Intelligent nonmodel-based fault diagnosis of electric motors using current signature analysis

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Abstract. This paper proposes an efficient technique for detecting mechanical faults in three-phase induction motors, without using mechanical sensors. Only measurements of the currents of every phase are used to identify the fault. The proposed system can diagnose two types of faults corresponding to shaft misalignment or imbalance, along with normal operation. The power spectrum of the experimental data is generated, followed by applying a soft-computing mathematical algorithm that will extract the peaks of the fundamental frequencies and their harmonics, while filtering out noise. Carefully selected peaks at certain frequencies will be collected and examined to generate a robust algorithm that can be used to produce a decision regarding the operating condition of the motor, via applying an intelligent soft-computing technique. Mathematical details regarding the consistency checks for validating the experimental data, and the testing/validation phases will be investigated. Detailed analysis of the obtained results is provided to highlight the advantages and limitations of the proposed algorithm. In addition, a comparison is made with similar techniques that use mechanical sensors to contrast their differences and highlight the superiority of the proposed system. The obtained results prove the intelligence and robustness of the proposed system and allow for versatile extensions that promote its application in real-time scenarios for many industrial applications.

1. Introduction and Literature Survey
Designing controllers for nonlinear systems has always been a challenging task, especially for Electric machines are widely used in process and energy industries; therefore, it is extremely important to keep them healthy and protected to avoid any major breakdown, which could possibly lead to losses in different forms [1]. Usually, operators of the maintenance departments are under continuous pressure to reduce maintenance costs and to prevent unscheduled shut downs that result in decrease of production and financial loss. To minimize those unforeseen shut downs, the operators should be provided with a monitoring system which will enable them to use online condition-based maintenance strategies, which can be used in parallel with the conventional planned maintenance schedules.

Accumulated electrical, magnetic, mechanical, thermal and/or environmental stresses, during different operating conditions, might lead to internal faults. Currently, there are no reliable non-invasive tools available for the early diagnoses of internal faults. Hence, these internal faults are likely to be left undetected, leading to various types of unexpected malfunctions. This results in the need for unscheduled maintenance, process shutdown, and huge financial losses in many industries. Thus, early detection of internal faults helps to save valuable resources by avoiding process shutdown/repair of electric machines. Recently, many researchers are investigating reliable non-invasive condition monitoring
techniques, especially for three phase squirrel cage induction motors [2]. There are several condition monitoring techniques, e.g. vibration and thermal monitoring. However, those monitoring techniques require sensors, which might be expensive and need invasive modification on the system.

Mechanical faults represent the major type of faults, found in electrical machines. In induction motors, this is usually due to movement of stator coil and rotor striking the stator [3]. Coil movement, which is mainly due to the forces that are proportional to the square of the current [4], may loosen the top sticks. This has the effect of causing damage to the copper conductor and its insulation. A common fault is when a rotor strikes the stator, due to rotor-to-stator misalignment, shaft deflection, or due to bearing failure. For such case, the striking force might cause the stator laminations to puncture the coil insulation resulting in coil-to-ground faults. Moreover, high mechanical vibrations may disconnect the stator winding, producing an open-circuit fault [5]. Faults under these categories may be further classification into broken rotor bar, mass unbalance, air gap eccentricity, bearing damage, rotor winding failure and stator winding failure. In this research proposal, detecting the most common mechanical faults will be investigated, while developing an intelligent diagnostic system that will mainly depend on artificial intelligence (AI) techniques. Both offline and online (real-time) techniques will be investigated.

The rest of this paper is organized as follows. Section 2 addresses the need to detect mechanical faults for motors to avoid their potential damages. The experimental setup of the proposed design is illustrated in Section 2.1, while the detailed design, testing and validation steps are covered in Section 2.2. Section 3 summarizes the obtained results and provides a comprehensive conclusion regarding the findings of the current study, in addition to recommendations for improvements and extensions.

2. Motivation and Problem Statement

Misalignment and unbalance are some of the most common mechanical faults that occur in induction machines. Faults in induction motors can be classified into two types, either electrical or mechanical faults, as illustrated in figure 1. Mechanical faults include air gap eccentricity, bearing faults, load faults, etc. On the other hand, electrical faults include those that are caused by winding insulation problems and rotor faults. Mechanical faults are the main focus of this research proposal, as they are responsible for more than 95% of all failures [6].

![Figure 1. Different types of faults of induction motors.](image)

Misalignment is one of the major failures of rotating machines, as it can decrease the efficiency. On the long-run, it causes a catastrophic failure because of excessive stress on motor and bearings and short-circuiting in stator and rotor windings. When misalignment happens in a motor, it usually combines both types of misalignment; offset and angular misalignment. Offset misalignment also known as parallel misalignment is the amount by which the alignment of the driver and the driven shaft are
out of parallel alignment. On the other hand, angular misalignment is the amount by which the alignment of the driver and the driven shaft are out of angular alignment [6]. Figure 2 illustrates some typical examples of the side view of both parallel and angular misalignments, in either the horizontal or the vertical directions, in (a) and (b), respectively.

Figure 2. Different types of misalignments.

Shaft misalignment has a great effect on the reliability of rotating machines. Although, several alignment techniques have been successfully applied on a wide range of machines for some time, the deterioration of the alignment state can continuously happen due to changes in the machine operating conditions. As a result, extensive forces can be imposed on the equipment rotating and static elements, thereby causing coupling or bearing failure.

Rotor or load imbalance is the main cause of vibration in a rotating machine. In real life, rotors can never be perfectly balanced due to manufacturing errors such as non-uniform density of materials and gain or loss of material during operation. Mass imbalance leads to the generation of a centrifugal force, which must be avoided by the use of bearings and support structures [7]. Rotor balancing is essential for all types of rotating machines for smooth machine operation. In an industrial unit, this is achieved on a balancing machine at a precision level determined by motor speed, size, and vibration requirements. Rotor balancing involves the entire rotor structure, which consists of several parts, including the shaft, rotor laminations, end heads, rotor bars, end connectors, retaining rings, and fans. The design and manufacture of these components must be controlled for achieving stable precision balance [7].
Rotor imbalance generates reaction force in the coupling, which is often a major cause of vibration in machinery [8]. Furthermore, there are several types of imbalance in rotating machines, mainly; static, coupled, quasi-static, and dynamic imbalances. Static imbalance is defined as the eccentricity relative to the center of gravity of a disk, caused by a point mass at a certain radial distance from the rotation center, as shown in figure 3. A mass-equal value, set at an angle of 180° with respect to the imbalance-causing point mass at the same radial distance, is required to restore the center of gravity to the center of rotation. Static balancing involves first resolving the forces in a plane and adding a correction mass in the same plane. Rotating parts that have many masses concentrated in only one plane can be treated as static balancing problems [9].

The proposed research will focus on detecting the major two types of vibrations that are generated by mechanical faults; namely, shaft misalignment and static imbalance in rotors. It is mainly aimed at three phase induction motors, as they are widely used in electrical drive systems and typically consume 40 to 50 percent of an industrialized nation's total generating capacity. The following sections illustrate the design methodology, along with the generated results.

2.1. The Proposed Design

The methodology and layout of the proposed research can be summarized in the following points:

1. Deciding on the measurable variables to be used to conduct the collection of data. Motor Current Signature Analysis (MCSA) technique will be used as a starting point [10-14].
2. Installing the experimental setup, and collecting data, as shown in figure 4.

3. Signal conditioning of data to remove noise and to present it using both time and frequency domains.
4. Performing a consistency check to validate the obtained data and to decide on their accuracy in order to diagnose the correct fault.
5. Building the intelligent pattern recognition system, using soft-computing, while employing an optimized MATLAB code.
6. Testing and evaluating the suggested technique.
2.2. Analysis of the Experimental Results:
In this section, consistency analysis for the experimental data is carried out, where power spectrums of the individual phase currents are calculated, for three different runs, while extracting the peaks for the fundamental frequencies to be used in the subsequent design phase.

![Power spectrums of the phase currents, along with their peak values – healthy condition.](image)

Figure 5. Power spectrums of the phase currents, along with their peak values – healthy condition.
Figure 5 shows the individual power spectrums of the healthy operating condition, for the currents of phases 1, 2, and 3, in (a), (c), and (e), respectively. The motor was running at a nominal speed of 1500 RPM, corresponding to 25 Hz at no load. Consequently, the corresponding individual peaks at multiples of 25 Hz, were recorded in (b), (d), and (f), respectively. The measurements were made at 1,024 samples/s (approximately 1 kHz).

When observing the data of the healthy operating conditions, it is expected to find peaks at the fundamental frequency of 25 Hz, and its harmonics. Masking off the power spectrum at the remaining frequencies, in the range from 0 to 500 Hz, was utilized to put more emphasis on the collected peaks [15]. The frequency range was limited to 500 Hz, which is almost half the data sampling rate to avoid obtaining redundant results. A duration of 10 seconds was used to obtain the data of the three runs for the currents of the individual phases. All testing was done at a steady temperature to rule out its effect on the operating condition. In addition, different durations of 20, 30, 40, 50, and 60 seconds were tried, and it was found out that a similar effect was obtained; hence, it was decided to use only 10 seconds for collecting the data, resulting in 10,240 samples for each phase current. Figure 6 illustrate the mask used to extract the peaks of the power spectrums, for each phase current, while equation (1) depicts the calculation of the normalized power spectrums.

\[
P_n(\omega) = \log_{10}(\max(P(\omega) \times M(\omega)))
\]  

where \(P(\omega)\) is the power spectrum and \(M(\omega)\) is the mask, illustrated in figure 6.

To ensure robustness of the obtained results, data with high standard deviation could be removed, while keeping only those with very low standard deviation that reflect high repeatability. This is quite obvious in figure 5-b, 5-d, and 5-f for the recorded data at the frequencies 50 Hz, 150 Hz, 250 Hz, and 350 Hz. A threshold of approximately –1.5 could be used to separate the required data, from the rejected ones. In addition, the obtained results were very close and independent of which phase was used to record the current. Equations (2), (3), and (4) show the obtained data, as vectors, for each phase.

\[
f_1 = \begin{bmatrix} 50 \\ 150 \\ 250 \\ 350 \end{bmatrix}, \quad P_n(50) = \begin{bmatrix} 3.4482 \\ 3.4456 \\ 3.4437 \end{bmatrix}, \quad P_s(150) = \begin{bmatrix} -0.1907 \\ -0.1861 \\ -0.2274 \end{bmatrix}, \quad P_s(250) = \begin{bmatrix} +0.2298 \\ +0.1687 \\ +0.1706 \end{bmatrix}, \quad P_s(350) = \begin{bmatrix} -1.3762 \\ -1.2930 \\ -1.3607 \end{bmatrix}
\]  

(2)

\[
f_2 = \begin{bmatrix} 50 \\ 150 \\ 250 \\ 350 \end{bmatrix}, \quad P_n(50) = \begin{bmatrix} 3.4156 \\ 3.4136 \\ 3.4128 \end{bmatrix}, \quad P_s(150) = \begin{bmatrix} -0.7675 \\ -0.7180 \\ -0.7874 \end{bmatrix}, \quad P_s(250) = \begin{bmatrix} +0.0808 \\ +0.0224 \\ +0.0283 \end{bmatrix}, \quad P_s(350) = \begin{bmatrix} -1.2768 \\ -1.1991 \\ -1.3327 \end{bmatrix}
\]  

(3)

\[
f_3 = \begin{bmatrix} 50 \\ 150 \\ 250 \\ 350 \end{bmatrix}, \quad P_n(50) = \begin{bmatrix} 3.4456 \\ 3.4418 \\ 3.4412 \end{bmatrix}, \quad P_s(150) = \begin{bmatrix} -0.3690 \\ -0.3353 \\ -0.4028 \end{bmatrix}, \quad P_s(250) = \begin{bmatrix} +0.0171 \\ -0.0303 \\ -0.0338 \end{bmatrix}, \quad P_s(350) = \begin{bmatrix} -1.6780 \\ -1.4820 \\ -1.7241 \end{bmatrix}
\]  

(4)
Figures 7 and 8 show the individual power spectrums and their normalized peaks, for the two faults that corresponds to the imbalance and the misalignment conditions, respectively. For consistency, the rotating speed and the data sampling rate were made equivalent to the normal no load healthy operating condition.

**Figure 7.** Power spectrums of the phase currents, along with their peak values – imbalance condition.
Examining the data of the imbalance fault, in figure 7, reveals that almost the same thresholding is still valid, with the introduction of two more peaks at 25 Hz and 75 Hz. A similar scenario is obtained for the misalignment fault, in figure 8, as another peak is introduced at 100 Hz.

Figure 8. Power spectrums of the phase currents, along with their peak values – misalignment condition.
2.3. Intelligent Diagnostic Methodology:
Assuming it is required to diagnose the nature of the mechanical fault, and differentiating it from the normal healthy operating conditions, only the normalized power spectrums of the frequencies 25 Hz, 50 Hz, 75 Hz, 100 Hz, 150 Hz, 250 Hz, and 350 Hz need to be examined. The following lookup tables can be used for such purpose:

Table 1. Average normalized power spectrums at the seven most important frequencies – Phase 1.

| f  | Average $P_n(\omega)$ of the condition | Comments                                      |
|----|----------------------------------------|-----------------------------------------------|
|    | Healthy | Imbalance | Misalignment |                                      |
| 25 | -1.7817 | -0.3649 | -1.7533 | Only imbalance is above the threshold |
| 50 | +3.4458 | +3.4243 | +3.4352 | All are almost the same                |
| 75 | -1.9739 | -0.2027 | -1.6609 | Only imbalance is above the threshold  |
| 100| -2.3201 | -2.1433 | -1.4318 | Only misalignment is close to the threshold |
| 150| -0.2014 | -0.2447 | -0.2403 |                                      |
| 250| +0.1897 | +0.1777 | +0.1946 |                                      |
| 350| -1.3433 | -1.1831 | -1.3296 |                                      |

Table 2. Average normalized power spectrums at the seven most important frequencies – Phase 2.

| f  | Average $P_n(\omega)$ of the condition | Comments                                      |
|----|----------------------------------------|-----------------------------------------------|
|    | Healthy | Imbalance | Misalignment |                                      |
| 25 | -1.9731 | -0.3345 | -1.7319 | Only imbalance is above the threshold |
| 50 | +3.4140 | +3.3907 | +3.4081 | All are almost the same                |
| 75 | -1.8705 | -0.1742 | -1.7260 | Only imbalance is above the threshold  |
| 100| -2.4952 | -1.7969 | -1.5251 | Only misalignment is close to the threshold |
| 150| -0.7576 | -0.7906 | -0.8209 |                                      |
| 250| +0.0438 | +0.0257 | +0.0307 |                                      |
| 350| -1.2695 | -1.1152 | -1.2858 |                                      |

Table 3. Average normalized power spectrums at the seven most important frequencies – Phase 3.

| f  | Average $P_n(\omega)$ of the condition | Comments                                      |
|----|----------------------------------------|-----------------------------------------------|
|    | Healthy | Imbalance | Misalignment |                                      |
| 25 | -1.8186 | -0.3432 | -1.8940 | Only imbalance is above the threshold |
| 50 | +3.4429 | +3.4144 | +3.4392 | All are almost the same                |
| 75 | -1.9273 | -0.1966 | -1.7065 | Only imbalance is above the threshold  |
| 100| -2.3520 | -2.0365 | -1.5301 | Only misalignment is close to the threshold |
| 150| -0.3690 | -0.3714 | -0.3481 |                                      |
| 250| -0.0157 | -0.0316 | -0.0044 |                                      |
| 350| -1.6280 | -1.4714 | -1.6721 |                                      |

Careful adjustment of the threshold level of the normalized power spectrums results in simplifying the process of the fault diagnosis. Tables 1, 2, and 3 could be further combined into Table 4, where the imbalance and the misalignment conditions can be checked at 25/75 Hz, and 100 Hz, respectively.

Table 4. Simplified diagnostic table.

| f  | Average $P_n(\omega)$ of the condition |
|----|----------------------------------------|
|    | Healthy | Imbalance | Misalignment |
| 25 |         |           |              |
| 75 |         |           |              |
| 100|         |           |              |
Thus, with references to Tables 1, 2, 3, and 4, the following pseudocode can be used to implement an intelligent diagnostic mechanism:

begin
  set threshold of the normalized power spectrum to \( P_{n,th} = -1.5 \);
  calculate average values \( P_{n,avg} \) for all phase currents;
  if \( \text{AND} \{ (P_{n,avg} < P_{n,th})_{f=25} , (P_{n,avg} < P_{n,th})_{f=75} , (P_{n,avg} < P_{n,th})_{f=100} \} == \text{TRUE} \)
    then: operation is healthy;
  else if \( \text{AND} \{ (P_{n,avg} < P_{n,th})_{f=25} , (P_{n,avg} < P_{n,th})_{f=75} , (P_{n,avg} > P_{n,th})_{f=100} \} == \text{TRUE} \)
    then: operation has an imbalance fault;
  else if \( \text{AND} \{ (P_{n,avg} > P_{n,th})_{f=25} , (P_{n,avg} < P_{n,th})_{f=75} , (P_{n,avg} < P_{n,th})_{f=100} \} == \text{TRUE} \)
    then: operation has a misalignment fault;
  else repeat the test (inconsistent data);
end;

Figure 9. Pseudocode of the proposed algorithm.

which could be implemented using any soft computing technique. This technique was applied to a total of 30 different runs, 10 for each case, with a 100% correct diagnosis.

3. Discussion and conclusion

Diagnosis of possible mechanical faults was investigated in this paper. The proposed technique was applied to a three-phase squirrel-cage AC induction motor, rated at 5 A, 380 V, 50 Hz, 2.2 kW, and running at 1500 RPM. Three current transformers were used to measure the individual currents for each phase. Temperature effects were eliminated to ensure consistency of the obtained experimental data and to promote its accuracy. The main goal of the research was to investigate the effect of the mechanical faults, using only electrical sensors, without the need to directly monitor vibrations. This should simply the proposed design and make more efficient in terms of cost and reliability.

The experimentally obtained data can form the core of any AI-based technique that can be used to automate the diagnosis process. The pseudocode in figure 9 could be effectively replaced by an artificial neural network (ANN) that applies automatic pattern recognition to detect the symptoms that correspond to each mechanical fault. The inputs to the ANN could be the vector representation of the most important and consistent peaks of the normalized power spectrum and the output could simply be the condition of the operation. This is a suggested extension to this paper, which matches similar work in the literature of this field. In addition, the layout of the pseudocode lends itself to Fuzzy-based inference, where rule-based functions are usually utilized to arrive at a certain decision. Moreover, a genetic-based algorithm can prove useful to generate more generalized results, especially when the motor is operating under different conditions. Only MATLAB was used to implement the suggested technique, using an offline approach. Other techniques can be used to report the motor status in real-time, using MATLAB/Simulink [13], LabVIEW [14], and FPGAs, which is added advantages [16], especially for continuous operation modes and/or the motor is part of a SCADA system [17].

Without loss of generality only no-load condition was tested; it is recommended to investigate the effect of applying different loading conditions on the performance of the proposed technique and to monitor newly introduced peaks, if any, to include them in the soft-computing algorithm.

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