an electrical machine [13]. The magnetic circuit is modeled by a mesh of small elements. The field values are then assumed to be a simple function of position within these elements, enabling interpolation of results.

3.1. Simulation of the induction motor using FEM approach

The first problem found while trying to simulate the induction machine is that the induction motor is defined by non-linear differential equations. Therefore, it is necessary to perform a transformation to a system of linear differential equations. These transformations are performed to facilitate the analysis of the engine.

The first transformation that is performed during this analysis is the change from a three-phase voltage reference (a, b, c) into a bi-phase voltage reference (α, β}). Being the three-phase system represented by the vector in the Equation (1)

\[ V_S = \frac{2}{3} (V_A + a \cdot V_B + a^2 \cdot V_C) \] (1)

which can be represented in the αβ reference with the following Equations (2) and (3)

\[ V_{S\alpha} = \frac{2}{3} (V_A - \frac{1}{2} V_B - \frac{1}{2} V_C) \] (2)

\[ V_{S\beta} = \frac{2}{3} (\sqrt{3} \frac{1}{2} V_B - \sqrt{3} \frac{1}{2} V_C) \] (3)

Normally, the motor parameters are measured from the stator winding, as shown in the Equations (4) and (5).

\[ V_{S\alpha} = \frac{d(\psi_{S\alpha})}{dt} + \psi_{S\alpha} \cdot w + R_S \cdot i_{S\alpha} \] (4)

\[ V_{S\beta} = \frac{d(\psi_{S\beta})}{dt} + \psi_{S\beta} \cdot w + R_S \cdot i_{S\beta} \] (5)

Therefore, it is convenient to refer all rotor parameters to the stator winding. As shown in the Equations (6) and (7)

\[ V_{R\alpha} = \frac{d(\psi_{R\alpha})}{dt} + \psi_{R\alpha} \cdot (w - w_R) + R_R \cdot i_{R\alpha} \] (6)

\[ V_{R\beta} = \frac{d(\psi_{R\beta})}{dt} + \psi_{R\beta} \cdot (w - w_R) + R_R \cdot i_{R\beta} \] (7)

Where \( w \) is the angular velocity of the random reference system and \( w_R \) is the angular velocity of the rotor.

According to Equations (4) – (7), one can determine the equations of the stator and rotor fluxes with the reference system fixed to the stator (\( w = 0 \)). It also has to be taken into account that the motor to be simulated in the present work is a squirrel cage model, therefore, the rotor voltages \( V_{R\alpha} \) and \( V_{R\beta} \) are zero. After introducing these variants and solving the equations system, the final fluxes equations are presented in Equations (8) – (11).

\[ \psi_{S\alpha} = \int V_{S\alpha} - R_S \cdot i_{S\alpha} \] (8)

\[ \psi_{S\beta} = \int V_{S\beta} - R_S \cdot i_{S\beta} \] (9)

\[ \psi_{R\alpha} = \int -\psi_{R\beta} \cdot w_R - R_R \cdot i_{R\alpha} \] (10)
\[ \psi_{RB} = \int \psi_{Ra} \ast w_R - R_R \ast i_R \]  

(11)

To obtain the equations from which one can calculate \( i_{S\alpha}, i_{S\beta}, i_{Ra} \) and \( i_{R\beta} \), the analysis process must begin with Equations (12) and (13)

\[ \psi_R = L'R_R + L_m i_S \]  

(12)

\[ \psi_S = L'S_S + L_m i_R \]  

(13)

Where \( L'_R = L_R + L_m \) and \( L'_S = L_S + L_m \).

After decomposing Equations (12) and (13) into their \( \alpha\beta \) components, solving the new equations for the values of \( i_{S\alpha}, i_{S\beta}, i_{Ra} \) and \( i_{R\beta} \), and solving the new system, it is obtained that

\[ i_{S\alpha} = \frac{L_m \psi_{Ra}}{L_m^2 - L'_R L'_S} - \frac{L_R \psi_{Sa}}{L_m^2 - L'_R L'_S} \]  

(14)

\[ i_{S\beta} = \frac{L_m \psi_{R\beta}}{L_m^2 - L'_R L'_S} - \frac{L_R \psi_{S\beta}}{L_m^2 - L'_R L'_S} \]  

(15)

\[ i_{Ra} = \frac{L_m \psi_{Sa}}{L_m^2 - L'_R L'_S} - \frac{L_S \psi_{Ra}}{L_m^2 - L'_R L'_S} \]  

(16)

\[ i_{R\beta} = \frac{L_m \psi_{S\beta}}{L_m^2 - L'_R L'_S} - \frac{L_S \psi_{R\beta}}{L_m^2 - L'_R L'_S} \]  

(17)

The generated torque of the motor can be obtained from Equation (18)

\[ M_{mi} = \frac{3p}{2} L_m (i_{S\alpha} i_{R\beta} - i_{S\beta} i_{Ra}) \]  

(18)

And the speed can be obtained from Equation (19)

\[ w_R = \int \frac{M_{mi} - M_C - \frac{f}{p} w_R}{J} \]  

(19)

Figure 1. Simulation of an induction squirrel cage motor in Simulink.
Finally, the three-phase currents must be recovered from the bi-phase reference with the Equations (20) – (22)

\[ i_a = i_\alpha \]  
\[ i_b = \frac{1}{2}(\sqrt{3}i_\beta - i_\alpha) \]  
\[ i_c = -\frac{1}{2}(\sqrt{3}i_\beta - i_\alpha) \]

Using the expression depicted in Equations (20) - (22), a simulation model can be implemented in Simulink as shown in Figure 1.

4. Simulation methodology of failures in induction motor

Since induction motors are rotatory machines with a simple construction, their most common causes of motor failure are bearing failures, insulation failures and rotor failures. However, as depicted in [14], almost 40% -50% of all motor failures are related to their bearings. In paragraphs detailed below, the most common failures in induction motors and their respective effects on the normal operation of the motor are described.

4.1. Broken bars

A problem that occurs in induction motors is that one or more rotor bars fracture. Despite this damage, the motor remains capable of operating in an apparently normal way. However, one of these little problems can end up with serious consequences since a fractured bar will progressively cause the fracture of more bars. Consecutively so many bars can break up causing that the motor stops operating normally in a sudden way [15]. The physical effect that one or more broken bars will have in the induction motor is the variation of the rotor resistance. Therefore, this failure can be replicated in the generated model by partially or totally decreasing the nominal value of the rotor resistance while running the simulation.

4.2. Short-circuit between copper turns

Short circuit between turns reduces the ability to produce a balanced magnetic field, which has consequences such as an increase in the vibration of the machine. This effect accelerates the degradation of the insulation and damage to the motor bearings. In most cases, the short circuit between turns includes the following possibilities: "turn-by-turn", "phase-to-phase" or "phase-to-ground", causing the motor to collapse.

4.3. Damaged bearings

Early detection of bearing failures allows the replacement of the bearings, instead of the replacement of the motor. Although replacement of defective bearings is the cheapest solution among the three causes of failure, it is the most difficult to detect. Bearings are formed by: interior track, balls or rollers, cage and an outer track. The deterioration of each of these elements will generate one or several characteristic frequencies in the frequency spectra that will allow a quick and easy identification. The four possible frequencies of deterioration of a bearing are:

- BPO (Ball pass frequency of the outer race), is the frequency of step of rolling elements due to a defect in the external track.
- BPI (Ball pass frequency of the inner race), is the frequency of step of the rolling elements due to a defect in the internal track.
- BSF (Ball spin frequency), is the frequency of deterioration of the rolling elements.
- FTF (Fundamental train frequency), is the rotation frequency of the cage that contains the rolling elements.

These different bearing failures can be simulated by adding some specific torques to the final rotor speed equation.
5. Analysis of results
This section presents simulated current signals in each fault and then be analyzed and interpret its
spectral characteristics of incipient failures as in the case of bearing wear, broken bars and short
circuits between turns of the same phase.

![Figure 2](image)

**Figure 2.** Presence of broken bars, diagnosis by upper and lower lateral peaks.

5.1. Broken bar fault simulated results
The analysis was developed for distorted three-phase currents when the motor presents broken bars
operated at nominal load. In Figure 2, it is observed that, during the range frequencies from 75 to 110
[Hz], the amplitude decreases drastically below -40 dBv with respect to the signals without fault
except for the spectrum amplitude in the frequency of 105 [Hz], characteristics that are repeated in the
three phases. This figure shows the existence of a lateral peak greater than 70 [Hz] and two lower
lateral peaks next to the fundamental one at 40 and 50 [Hz], the latter having an amplitude of
approximately -10 dBv in the three phases that make up the system, which means that the motor has a
fault inside caused by broken bars in the squirrel cage. For a better analysis on broken bar faults, the
signal was broken at 100 Hz and it was centered on the fundamental frequency. It can be considered
that for defining such broken bar fault.

5.2. Short circuit fault simulated results
Figure 3 shows the distortion effects of the stator currents generated by a short circuit in 28 turns of
phase 3 with respect to the signals. There is an increase in the spectral amplitude over the noise level
for the three phases that is found in the frequency of 180 Hz. By means of this diagnosis, the existence
of stator faults was also determined. Phase 3 is the only one that presents a slight increase in amplitude
in the frequency of 300Hz, approximately 0.53 dBv over the noise level, meaning that there is a short
circuit in the turns of this phase. Continuing with the same test, the fault was increased by shorting 28
more turns of the phase 1 with which, all the spectral signal moved about 11 dBv over the fundamental
without fault, showing an increase and distortion of the three-phase currents. Additionally, the
spectrum in the frequency of 180 Hz significantly grew around 23.44 dBv over the noise level in all
the phases, with which the simulated signals show the existence of a stator fault.
5.3. Bearing fault simulated results
The induction motor performs as an effective transducer for load variations within itself (such as winding faults, bearing faults etc.) and besides outside it for example for load machine attached to it. With this aim, this work-study has been done specifically only for the simulation of a faulty bearing (an outer race fault) in rotating machinery using motor current signature analysis. Figure 4 shows the spectral amplitude change in the three phases of the system around a range of frequencies from 68 to
110 [Hz], in these frequencies a decrease in the spectral amplitude is less than -40 dBv. Besides, there is a slight increase in amplitude in the frequency of 300 Hz in regard to the signals of a healthy motor.

The reason for the increase in signal spectral amplitude is because the engineering tool simulates a degradation process of the bearings. In a real motor when a bearing is contaminated with external material, load rippling is generated by external substances jammed between the cage and the bearing outer ring. The vibrational frequency of load ripples is equivalent to the frequency of the cage damage. This increases the signal spectral amplitude in the current of the motor. This approach is used in the simulation made by the engineering tool developed in this research.

6. Conclusions and future work
With the use of the software tool Simulink, a generic model of an induction motor is generated. This model is designed so it can also be capable of simulating failures in the motor such as: broke bars, short-circuit between copper wind and bearing failures. These failures can be replicated in the model by adding portions of code that modify some specific parameters such as rotor resistance, stator inductance and rotor speed.

This model is developed with the aim of that in future works, we can generate the data needed to create a machine learning based system capable of detecting failures in induction motor while the whole industrial system is running.

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References
[1] Wang X and Fang F 2011 Bearing failure diagnosis in three-phase induction motor by chirp-Z transform and zoom-MUSIC 2011 International Conference on Electrical and Control Engineering [Internet]. Yichang, China: IEEE; 2011 [cited 2019 Jul 11] pp 1016–9 Available from: http://ieeexplore.ieee.org/document/6057197/
[2] Bo L, Liu X and Xu G 2019 Intelligent Diagnostics for Bearing faults Based on Integrated Interaction of Nonlinear Features IEEE Transactions on Industrial Informatics 1-1
[3] Niu J, Lu S, Liu Y and Wang Q 2019 Bearing fault diagnosis of BLDC motor using Vold-Kalman order tracking filter under variable speed condition 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA) [Internet]. Xi’an, China: IEEE; 2019 [cited 2019 Oct 1]. pp 2379-83 Available from: https://ieeexplore.ieee.org/document/8834107/
[4] Filippetti F, Bellini A and Capolino G 2013 Condition monitoring and diagnosis of rotor faults in induction machines: State of art and future perspectives. 2013 IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD) [Internet]. Paris: IEEE; 2013 [cited 2019 Jul 11]. pp 196-209 Available from: http://ieeexplore.ieee.org/document/6525180/
[5] Toliyat H A 2013 Electric machines: modeling, condition monitoring, and fault diagnosis. Boca Raton, FL: Taylor & Francis
[6] Thomson W T and Fenger M 2001 Current signature analysis to detect induction motor faults IEEE Industry Applications Magazine 7 26-34
[7] Konar P and Chattopadhyay P 2011 Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs) Applied Soft Computing 11 4203-11
[8] Glowacz A 2019 Fault diagnosis of single-phase induction motor based on acoustic signals Mechanical Systems and Signal Processing 117 65-80
[9] Benbouzid MEH, Vieira M and Theys C 1999 Induction motors’ faults detection and localization using stator current advanced signal processing techniques IEEE Transactions on Power Electronics 14 14-22
[10] Sadeghi M H and Lotfan S 2017 Identification of non-linear parameter of a cantilever beam model with boundary condition non-linearity in the presence of noise: an NSI- and ANN-based approach Acta Mechanica 228 4451-69

[11] Lotfan S, Salehpour N, Adiban H and Mashroutechi A 2015 Bearing fault detection using fuzzy C-means and hybrid C-means-subtractive algorithms 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) [Internet]. Istanbul, Turkey: IEEE; 2015 [cited 2019 Oct 1]. pp 1-7 Available from: http://ieeexplore.ieee.org/document/7338049/

[12] Antonino-Daviu J A, Quijano-Lopez A, Rubbiolo M and Climente-Alarcon V 2018 Advanced Analysis of Motor Currents for the Diagnosis of the Rotor Condition in Electric Motors Operating in Mining Facilities IEEE Transactions on Industry Applications 54 3934-42

[13] Mohammed O A, Abed N Y and Ganu S 2007 Modeling and characterization of induction motor internal faults using finite element and discrete wavelet transforms 2007 IEEE Electric Ship Technologies Symposium [Internet]. Arlington, VA, USA: IEEE; 2007 [cited 2019 Oct 1]. pp 250-3 Available from: http://ieeexplore.ieee.org/document/4233830/

[14] Song W, Lai M, Li X, Song Y and Gao L 2019 A New Spectral Clustering Based on Particle Swarm Optimization for Unsupervised Fault Diagnosis of Bearings 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE) [Internet]. Vancouver, BC, Canada: IEEE; 2019 [cited 2019 Oct 1]. pp 386-91 Available from: https://ieeexplore.ieee.org/document/8843232/

[15] Villada F and Cadavid D R 2007 Diagnostico de Fallas en Motores de Induccion Mediante la Aplicacion de Redes Neuronales Artificiales. Informacion tecnologica [Internet]. 2007 [cited 2019 Jul 30]; 18 Available from: http://www.scielo.cl/scielo.php?script=sci_arttext&pid=S0718-07642007000200016&lng=en&nrm=iso&tlng=en