IoT and Artificial Intelligence for Fault Classification in High Efficiency Motors

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Keywords: Intelligent Classification, Incipient Failures, Standard Deviation Statistical Tool, Classification Deep Neural Network, IoT.

Abstract: High-efficiency three-phase induction motors are used in most industrial production processes; however, its malfunctioning may cause unexpected interruptions, putting at risk both manufacturing operations and operators. Consequently, it is desired to diagnose in real-time the most common incipient failures that may occur in this type of rotating machinery. Thus, this document presents a study of intelligent classification of incipient failures in an induction motor, diagnosis that is visualized from a dashboard in the cloud through a one-way IoT architecture. Using the traditional Park transform technique, torque (iq) and magnetizing (id) currents were obtained and analysed through the standard deviation statistical tool, to identify the dispersion of their operating amplitudes when the motor is at normal (H) or faulty (ECF and SC) operation conditions; these values were normalized and provided as input data to a classification deep neural network. The results given by this AI technique in the diagnosis, for both the iq and id components, showed a mean accuracy of 100% for SC and a mean classification error of 20% and 25% for H and ECF, respectively.

1 INTRODUCTION

Three-phase induction motors are very important in industry since they take part of most production processes, showing to be robust, low-cost and easy to maintain (Bessous, 2020)(Torres et al., n.d.). Nevertheless, their malfunctioning may cause unexpected interruptions of operations (Otero et al., 2020).

Some methods traditionally used for maintenance of induction motors include: motor current and motor voltage signature analysis (MCSA and MVSA), Hilbert-Huang transform (HHT), continuous wavelet transform (CWT) (Saucedo-Dorantes et al., 2017), Park vector demodulation (PVD) (Oñate et al., 2022) and statistical analysis (Torres et al., n.d.). However, the operator should be trained to understand the statistics of the plots, either time or frequency-domain, considering that many of these publications indicate possible ambiguities in the diagnosis. Being aware of current manufacturing processes and the parts that constitute the industry of this era (Castellino et al., 2020), it is important to have intelligent systems that operate in real-time and facilitate the decision-making process for operators (Alberto et al., 2021). Consequently, there are currently being developed systems that integrate traditional and intelligent methods, such as (Yang et al., 2016), (Prins et al., 2018), (Ghosh et al., 2020) and (Zamudio-Ramirez et al., 2020), with a predominance of MCSA and Park's vector modulus (PVM) for a single component; such studies consider as focal point the diagnosis of broken bars (BRB) and bearings (BF) failures, side-lining other common incipient failures such as short-circuit (SC) and eccentricity (EF), which account for 38% and 10% of the cases, respectively (Bessous, 2020)(Otero et al., 2020)(Dhamal & Bhatkar, 2019).

Thus, the purpose of this work is to provide the operator with access to a dashboard in the cloud for visualizing failure diagnosis through a one-way architecture. The system carries out the ADC of the stator currents supplied to the motor, then extracts the

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Guerrero, C., Villegas, F., OÃśate, W. and Caiza, G.
IoT and Artificial Intelligence for Fault Classification in High Efficiency Motors.
DOI: 10.5220/0011949200003612
In *Proceedings of the 3rd International Symposium on Automation, Information and Computing (ISAIC 2022)*, pages 405-409
ISBN: 978-989-758-622-4; ISSN: 2975-9463

iq and id components through Park transform, and further identifies the operating amplitudes of the motor currents with and without failure using the standard deviation. This process will enable to feed the input layer of a deep neural network for classifying the operating state of the motor as being in good or faulty conditions (H, ECF and SC).

This document is constituted by section 1 introduction, section 2 methodology and procedure, section 3 analysis of results and finally conclusions in section 4.

2 METHODOLOGY AND PROCEDURE

Figure 1 shows the different stages that constitute the failure diagnosis system, starting with the data acquisition of the three-phase stator currents of the motor, which is operated in a testbench as shown in Fig. 1. Afterwards, Park transform is used to calculate torque and magnetization currents that vary with time, and the standard deviation is applied to this data as a statistical tool to analyze its trend and enable the implementation of a neural network for failure diagnosis, which are further sent to a server in the cloud for their visualization.

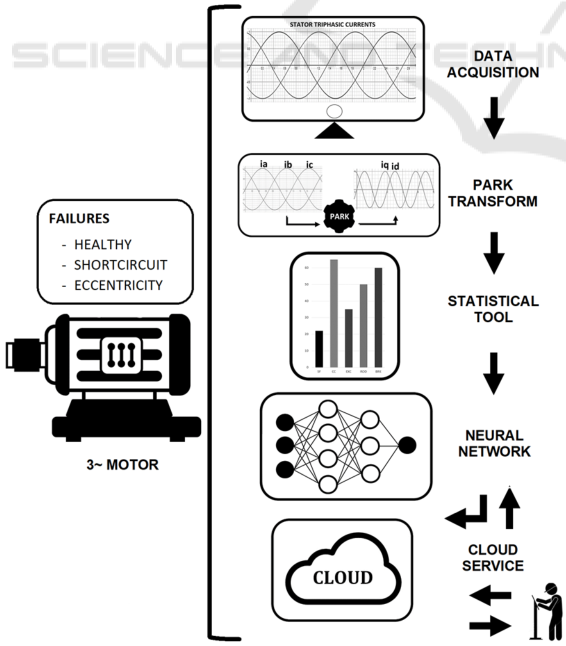

Figure 1: Block diagram of the proposed intelligent system for detecting failures in a high-efficiency motor.

Figure 2 shows the test module, in which the motor is coupled to a magnetic brake system controlled in closed-loop to maintain the nominal operation values.

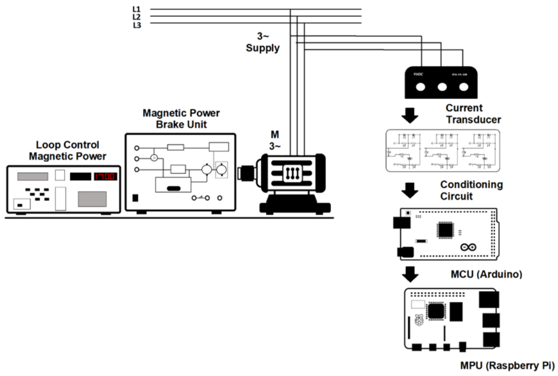

Figure 2: Test module.

2.1 Data Acquisition

In the test module of Fig. 2, the data of the motor currents are acquired and transformed into voltage through a YHDC 3TA17-200 transducer. In order to reduce the processing load on the Raspberry Pi boards (Park transform, statistical tool and neural network), an Arduino board was included to perform the ADC with 10 bits and a sampling time of 10 ms. After various experimental tests, a total of 60000 data were acquired for each line of the three-phase system and for each test (without failure, short-circuit and eccentricity).

A WEG W22 high-efficiency motor is used in the tests, intentionally causing failures such as: short-circuit (SC) to a loop of a supply line, and eccentricity (ECF) with a slope of 4.39° with respect to the shaft of the magnetic brake. The motor features are illustrated in Table 1.

Table 1: Features of the WEG W22 high-efficiency motor.

Features	Valour
Number of phases	3
Number of poles	4
Nominal Voltage	220 / 380 - 440 v
Nominal Current	1.87 / 1.08 – 1.12 A
Power	0.37 KW – 0.5 HP
Frequency	60 Hz
Speed	1700 / 1725 RPM

2.2 Park Transform and Statistical Method

Once the data of the currents supplied to the motor has been discretized, Park transform was applied to obtain the torque (iq) and magnetization (id) currents (Torres et al., n.d.)(Asad et al., 2018), which were subject to a statistical method based on the standard deviation to analyze the dispersion of the results when the motor is in excellent and faulty operating conditions (García, 2018).

2.3 Neural Network

Due to the large amount of data that may be acquired during the operation of the motor, it was used a classification model based on a deep neural network with a supervised training technique. Such AI technique consists of the following blocks: libraries (NumPy, Keras, Pandas and TensorFlow), import the iq and id components from an .xlsx file, split the data for training (70%) and testing (30%), a network with sequential architecture between input, hidden and output layers, an SGD (Stochastic Gradient Descent) training optimizer to stabilize the learning rate, and thus establish experimentally a network with 3000 propagation correction cycles to reduce data losses. Finally, the model with extension .h5 is implemented in a board with Cortex processor. Figure 3 shows the red squares that indicate the attributes that were modified in the AI model for its execution.

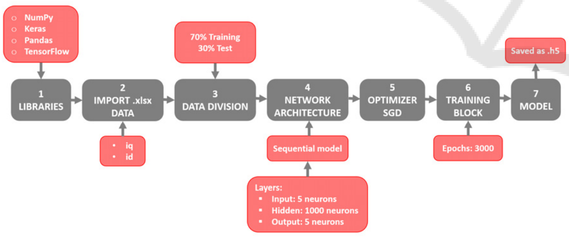

Figure 3: AI model.

2.4 One-Way IoT Architecture

A communication architecture from the plant to a dashboard was implemented to visualize the results of the failure diagnosis in the Web; such architecture is shown in Fig. 4. The tags corresponding to the results of the neural network are sent through a Mosquitto MQTT broker (Moreno Cerdà, 2018) to the Node-Red service within the AWS platform (Chanthakit & Rattanapoka, 2018), where the operator logs in through authentication.

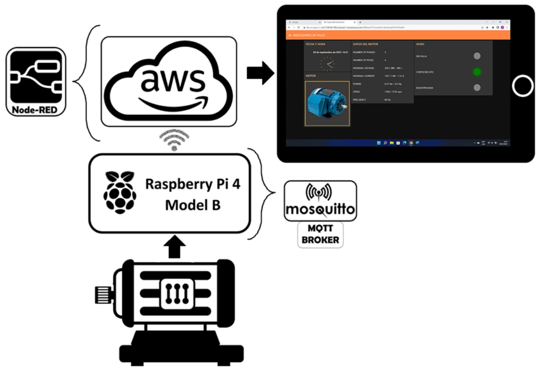

Figure 4: Communication architecture.

3 ANALYSIS AND RESULTS

Considering the MPU processing capacity, several samples were used as input data to the sequential model of the network, identifying that the component that has the larger dispersion among the operating amplitudes of the motor occurred for 50 samples, as shown in Table 2., this is 70% (840 inputs) for training and 30% (360 inputs) for experimental tests.

Table 2: Percentage operation amplitudes of the motor.

	iq		
Number of samples	W/O Failure	Eccentricity	Short-circuit
1000	100%	98.5%	90.78%
100	100%	98.49%	88.65%
50	100%	98.48%	87.98%
25	100%	98.74%	88.16%
10	100%	98.92%	88.27%
	id		
Number of samples	W/O Failure	Eccentricity	Short-circuit
1000	100%	98.45%	90.66%
100	100%	98.44%	88.69%
50	100%	98.44%	88.08%
25	100%	98.63%	88.33%
10	100%	98.86%	88.52%

Figure 5 shows the percentages of correct answers of the intelligent classification system during the diagnosis of failures in a motor, after various functional field tests evaluated at the torque (iq) and magnetization (id) currents.

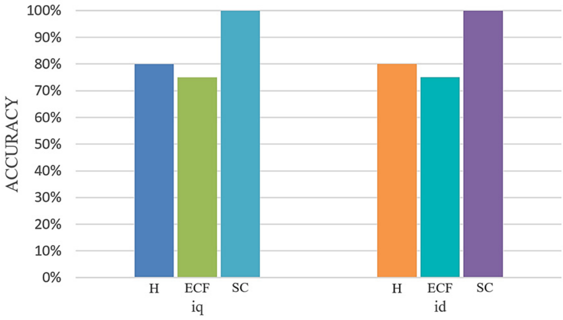

Figure 5: Result of motor operation.

Figure 5 shows some results to verify the performance of the failure diagnosis using neural networks. It was obtained a correct diagnosis in 80% of the cases corresponding to the motor in good condition. On the other hand, a correct diagnosis was obtained in 75% of the cases corresponding to the eccentricity failure, whereas a correct diagnosis was achieved in 100% of the cases of the short-circuit failure. Regarding the dispersion among the operating amplitudes of the motor, Table 2 shows that the dispersion of H with respect to ECF and SC was 1.52% and 12.02%, respectively.

4 CONCLUSIONS

In this work, a classification deep neural network was used in conjunction with the standard deviation as a statistical tool to define percentages of dispersion of the operating amplitudes of the motor, obtaining a difference of only 1.52% between H and ECF and of 12.02% between H and SC; these data were used in the diagnosis, both for the iq and id components, with a mean accuracy of 100% for SC and a mean classification error of 20% and 25% for H and ECF, respectively. The aforementioned results were obtained with the experimental modification of attributes in a deep neural classification model constituted by 5 features in the input layer, each with 1200 input data (iq or id), a hidden layer with 1000 neurons and 5 outputs as classes corresponding to the inputs. In order to contribute with the intelligent system for diagnosing failures in induction motors, it is foreseen to improve the amplitude of the operating dispersions of the motor, and to avoid overlapping conflicts in the system, it is possible to improve the ADC of the data acquisition system.

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