# Armature fault diagnosis of universal motors using time-series data in neural networks

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***Abstract*—A common issue of DC and universal motors is the quality of the armature circuit and the commutation process. Some faults that could happen during the final assembly process, such as a short circuit between two segments or a broken segment in the armature's commutator, may not be detected by a visual inspection or the regular no-load end-of-line test. A more detailed analysis, using the feedback of various auxiliary sensors, usually requires implementing systems with more complex and expensive hardware. It also may take longer to get a precise analysis, which may not be suitable for the production process. As a method to do a fast and accurate detection and classification of faults in the armature's circuit of universal motors, this paper suggests the analysis of the armature voltage and current waveform by an artificial neural network (ANN). The current and voltage signals acquired during the no-load test formed a time-series waveform that was applied to an ANN trained to classify the signal in three possible outcomes: healthy armature, armature with short-circuited segments, and armature with a broken part. The results achieve effectiveness above 98% in the task of detection and classification of faults. The solution was tested in the production line of universal motors and proved to be fast, reliable, and efficient for the usual no-load test, proving to be suitable in an industrial context.**

***Index Terms*—Artificial neural networks, fault diagnosis, universal motors.**

## I. Introduction

Although DC and universal motors have been replaced in some industrial applications by induction motors driven by power electronic circuits, especially for applications where velocity control is needed, there are still applications where they are preferred [5], [28]. To feed these machines with a direct current, a process known as commutation is necessary, which is responsible for periodically reversing the current flowing in the individual armature coils to maintain unidirectional torque as the armature coils move [5].

Maintenance problems at the armature circuit, formed by the brushes, commutator, and armature winding, are common, as it is in constant wear. Depending on the motor's construction, faults such as a short circuit between two commutator segments or a single broken segment do not cause the machine to stop. However, these faults can compromise the commutation's quality, causing torque oscillations and excessive sparking, which causes rapid wear of both commutator and brushes [4], [5], [27].

Supported by organization WEG S/A.

Many approaches have been developed through the years for the monitoring, detection, and identification of faults in the armature circuit [4], [7], [8], [12]–[16], [18], [20]–[22], [24], [29], [30].

As failures in the commutation process usually result in excessive sparking between the commutator and the brushes, some standards, such as the IEC Technical Report 60638 [1], suggest a visual inspection for assessing the quality of the commutation. To make this analysis more objective, it presents a pattern for classifying and grading the sparks to differentiate regular sparking from dangerous and possibly fault-related sparking. Although, there is no direct correlation between the sparking level and format with a specific failure. But even with a classification pattern, it is still in the subjective visual accuracy of the inspector.

This study aims to identify the faults of an armature with short-circuited segments and an armature with a broken segment in the universal motor, considering the test scenario of a no-load test in the production line. The results are based on the impact on production line optimization, substituting tacit knowledge with a more reliable, fast, and efficient solution. The originality of this solution is not based on the theory development but on the utilization of the standard voltage and current motor signals for the diagnosis and the practical application with almost zero modifications in the production line.

Section II presents the fault characterization problem with related solutions found in the bibliography, the difficulties, and which characteristics of the universal motors could be used for identifying the faults. Then, in Section III, the paper's proposal is exposed together with the test setup, and in Section IV, the signal analysis, based on the selection of the neural network, is shown. After that, Section V brings information about the classification method, the data set, the training scenario, and the effectiveness obtained. Lastly, Sections VI and VII show the results of tests in the motor's production line and the conclusions, respectively.

## II. Armature Faults Inspection Problem

Through the years, several studies have proposed the replacement of visual inspection with a more precise and objective system.

One of the options studied was the usage of photo sensors and cameras for fault-related sparking detection. [3] gets a spark index from the response of an optical sensor, and [10] uses a video camera image of the sparking at the brush-commutator interface together with a vibration frequency measurement for the investigation of excessive commutator and brush wears. More recently, [12] uses a camera coupled to the motor for each brush and determines the sparking severity degree by analyzing its brightness, shape, color, and distribution along the brush.

As the sparking phenomenon generates radio-frequency interference, another method for getting a sparking level index is using antennas and analyzing the magnitude and the frequency of the received signals, as presented by [7] and [20]. Those non-invasive methods could indicate a sparking level and analyze its severity and frequency to find a possible motor fault.

But, even though some faults present a characteristic form in both methods, they could be more efficient in determining what kind of failure has occurred. Furthermore, cameras must be positioned on each brush for an adequate quality assessment with image monitoring. Therefore, due to their proximity to the motor, they can become covered with carbon dust, grease, and other contaminants. RF methods also have some issues, as they are susceptible to electromagnetic interference, which may lead to system misjudgment.

Following the advances in data acquisition and analysis, many approaches were developed for fault monitoring, detection, and identification by the electrical signals' direct measurement.

For instance, [18] used the measurements of the input and output signals of brushless DC motors for parameter estimation. A difference between the estimated and the rated parameters of the motor could indicate a fault. [16] expand this concept using a multilayer perceptron neural network to classify the fault type based on the identified differences.

Also working on parameter estimation of a signal through time, [17] uses the DC motor current ripple to select the signal component related to rotation ripple that could be used for fault identification.

More recently, [30] and [8] expanded this concept for the general DC motor using the feedback of many other signals in the test setup, besides the ones taken from the motor, to determine more complex faults. This concept sometimes shows good discrimination between healthy and faulty signals. However, it requires the reference of input and output signals, a longer acquisition time, and a high computational cost.

Some studies used a direct signal evaluation instead of a parameter estimation, as [13] and [14]. They use vibration and current signature analysis for different types of motors, including DC motors, for classifying as a healthy motor, a motor with a short-circuit in the commutator, and a motor with a displaced permanent magnet out of poles in the polar axis. The suggestion is that this analysis be implemented in a diagnostic procedure using a neuro-fuzzy system.

Also, [15] shows an interesting correlation between the wavelet analysis of a DC motor current and an optical sensor for sparking monitoring. Both studies show that the current signal carries the fault information, and it may be possible to use it as a diagnostic tool. Yet, the current signal alone could not determine the fault, so the speed rotation feedback was also necessary. Besides that, for a more generalized model for different types of motors, a detailed analysis of the faulty frequencies may be needed.

Some papers applied neural networks or fuzzy inference systems as a classification method. [22] suggests replacing the surge test for armature fault identifications with the frequency response analysis method of the DC machine's impedance. Analyzing the impedance curve for all bars and frequencies, they realized that the faulty and healthy curves for the armature circuit presented some differences. It was used to classify the fault type in a neural network, achieving a classification rate of almost 90%.

Both [29] and [4] used fuzzy inference systems for the identification and classification of faulty motors, in which the former did a wavelet analysis of the transient startup current from a DC motor and the latter did the measurement of the current and voltage of a DC starter motor in a performance test, getting a fault diagnosis success rate of 90%.

More recently, [24] uses the AdaBoost technique to classify a brushless DC motor as healthy or faulty and also detects an incipient failure with 97% accuracy. It uses a fast Fourier transform (FFT) analysis of vibration and electric current signals into the AdaBoost to identify a stator short-circuit fault.

Also, using an FFT analysis on the same signals, [21] applies a neural network for determining the presence of some faults in a three-phase motor. The accuracy ranged from 92% to 100%, depending on the level of the network's featurization. The method also showed a fast response, even when dealing with a high computational cost, which proved to be an applicable method for the industry.

[17] compares the usage of a time-series current signal in a Convolutional Neural Network and a wavelet transform for the classification of magnetization faults in a Permanent Magnet Synchronous Motor, obtaining above 98% effectiveness in both methods.

Although these papers worked with other types of motors, the AI concept for fault identification proved to be a precise method for detecting faults. This indicates that using AI in the classification process is a natural step for other types of motors.

All these previous works show that electrical signals can carry the fault information, and some methods exist to identify it. Most of them used mechanical measurements, such as rotation speed or vibration, or an output signal, as torque, besides the electrical measurement and analysis. Yet, some propose the utilization of many sensors, which can add complexity, increase test time, and make the system's applicability unfeasible in an industrial context. It is essential to note that none of the previous solutions were applied online to the production line or universal motors.

## III. Inspection Solution Proposal

This study proposes a method for identifying the faults of a universal motor during the no-load test using only the electrical signals. The armature's electrical voltage and current signals time-series data are measured and analyzed by a multilayer perceptron neural network. As the faults of short-circuited segments in the armature or an armature with a broken segment in the universal motor appear at each rotation, the analysis of the time-series waveform of just a few turns could be enough to characterize the faults. These features can provide a fast and easy-to-setup test applicable in an industrial environment.

During a no-load evaluation of universal motors, faults such as a short circuit between two segments or a broken segment in the armature circuit may not be detected by a simple measurement. Depending on the armature's physical characteristics, these faults could cause slight changes in the current and voltage signals' root mean square (RMS) values.

One indicator of these faults is the increased sparking in the commutator. But, as sparking in the commutator of a universal motor is a common phenomenon due to the armature reaction, even a careful visual inspection may not detect the commutation faults.

Therefore, there is a high risk that some commutator fault may overcome the general no-load production line test. Although these faults may cause slight changes in the RMS values of the current and voltage signals, their waveform presents a characteristic distortion due to a change in the number of commutations at each rotation and a change in the commutation time over the faulty segment. As the distortions in the waveform at each turn carry the fault's signature, an analysis of the time-series waveform data of one or more turns could be enough for a pattern identification artificial intelligence algorithm to detect the fault.

Hence, the signals were analyzed for this development, searching for the type, size, and characteristics that contain sufficient information for the classification pattern development. Both signals were tested as the universal motors can be supplied with an AC or DC power supply. Then, the waveform signals for the classification model were acquired. After that, the development and training of the appropriate classification AI algorithm aimed, as output, a classification of the motor as healthy, open-circuited, or short-circuited.

### A. Test Setup

For the data acquisition, development, and test of the detection and classification system, a setup similar to the production line test was assembled, as shown in Figure 2.

A relay activated by a multi-function I/O board was implemented for starting the test (A). The motor supply current was measured by an LTS 6 NP current transducer (B). The output, armature, and field voltage signals were acquired with a voltage transducer and a National Instruments voltage acquisition module NI-9239 (C), configured with an acquisition rate of 50kHz. For the data transfer, the TCP/IP communication module cDAQ-9185 (D) from National Instruments was used, enabling real-time data analysis by the software developed in LabVIEW.

A test software routine was developed using LabVIEW for data acquisition and control of the test's start and stop. A total of 30 healthy universal motors were available for this development. The universal motor is a washing machine line model [9], supplied by WEG, with the field and the armature windings connected in series for the tests.

## IV. Signal Analysis

The first analysis aimed to evaluate which signals' characteristics could be used for the motor's condition detection and classification. The armature voltage and current signals of six universal motors were measured. Two of those motors were healthy, and the others were faulty. Two motors had a short circuit between two segments in the commutator, and the other two had a broken segment.

Although the AC signals presented a harmonic distortion in the waveforms corresponding to the faults described (Figure 1), it was difficult to establish a repetitive pattern for detection. They presented very different distortion levels in the motors showing the same condition. Therefore, the analysis could not set a standard possible to distinguish a healthy motor from a faulty one.

The DC signals showed an interesting pattern for the classification, as the differences between the waveform of the healthy motor and the waveforms of the two types of faults exhibited different shapes and amplitudes, which was more clear to identify. Figure 3 shows the armature's voltage and current signals in the three other conditions. Besides that, the waveforms showed the same patterns among different motors.

In the DC signals analysis, it was also possible to determine that the period of the fault's signal is the same as the motor's rotation, as the faults in a commutator's segment will appear once in each motor turn. The size of the signal corresponding to one complete turn of the motor was between 400 and 500 points due to slight differences in the velocity of the motors.

Because of that, the input array size used in the tests were 500, 1000, and 2000 points. These values correspond to the period of one commutation cycle, two commutation cycles, and four commutation cycles, respectively. From that, it was possible to evaluate which data size would provide the best relationship between the effectiveness and the analysis time, a critical characteristic of this application.

## V. Classification Method

As the objective is a pattern recognition model for classifying a non-linear time-series input, an artificial neural network (ANN) has been chosen. Emulating the brain architecture, an ANN represents a class of non-linear models capable of learning from data. One successful and well-consolidated model of ANN for pattern recognition is the multilayer perceptron

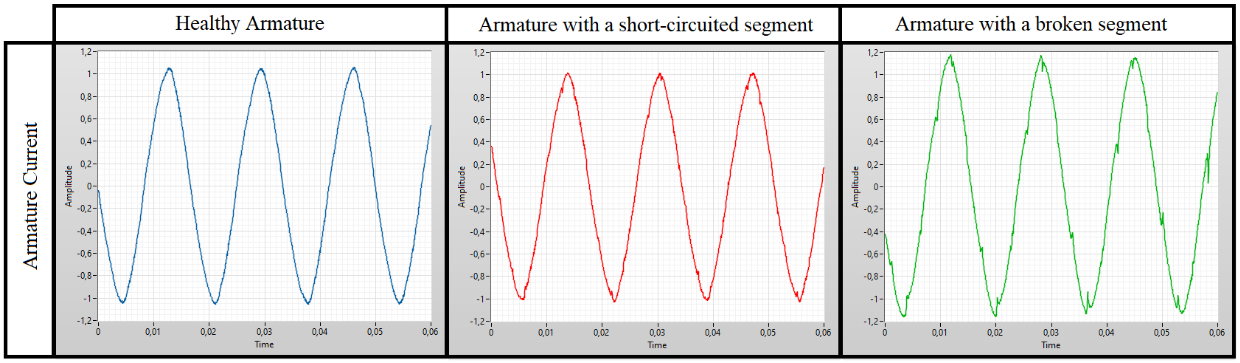


Fig. 1. AC waveforms of the faults.

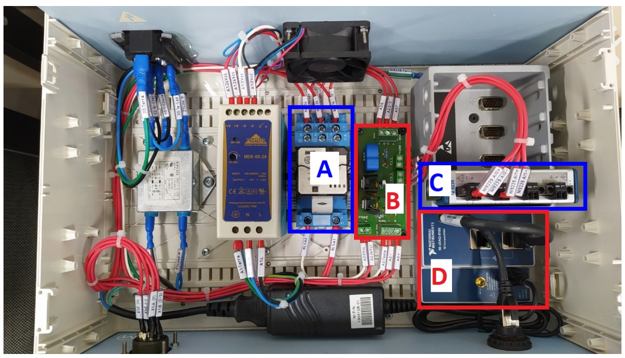


Fig. 2. Test setup - (a) relay, (b) current transducer, (c) NI-9239, (d) cDAQ-9185.

(MLP), a straightforward type of neural network with a wide range of applications.

Therefore, an MLP neural network was developed using a backpropagation algorithm with stochastic gradient descent (SGD) and momentum. The algorithm implemented in LabVIEW 2017 was based on the multilayer perceptron presented in [2] and [19], and the application of momentum in [23] and [26] was used.

The proposed solution uses three layers of neurons (two hidden layers and one output layer). The NN input layer is a 1D array composed of the armature's current and voltage signals through time, as depicted in Section IV. The output layer is formed by three neurons, corresponding to the motor status of a Healthy Motor, a Motor with Short-circuited Segments, and a Motor with a Broken Segment.

The activation functions for each layer were Sinusoid, Softplus, and Sigmod.

Applying periodic activation functions, such as the sine function, is uncommon and generally not recommended because they are monotonic and can often converge to local minimums. However, the periodic functions in at least one of the layers could be applied as a generic Fourier decomposition of the main frequencies. [11] shows a neural network that uses a sinusoidal activation function to fit repeating nonlinearities in the data.

Considering the time-series data presented by the universal motor classification problem, showing different frequencies for each possible motor state, was adopted the sinusoidal function at the first hidden layer.

The chosen architecture is fixed, so the number of layers doesn't change. However, it sought the best number of neurons for each layer, choosing different implementations and varying the number of neurons for each hidden layer, evaluating the performance of every setup. These tests are summarized in Section V-B.

Further, for the training, the neurons' weights were initialized randomly between 0 and 0.1 to avoid the problem of the local minimum associated with the periodic function at the first hidden layer. The benefits of a correct weight initialization in a periodic function should provide faster learning than the sigmoid function, as seen in [25].

### A. Data Set

A total of 30 universal motors were available for data acquisition. The acquired data were used for the NN analysis, training, and performance test.

A test software routine was developed using LabVIEW to execute the data acquisition using the test setup described in Section III-A. The software acquires the armature's voltage and current signals for 0.3 seconds, a sufficient period for acquiring at least ten complete motor turns. This period could provide enough cycles to evaluate the motor's condition, even if part of the signals presented some electrical noise that could lead the analysis to a wrong response. After that, the routine turns the motor off and waits 2 seconds for the complete stop, ending the acquisition cycle.

Ten consecutive acquisition cycles were measured in each of the 30 healthy motors. After that, in 10 of these motors, a short circuit between two commutator segments was put. In another ten, it was cut one of the commutator's segments generating the open circuit fault.

For each one of these faulty motors, ten acquisition cycles were executed.

After all these tests, a total of 500 signals were acquired and were separated for the training process as follows:

- 20% of the data for the validation;
- The 80% left was split in half:

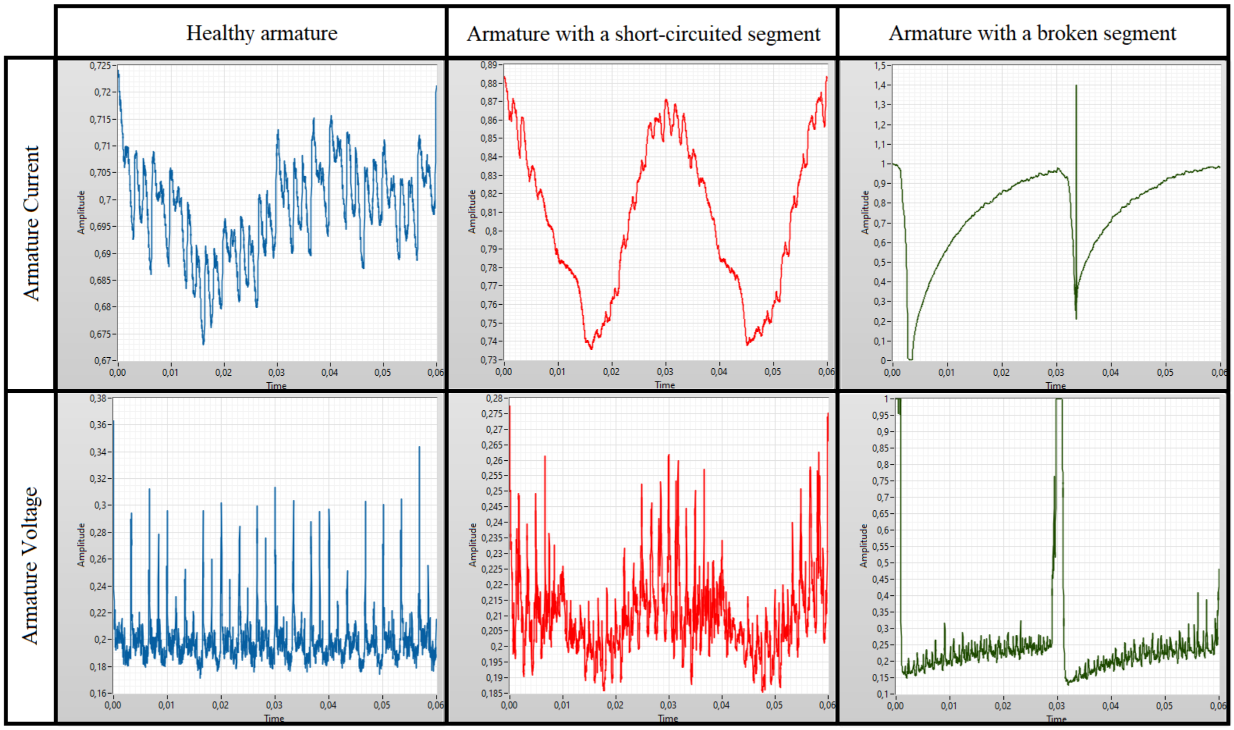


Fig. 3. DC waveforms of the faults.

- 200 signals for the training;
- 200 signals for the performance test;

This separation was based on [6], which recommends using a ratio between the training and test data in the range of 50/50 to 70/30 for obtaining a network optimally generalized and trained.

### B. *Training and effectiveness*

The ANN training was implemented, varying the parameters of the input signal size, input signal type, and the size of the hidden layers, seeking the best performance.

The graphs in Figures 4, 5, and 6 represent the results for the three different input signals. The x-axis and y-axis in each graph represent the number of neurons in the hidden layers, the colors of the points are the effectiveness values, and the number above each point is the input array size.

Using armature voltage as an input signal shows low success at training performance, frequently falling in local minimums and presenting maximum effectiveness of 85% (Figure 4).

The armature current signal presented better results than the armature voltage, obtaining results between 84% and 98% effectiveness (Figure 5).

The best result was achieved in using a composition of the armature's current and voltage signals, presenting at least 97.25% effectiveness in classifying the motor in the three possible outcomes and results between 99% and 100% when classifying the signals as just healthy or faulty, without indicating the problem (Figure 6).

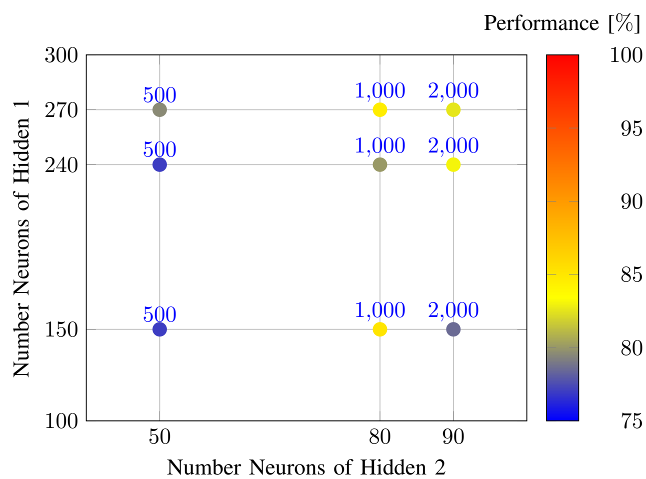


Fig. 4. Voltage Signal Results.

## VI. Classification Method Validation

The best four trained networks, which presented 100% effectiveness in the test set, were applied in the validation test. These networks were implemented into the final test software, used in an environment closest to the production line test. This test setup made possible the evaluation of the test effectiveness and the analysis time.

The test was divided into four stages: starting the motor and stabilization, acquiring data (voltage and current), turning the motor off, and data analysis. Using the software developed in LabVIEW, it was possible to identify the times of each

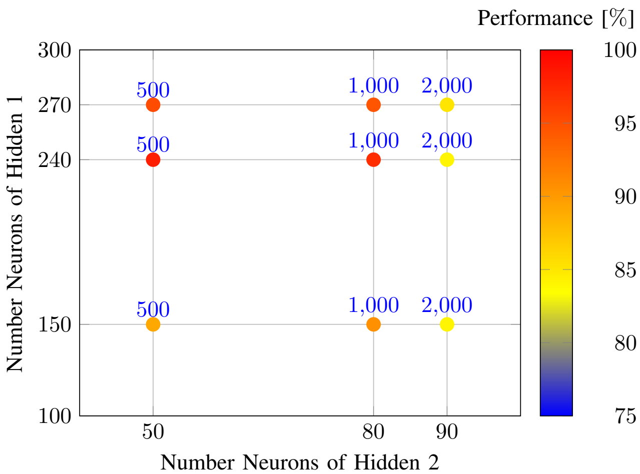


Fig. 5. Current Signal Results.

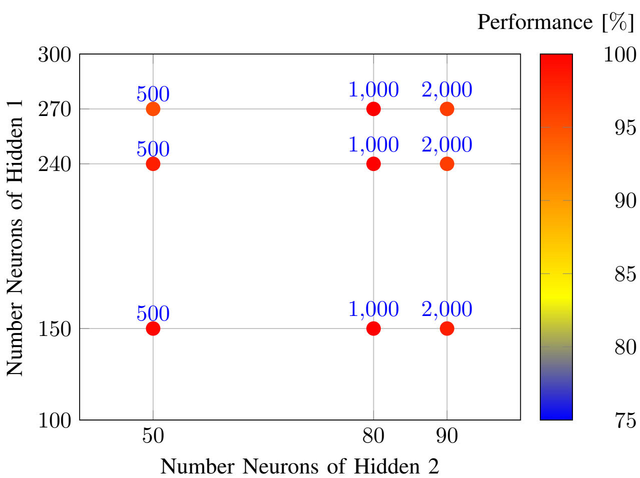


Fig. 6. Voltage and Current Signal Results.

step and assess the impact of the test on the production line. Figure 7 presents a graph of the test time at each step.

The effectiveness results for all four networks presented values above 90% and effectiveness of 98% as the best result. The network got an incorrect outcome in only two cases, where a short circuit between segments was identified as a broken segment. However, the ANN still signaled the motor as a faulty motor. The differences in the deepness of the networks under test caused a slight variation in the total testing time, but all times presented were small enough not to represent an issue on the production line time.

The solution was integrated into the production line, providing an objective and fast way to classify the armature faults. Figure 8 shows a motor under test with the software user's interface showing the result of it, correctly detecting the problem.

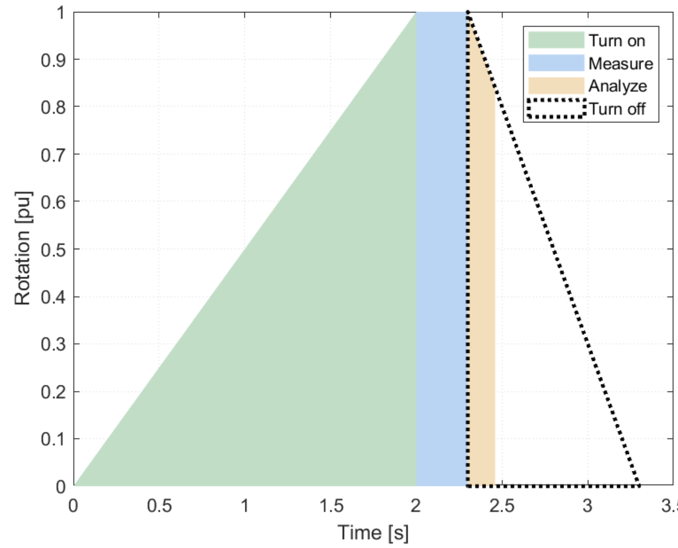


Fig. 7. Test time.

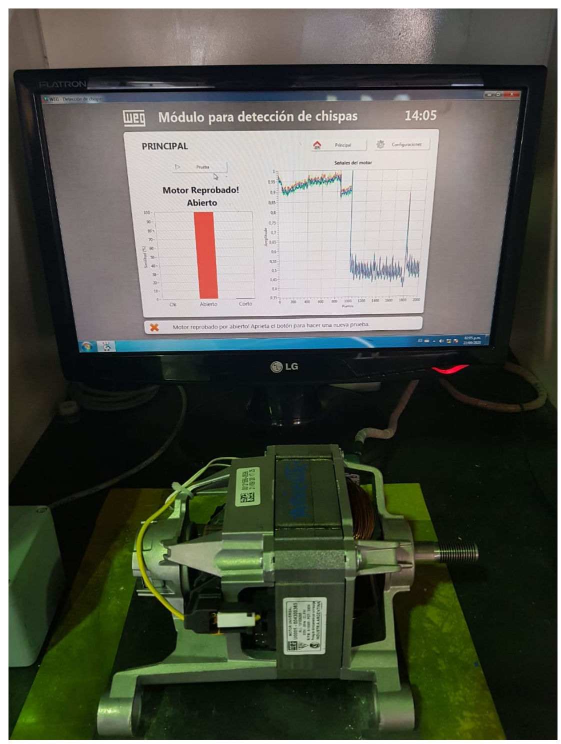


Fig. 8. Software's interface and motor under test.

## VII. Conclusion

A solution was developed for detecting and classifying universal motors' armature faults in the production line using AI. It focused on identifying a short-circuit between segments and a broken segment of the commutator, types of faults that could pass unnoticed in the fast and general no-load tests.

The implemented neural network could correctly detect an armature fault in all tested motors. Also, it could classify in one of the two described problems with 98% efficacy, replacing a subjective visual test with a reliable and objective one. The fault classification could also accelerate the process of fault investigation, indicating what kind of fault has occurred, leading to a more precise action course for solving it.

The method was implemented in the production line with a no-load test, using the measurements of the armature's voltage and current signals. Using only the electrical signals allowed the new detection method to be implemented without additional hardware or mechanical coupling.

Besides that, the method proved to be fast, with less than 200 ms analysis time, so the total test time was similar to the usual production line test time, assuring quality with a low impact on the production rate. Those characteristics were essential for a fast and low-cost test that could be implemented in an industrial environment.

It's possible to conclude that using just the electrical signals time-data array with an ANN is sufficient for evaluating the faults of short-circuit between two segments and a broken commutator segment in a regular and fast no-load test, where these faults may not be evident.

## Acknowledgment

The authors thank the WEG Electrical Equipments S/A Group and the university UDESC for their financial and technical support. Also, this work received support from the Coordination for the Improvement of Higher Education Personnel FAPESC (2023TR000333).

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