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Comprehensive Motor Condition Monitoring Integrated in Advanced Protection Relays – A real case study

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SUMMARY

Rotating machines are widely used in almost all industries as a critical component for process availability. Inadvertent failure of rotating machines causes high repair expenses and loss of revenue. These undetectable faults can belong to electrical, thermal or mechanical failures, e.g. broken rotor bar, bearing, stator inter-turn, foundation looseness, shaft misalignment, and static\dynamic eccentricity. Early detection of these failures requires online\offline monitoring and diagnostic (M&D) equipment, additional sensors, wiring and installation.

This paper proposes a new autonomous electrical signature analysis (AESA) based M&D technique. The proposed technique provides earlier detection of failures such as bearing, stator inter-turn, foundation looseness, shaft misalignment and static\dynamic eccentricity. To verify the proper working and performance of the proposed method, various tests were performed on the actual 1000 HP and 300 HP motors with mechanical faults in a machine repair shop. Performance of the proposed method was further validated using commercial motor current signature analysis (MCSA) based M&D equipment.

Moreover, extensive testing of the proposed method was performed on four motors installed in an iron ore pellet plant. These motors drive fan loads rated between 3750 to 5000HP, which are crucial equipment in a pelletizing process. Each production line produces 600 tons iron per hour having market value of 50 USD/ton. Disruption of the process due to an inadvertent mechanical failure on any of these motors can result a downtime of up to 30 hours for each production line, resulting into revenue loss of approx. one million USD plus high maintenance, repair and/or replacement costs.

KEYWORDS

AC machines, Electric Motors, Fault diagnosis, Induction motors, Preventive maintenance, Power system protection, Power systems Protective relaying, Signal processing

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1. INTRODUCTION

Motors, widely known as the industry backbone, play a key role in running industrial processes. While industrial processes consume the largest part of the total electricity, motors alone consume 45 percent of the total [1]. Any disturbance resulting in disruption of the process can cost multi-million dollars in loss of revenue as well as maintenance costs. According to the 1999-2012 Equipment Breakdown Structure (EBS) report published by the Electric Power Research Institute (EPRI), 80 percent of the total outages in processing plant are unplanned. Various motor reliability surveys and reports [2]-[6] itemize the specific failure modes of electrical machines. Fig. 1, summarizes the major motor failure causes, with 53 percent of the failures being mechanical: 41% bearings, 12% balance and mis-alignment, while 47 % are electrical failures: 37% winding and 10% rotor.

To prevent motors from these failures, various maintenance strategies are adopted by the industry. Three commonly used approaches are reactive, preventive and proactive maintenance. A fault that remains undetected leads to partial or complete damage to the machine therefore, resulting in unscheduled outage. In the reactive approach, after a failure caused damage, the machine is repaired or replaced during an unscheduled outage. This approach is not acceptable in critical industrial processes. In the preventive approach, the machine is inspected during a planned or scheduled outage time and is repaired, if required. This approach helps in detecting failures at an early stage. The disadvantage of this approach is the requirement for expensive test equipment or third-party services to test and diagnose possible failures. Moreover, fault detection remains dependent on the scheduled outage time, causing latency in early detection of the fault before it evolves into a complete failure.

The proactive approach, on the other hand, resolves the issue of outage time dependency by continuously monitoring the machine while it is online. Online monitoring also helps in early detection of faults and therefore, allows time to plan a maintenance strategy if required. However, proactive approach of continuous monitoring has to be autonomous – such that anomaly in a motor is detected without human intervention. This requires detection techniques to be more secure to avoid any false alarms. The proactive approach can help to achieve additional value in the following areas:

- Preventive Maintenance (PM) or Condition Based Maintenance (CBM);
- Asset Performance Management (APM);
- Risk mitigation by asset level visibility and Risk Assessment (RA);
- Root Cause Analysis (RCA) or post-event analysis
- Early-Warning or Alarming to schedule maintenance and outage
- Reduce process loss (outage time) to limit loss of revenue
- Reduce cost and time of motor repair

This paper proposes an autonomous electrical signature analysis (AESA) technique which helps to detect mechanical anomalies earlier to take preventive or condition-based maintenance approach. To achieve autonomous M&D, various novel security mechanisms are proposed for the conventional Machine Current Signature Analysis (MCSA). The algorithm test results from the 1000 HP motors performed in a motor repair shops are presented with various scenarios.

2. CONVENTIONAL METHODS OF DETECTING OF MOTOR MECHANICAL FAULTS

A. Mechanical Vibration Analysis

Mechanical vibration-based analysis to detect motor mechanical faults has been in use for more than 70 years, with abnormal vibrations the initial sign of a likely mechanical fault. Faults such as load and shaft misalignment, foundation looseness, dynamic or static eccentricity, bearing damage, or broken rotor bar are the major sources causing these vibrations. Vibration analysis allows earlier detection of these faults and so action can be taken before they evolve into full-fledged failures and resulting in machine damage.

Conventionally, vibration frequency spectrum is analyzed using Fast Fourier Transform (FFT) to capture the magnitude of the fault frequencies at multiples of the rotating speed or corresponding frequency. Broken rotor bar, for instance, usually shows up in the close vicinity of the operating speed or frequency. Other mechanical faults such as a bent shaft, bad coupling, or oversized bearing housing normally appear at twice the motor speed [7].

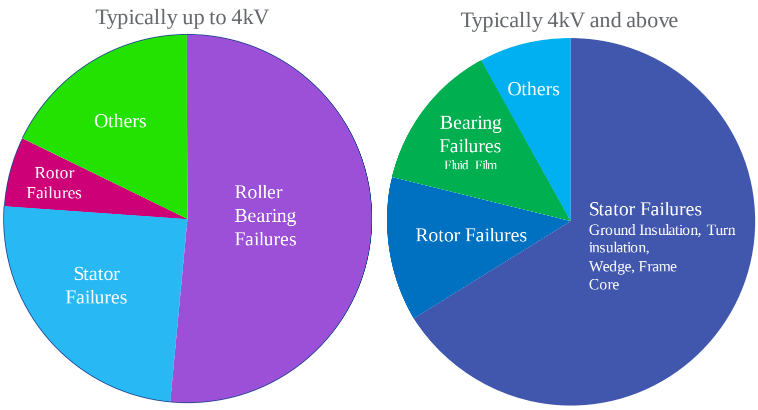


Fig. 1. Electric machine failures [2], [3]

B. Motor Current Signature Analysis

Motor Current Signature Analysis (MCSA) or Electric Signature Analysis (ESA), is used to detect various failure modes in a rotating machine by analyzing the stator current signal. The mechanisms surrounding MCSA have been in commercial use for over three decades, however, the technology can be applied in new ways for easier detection of faults that challenge other technologies such as vibration analysis, and for enhancing maintenance and troubleshooting programs. The MCSA-based method is commercially used to detect mechanical failure such as broken rotor bar, static and dynamic airgap eccentricity, stator inter-turn, bearing damage, and shaft misalignment [9]. MCSA systems rely upon FFT analysis, much like vibration analysis, to determine the fault frequencies.

The following sections explain the formulations used to determine the fault frequencies of various faults.

1) Bearing Faults

A fault or defect in the bearing generates predictable frequencies in the current signal. Current frequencies related to bearing damage are computed using the following equation [8]:

$$F_{bearing}(k) = F_{Supply} \pm k \times F_{vib} \tag{1}$$

where k is the integer multiple of the vibration frequency, F_{supply} is the actual source supply frequency, and F_{vib} is the calculated vibration frequencies obtained from (2). Each part of bearing has its associate vibration frequency [8]

$$F_{bearing} = \begin{cases} \frac{N_b}{2}\frac{W_r}{60}\left(1-\frac{D_b}{D_c}\right) & inner\ circle \\ \frac{N_b}{2}\frac{W_r}{60}\left(1+\frac{D_b}{D_c}\right) & outer\ circle \\ \frac{D_c}{D_b}\frac{W_r}{60}\left(1-\frac{D_b}{D_c}\right) & ball\ damage \end{cases} \tag{2}$$

where D_b is the rolling element ball diameter, D_c is the cage diameter, N_b is number of rolling elements, and w_r is the motor speed in rpm, as shown in Fig. 2.

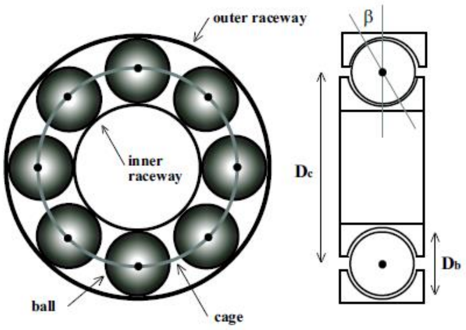


Fig. 2. Bearing geometry

2) Mechanical Faults

Although foundation looseness, eccentricity and mis-alignment are markedly different mechanical fault conditions in a rotating machine, they can be identified from the same set of stator current frequencies related to eccentricity damage.

The fault frequencies associated with these faults are computed using equation (3) as follows:

$$F_{FEM}(k) = F_{Supply} \times \left(1 \pm \frac{2 \times k \times (1-s)}{P}\right) \tag{3}$$

where k is the integer multiple of the vibration frequency, s is the slip, P is no of poles and F_{supply} is actual source supply frequency.

3) Stator Inter-turn Faults

Stator intern-turn faults frequencies can be determined from the following relations:

$$F_{Stator\_mechanical} = CF \pm F_{Supply} \tag{4}$$

$$F_{Stator\_electrical} = CF \pm F_{Supply} \pm RPS \tag{5}$$

where

Center frequency, *CF = RPS x Number of Stator Slots*

and Rotational frequency, *RPS = Motor RPM/*F_{supply}

3. PROPOSED AESA-BASED METHOD

Existing MCSA-based tools successfully determine fault frequencies and their corresponding magnitude; however, they require an expert to analyze the data manually to diagnose the possible failure. Thus, these tools are not autonomous in functionality. Like existing MCSA-based methods, the proposed AESA-based method properly monitors the current signature to extract fault frequencies and calculate the corresponding magnitude. In addition to monitoring, the proposed algorithm securely and reliably diagnoses the failure, so that is no need to involve an expert for diagnosis.

The proposed method offers AESA-based technique to detect various failure modes in a rotating machine and its assembly by analyzing the stator phase A current. This method provides detection of motor failures such as stator inter-turn fault, roller/ball bearing fault, and mechanical faults like foundation looseness, load shaft misalignment, static and dynamic eccentricity. The proposed method doesn't require additional measurements such as noise, vibration, or temperature.

The algorithm uses FFT computation of the Phase A current signal to determine fault frequencies related to the corresponding fault condition. Fault frequencies are determined using the relations (1)–(5), as described in section II-B. For simplification purpose and since amplitude of the fault frequency is more significant at lower k integer values, the algorithm only considers k = 1, 2 and 3.

The algorithm computes thirty fault frequencies: eighteen bearing fault frequencies, six mechanical fault frequencies and six stator inter-turn fault frequencies. Among these eighteen bearing fault frequencies, each bearing part (ball, inner-, and outer-race) has six associated fault frequencies.

The algorithm also computes peak magnitude and energy in dB for each fault frequency and calculates the change in dB magnitude with respect to the baseline peak magnitudes (the healthy mode of the motor without misalignment) and energy at the corresponding fault frequency with respect to each load operating zone or load bin.

Load Bin, Baseline Mode, and Monitoring Mode mechanisms are described in more details in the following sections.

A. Load Bin Mechanism

The magnitude of the fault frequency is impacted by the motor loading and therefore the magnitude (dB) changes as the motor load changes. The proposed algorithm handles the load changing condition by using a load bin mechanism. A load bin is defined as the load interval of 10% within the 0% to 120% range of motor load operation, with a total of 12 load bins, as shown in Fig. 3.

During AESA baseline mode operation, peak and energy dBs are computed and averaged over the entire configured period and then stored as averaged normalized dB with respect to each load bin of the motor.

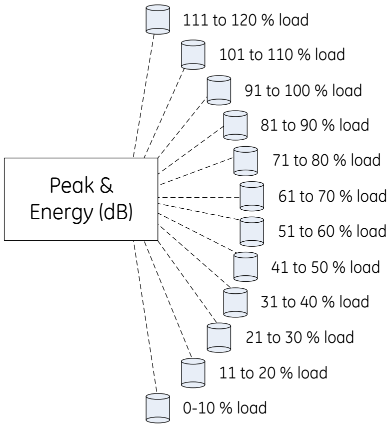


Fig. 3. Allocation of Peak & Energy dB values with respect to Load Bin during Baseline Mode Motors under test

B. Baseline/Learned Mechanism

For an ideal motor having no bearing, mechanical or stator faults, the dB magnitude of any fault frequency corresponding to load bin is ideally -100dB, meaning that the magnitude of fault frequency is zero. However, in practice this may not be the case since a motor without any faults may still generate some or all fault frequencies at low dB levels. The algorithm establishes the baseline dB of the inherent fault frequencies for all possible load bins during the settable baseline period or learning phase.

C. Monitoring Mechanism

In monitoring mode, the AESA algorithm runs FFT on phase A current samples to capture the peak magnitude and energy for each possible harmonic factor ($k = 1,2,3$) related to the bearing, mechanical and stator faults. Computed AESA dB magnitudes at all fault frequencies after each 1 minute interval are compared with baseline magnitudes to extract the maximum change in dB. For secure operation of the fault declaration algorithm, data quality checks and AESA accuracy checks are performed prior to recording data.

D. Robust Data Quality Check

Before computing the FFT of the current signal, a quality check of the input supply data is performed by the AESA algorithm. If any of the following data checks fail, AESA does not perform the FFT or data recording.

- Fundamental frequency measured must be within +/- 5% limits of the nominal frequency.
- Voltage measured must be within +/- 10 % limits of the nominal voltage.
- THD (total harmonic distortion) of the phase current must be less than 5%.
- ROCOF (rate of change of frequency) computed must be less than 5%.
- Current unbalance in the system computed must be less than 10%.

E. High-Level Architecture of the Proposed AESA Algorithm

This section provides a by step high-level architecture, as shown in Fig. 4, and procedure for the proposed AESA-based algorithm.

Step 1. Measure the current signal from the Phase A current transformer (CT)

Step 2. Perform a data quality check to assess the input power supply condition and then sample for processing.

Step 3. Compute rotor speed and slip and supply frequency.

Step 4. Compute fault frequencies for all fault types using relations (1)-(5).

Step 5. Compute normalized dB magnitudes at fault frequencies w.r.t measured supply fundamental frequency.

Magnitude in dB can be calculated as:

$$dB = 20 \times \log_{10} \frac{X1}{Xf} \tag{6}$$

where X_1 and X_f are the magnitudes at fault frequency f_1 and fundamental frequency f_s, respectively.

Step 6. Compute peak magnitude and energy in dB during baseline mode as an average of all dBs computed in the baseline period and stored as baseline data w.r.t each load bin interval (10%) of the motor operational load. Peak magnitude in dB is computed as the highest magnitude observed at all fault frequencies and Energy in dB is computed as the ratio of area within +/- 0.5Hz vicinity at frequency corresponding to peak magnitude and at fundamental frequency. Energy in dB can be calculated as:

$$dB = 20 \times \log_{10} \frac{E1}{Ef} \tag{7}$$

where E_1 and E_f are the areas within the vicinity of the fault frequency f_1 and fundamental frequency f_s, respectively.

Step 7. Compute peak normalized magnitude and energy in dB during monitoring mode over each computational interval and compare with the baseline dB to determine the change in dB(ΔdB) with respect to each load bin interval. Change in dB(ΔdB) specifies the difference between pre-fault (baseline) dB level and fault dB level.

$$\Delta dBk_{norm} = dBk_{norm\_fault} - \Delta dBk_{norm\_baseline} \tag{8}$$

$$\Delta dBk_{energy} = dBk_{energy\_fault} - \Delta dBk_{energy\_baseline} \tag{9}$$

where k = 1, 2, 3

Step 8. A fault is declared when the following logical criteria becomes true:

$$\begin{gathered} \Delta dBk_{\max\_norm} \geq threshold\ level \\ and \\ \Delta dBk_{\max\_energy} \geq threshold\ level \end{gathered} \tag{10}$$

where

$$\Delta dBk_{\max\_norm} = \max(\Delta dB1_{norm}, \Delta dB2_{norm}, \Delta dB3_{norm})$$

$$\Delta dBk_{\max\_energy} = \max(\Delta dB1_{energy}, \Delta dB2_{energy}, \Delta dB3_{energy})$$

4. VALIDATION AND TESTING ON REAL MOTORS

Unlike electrical faults, it is not possible to accurately simulate a mechanical fault using computer-based simulation software. Therefore, to test and validate, the proposed algorithm was tested on actual motors with mechanical faults. For this purpose, the proposed method was tested on two motors with ratings 1000HP 4kV, and 300HP, 600V. These tests were performed at a motor repair shop facility in Canada. Furthermore, to ensure the proper working and validation of the algorithm, the test results were

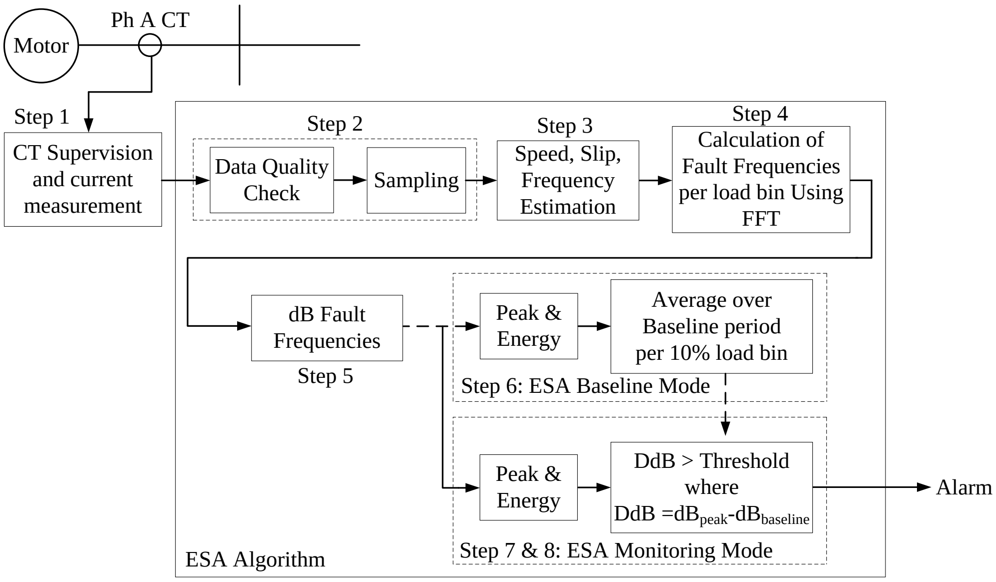


Fig. 4. Architecture of the Proposed AESA-based Solution

TABLE I
Calculated Fault Frequencies

Bearing Fault Frequencies(Hz)			Mechanical Fault Frequencies (Hz)	Stator Fault Frequencies (Hz)
Inner Raceway	Rolling Element	Outer Raceway		
44.28	194.71	322.32	15.00	0.00
67.17	223.71	372.79	30.00	29.67
103.83	252.81	387.75	45.25	30.00
148.55	267.69	431.52	74.84	90.00
164.41	268.63	442.36	90.00	121.99
187.23	314.84	551.46	105.00	150.90

compared with the results of commercially available MCSA-based equipment.

Before discussing the test results, it is important to understand that the commercial MCSA-based equipment is only used to validate the proper calculation of the fault frequencies and corresponding dB levels. As mentioned in the beginning of section III, an expert is required to diagnose the failure when existing MCSA-based tools are used. On the contrary, the proposed method is autonomous in functionality and can securely and reliably diagnose the fault without the involvement of an external expert.

Moreover, working of the proposed technique has also been applied to four motors installed in an iron ore pellet plant. These motors drive fan loads rated between 3750 to 5000HP, which are crucial equipment in a pelletizing process. Each production line produces 600 tons iron per hour having market value of 50 USD/ton. Disruption of the process due to an inadvertent mechanical failure on any of these motors can result a downtime of up to 30 hours for each production line, resulting into revenue loss of approx. one million USD plus high maintenance, repair and/or replacement costs.

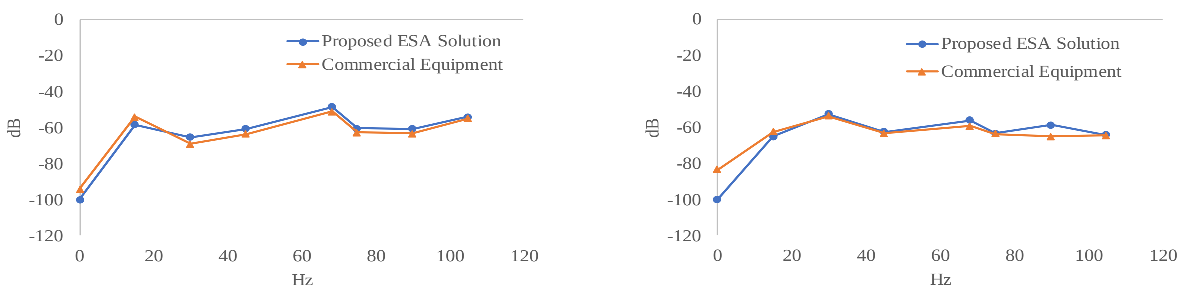
A. Computation of the Fault Frequencies

As described in section III, the proposed method calculates all the fault frequencies associated with bearing, mechanical and stator faults. Proper calculation of these frequencies requires motor slip, number of poles, and nominal frequency. In addition, for bearing fault frequencies calculation, the algorithm requires bearing geometry such as the number of balls, and inner and outer circle diameter as well as ball diameter.

Table 1 shows the fault frequencies autonomously calculated by the AESA algorithm for the motors under test using relations (1)-(5).

B. Validation of the dB Level vs Frequencies

Fig. 5, shows dB level corresponding to mechanical fault frequencies determined by the proposed method (line with dots) and commercial equipment (line with triangles). For validation purposes, the



(a) (b)

Fig. 5. Comparison between the proposed solution and the commercial equipment for mechanical faults: (a) foundation looseness with motor running at 50%, (b) shaft misalignment with motor running at 90%

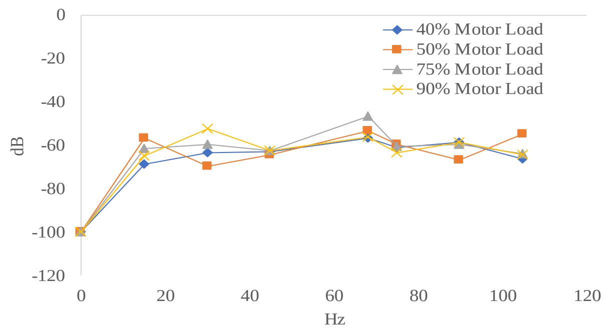


Fig. 6. Impact of Motor Load on Fault Frequencies

1000HP motor with foundation looseness and shaft misalignment faults was tested at 50%, 75% and 90% rated load. A comparison of the test results of both the proposed solution and commercial equipment reveal that there is a good match between both the solutions.

The matching of the dB values based on our proposed method and the dB value determined by the commercial equipment (which is accurate & calibrated for Fourier Transform results) shows that our proposed technique accurately monitors and diagnoses these faults.

C. Impact of Motor Loading on Fault Frequencies

To justify the inclusion of the proposed Load Bin mechanism, the AESA algorithm was tested for various motor load conditions. For this purpose, the motor was operated at load 40%, 50%, 75% and 90% of the rated load. Fig. 6 shows the dB level of the mechanical fault frequencies for these load conditions. It can be observed from the results that magnitude of the fault frequencies changes as the load changes, which verifies the need of Load Bin mechanism for baseline and monitoring to achieve autonomous & secured measurements.

D. Change in dB to Detect Anomalies

As mentioned in section III-E, a fault is declared when both ΔdBmax_peak and ΔdBmax_energy exceed the threshold level. Test setup limitations didn't allow for running the learning of the data (baseline mode) due to safety concerns. As a result, the algorithm considered -100dB as the baseline for both peak and energy baseline values, (dBkpeak_baseline, dBkenergy_baseline). To declare the fault, a threshold level of -65dB was selected based on the test data as shown in Table II. To declare the fault, the fault dB must be equal or greater than -65dB such that change of dB(ΔdB) equals 35dB (=-65dB - (-100dB)) or greater.

Table II shows change in dB captured for both peak and energy to detect foundation looseness & shaft misalignment, respectively, at various motor load conditions. Threshold comparator takes maximum of the peak and energy dB into account to declare the fault.

Fig. 7 (a) and (b) illustrate the maximum change in dB for both faults in comparison to threshold level. It can be observed that both peak and energy dB levels are above the threshold level that gives the

TABLE II
Change in dB to Detect Foundation Looseness

Motor Load (% of Load)	Foundation Looseness						Load Misalignment					
	ΔdBk_{peak}			ΔdBk_{energy}			ΔdBk_{peak}			ΔdBk_{energy}		
	k=1	k=2	k=3	k=1	k=2	k=3	k=1	k=2	k=3	k=1	k=2	k=3
40%	44	47	38	42	41	35	46	41	35	43	37	32
50%	41	34	46	37	32	40	40	36	43	37	33	37
75%	39	44	42	37	38	36	39	43	41	35	37	35
90%	48	26	22	45	27	22	38	48	36	37	42	32

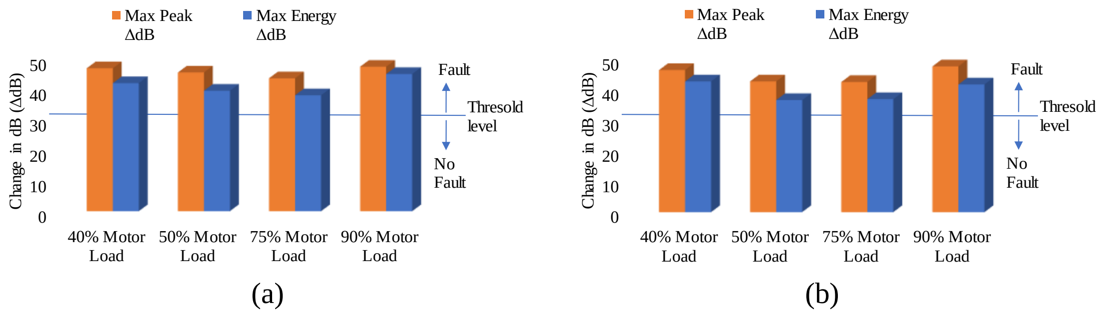


Fig. 7. Change in dB for mechanical fault (a) foundation looseness, (b) load-shaft misalignment

clear indication of the faults.

The proposed mechanisms such as data quality checks, load bin, baseline mode, monitoring mode and evaluation of the both peak and energy dB made it possible to achieve the reliable solution. On the contrary, conventional MCSA-based equipment requires an external expert to diagnose the fault by analyzing the fault data consisting of frequency spectrum.

BIBLIOGRAPHY

[1] IECEE. (2016). The IECEE Global Motor Energy Efficiency Programme. [Online]. Available https://www.iecee.org/about/gmee/

[2] Albrecht, et.al., "Assessment of the Reliability of Motors in Utility Applications," IEEE Trans. Energy Conversion, vol. EC-1, no. 1, pp. 39–46, March 1986.

[3] P. Zhang, et.al. "A Survey of Condition Monitoring and Protection Methods for Medium-Voltage Induction Motors," IEEE Trans. Industry Applications, vol. 47, no. 1, pp. 34–46, Jan. 2011.

[4] "Report of Large Motor Reliability Survey of Industrial and Commercial Installations, Part I," IEEE Transactions on Industry Applications, vol. IA-21, no. 4, pp. 853–864, July/August 1985

[5] O.V. Thorsen and M. Dalva, "A Survey of Faults on Induction Motors in Offshore Oil Industry, Petrochemical Industry, Gas Terminals, and Oil Refineries," IEEE Trans. Industry Applications, vol. 31, no. 5, pp. 1186–1196, September/October 1995

[6] A. H. Bonnett, "Root Cause Failure Analysis for AC Induction Motors in the Petroleum and Chemical Industry," in Proc. PCIC, San Antonio, Tx, 2010, pp. 381-393.

[7] Y. Chuck. Vibration analysis: what does it mean? [Online]. Available https://www.plantservices.com/assets/knowledge_centers/vibralign/assets/ra_vibration_analysis.pdf

[8] W. T. Thomson and I. Culbert, "Current Signature Analysis for Condition Monitoring of Cage Induction Motors," in Current Signature Analysis for Condition Monitoring of Cage Induction Motors, Piscataway, NJ: IEEE Press, 2017, ch. 12, sec. 12.4, pp. 368–371.

[9] W. T. Thomson and R. J. Gilmore, "Motor Current Signature Analysis to Detect Faults in Induction Motor Drives - Fundamentals, Data Interpretation, And Industrial Case Histories," in Proc, Texas A&M University Turbomachinery Symposium, College Station, Tx, 2003, pp. 145-156.