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Artificial Intelligence-Based Recommendation System for Detecting and Diagnosing Broken Bars in Induction Motors Under Transient Operation

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Abstract: Three-phase induction motors are the main elements for converting electrical energy into mechanical energy and are extensively used in industry. Reducing maintenance costs becomes an incentive for developing systems capable of identifying defects. This research proposes a framework for recommending machine learning algorithms that diagnose and detect broken bar defects in three-phase induction motors under transient operation based on artificial intelligence. Employing experimental data, features were extracted and selected based on current, voltage, and vibration. A protocol of insertion of white noise showed that the proposed framework admitted 80% of noise without losing the predictive capacity based on a multicriteria performance measure.

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Keywords: condition monitoring, fault detection, fault classification, machine learning, maintenance engineering, smart systems, three-phase induction motor.

1. INTRODUCTION

Most industrial applications that convert electricity into mechanical energy use rotating electrical machines, such as induction motors, because the low cost associated with robustness reflects their most attractive characteristics. Besides, the growing need of the productive sectors in the face of preventive and predictive maintenance aims at reducing maintenance costs, minimising inconvenience caused by unplanned disconnections of production lines, and even inhibiting the risks of accidents at work, motivating the development of systems capable of identifying incipient defects inherent in the machines.

Broken bars have several symptoms, and among the most common defects in electric motors are prevailing force in the machine cables and unbalanced line currents, increased torque ripple, decreased average torque, reduced efficiency, and excessive heating. In this way, this research was directed entirely to the defect of broken rotor bars in detail.

When a rotor bar is interrupted, no current flows through it. As a result, no magnetic flux is generated around the bar. Thus, asymmetry is generated in the rotor's magnetic field, causing a backward rotation field in the rotor's sliding frequency, leading to the induction of the harmonic fault component in the stator current. According to Katona, Kuczmann, and Orosz (2023), these overlapping harmonics are used as a signature of broken bar failure by techniques commonly used for diagnosis, such as the Motor Current Signature Analysis.

Most of the applications developed for detecting and diagnosing defects of broken rotor bars at induction motors are applied to signals in the steady state, as presented by Kang et al. (2018) and Elhaija and Al-Haija (2023). However, detecting defects and indications of occurrences in the initial phase of operation or the transient regime for some applications is attractive. These applications are based on intermittent machine starts, load and speed variations, real-time analysis and interventions, and initial commissioning tests after installation. Practical examples include wind power generation, electric vehicles, motors driven by electronic converters in closed-loop controlled systems, elevators, fluid pumping systems, air conditioning systems, industrial conveyors, and machine tools.

As the detection and diagnosis of defects in the transient operating regime is subject to several random factors (Rocha et al., 2020), such as excessive noise and the transient effect on harmful frequencies to the system, the techniques used must be robust to noise and generalist, reducing the error rate and false alarms (Abd-el-Malek, Abdelsalam and Hassan, 2017).

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Based on the previously mentioned interests of modern industry focusing on digitalisation and real-time information, the main contribution of this paper is a framework for recommending techniques for detecting and diagnosing broken bar defects in three-phase induction motors in the transient regime according to the imposed conditions.

The sequence of this paper is organised as follows. Section 2 addresses a literature review focusing on analysing faults in the transient state of electrical machines and applications of machine learning methods for this purpose. Section 3 presents the proposed framework for machine learning algorithms recommendation fault diagnosis and detection in three-phase induction motors. Section 4 shows how the dataset was collected, describing the experimental workbench. Section 5 presents the results, focusing on each step of the framework. Finally, section 6 addresses this research's conclusions and future works.

2. LITERATURE REVIEW

In industry digitalisation, using artificial intelligence (AI) information systems is associated with the capacity and capability to adapt, becoming a key factor of competitiveness in the industry today (Zdravković, Panetto, and Weichhart, 2022). Maintenance is a critical aspect of reducing production costs (Zhang et al., 2024), and rotative actuators as three-phase induction motors are constantly in evidence due to their wide range of applications.

To identify faults in the transient state of electrical machines, the most used technique available in the literature is the Wavelet transform (Li, 2024), Weibull analysis (Ali, 2015), deep learning (Sedghi, 2024), ensembles of learning techniques (Attallah, 2022), Fuzzy methodologies (Raja and Rathinakumar, 2023) and hybrid feature selection techniques (Ehya, Skreien and Nysveen, 2021). In this sense, the most accurate methods are based on computational intelligence, as they are more general and allow the analysis of a greater range of interdependent variables. Analytical methods, such as the application of the Wavelet transform, perform well in defect identification but are not frequently used to detect the type and severity of the defect. The lack of generalisation of this category of methods attests to this fact.

The interest in detecting and diagnosing defects in the transient regime is motivated by the excellent performance of the techniques in conditions in which the steady-state methods present low performance, such as in the detection of broken bars in machines with low nominal slip (de Deus et al., 2020), breakages of an outer bar in the double cage induction machine (Firas and Braham, 2020), bar breaks in machines with axial air ducts (Goktas and Arkan, 2023), asymmetries and eccentricities of rotors in machines with continuous load oscillations (Aguayo-Tapia et al., 2023). In these cases, failures are hardly detected in the steady state of operation because they are coupled to the fundamental component or noise.

Diagnosis in transient conditions is based on analysing the diagnostic quantities in a wide range of working conditions, in contrast to the diagnosis in a steady state, which evaluates the machine's behaviour in a regime. Consequently, a diagnosis in transient conditions is conceptually more reliable and generic than a diagnosis in a steady state.

The systematic review of the literature published by Maciejewski, Treml, and Flauzino (2020) showed results related to this research. Their results showed that 40.83% of the research works evaluated studied the bearings' defects, 8.85% the stator defects, 20.71% the defects of the broken bar in the rotor, and 17.75% the defects of eccentricity. Some studies analysed defects, 11.83%, and discretised the defects or not. As for the analysis regime, the studies that implemented the steady-state analysis methods were 79.88%, a transient regime of 2.96%, and a hybrid regime of 17.16%.

Most conventional steady-state diagnostic methods are based on identifying distinct fault components in a current spectrum. Likewise, transient diagnostic methods are generally based on intelligent systems, combining feature selection and machine learning techniques to identify the evolution of failure components. To this end, the features extracted from the signals constitute the fundamental step in diagnosing defects in the transient regime (Yakhni, 2023).

3. FRAMEWORK FOR RECOMMENDING INFERENCE SYSTEMS

The system's structure for detecting and diagnosing broken rotor bars in induction motors proposed in this paper is illustrated in Fig. 1. This paper used the electric current, the motor's stator phase voltage, and mechanical vibration speed signals. In the data pre-processing step, the data is normalised to a predefined interval, such as [0, 1], based on the torque applied to the induction motor shaft. Furthermore, signal regions corresponding to the transient operation regime were identified during the data pre-processing. Applying the first and second-order numerical derivatives to each data point in the experimentally acquired time series achieved a transient operation regime. Thus, the transient regime was determined to lie between the points of the first zero-order derivative, with the first point succeeding the maximum point and the second succeeding the minimum point of the first-order derivative.

The following features and their categories were extracted from the experimental time series: (1) Statistical: Average, standard deviation, variance, median, extreme values, quartiles, kurtosis, asymmetry, covariance, sum, mode; (2) Information-based: Entropy, signal energy, signal contrast, homogeneity of the signal, moment of 3rd order of the signal, signal strength, noise ratio, total harmonic distortion, noise and signal distortion rate, 3rd order intersection point of the signal, signal free dynamic range; (3) Based on complexity: Fractal dimension; (4) Based on systems analysis: Root mean square, trace of the symmetric matrix of the signal, 1st order eigenvalue of the signal.

In the same way, the process of feature selection is executed. During this step, the features are chosen from the pre-processed dataset. Four distinct feature selection algorithms were assessed: Consistency-based Filter (CBF), Correlation-based Feature Selection (CFS), InfoGain, and ReliefF.

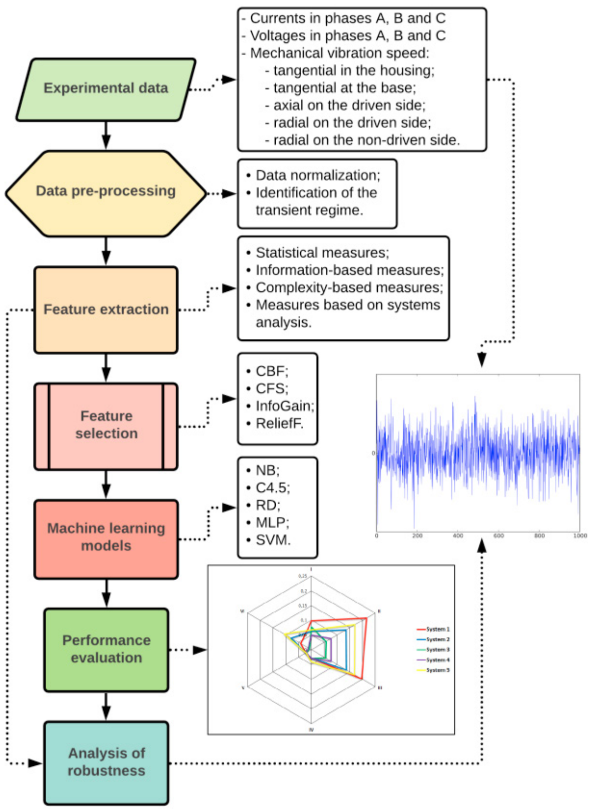

Figure 1. Inference system for detection and diagnosis of broken rotor bars in induction motors.

With the selected features, machine learning techniques were assessed for defect detection and diagnosis. Two classification approaches were considered: binary and multiclass. The binary classification involves distinguishing between the defect and non-defect conditions. In contrast, the multiclass classification categorizes the rotors into non-failure conditions and conditions indicating the severity of the defect (1, 2, 3, or 4 broken bars). The machine learning models under evaluation included Naïve Bayes (NB), decision tree C4.5 (C4.5), Random Forest (RD), Multilayer Perceptron (MLP), and Support Vector Machine (SVM).

The performance of the system was evaluated through a multicriteria analysis, considering the following indicators: (I) false positive or false alarm or type I error; (II) false negative or type II error; (III) accuracy; (IV) learning time based on the computational complexity of the feature selection and machine learning algorithms; (V) percentage of selected features; (VI) complement area under Receiver Operating Characteristics (ROC) curve. The indicators were normalized and employed to construct radar-type graphs, forming a multicriteria hexagon. The internal area of this hexagon served as the performance indicator, where a lower value reflects a superior performance of the inference system. The specific value of the multicriterial hexagon area is influenced by the placement of the indicator axes and their neighbouring axes. Nonetheless, the ranking of inference systems remains independent of the positioning of the axes within the multicriteria hexagon.

All parameters and hyperparameters of the proposed recommendation system, such as features, feature selection and machine learning algorithms, and performance evaluation criteria, were determined by observing gaps in the state-of-the-art and established methods in related literature. The paper proposed by Maciejewski, Treml, and Flauzino (2020) compiles these parameters.

A robustness assessment was conducted to complement the analysis. The approach involved testing the models using input signals corrupted with white noise. The steps followed for this assessment might be summarized as follows: (1) Corruption of the input signals: white noise was introduced to all samples in the dataset, with an intensity proportional to the signal's energy. The intensity ranged from 0 to 100%, with a step size of 5%; (2) Features extraction and selection: a subset containing the most important features was chosen from the original dataset using the feature selection techniques and algorithms described earlier; (3) Modeling of intelligent systems: the previously mentioned machine learning models received, as inputs, the new corrupted dataset during the test phase; (4) Robustness of the inference system: by considering the machine learning model's response. The robustness analysis enables inference regarding the model's generalization ability. Additionally, multicriteria analysis was implemented for the models tested with the corrupted dataset.

4. EXPERIMENTAL SETUP FOR DATA ACQUISITION

The experimental setup depicted in Fig. 2 was assembled to construct the dataset for this study. This configuration comprises a three-phase induction motor connected via a rotary torque meter to a direct-current (DC) machine, functioning as a generator. The DC machine simulates a resistive load, imposing mechanical resistance to the shaft.

The three-phase induction motor is of the squirrel cage type, with 34 bars. This motor is rated at 1 cv, with voltage specifications of 220 V/380 V, current ratings of 3.02 A/1.75 A, and four poles. It operates at a frequency of 60 Hz, with a nominal torque of 4.1 Nm and a nominal speed of 1715 rpm.

Drilling the squirrel cage rotor was necessary to simulate the broken bar. This procedure involved using a bench drill equipped with a 6 mm diameter drill to ensure that the hole's diameter exceeded the width of the rotor bar. The hole was drilled in the middle of the longitudinal length of the rotor.

The data acquisition involved testing five different rotor configurations: a rotor without defects, a rotor with one broken bar, a rotor with two adjacent broken bars, a rotor with three adjacent broken bars, and a rotor with four adjacent broken bars. The holes were drilled in adjacent bars, as broken rotor bars are typically adjacent in practice. For each rotor configuration, eight loading conditions were defined, ranging from a minimum torque of 0.5 Nm to a nominal torque of 4.0 Nm, with a 0.5 Nm increment. Furthermore, for each configuration, the test was conducted ten times. Details of the experimental setup have been published and are available in the IEEE DataPort database by Treml et al. (2020).

The speed signals were obtained using an integrated, modular, compact data acquisition system capable of signal conditioning, amplification, and filtering. Both electrical and mechanical signals were simultaneously acquired, utilizing time windows of 20 s, with the last 16 s designated as a steady-state regime. In this case, 11 signals were acquired, comprising 3 phase electric currents, 3 supply voltages, and 5 mechanical vibration speeds. Each feature identified was extracted for every signal, resulting in 319 features. This procedure was carried out for all experimental conditions, encompassing the eight loading conditions for the five motor health conditions, totalling 400 experimental time series.

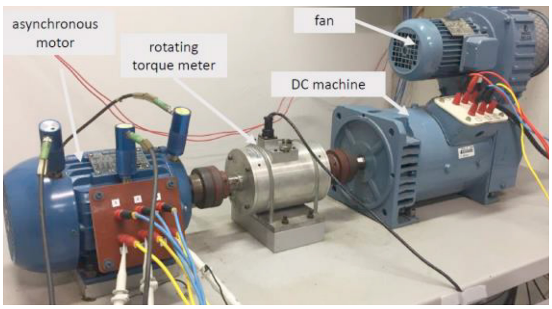

Figure 2 - Experimental workbench.

5. RESULTS

The results are presented according to the two classification approaches: the binary case for detection and the multiclass case for defect diagnosis.

5.1 Analysis of selected features

For the binary case, regarding the number of features selected, the InfoGain algorithm was the one that set the subsets with the most features, ranging from 7.52% to a maximum of 100.00%. Notably, the CBF algorithm exclusively picked statistical measures for all its selected features, while the CFS algorithm exhibited 63.16% of features from this category. Similarly, the InfoGain and ReliefF algorithms had 61.11% and 28.57%, respectively, of their selected features belonging to the statistical-based category.

The measures based on systems analysis, commonly employed as time series descriptors in literature, were not selected by any feature selection algorithm for the binary case. This situation may have occurred because the statistical measures, such as mean and standard deviation, overlapped the measures in question, making them irrelevant to this analysis. Remarkably, information-based measures representing signal characteristics, such as noise, dynamic range, and distortion rates, emerged as frequent selections, particularly in the context of the binary case. This suggests their significance in capturing essential aspects of the signal under consideration.

Regarding the number of features selected, the CFS algorithm selected the biggest subsets, with 8.15% of the total features for the multiclass case. Among the selected features category, the CBF and CFS algorithms demonstrated a preference for statistical measures, respectively composing their datasets with 85.71% and 84.62% of statistical features. Both algorithms are configured using the Best First search strategy, where the best descriptors of the dataset are selected. An additional analysis regarding the features probability distribution was implemented. For this, the Kolmogorov-Smirnov normality test was applied, with a significance level of 5%. It was verified that only statistical-based and information-based features follow the normal distribution. Such features are more significant for the diagnostic system and represent the greater share of features selected by the feature selection algorithms. Therefore, the probability distribution of a given feature is directly related to its predictive capacity, as shown in the classification results. Thus, based on the results presented, it is recommended that descriptors that pass the normality test and follow a normal distribution be implemented for greater intelligent system relevance.

5.2 Comparison of induced models

After the feature extraction and selection stage, the machine learning models were trained, validated, and tested using 50%, 25%, and 25% of the data. Fig. 3 illustrates the multicriteria hexagons for each combination between the feature selection algorithms and the machine learning models for the multiclass approach. Four feature selection algorithms were confronted with five machine learning models for binary and multiclass cases, resulting in 20 scenarios.

Each multicriteria hexagon's internal areas were calculated, making ranking the intelligent system configurations possible. For the binary case, it is observed that the best results were achieved by systems that applied the CBF algorithm. The CBF works based on the feature's consistency regarding its class. For the detection system in the first position, only one feature was selected by the CBF: the second quartile of the axial vibration signal. The system obtained the best outcome using the SVM as the machine learning model. This outcome may be attributed to the proficiency of such an algorithm in handling minor dimensionality problems, enabling the SVM to create an optimal hyperplane for class separation. The second position in the ranking was occupied by systems that utilized the RD algorithm. Like what occurred for the first position, the RD algorithm excelled because the CBF selected only one feature, resulting in a low-complexity tree with few branches.

For the multiclass case, the diagnosis systems occupying the first two positions in the ranking applied the CBF. Concerning the machine learning model, the rank reveals that the RD and MLP algorithms excel in the multicriteria hexagon area, securing the first and second positions, respectively. The main drawback of MLP lies in its training time and the necessity of a large and high-quality dataset. The RD offers simpler training and testing processes while delivering reasonable results, making it well-suited for embedded applications.

The hexagon analysis revealed that the false positive rate parameter was a relevant criterion. A lower rate of false alarms indicates a more economical model. In practical applications, reducing false positives can help to minimize maintenance and logistics costs associated with addressing the identified issues. When there is a tie between methods or mathematical similarity, the analysis of the multicriteria hexagon area, particularly considering the false positive rate, should be used as a discriminative measure to guide decision-making.

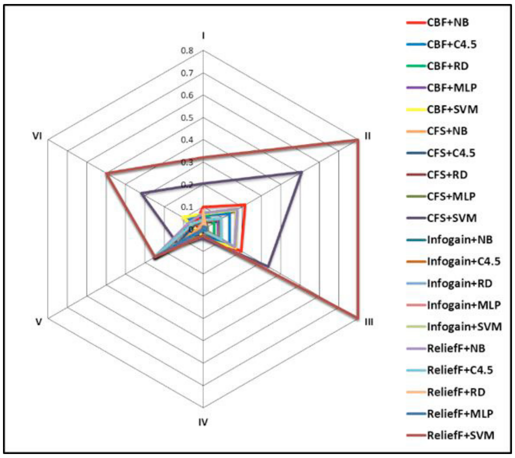

Figure 3 - Illustration of the multicriteria hexagon applied for the performance evaluation of the machine learning models for the multiclass case.

5.3 Robustness analysis

The robustness analysis aims to determine how robust the detection system is when confronted with corrupted signals. The limit of a given detection system's robustness is the amount of white noise the system supports until a statistically significant difference exists in its performance. This behaviour might be evaluated through the internal area of the multicriteria hexagon. Using the Shapiro-Wilk normality test, with a significance level of 5%, it was observed that the robustness limit for all the analyzed systems was 60% for the binary approach, except for CFS+SVM, Infogain+SVM, ReliefF+SVM, and ReliefF+RD, that did not show statistically significant similarities in the criterion evaluation.

In this way, it is possible to quantitatively verify the inference systems that performed best when there were noises in the test features. The first positions of the rank refer to detection systems that applied the CBF, which performed well in previous analyses. As for the machine learning model, RD and NB performed the best. The SVM achieved the third rank. This model usually performs well in binary classification problems when there are both large amounts of features and redundant features. This model presented a reasonable performance due to its association with the CBF, presenting worse performance when combined with other feature selection algorithms.

In this robustness analysis, the features lose the differentiation quality as the noise percentage increases. The selected features must represent the physical system enough to withstand noise and not become redundant. With few representative features, the algorithms need clarification and consider destructive features applicable only by chance, generating random errors observed in the growth of robustness analysis curves. Statistically analyzing the robustness analysis curves in the multiclass case, at the 5% confidence level with the Shapiro-Wilk test, it was found that the robustness limit for the inference systems was 80% for all cases, except for CBF+SVM, CBF+NB, CFS+SVM, Infogain+SVM, and ReliefF+SVM. These exceptions showed statistically significant differences before 80% of white noise.

For the multiclass case, the first two places have relatively close values. Both systems, one constituted by CFS+MLP and the other by CBF+RD, are generalists due to their construction nature. These algorithms have linearity for the classification, which was beneficial for tests with corrupted features due to class identification's simplicity. This fact does not occur with statistical-based algorithms, as the features become increasingly irrelevant for the class when analysed in isolation. The difference between the robustness limits from the binary and multiclass approaches is significant, 60% and 80%, respectively. One hypothesis for this occurrence is that the diagnosis systems for the multiclass case present rules and mathematical relationships between the features to describe a specific class. Therefore, the system is more robust due to the difficulty of destroying such relationships by adding noise to the data. There is less probability of random errors occurring during the construction of machine learning models.

5.4 Detection and diagnosis

In the case of defect detection, the most recommended system for this task has the following characteristics: (1) Types of features: Features of the statistical category, more specifically the second quartile of the mechanical axial vibration speed signal; (2) Experimental Performance: Configuration of the CBF with the SVM; (3) Robustness analysis: The configuration of CBF with RD was the most robust for the specific application of defect detection in induction motors, with a robustness limit of 60% of admitted white noise.

For the case of diagnosis of the severity of defects, or multiclass classification, the system recommended based on the results must have the following characteristics: (1) Types of features: features mostly from the statistical category, such as the standard deviation of voltage signals in phase A and current in phase B, median axial vibration signal, third quartile of radial vibration signals on the driven side, and voltage in phase B. Voltage signal noise ratio feature in phase A, belonging to the information-based category, and the fractal dimension of the radial vibration signal on the driven side, belonging to the complexity-based category; (2) Experimental performance: Configuration of the CBF with the RD; (3) Robustness analysis: The configuration of CFS with MLP was the most robust for the specific application of defect diagnosis, with a robustness limit of 80% of admitted white noise.

Other methods were well placed in the multicriteria hexagon area, such as MLP using CBF and CFS. Thus, the method's determination to be used depends on the application, and the three methods mentioned presented promising results in terms of precision and sensitivity according to the variables of the multicriteria hexagon. Concerning robustness, the application and available instruments must be observed primarily for binary and multiclass classification. These factors can influence the configuration of techniques to be robust through the physical system parameters, such as sampling frequency and operating conditions.

6. CONCLUSIONS

This paper presented a framework for recommending intelligent generalist techniques to detect and diagnose the severity of defects in induction motors. The possibility of adding new machine learning methods to the proposed architecture showed that the way the framework was conceived could be used for various industrial defect detection/diagnosing applications.

It is important to mention that the generalization of the application depends on tests using supervised data from different systems; however, how does the proposed model favor the adaptability of the method presented in this research in different systems?

The next step of this research would be to couple more than one classified defect in the induction motors and test new paradigms of intelligent systems. This will make it possible to build a general recommendation methodology regarding defects and components of intelligent systems.

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