An experimental method for diagnostic of incipient broken rotor bar fault in induction machines

Hamza Sabir a,*, Mohammed Ouassaid b,**, Nabil Ngote b

a Engineering for Smart and Sustainable Systems Research Center, Mohammadia School of Engineers, Mohammed V University in Rabat, Morocco
b ENSMR Engineering School, Rabat, Morocco

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ABSTRACT

Induction Motors (IMs) have multiple advantages, as they are robust and easy to maintain. A small fault in a single rotor bar could cause the break of this bar, subsequently breaking a large adjacent bar number because of the oscillations created by the unbalance of the rotor. For this reason, early detection of any small failure is recommended to remove some posterior damage and the maintenance expenses. This work proposes a new and original method that uses the cyclostationnarity of the electrical signal instead of the vibratory signal to detect the incipient failure. The experimental data has been manipulated. The results prove that this new designed strategy can identify and classify the level of cracking that occurs in a single rotor bar, even under various loads.

1. Introduction

1.1. Background and motivations

Three-phase asynchronous motors are omnipresent in diverse industrial areas such as aeronautics, chemicals, thermonuclear energy, automotive, and food industry because they have robust construction, miniature size, flexibility to control with an easily accessible power supply. However, these motors may be affected by numerous factors that deteriorate their performances, like temperature, humidity, dust, and overloads. The presence of any failure in the induction motor decreases its performance, consequently affecting its proper operation. Furthermore, the preponderance of failures suspends the industrial process, decreases production, and influences other associated devices. Therefore, the demand for a suitable and relevant fault CM system becomes imperative to predict the failure, optimize the maintenance, reduce downtime, and improve the reliability. For these reasons, a costly investment that requires the financial ability and dependability of the motor is required [1, 2].

1.2. Literature review

The IM damages are categorized into two major types, electrical defects and mechanical failures. The most frequently electrical damages are Broken Rotor Bar (BRB), unbalance supply, stator winding inter-turn short circuit, overload, under or over voltage, winding phase to phase. This IM might be attacked by mechanical faults such as bearing, eccentricity, and mass unbalance [3, 4]. The CM of the IM and the extraction of the failures are established using several detection techniques. Various reviews have been elaborated so far to examine the performances, reliability, and defects of induction motors [5]. The statistical study of IEEE (Institute of Electrical and Electronics Engineers) and the fault investigation of EPRI (Electric Power Research Institute) on induction motor faults are reported in the following papers [6, 7]. According to their report, the most preponderance IM failures are shown in Figure 1. These studies on various IM faults attest that rotor faults are among the faults that could happen to the machine. The examination of the input parameters such as vibration, temperature, flux, and current can serve to supervise the functioning status of the induction motors and detect the BRBs failure, by using different detecting procedures.

Table 1 illustrates some types of failures and the associated analysis methods based on electric current. Indeed, an incipient failure at one
The improvement of a new failure class particularly under a no-load induction motor. The paper [15] concentrates on healthy induction motor, thus assessing the severity of failures, techniques regarding the accurate differentiation between a defective and a failure. The results of this methodology are obtained and discussed. The earlier discovery of such failures in their most early stage to eradicate any additional damage may eliminate some subsequent stator winding damage as the rotor rubs undetectable incipient fault. The earlier discovery of these rotor failures overcome this problem, it is necessary to provide a method to extract this except that it might produce fatal effects in a short period of time, to such failures in their most early stage to eradicate any additional damage to the IM and minimize outage time.

Obviously, in industrial activity, where IM is the essential constituent of the installation, unexpected rotor failure will generate in short-time an overall interruption. For these reasons, a precocious detection of this kind of defect has been a significant matter for an appreciable number of researchers. In [12] a fault diagnosis technique for induction machines under the rotor and stator failures is carried out, considering the harmonic components in the current signal. This method of diagnosis is accomplished using the MCSA method. The sideband components of the spectrum of current are extracted and analyzed to prove rotor defects. Reference [13] presents a technique to detect frequencies of BRBs from spectra in induction machines employing MCSA method. Simulation and vibration analysis and theory of cyclostationarity. However, there is no methodology for the cyclostationarty of electrical signals, hence growing BRB defect which are less severe than the half BRB defect. A limited number of researchers in the field of diagnostics have successfully conducted new methods for early detection of such incipient defects. The work [23] provides a powerful CM system to detect BRB at early stage. In this study, they detected bar breaks between two case 0 mm (healthy case) and 4.3 mm (defective case) in a 17 mm deep bar. In reference [24], the authors studied incipient damage occurring on rotor bars. This incipient defect is obtained by drilling a small hole with a depth of 4.2 mm in order to improve the accuracy of early identification of BRBs.

Table 1. Induction machine fault, causes, input signal and detection methods used for rotor fault diagnosis.

| Fault Type       | Causes                                  | Input Signal          | Detection Methods       | Reference |
|------------------|-----------------------------------------|-----------------------|-------------------------|-----------|
| Bearing          | lubrication defects, incorrect lubrication, overload. | Current               | Continuous Wavelet Transform (CWT) | [8]       |
| Broken rotor bars (BRB) | Thermal-stresses, corrosion, Poor manufacturing | Current               | Hilbert transform and neural networks | [9]       |
| Rotor unbalance  | Misalignment, bearing wear              | Current               | Discrete Wavelet Transform (DWT) | [10]      |
| Stator winding   | Over-heating, mechanical stresses, over-voltages, | Current               | Park's vectors and MCSA | [11]      |

For discovering mechanical and electrical failures in induction machines. In the paper [16], a spectral analysis and ZSC procedure are performed to locate the rotor fault. These advanced methods are demonstrated theoretically and confirmed experimentally by testing the motor under varying load. The outcomes prove that this advanced technique can recognize the fault under low loads. These methods are suitable for the identification of more than one BRBs. Concerning the incipient BRB, the majority of the work involves the identification of a half BRB. In [17] the standard deviation from samples between zero crossings (ZCs) and the time between successive ZCs is used to detect one broken and a half-broken rotor bar. Reference [18] presents a methodology to detect a half-BRB in a light-load motor using the combination of MCSA and MUSIC methods. Reference [19] proposes a new approach based on the monitoring of some statistical indicators obtained by analysing the starting stator current envelope. The proposed method using Hilbert Transform (HT) has been tested and verified using experimentation in the electrical laboratory. Reference [20] proposes a new approach as a deterministic method for diagnosing an incipient BRB in IM. This approach can identify and discriminate between half or one BRBs. In reference [21], the authors propose a new approach using the MUSIC method to facilitate the identification of incipient bar ruptures for early detection. This incipient defect is a hole of about 9 mm in depth for the bars of a cage rotor which measure 18 mm in depth. The paper [22] presents a new approach where MUSIC analysis of the motor square current is used for diagnosing a half BRB fault at light load. Regarding the emerging BRB defect which are less severe than the half BRB defect. A limited number of researchers in the field of diagnostics have successfully conducted new methods for early detection of such incipient defects. The work [23] provides a powerful CM system to detect BRB at early stage. In this study, they detected bar breaks between two case 0 mm (healthy case) and 4.3 mm (defective case) in a 17 mm deep bar. In reference [24], the authors studied incipient damage occurring on rotor bars. This incipient defect is obtained by drilling a small hole with a depth of 4.2 mm in order to improve the accuracy of early identification of BRBs.

1.3. Contribution

In the present work, a new CM strategy for the detection and classification of an incipient rotor bar defect is developed. The objective of this diagnosis strategy is to detect a small defect at its early stage. Especially, under no loaded motor. The classical methods of the diagnosis and the classification of the incipient rotor bar fault are obtained according to vibration analysis and theory of cyclostationarity. However, there is no research that focuses on the cyclostationarity of electrical signals, hence the opportunity to focus on this area of research. A new electrical-Time-Synchronous-Averaging (ETSA) method was made an effective separation between the components of the stator current linked to the electrical part and those linked to the mechanical part. This new technique, mixed with the classical methods, is employed for dealing with the early identification of an incipient defect occurring at the rotor bar and

Figure 1. Fault appearance percentage on induction machine.
classification of the severity of this defect. The proposed method is applied in steady state for different scenarios. The incipient fault detection problem is solved without losing the machine performance and without cutting off the power supply. The main contributions of this paper are as follows:

- The segregation of the fault and noise is possible and good results under low slip conditions.
- Without previous knowledge of the default frequency, the advanced method is proposed to estimate the residual fault.
- Good identification and classification are provided against various load conditions and noise measurements.
- The method is non-invasive, simple to implement and single-phase measurement is enough.
- The proposed method can be implemented to the inaccessible motors of the emerged pump and generators offshore wind turbine, unlike the techniques founded on the investigation of the signal obtained by the accelerometer, where direct access to the machine is compulsory.
- Implementation in the factories producing electric motors as a successful tool for an early diagnosis of the motor rotor.

1.4. Paper organization

This paper suggests a hybrid approach combining ETSA, DWT, and Fuzzy logic algorithm (FLA) techniques. The defect frequency band is achieved using ETSA and DWT to locate the defect, then after the fuzzy method is done to classify the severity of this defect. This work is arranged as follows. The second section outlines a brief background of the ETSA, and the DWT methods followed by the suggested approach. The next section is devoted to the findings and the discussion. In the last section, some conclusions are provided.

2. Architecture of the suggested hybrid approach

2.1. New electrical-Time-Synchronous-Averaging method

The Time-Synchronous-Averaging method is established using only the vibration signals, by MacFadden in 1987, to offer a good extraction of the anomaly [25]. As a result, this strategy of CM takes into account the discovery of any fault from vibratory signals. The new concept of this work is to implement an electrical signal instead of vibratory signal [26]. As a consequence, a synchronization of K stator-current cycles of period T_h is mathematically calculated using the following formula:

\[
\langle i_{s} \rangle_{T_h} = \lim_{K \to \infty} \frac{1}{K} \sum_{k=0}^{K-1} i_s(t + K.T_h) = i_{si}(t)
\]  

On the average signal, only the fundamental component of the power supply corresponding to the fundamental frequency remains. Accordingly, the residual stator current I_{res} is calculated using the following formula:

\[
I_{res}(t) = I_{s}(t) - \langle i_{s} \rangle_{T_h}
\]

Finally, it is an exceptional and new property that permits to establish an electrical diagnosis linked indicator detecting early faults.

2.2. Discrete wavelet transform technique

Several signal processing tools have been designed to identify the broken bar failure that affects induction machines. The habitual one for detecting the rotor failure is the DWT. This well-used technique is established, by Ingrid Daubechies in 1988 [27-28]. The multi-decomposition is designated in Figure 2, two levels of multi-resolution decomposition are established. The initial signal S(n) is passed by a successive sequence of high-pass filtering (H–P–F) to achieve the high frequency analysis (HF), in parallel, the same signal is processed through successive low pass filters (L-P-F) to obtain an analysis of low frequencies (LF). Indeed, the DWT of an input signal makes to extracting an approximation-signal (a) and a detail-signal (d). The detailed high frequency signal (d1) comprises the HF components of the signal, these components are included in the interval [fs/4; fs/2], fs is the used sampling frequency. The approximation signal a1 comprises the LF components of the signal obtained in the interval [0; fs/4]. Successively, the obtained a1 signal is also decomposed carefully into a signal d2 of detail 2 in the interval [fs/8; fs/4] However, an approximation-signal a2 is obtained in the frequency band [0; fs/8]. The decomposition is reiterated for each approximation signal until the overall decomposition of the input signal is completed, this procedure is called Mallat’s algorithm [29].

![Figure 2. The Mallat algorithm.](image-url)
of the DWT, which contain these specific frequencies calculated as follows [30]:

$$\begin{alignat}{2}
    f_{d1} &= (1 - 2s)f_s \\
    f_{d2} &= (1 + 2s)f_s
\end{alignat}$$

(5) (6)

where $f_{d1}$ and $f_{d2}$ are the BRB frequencies, $s$ is the motor slip, and $f_s$ is the electrical supply frequency in Hertz [31].

The multi-resolution equations are described as follows:

$$q_i(n) = \sum_{j} h_{s}(j) a_{i-1}(n-j)$$

(7)

Figure 3. Flowchart of the combination of the proposed algorithms.
\[ a_i(n) = \sum_{j} l_p(j) a_{i-1}(n-j) \]  

(8)

where \( h_p \) and \( h_l \) are vectors of the (H–P–F) and (H–P–F), respectively, \( a_i \) and \( d_i \) are the approximation and detail at resolution \( i \), \( a_{i-1} \) is the approximation of the level above the level \( i \) and \( m \) is the vector length.

2.3. The proposed approach

The integral proposed algorithm for the localization and classification of BRB fault is described by the flowchart in Figure 3. The default localization consists of three main steps:

- Measurement of the current of a stator line \( I_s \).
- Extraction of the residual-current signal \( I_{res} \) from \( I_s \) using the new electrical-TSA algorithm.
- Analysis of \( I_{res} \) by the DWT method to determine the frequency bands of BRB defects.

The default classification consists of two steps:

- Calculation of the RMS value of 8th level detail of the residual current.
- The RMS and load at three levels are used as inputs to the fuzzy logic diagnostic tool to classify the severity of the rotor fault.

3. Experimental results & validation

3.1. Experiment platform

A three-phase induction motor, whose parameters are given in Table 2, is connected to the electrical grid of 230V/400V and 50 Hz. A layout of the laboratory setup adopted during the experiment for the detection of an incipient rotor bar fault is depicted in Figure 4-(a). The IM has 32 bars, each bar is 132 mm of length. The incipient failure was created by drilling a hole in one of the rotor bars. The IM rotor bars have a depth of 36 mm. Two rotor conditions are tested: a healthy case and an incipient BRB with a hole drilled 2 mm deep, as shown in Figure 4-(b) and 4-(c). Three motor load levels are also established to investigate their influence on the identification of incipient rotor bar failure. The stator current signal is measured through one current sensor LEM LT100-S and acquired using a data acquisition system based on a 16-bits analog-to-digital converter (DAQLAB, 200 kHz). The acquisition is done, with a sample rate of \( f_s = 25 \text{ 600 Hz} \). Thus, the total samples number per period of 50 Hz is 512. Finally, the speed value is measured through an optics tachometer.

3.2. Performances and comparison of DWT and DWT/ETSA method

The induction machine is tested in its healthy state to acquire the stator current. Afterward, the same experiment is repeated, but with an
Figure 5. The three higher levels of decomposition of stator current, no-load motor.

Figure 6. The three higher levels of decomposition of stator current, half-load motor.
incipient failure at only one rotor bar under no-loaded, half-loaded, and full-loaded induction motor.

In this work, DWT technique is considered for defect analysis. Among all the other diverse wavelet families, the Daubechies family with five vanishing moments as $db5$ is selected as the mother wavelet, with sampling frequency $f_s = 25600$ Hz and ten decomposition levels. Each level possesses its original detail coefficient and specified frequency band, as described in Table 3. The acquired stator signal $I_s$, the last approximation level $a10$, and the three higher levels of detail DWT signals $d10$, $d9$, and $d8$, from the healthy and defective cases, are presented in Figure 5 at the no-load motor, in Figure 6 at the half-load and Figure 7 at the full-load. Indeed, a comparison between the upper-level...
signals of DWT in defective and healthy rotor cases illustrates that the current signals have practically the same waveforms. Besides, the $9^{th}$ level \( d_9 \) presents a slight distinction between the considered cases, due to the supply frequency. This difference is further small to be notable in all three levels of motor load. Consequently, the application of this method directly to the captured stator current signal but one rotor bar damage. From the literature, several studies have elaborated the DWT technique to analyze the BRB defect. In [32] O. A. Mohammed et al. have used the DWT of the stator-current to diagnose one BRB defect of the induction motor. Jordi Cusidó et al. have used, in their work [33], DWT and PSD method to reveal BRBs faults in an induction motor. In [34] Nasreddine Lahouasnia et al. have demonstrated the identification of one BRB fault of an induction machine using the DWT analysis. In contrast to these studies, the problem of non-stationarity of the stator current is removed by the use of the discrete wavelet transform. Although this approach is effective, the incipient rotor defect cannot be detected specially for low values of slip. To overcome this problem, a new tool of conditioning the stator current signal is recommended to make a significant distinction between the case of a defect in its nascent stage and the healthy case.

Figure 9. The three higher levels of decomposition of residual current, half-load motor.

Figure 10. The three higher levels of decomposition of residual current, full-load motor.
The electrical-TSA algorithm is performed, with $K = 1000$ periods, each period contains $T_h = 512$ samples. Once again, the same DWT strategy of diagnosis is founded by an easy multi-level residual current decomposition in 10 levels. Figures 8, 9, and 10 represent the residual-current signal and the three higher-levels of the decomposed residual-current for both health and fault cases in the case of the motor at no-load, half-load, and full-load, respectively.

These obtained results attest distinctly that the waveforms of healthy and defective cases have not the same amplitude. Indeed, the differentiation between cases of the 8th and 9th detail-level is completely clear and detectable, especially at full load, as a consequence, the DWT method performed to the extracted residual stator current signal gives the green light to locate the frequency intervals of the fault.

From an energetic aspect, the consumed energy at each level of decomposition is calculated to find and prove the frequency bands containing the frequency of the defect [35]. Especially, for both faulty and healthy cases under motor at no-load, half-load, and full-load. For this purpose, the energy linked to each detail-signal of the stator and the residual stator currents is expressed as follows:

$$E_i = \sum_{n=1}^{N} |d_i(n)|^2$$

where $E_i$ is the energy of the detail level $i$, $d_i$ is the signal of the detail level, and $N$ is the sample number in $d_i$ signal. The time of observation is 1 s, the sampling frequency is 25.6 kHz, $i = 10$ levels and $N = 51200$ samples. The energy consumption corresponding to the stator current is widely used in the literature review, to detect one BRB and more, but was not used to diagnose a small defect in one BRB. In [36] Ahcène Bouzida et al, use the energetic calculation tool related to each level of

![Figure 11. The comparison of the total energy.](image1)

![Figure 12. The comparison of the residual energy.](image2)
decomposition to diagnose BRB. In [37, 38] the experimental outcomes show the effectiveness of the energy calculation of the wavelet for detection of one BRB and more. Contrary to these studies, the same energy calculation is used in this work, but no longer able to identify the incipient failure in one rotor bar. Figure 11 shows that the energies of the healthy and defective cases are approximately equal, Especially, at no and half loaded motor. Besides, the energy values of the 9th level are the most important. These high values are due to the frequency supply, which is equal to 50 Hz, included exactly in the d9 detail, as shown in Table 3. Figure 12 shows the residual energy results, in the case of no-loaded, half-loaded, and full-loaded motor, respectively. According to these figures, the residual energy consumption at the 8th and 9th levels, in the defective case, is larger than in the healthy state. Likewise, the values of the measured speed, in the healthy and defective cases for three load levels, as well as the values of slip and the defect frequencies calculated using Eqs. (5) and (6), are given in the following table.

The examination of rotor failing is difficult. For this reason, the RMS value of the residual current is calculated and used as a residual fault diagnostic index (RFDI) to illustrate the accuracy of the proposed combination of the TSA and DWT method for distinguishing between the case of a defect in its nascent stage and the healthy case. The RMS value is calculated using the following expression:

$$I_{\text{rms}, \text{d9}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} I_{\text{res}, \text{d9}}^2 (n)}$$  \hspace{1cm} (10)  

Figure 13 shows the RMS value of residual current corresponding to each wavelet level, in the case of no-loaded, half-loaded, and full-loaded motor, respectively.

The most predominant frequency component identified as the component that exists in the interval where the rms value of the signal is the highest. Consequently, the defect frequencies values \(f_{d1}\) and \(f_{d2}\) presented in Table 4 are respectively contained in the 8th [25–50] and 9th [50–100] detail levels. As a consequence, the ranges in which the defect frequencies present can be identified.

Finally, the RFDI authorizes an easy differentiation between defective and healthy case for a fixed load. Unless, it is no longer suitable to classify between an incipient and a large defect under variable load. To surmount the above limitation, a (FIS) Fuzzy inference system is performed.

### 3.3. Performances of the proposed method

The fuzzy inference system (FIS) designed for BRB classification is represented in Figure 14 [39,40]. The fuzzy method was accomplished using the Matlab fuzzy toolbox. This FIS is of Mamdani type, 2.0 version with minimum implication [41]. Indeed, the RMS value of the 8th level detail of the residual current and load at three levels are changed into a fuzzy variable, then consider as inputs of the FIS. Subsequently, by the fuzzy inference process, the failure of the motor rotor is classified and given as an output decision.

#### 3.3.1. Fuzzification

A membership function is created by observing the database values, the human knowledge about the defect rotor diagnosis of asynchronous
motors are ciphered as an ensemble of linguistic rule bases, to construct a learning base that contains rule base and an accurate database \[42, 43\]. Each membership function permits a value, as RMS value of the 8th level detail of the residual current and load at three levels (input), to be associated quantitatively to a linguistic variable considering the category of the rotor failure. The degree of membership for input variables is shown in Figures 15 and 16. Indeed, the shape of the membership function is classified using five linguistic variables for the first variable as: ‘Very Small’ (VS) ‘small’ (S) ‘means’ (M), ‘large’ (L) and ‘Very Large’ (VL), however, three linguistic variables for the second variable are classified as follows: ‘low-load’ (LL), ‘half-load’ (HL) and ‘full-load’ (FL).

The shapes of membership functions of the output condition monitoring are chosen as trapezoidal function, interprets the condition of the rotor, which have seven linguistic values ‘H’ (healthy rotor), ‘1BRB’ (incipient BRB defect), ‘+BRB’ (one BRB or more).

Figure 17 illustrates the CM output interval for each category. The triangular membership functions are chosen because they allow simple calculations that can be understood by researchers in the diagnostic domain. Gaussians can also be used, but are preferred when the rules are learned automatically.

3.3.2. Fuzzy logic rules

When each membership function shape has been fixed, the fuzzy rules are defined using “If-Then” conditions, “and” connection and a weight equal 1. The following rules cover all defective cases of this classification.

Rule (1): If (Ires-d8 is VS) and (Load is LL) then (CM is H).
Rule (2): If (Ires-d8 is S) and (Load is LL) then (CM is 1-BRB).
Rule (3): If (Ires-d8 is S) and (Load is HL) then (CM is H).
Rule (4): If (Ires-d8 is S) and (Load is FL) then (CM is H).
Rule (5): If (Ires-d8 is M) and (Load is HL) then (CM is 1-BRB).
Rule (6): If (Ires-d8 is L) and (Load is FL) then (CM is 1-BRB).
Rule (7): If (Ires-d8 is VL) and (Load is LL) then (CM is +BRB).
Rule (8): If (Ires-d8 is VL) and (Load is HL) then (CM is +BRB).
Rule (9): If (Ires-d8 is VL) and (Load is FL) then (CM is +BRB).

3.3.3. Defuzzification

The linguistic variables are converted into real values via the maximum aggregation and centroid defuzzification.

To prove the performance of the electrical-TSA/DWT method with fuzzy inference for early rotor fault diagnosis. Figure 18 shows the results of the fuzzy method for rotor failure diagnosis under several loads. This figure shows the surface viewer from the input variables and the output of the FLA using standard color map jet. As it can be deduced, the results promote the implementation of the proposed method. Consequently, the rotor failure is highlighted by a change in the output values of the FIS. Accordingly, the suggested strategy can classify a rotor fault with high accuracy. Advantages, disadvantages and limitations of the proposed CM system are listed in Table 5. Table 6 gives an overall comparison between the proposed strategy and other strategies developed in the literature since 2015.

![Figure 17](image1.png)

**Figure 17.** The membership functions for the output (CM).

| Proposed method | Advantages |
|-----------------|------------|
| DWT/ETSA and FLA | • Non-invasive, simple to implement and single-phase measurement is enough. • can be implemented to the inaccessible motors of the emerged pump and generators offshore wind turbine, unlike the techniques founded on the investigation of the signal obtained by the accelerometer, where direct access to the machine is compulsory. • Frequency resolution of the defect is more remarkable, especially, with no-loaded motor. • Gives the green light to locate the signature of the fault. • provides an information about the presence of an incipient fault. • Allows a good classification of the severity of defects. • Implementation in the factories producing electric motors as a successful tool for an early diagnosis of the IM machines. • The CM system is flexible and all the rules can be modified for every IM configuration. • The CM system is cheap to implement |
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|-----------------|------------|
| DWT/ETSA and FLA | • Non-invasive, simple to implement and single-phase measurement is enough. • can be implemented to the inaccessible motors of the emerged pump and generators offshore wind turbine, unlike the techniques founded on the investigation of the signal obtained by the accelerometer, where direct access to the machine is compulsory. • Frequency resolution of the defect is more remarkable, especially, with no-loaded motor. • Gives the green light to locate the signature of the fault. • provides an information about the presence of an incipient fault. • Allows a good classification of the severity of defects. • Implementation in the factories producing electric motors as a successful tool for an early diagnosis of the IM machines. • The CM system is flexible and all the rules can be modified for every IM configuration. • The CM system is cheap to implement |

![Figure 18](image2.png)

**Figure 18.** Effect of residual current and load variations on the condition monitoring via three-dimensional FLA.
Table 6. Comparison between the proposed technique and other techniques presented in the literature.

| Work (years) | Applied Method/Approach | Operating condition | Validation | Load % | Level defect |
|--------------|-------------------------|---------------------|------------|--------|-------------|
| 2015 [17]    | Empirical Mode Decomposition (EMD) and MCSA | Steady-state | Experimental | 50 and 75 | Incipient BRB (Half BRB) |
| 2016 [18]    | MUSIC and MCSA | Steady-state | Experimental | Light load | Incipient BRB (Half BRB) |
| 2017 [19]    | HT and estimation of statistical parameters | Startup-transient | Experimental | 0 and 100 | Incipient BRB (Half BRB) |
| 2017 [20]    | Homogeneity | Startup-transient | Simulation | Quarter load | Incipient BRB (Half BRB) |
| 2017 [21]    | MUSIC for frequency location  
- FFT for severity estimation | Steady-state | Experimental | 50 and 100 | Incipient BRB (9 mm) |
| 2018 [22]    | MUSIC and MCSA | Steady-state | Experimental | 5,10, 20, 30, 50 and 75 | Incipient BRB (Half BRB) |
| 2018 [24]    | random forest (RF) classifier | Steady-state | Experimental | Medium and high | Incipient BRB (4.2 mm and 9.4 mm) |
| 2019 [44]    | MCSA is used for fault extraction.  
- Neural Networks (NN) is used for classification | Steady-state | Experimental | 50 and 75 | Incipient BRB (5 mm and 10 mm) |
| 2020 [45]    | Short Time Fourier Transform (STFT) is employed to transform the measured signals to images.  
- A Convolutional Neural Networks (CNN) is used as features classifier | Startup-transient | Experimental | - | Incipient BRB (5 mm) |
| 2021 [46]    | The combined ETS/A/MCSA method is used for fault extraction  
- FLA is used for classification | Steady-state | Experimental | 0, 50 and 100 | Three levels of Incipient BRB |
| Proposed work | The combined DWT/ETSA method is used for fault extraction  
- FLA is used for classification | Steady-state | Experimental | 0, 50 and 100 | Incipient BRB fault (2 mm) |

4. Conclusion

In this article, a new experimental stator line current-based incipient failure diagnosis technique for the induction motor is proposed. There are six crucial aspects of elaborating the determination and the classification, which are as follows:

1) Extract the stator current to be supervised with data acquisition in the laboratory.
2) Create the defect in the rotor to be detected and classified with an intelligent system. invalidity
3) Show the weakness of the DWT applied to stator line current to extract the existence of the defect which happens in the rotor bars.
4) Locate the interval in which the rotor defect frequency exists using the combined DWT-ETSA method.
5) Validate the combined DWT-ETSA method according to an energetic viewpoint.
6) Classify between healthy rotor bars, incipient failure at one broken bar, and one or more than broken bar using the proposed algorithm composed by combining the ETS/A, DWT, and Fuzzy logic.

The experimental results attested that the residual current analysis performed by the proposed method permits a seriousness identification and evaluation of incipient rotor faults. This method can be implemented in the factories producing electric motors as a successful tool for an early diagnosis of the induction machine rotor. In the industrial sector, the proposed intelligent system can be implemented on inaccessible motors such as pumps in tanks and large generators in offshore wind turbines, unlike techniques based on the study of the signal obtained by the accelerometer, where direct access to the machine is required. Hence the opportunity to focus on this simple and cheaper diagnostic system that requires a one current probe, a data acquisition card connected to a computer.

Declarations

Author contribution statement

Mohammed Ouassaid, Nabil Ngote: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.
Hamza Sabir: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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