A Methodology for Selection of Condition Monitoring Techniques for Rotating Machinery

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ABSTRACT

Rotating machinery generally consist of a driver machine such as a motor and a driven machine or load such as a compressor or pump. Several condition monitoring (CM) techniques have been developed over the years for the predictive maintenance of rotating machinery. An appropriate selection of these techniques needs to be established for maximizing the ROI (Return on investment) of such systems. This paper proposes a methodology for the proper selection of CM techniques based on factors such as fault detectability, fault severity, cost, ease of data collection, noise, and system criticality. Effective techniques are recommended based on applicability in the industrial scenario and research done till now. A careful scoring system was adopted and weightage was given to each factor by expert opinion depending on its importance in the industrial environment. Multi-criteria decision-making (MCDM) was used to obtain comparable technique combination scores. The effectiveness of a single technique was found limited in rotating machinery, effective combinations were made and scored according to important factors. Final scores were obtained and top combinations were chosen for non-critical, sub-critical, and critical systems. A possible way of implementation is also shown for remote monitoring through literature.

Keywords: industrial asset CM, fault diagnosis, Induction motors (IM), CM techniques, industrial downtime, remote monitoring, industrial loads.

1. INTRODUCTION

A motor connected to a load is the most common form of industrial asset. Especially Induction motors (IM) consume nearly 30-40% of the total world's energy, and 20% of total energy is used in systems for moving fluids in which pumps especially centrifugal pumps are mostly used in many industries as a load (Resa et al., 2019), (Stopa et al., 2014). The majority of the AC motors are IM and 90% of motors used in industries are IM. The 3-phase IM is more common in the industry, being more efficient than a single-phase motor (Kuphaldt & Haughery, 2000).

IM is so commonly used in industries, as it has so many advantages such as less frequent maintenance requirements, IM has a few things going towards them like robustness, low cost, low maintenance, load handling, and speed control (A. Singh et al., 2016).

Pumping systems are utilized in a variety of industries and are capable of performing a wide range of tasks, making them highly sought after. Industrial pumps, which are one of the different types of pumping systems, are in high demand in industries including oil and gas, power, and food and beverage.

This paper addresses the real-time application and common faults for the most commonly used rotating machinery having IM and a common load such as pumps, compressors, fans, and conveyors. Many factors which are like hurdles to implementing the solution were considered. Researchers have focused on fault detection by suggesting methods and tools for IM and pumps separately (Djeddi et al., 2007; Kanovic et al., 2013; Gugaliya et al., 2018; Mehala & Dahiya, 2007; Ye & Wu, 2000; Jin et al., 2016; Glowacz & Glowacz, 2017; Glowacz, 2018; Vitek et al., 2011; Goktas et al., 2017; Dutta et al., 2018; Stopa et al., 2014; Henriquez et al., 2014; Goman et al., 2019), but this paper will suggest an algorithm to determine the latest technique and sensors to cover both motor and load side. Also suggesting how to implement it with the latest technologies like the Internet of Things (IoT), wireless monitoring, online CM, networking multiple setups for remote monitoring.

The estimates say that 23.9% of total manufacturing cost goes towards downtime cost and 13.3% goes towards

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planned production time with added hourly downtime cost, planned or unplanned is high enough to be unseen (Tabikh, n.d.).

As per statistics of many industrial settings, the unplanned downtime is much higher than the cost of scheduled downtime, typically the average hourly cost of unplanned downtime is 40K USD. The total estimated cost for industrial manufacturers tops 50 billion USD per year. Some examples of downtime costs for industries are shown in Table 1 (https://Behrtech.Com/Blog/Infographic-20-Mind Boggling-Stats-on-Cost-of-Industrial-Downtime/, n.d.). Fortune 1000, 82% of companies having unplanned downtime in 3 years had an average of 4-hour downtime per failure, costing an average of 2 million USD. Unplanned downtime does not only cost money but also customer trust and productivity (Elliot, 2015).

Downtime costs incurred across some industries	
Automobile	22000 USD lost every minute of downtime
Mining	5 million USD for losing an excavator for a day
Oil & Gas	38 million USD of financial loss due to unplanned downtime annually
Process Industries	5% of total output value loss due to unplanned downtime

Table 1. Downtime cost across some industries (*https://Behrtech.Com/Blog/Infographic-20-Mind-Boggling-Stats-on-Cost-of-Industrial-Downtime/*, n.d.)

Usually, the failure of IM is not sudden but gradual degradation or faulty parts. The efficiency of the motor keeps decreasing due to the occurrence of faults and if remains unchecked it eventually fails. Fault can occur from many reasons such as natural wear, incorrect installation, broken parts, overheating, stress, and much more. Looking at the part failure percentage of IM it is clear that which parts fail the most and how to monitor the motor precisely by planning and scheduling maintenance becomes important (Parekh, 2003). Figure 1 shows the part failure probability data and common loads connected to IM. Common faults from the most used loads with a motor will be the priority in this paper as shown in Figure 2. The other loads connected with the IM have faults that are either non-diagnosable with CM techniques or non-significant to be a concern to the industry. Cavitation in pumps will be considered in our methods with other common faults on the load side (Terron-Santiago et al., 2021; Goman et al., 2019).

We have to effectively plan the maintenance for when there is a change in the efficiency of IM. To catch the fault at the incipient level, CM tools and techniques help to ensure the detection of the fault. We can schedule the maintenance or order spare parts beforehand to avoid any downtime costs. With the correct CM techniques in place incipient faults can be detected and according to the priority of fault spare parts can be arranged beforehand to help with the maintenance and extra costs. (S. Kumar et al., 2019; Loiselle et al., 2018; Muthanandan & Nor, 2019)

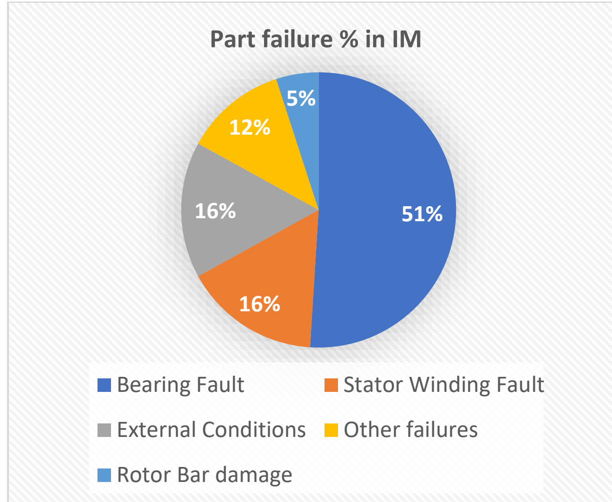

Figure 1. Failure distribution in IM

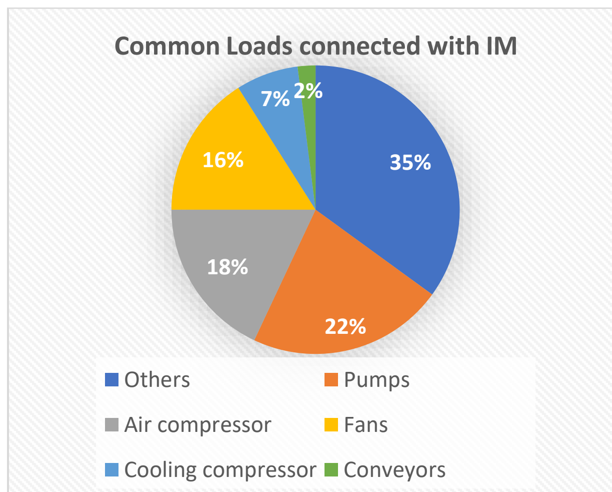

Figure 2. Failure distribution in common loads connected to IM (Terron-Santiago et al., 2021), (Goman et al., 2019)

There are additional operational costs (e.g., electricity bill) due to reduced efficiency based on the Duty Cycle, common electric motor duty cycles are given in Table 2 (Hamid A. Toliyat, 2004). CM is unorganized and industries do not have a clear way of using it to reduce their downtime. A huge amount of cost goes towards unplanned maintenance. Many approaches for the selection of techniques according to cost benefits are found in the literature. But only a few consider all the variables from data collection to implementation which is a major challenge as every industry has its own goals and expectations from an asset.

There is a need for a common methodology that incorporates cost as well as other factors while selecting CM techniques. (Buckley, 1987; Carnero, 2009; Liu et al., 2016; Mechefske & Wang, 2001; Moore & Baker, 1969; Parsaei & Wilhelm, 1989; Petkov et al., 2020; Utne et al., 2012; Wang & Wang, 2013)

Common Motor Duty Cycle as per Importer Exporter Code (IEC) Standards		
S1	Continuous Running	Constant load operation of sufficient duration to reach thermal equilibrium
S2	Short-time duty	Constant load for a specific time but less than that to reach thermal equilibrium followed by rest to reach coolant temp.
S3	Intermittent Periodic duty	Identical duty cycles sequentially with constant load and rest without a connection

Table 2. Motor duty cycle as per IEC standards (Hamid A. Toliyat, 2004)

This paper proposes a methodology for more effective implementation of CM techniques for industrial applications. A complete solution considering motor as well as load side fault situations is suggested. The article will cover Fault Diagnosis as well as Fault severity monitoring with the proper selection of sensors or their combination. New possibilities of how the techniques can be used will also be discussed in this paper so to help the engineers collect data easily and safely. Figure 3 shows the complete asset schematic system.

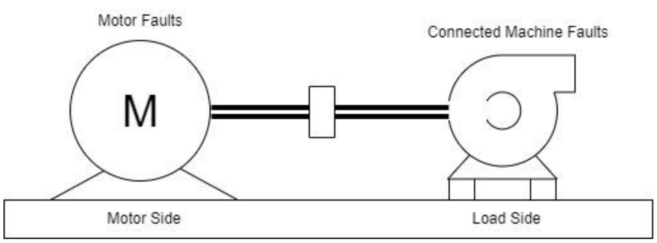

Figure 3. An industrial asset with motor and load

There are two types of modes in which we apply CM, **Online**- Applied when the machine is in working condition (e.g., vibration analysis, current analysis, thermography), **Offline**- Applied when the machine is not working (e.g., checking misalignment)

Data collection is done on a continuous and periodic basis, generally, the critical machines need to be monitored continuously due to the high-cost risk and safety hazards involved. For general-purpose machine's periodic data collection method will be well suited where preventing a failure will lead to profit on investment (Laws & Muszynska, 1987). Machine-mounted sensors with the integrated system will give real-time data in case of continuous monitoring and periodic analyses of signals collected in data loggers are essential.

The rest of the paper is organized as follows: Section 2 explains common CM techniques like vibration, current, thermal, acoustic, and flux. Flux sensors are relatively new in the field of CM, with very less research done in this area. Different types of faults that can be detected by these techniques and their effectiveness in fault detection are also shown. Section 3 proposes a methodology for proper technique selection, considering important factors essential for real-time industrial applications, and also proposing a wireless setup for multi-sensor industrial asset applications. Section 4 concluded the results and findings of the paper.

CM techniques will be discussed in Section 2 with their capabilities to detect different types of faults.

2. CM TECHNIQUES

In this section various CM techniques, their effectiveness in detecting different types of faults, and severity levels of diagnosis have been presented.

2.1 Vibration Monitoring

Vibration analysis works on the directional measurement of vibration signals which are collected by data acquisition systems through sensors (accelerometer). This technique is used to detect faults like misalignment, imbalance, bearing failure, cavitation, gear faults, and eccentricity (Han & Song, 2003). The possibility of detecting stator winding faults, uneven air gaps, unbalances in drive load, and asymmetrical power supply when the sensor is placed on the stator is an advantage (Thorsen & Dalva, 1998). Vibration in any machine is not desirable. It can be used to detect faults in the early stages, careful understanding and correct application are essential for a maintenance engineer (Soother & Daudpoto, 2019). Figure 4 shows the vibration severity levels for determining a machine's health ISO:10816-6 1995. It is widely used to determine if the machine requires maintenance.

Vibration measurements can be done in either radial or axial directions (Yu, 2020). If there is a change in the flux distribution of the motor it will cause a change in the spectrum of vibration, this change can be measured to get results regarding the type of fault and severity level of fault. The faulty signal can be compared to a reference point (healthy spectrum) (Gundewar & Kane, 2021). Changing the placement of the sensor can be used to identify different type of faults.

Vibration signal analysis is very useful tool especially in the case of mechanical systems in rotating machines. Unplanned downtime, maintenance costs can be reduced significantly with proper CM using vibration signals.

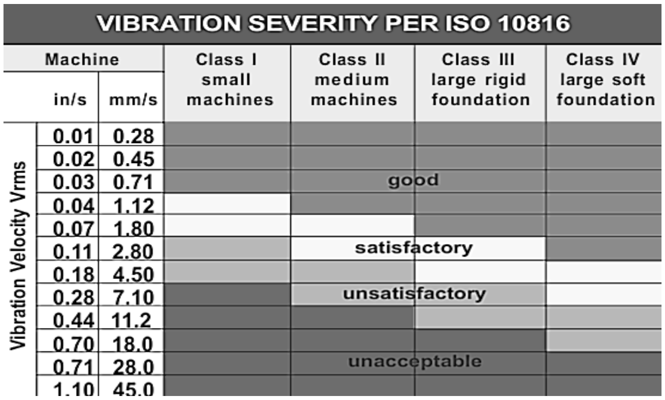

Figure 4. Vibration severity chart of machine's health as per ISO:10816 (*International Organization for Standardization (ISO) 10816-6:1995, Mechanical Vibration - Evaluation of Machine Vibration by Measurements on Non-Rotating Parts - Part 6: Reciprocating Machines with Power Ratings above 100 KW.*, n.d.)

Bearing faults can happen by a defective race, cage, or ball with single or multiple fault locations. A vibration sensor is attached to the bearing to collect vibration data that is sent to the data acquisition system and analyzed in the signal processing software. The healthy or newly commissioned machine vibration spectrum is compared with the faulty spectrum to find changes in the machine's health. Cross-referencing the difference in vibration spectrum with the characteristic fault frequency, we can get an idea of what part of the bearing is defective. Depending on the amplitude of fault frequency, the severity of the fault can be deduced by the International Organization for Standardization (ISO) severity chart Figure 5**.**

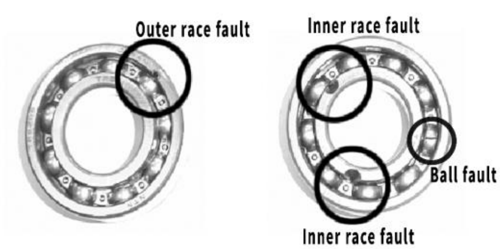

Figure 5. Typical bearing faults in a machine

Vibrations are produced at every rotation of the rolling elements. Localized faults on every impact cause a series of vibrations, the position, and amplitude of vibrations for every speed can be calculated by knowing bearing dimensions and rotational speed. These are called characteristic fault frequencies (CFC) and are different for every part of the bearing. By cross-referencing each CFC with impulses generated by faulty bearings we can detect which part of the bearing is faulty using mechanical vibration analysis techniques (Djeddi et al., 2007).

Cage Characteristic Fault frequency,

$$f_{cf} = \frac{1}{2} f_r \left(1 - \frac{d\cos(\theta)}{p}\right) \tag{1}$$

Outer Race Characteristic Fault frequency,

$$f_{orf} = \frac{n}{2} f_r \left(1 - \frac{d\cos(\theta)}{p}\right) \tag{2}$$

Inner Race Characteristic Fault frequency,

$$f_{irf} = \frac{n}{2} f_r \left(1 + \frac{d\cos(\theta)}{p}\right) \tag{3}$$

Ball Characteristic Fault frequency,

$$f_{cf} = \frac{p}{2d} f_r \left(1 + \left(\frac{d\cos(\theta)}{p}\right)^2\right) \tag{4}$$

Where $\boldsymbol{f_r}$ is rotational frequency**,** $\boldsymbol{d}$ is ball diameter**,** $\boldsymbol{\theta}$ is ball contact angle**,** $\boldsymbol{p}$ is ball pitch diameter**,** $\boldsymbol{n}$ is the number of balls.

The CFC that should be observed for detecting bearing faults can be calculated by equations **(**1-4) (Gugaliya et al., 2018) also some typical bearing faults can be seen in Figure 5**.**

Rotor bar Faults (breakage) are the main fault of the rotor in the IM as shown in Figure 6**.** Breakage of one bar increases the stress on other nearby bars which deteriorates their health as well. Generally, vibration monitoring is used to detect mechanical faults but in the rotor case, this technique can be used successfully because the broken rotor bar will excite the electromagnetic field disturbance which increases the torque modulations and hence lead to vibration which is easily measured by accelerometers (Kanovic et al., 2013).

The current will not flow in a broken rotor bar and the surrounding field will not exist. Because of that, the forces will be different from both sides of the rotor, unbalanced magnetic which rotates at rotational speed and modulates several poles times slip frequency will be created. So, the spectrum will have an increase in amplitude with sidebands at the rotational frequency (Kanovic et al., 2013).

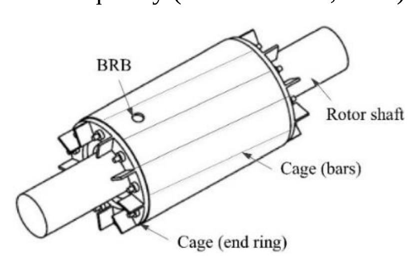

Figure 6. Broken rotor bar fault in IM (Gangsar & Tiwari, 2020)

Eccentricity Faults occur due to an uneven air gap between the stator and rotor in the motor. The eccentricity faults are divided into 3 parts: Static, Dynamic, and Mixed eccentricity as shown in Figure 7**.** Considering the literature, eccentricity faults can be detected by vibration monitoring by observing sidebands concerning rotor slot frequency or by supply frequency (Ch et al., 2015).

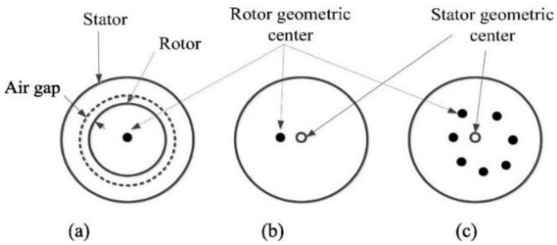

Figure 7. Eccentricity faults (a) normal (b) static (c) dynamic eccentricity (Gangsar & Tiwari, 2020)

For analysis purposes, the motor will be in two states coupled and decoupled. Coupled motor will be seen as a whole system (motor + load) assembly and the decoupled motor will only consist of the motor side. From the literature (Ch et al., 2015), we can reliably say that current monitoring methods are more successful in monitoring eccentricity faults in decoupled motors on the motor side. But when we see it as a whole system, vibration monitoring is more successful because the fault can be on the load side and the current monitoring would not be able to detect the fault at an early stage.

For studying eccentricity, the sidebands can be observed concerning either rotor slot frequency (5) (Barbour & Thomson, 1997) or supply frequency (6) (Benbouzid, 2000)

$$f_{ecc} = f_s\left[(R \pm n_d)\left(\frac{1-s}{p}\right) \pm n_{ws}\right], \tag{5}$$

or

$$f_{ecc} = f_s\left[1 \pm m\left(\frac{1-s}{p}\right)\right] \tag{6}$$

$\boldsymbol{f_{ecc}}$ is the eccentricity frequency, $\boldsymbol{f_s}$ is the supply frequency, $\boldsymbol{R}$ is the no. of rotor slots, $\boldsymbol{n_d}$: 0 for static and 1 for dynamic**,** $\boldsymbol{s}$ is slip, $\boldsymbol{p}$ is no. of poles, **m** is 1,2,3…., $\boldsymbol{n_{ws}}$ is 1,3,5,7.

Unbalancing Faults, in general, occur in rotating parts of a machine, e.g., rotor unbalance in an IM which happens when the center of mass does not coincide with the geometric center of the motor. The main causes are manufacturing defects, unwanted chipping or addition of mass on the rotor, thermal expansion, or bending of the shaft. Classified into 3 categories Static, Couple, and Dynamic unbalance. A centrifugal force is produced by the unbalancing due to which there are vibrations at a frequency equivalent to relative shaft speed and due to mutual inductances becoming unsymmetrical between stator and rotor the stator current harmonics occur at frequencies (Rahman & Uddin, 2017) calculated by (7) (Gugaliya et al., 2018).

$$f_{unb} = f\ [\ 1 \pm \frac{k(1-s)}{p}] \tag{7}$$

$\boldsymbol{f_{unb}}$ is the unbalanced rotor frequency, $\boldsymbol{f}$ is the electrical supply frequency, $\boldsymbol{k}$ is per unit slip, $\boldsymbol{p}$ is the number of poles.

Misalignment Faults are common faults like unbalance and occur when the coupled shaft center is not coinciding with each other as shown in Figure 8**.** In short term, it reduces the efficiency of the machine and in long term, it can also cause the failure of the machine. Flexible couplings are usually used to eliminate this fault. These are classified into parallel and angular misalignment. Vibration analysis and current analysis are used to detect the misalignment fault by observing harmonics, 3x will be highly excited as compared to 2x, 4x, and 5x harmonics of vibration and current (Kumar Verma et al., 2013).

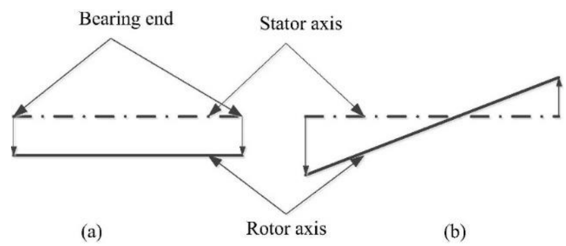

Figure 8. Misalignment faults (a) Parallel (b) Angular misalignment (Gangsar & Tiwari, 2020)

Cavitation is a general issue when it comes to pumps, the phenomenon happens when the water pressure drops below the threshold value which causes vaporization and formation of tiny bubbles, the bubbles create a shockwave while imploding and hence excessive vibration on the pump casing which is detectable. It causes low performance, damage to the impeller and volute, bearing failure, and seal failures so it is very important to detect and eliminate the fault at the incipient level Figure 9**.** Shows cavitation in centrifugal pumps (Dutta et al., 2018)(Stopa et al., 2014).

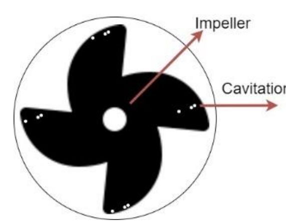

Figure 9. Pitting due to cavitation in centrifugal pumps

2.2 Current Monitoring

Winding faults can happen due to heating, electrical, environmental, and mechanical stresses which affect the stator, the insulation breaks and causes a short circuit in the motor due to which the motor can heat excessively, high current flow, high voltage flow, physical damage, etc. The Park vector approach is a good method to determine winding failures. Equations shown below (8-12) (Ye & Wu, 2000) represent a circular locus centered at the origin of the coordinates. The Equations (11-12) will not be valid for any abnormalities in the motor.

$$i_d = \left(\frac{\sqrt{2}}{\sqrt{3}}\right) i_a - \left(\frac{1}{\sqrt{6}}\right) i_b - \left(\frac{1}{\sqrt{6}}\right) i_c \tag{8}$$

$$i_d = \left(\frac{\sqrt{2}}{\sqrt{3}}\right) i_a - \left(\frac{1}{\sqrt{6}}\right) i_b - \left(\frac{1}{\sqrt{6}}\right) i_c \tag{9}$$

$$i_q = \left(\frac{1}{\sqrt{2}}\right) i_b - \left(\frac{1}{\sqrt{2}}\right) i_c \tag{10}$$

Under ideal conditions, 3-phase current corresponds to Parks vector with these components

$$i_d = \left(\frac{\sqrt{6}}{2}\right) i_m \sin(\omega t) \tag{11}$$

$$i_q = \left(\frac{\sqrt{6}}{2}\right) i_m \sin(\omega t - \frac{\pi}{2}) \tag{12}$$

$\boldsymbol{i_a}, \boldsymbol{i_b}, \boldsymbol{i_c}$ are main phase variables, $\boldsymbol{i_d}, \boldsymbol{i_q}$ are Park vectors current components, 'i_m'is the maximum value of supply phase current (A), $\boldsymbol{\omega}$ is angular supply frequency (rad/sec), $\boldsymbol{t}$ is the time variable. The diagnosis is based on the elliptical pattern which corresponds to the motor current parks vector form. Ellipticity changes and major axis orientation will tell fault and severity in the diagram(Ye & Wu, 2000).

Rotor bar faults will produce a rotor asymmetry which will lead to the resultant backward rotating field at the slip frequency respective to the forward rotating rotor, due to this backward rotating field concerning the rotor induces electromagnetic force and current in stator winding (Mehala & Dahiya, 2007). The sidebands can be detected at twice slip frequency (12) (Mehala & Dahiya, 2007)

$$f_{sb} = f(1 \pm 2s) \tag{13}$$

$\boldsymbol{f_{sb}}$ is sideband frequency, $\boldsymbol{f}$ is supply frequency, $\boldsymbol{s}$ is slip

Current monitoring techniques like Motor Current Signature Analysis (MCSA) are equipped with tools to detect rotor bar faults.

Eccentricity faults cause special patterns unique to the fault and can be detected by current spectrum analysis. The rotating wave approach method is used by which the magnetic flux waves in the air gap are calculated by magnetomotive force waves multiplied by permeance.

Frequency component $f_e$can be calculated by Equation (14) (Ye & Wu, 2000)

$$f_e = \left[\frac{(kR \pm n_d)(1-s)}{p \pm v}\right] f \tag{14}$$

$\boldsymbol{f}$ is supply frequency**,** $\boldsymbol{n_d}$ is eccentricity order: 0 for static: 1,2,3 for dynamic, $\boldsymbol{R}$ is the number of rotor slots, $\boldsymbol{v}$ is stator MMF harmonics present in the supply, $\boldsymbol{K} = 1,2,3\ldots$

Bearing faults associated with components like cage, balls, inner race, an outer race are detected by their respective CFC which could be done by vibration or current spectrum, $\boldsymbol{f_{brg}}$ is used to diagnose bearing faults in the current spectrum (15) (Gugaliya et al., 2018)

$$f_{brg} = |f_s \pm k f_b| \tag{15}$$

$\boldsymbol{f_{brg}}$ is the relative frequency between f_s and f_b, $\boldsymbol{f_s}$ is supply frequency, $\boldsymbol{f_b}$ is characteristic fault frequency, k=1, 2, 3...

Gearbox faults lead to failure of machines, malfunctions, and financial losses so it's essential to conduct CM and diagnosis of faults. The gears can have gear cracks or broken teeth that have to be detected. Vibration signals show modulations by output shaft rotating frequency, current signals are highly modulated by input shaft rotating frequency in case of gear cracks and two broken teeth. The current-based approach is more sensitive to low-frequency ranges and vibration is more sensitive to higher ranges, compared to vibration current monitoring is non-intrusive and less sensitive, so it has a high potential to be used in the commercial sector (Jin et al., 2016).

2.3 Thermography Monitoring

Infrared thermal imaging for motors and machines is a non-invasive method to detect faults that produce localized heat. Thermal image cameras like FLIR can be used efficiently to take a thermal image of a running motor or load and determine if there is an unusual or comparative difference in temperatures from the healthy motor thermal image temperatures.

Comparisons are done on the relative temperatures Δt by (16) (Reljić et al., 2016)

$$\Delta t = t_x - t_a \tag{16}$$

$\boldsymbol{t_x}$ is the local temperature (interest point) $\boldsymbol{t_a}$ is ambient temperature

By Δt we can determine the temperature rise in our point of interest on the machine. If the rise is severe, it is a sign that a fault is present at that location of temperature rise Figure 10**.** (Reljić et al., 2016). Shows the broken rotor bar fault with its effect on its neighboring bars and it is very clear what type of fault is visible Figure 11**.** (Choudhary et al., 2019). shows different types of bearing faults (a) lack of lubrication (b) inner race defect (c) outer race defect (d) healthy motor. The images can also be processed for better color resolution, as we can see in the images that all the faults have a different thermal image which can be used to detect and identify faults.

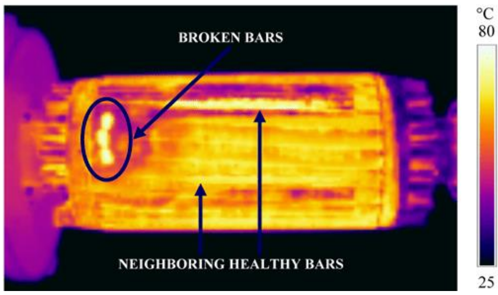

Figure 10. Broken bar fault (Reljić et al., 2016)

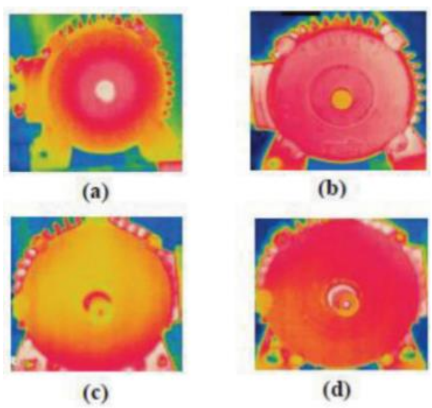

Figure 11. Bearings faults (Choudhary et al., 2019)

Latest motors now come with inbuilt thermocouples (Positive Temperature Coefficient (PTC) / Resistance Temperature Detector (RTD)) sensors which are connected to stator winding for measuring temperature rise in the motor, so these are a cheap alternative to thermal cameras which are pretty costly. The installed sensors can help us identify if there is any abnormality inside the IM and we can take preventive measures on maintenance Figure 12. Shows the inbuild thermocouple already installed with the motor while purchased. (Glowacz & Glowacz, 2017)

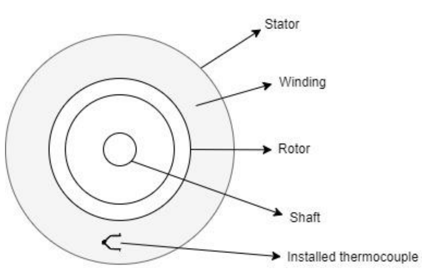

Figure 12. Inbuilt thermocouple in latest IM

2.4 Acoustic based Monitoring

Acoustic is sound-based monitoring and fault diagnosis technique that can be done by low-cost capacity microphone-computer setup or digital voice recorder. For CM frequencies below 100Hz are essential so the sound recorder should be able to capture to work in low-frequency ranges. Data collection is very cheap in this method, the process is noninvasive, and instant collection of data can be done. A basic layout of the acoustic-based CM system is shown in Figure 13**.** Many faults like multiple broken rotor bars, the broken ring of squirrel cage, differentiating healthy with faulty IM, and more, with good accuracy, can be achieved by this type of system in addition to signal processing techniques (Glowacz, 2018).

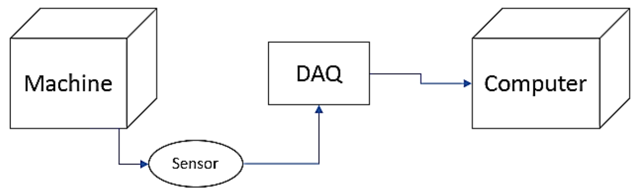

Figure 13. Acoustic monitoring setup

The acoustic emission technique is also a good technique for detecting electrical and mechanical faults, it works better for electrical faults. The technique uses a load or stress which is generated at the machine and is detected by the sensor, the wave is then sent to the analyzing instrument to detect faults. A schematic diagram is shown in Figure 14**.**

Figure 14. AE based monitoring setup

2.5 Flux Monitoring

Flux monitoring works on the external magnetic field or leakage flux or stray flux, the magnetic flux density is used with stator current and compared in the frequency domain to detect different types of faults. Error! Reference source not found.Figure 15 and Error! Reference source not found. (Negrea, 2006) show the flux leakage and set up with the sensor (Soother & Daudpoto, 2019)(Negrea, 2006).

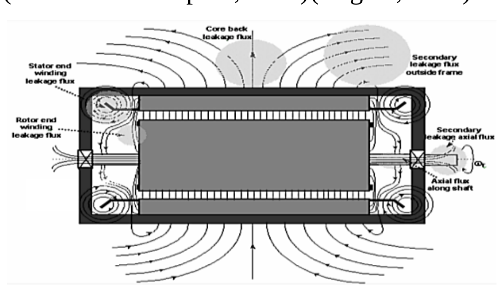

Figure 15. Leakage flux (Negrea, 2006)

Flux monitoring is a good technique to find rotor cage faults with good accuracy proportional to motor loading. The short circuit in the stator winding is also detectable easily. Dynamic eccentricity can also be detected with circulating currents with ease. Rotor bar faults are seen but can be difficult to differentiate the signature with winding inter-turn fault (Goktas et al., 2017). Bearing fault and static eccentricity were not detectable by this method (Vitek et al., 2011; Negrea, 2006).

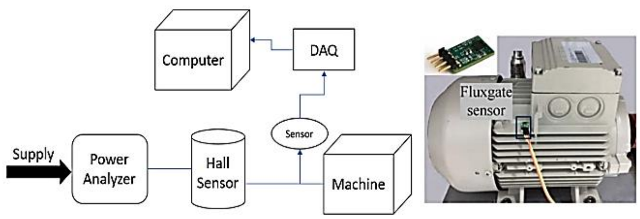

Figure 16. Leakage flux and flux sensor

Fault diagnosis capability, in terms of type and severity level of faults, of several CM techniques has been discussed in this section. The next section proposes a methodology to rationally select the most appropriate (combination of) CM technique (s) for a given industrial application.

3. SELECTION OF CM TECHNIQUES

For complete asset CM, it is important to consider both motors as well as the load-side faults. Every technique has its uniqueness to detect faults at an incipient or severe level. In this paper, a method is proposed to find which technique is the best for complete asset monitoring by considering many factors associated with real-time applications for every technique which is a major concern for industries and generally not considered by researchers.

The industries are moving closer to industry 4.0 by adopting new and better methods like remote monitoring, industrial IoT, and wireless data transfer to make data collection easier. Conventionally the engineer will go to the site and collect data from the data acquisition system (DAQ) system near the machine, by adopting new concepts and making things smarter and automated the sensors can send the data to the IoT gateway using serial communication or using Arduino chips as DAQ to collect data and then transfer to the cloud. From the cloud, we can get the data into our system by analyzing software that can diagnose the data continuously. If there is a fault it can be repaired before it has a significant impact on the working of the whole system (Prasanna et al., 2017; Shyamala et al., 2017; Yaseen et al., 2017)

Only a few papers have discussed the proper selection of CM techniques for rotating machinery, most of them only consider the cost aspect. Some researchers also focused on sewers and water mains applications. On a general basis selection of the most suitable technique is a challenging task with a lot of variables. MCDM techniques are widely used for the selection process with multiple criteria, which can be used in the selection of CM techniques. Emphasis should be on the chosen factors and their applications. (Chatterjee & Chakraborty, 2013; Davis et al., 2013; Emovon & Oghenenyerovwho, 2020; Kabir et al., 2014; A. Kumar et al., 2017a, 2017b; Maniya & Bhatt, 2010; Mechefske & Wang, 2001; Sabaei et al., 2015; Sayadi et al., 2009; Velasquez & Hester, 2013)

Demerits of some techniques are shown in Table 3 compared to the proposed methodology. As the process involves extensive knowledge of machines, strategies, net present value, internal rate of return, faults, economic analysis, and many other important factors. Expert opinion for making a wise decision becomes a must. Hypothetical examples are given by researchers to deal with multiple variables and some case studies are presented to combine factors into an informed decision but still, the process lacks in the signal processing aspects related to sensor data, data collection, fault category combinations, and criticality of the asset. These factors are very critical to the industry and it needs to be addressed. The proposed methodology addresses these problems and overcomes the disadvantages of other methods as well.

Methods	Demerits	Inventor
AHP	Complexity increases with variables	Thomas Saaty: 1970
TOPSIS	Correlation between factors not considered	Hwang and Yoon:1981
PROMETHEE	High complexity	J. P. Brans and P. Vicke: 1982
ELECTRE	Computationally difficult	Benayoun Roy: 1968
VIKOR	Challenging in conflicting scenario	S. Opricovic: 1990
ASHBY	Only 3 criteria allowed	Ashby, M.F:1992
COPRAS	Quite unstable	Zavadskas and Kaklauskas:1996
PSI	High computational time	Maniya and Bhatt: 2010
MAUA	Decision attribute outcome is uncertain	P.C. Fishburn: 1965, R.L. Keeney:

Table 3. Demerits of popular methods compared to the proposed methodology

The proposed methodology uses the weighted sum model (WSM) of MCDM with an addition of a justification factor for fault categories. It is simple, easy, non-computational, less complex, includes many criteria, and has a certain outcome. This ensures that every industry can adopt and implement a maintenance strategy.

The validity of the proposed methodology is generalized for rotating machinery having a load driven by a motor. As discussed in Section 1, the most common motor and loads have been considered from the literature for which data is presented in Figure 1 and Figure 2. The methodology can be generalized for other types of assets taking help from an expert. Most common faults are considered for both motor and load sides as discussed in Section 1 and Section 2.

The proposed methodology for finding the technique ranking per industrial factor is shown in Figure 17.

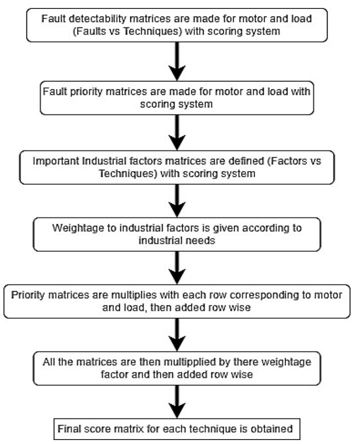

Figure 17. Proposed methodology for ranking techniques as per industrial needs

The proposed methodology for the best technique combination including industrial implementation factors and different system requirements is shown in Figure 18**.**

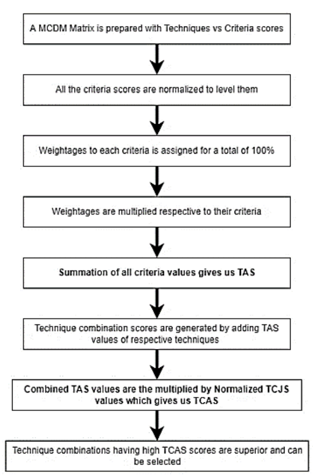

Figure 18. Proposed methodology for choosing technique combination for various industrial applications

For assessing different criteria in the implementation of the techniques MCDM technique was used with the weights taken as per the experts in the field and on the criticality of the system consideration. For determining the ranking of the techniques, Technique Asset Score (TAS) is obtained which contains the final scores when the techniques are applied independently. Technique Combination Asset Score (TCAS) contains the scores for the combination of techniques. Technique Combination Justification Score (TCJS) is used as the final parameter, it justifies the technique combinations which have the best techniques for fault detection in mechanical as well as electrical faults. These techniques are given priority to other techniques working on the same type of fault categories or having a lower score in any fault category.

For determining the correct technique, matrices are developed by carefully considering important factors shown in each matrix, Matrix *A* is developed for common and critical motor faults detectability by famous CM methods and the scores are given by the knowledge provided from past research papers and real-time industrial experience. Matrix *B* is developed by considering common load side faults from machines such as pumps, compressors, and fans which are the most commonly used loads with IM. Only the faults which can be diagnosed and are important from the CM point of view are considered. (Djeddi et al., 2007; Kanovic et al., 2013; Gugaliya et al., 2018; Mehala & Dahiya, 2007; Ye & Wu, 2000; Jin et al., 2016; Glowacz & Glowacz, 2017; Glowacz, 2018; Vitek et al., 2011; Goktas et al., 2017).

Fault Level	**Incipient**	**Severe**
Bearing faults	Single crack	Pitting, roughness
Winding faults	1-3 turn short	High turn short/coil short
Broken rotor bar	Single broken rotor	Multiple broken rotor
Cavitation	Light popping noise	Steady rumbling noise
Gear faults	Surface pitting	High wear
Eccentricity	<3mm eccentricity	>5mm eccentricity
Misalignment	5-6mm offset	6-7mm offset

Table 4. Fault severity description

Rating Scale:

A general rating scale of 3 criteria (0,1,2) is chosen. High scores are desirable and 0 is the worst. Details for each factor are given separately in their respective score distribution descriptions.

Score distribution description for matrices A and B
Scores are proposed as per the capability of the techniques to detect a fault at different severity levels. Table 4 shows the fault severity descriptions of all discussed faults. Table 5 and Table 6 show the distributed scores according to the level of fault detectability of a technique. The scores given are described below.

BRG: Bearing fault
WND: Winding fault
RB: Rotor bar fault
CVT: Cavitation
GD: Gear defects
ECC: Eccentricity
MIS: Misalignment

0: Technique is not able to detect the fault
1: Technique can detect fault at the severe level
2: Technique can detect fault at incipient level

Techniques	**Motor faults**		
	BRG	*WND*	*RB*
Vibration	2	1	1
Current	1	2	2
Thermography	1	1	1
Acoustic	1	0	1
Flux	0	2	2

Table 5. Fault detectability score matrix A (motor side)

Techniques	**Load faults**				
	BRG	*CVT*	*GD*	*ECC*	*MIS*
Vibration	2	2	2	2	2
Current	0	1	0	0	1
Thermography	1	0	0	0	0
Acoustic	1	1	1	0	1
Flux	0	0	0	0	0

Table 6. Fault detectability score matrix B (load side)

Technique scores for each fault category Mechanical and Electrical are shown in Table 7. The best techniques with their next best alternative are chosen from Table 7 and presented in Table 8.

Techniques	***Mechanical faults (BRG + CVT + GD + ECC + MIS)***	***Electrical faults (WND + RB)***
Vibration	*12*	*2*
Current	*3*	*4*
Thermography	*2*	*2*
Acoustic	*5*	*1*
Flux	*0*	*4*

Table 7. Technique scores for mechanical & electrical faults

Fault category	**Best technique**	**Best Alternative**
Mechanical	Vibration	Acoustic
Electrical	Current	Flux

Table 8. Best techniques for each fault category

Matrix *C* Table 9 is the motor fault detection priority distribution matrix, the score is distributed according to the criticality of the fault at the incipient level. Bearing and winding faults are the major issues that occur in motors, in which winding fault is considered more severe. It increases the stresses and causes temperature rise which according to a rule 10° rise in temperature reduces the life of insulation by half. If a winding fault happens it takes a considerable amount of time to repair and downtime is high increasing industrial losses (G. Singh et al., 2016). Matrix *D* Table 10 contains the priority for load-side faults, in which pumps are mostly used. Cavitation causes erosion, implosion, misalignment, decrease flow, and greatly reduce efficiency, so it is very important to detect cavitation faults at the incipient level (Dutta et al., 2018; Stopa et al., 2014).

Score distribution description for matrices C and D:
The score is proposed according to the criticality of faults, fault priority is given high if it can have a preposterous effect if not detected at the incipient level.

1: Incipient level of fault detection is not necessary
2: Incipient level of fault detection is necessary

Techniques	**Motor Fault Priority**		
	Bearing	*Winding*	*Rotor Bar*
Priority	1	2	1

Table 9. Fault priority score matrix C (motor side)

Technique	**Load Fault Priority**				
	Bearing	*Cavitation*	*Gear defects*	*Eccentricity*	*Misalignment*
Priority	1	2	1	1	1

Table 10. Fault priority score matrix D (load side)

Matrices *E*, *F*, *G*: Table 11 is based on important factors which have to be considered while implementing the technique. Matrix *E* is the cost factor score, cost is considered a major concern for many industries when it comes to implementing and adopting a new system, because of the cost many industries don’t even consider implementing CM. But for critical systems, it is a necessity, or it can have major implications like shutdown or production loss. Matrix *F* is how easily the data collection process is done by a technique that is necessary for saving the time of engineers. Matrix *G* is the noise factor, industries have a lot of machines running round the clock, and a lot of external noise affects the monitoring system, especially the acoustic sensors are very sensitive to external sound and so a less score is given to the technique.

Score distribution description for matrix E, F, G:

The scores are proposed according to the importance of factors considered by industries when selecting a CM technique. The higher the importance of the factor the higher the score is given.

Cost:
1: Equipment cost is relatively higher
2: Equipment cost is relatively lower
Ease of data collection (EDC):
1: Data collection will require personnel to visit the machine
2: Data collection can be done from a control center
Noise factor (NF):
1: Technique is very sensitive to background noise
2: The technique is not sensitive to background noise

Techniques	*Cost (Mat E)*	*EDC (Mat F)*	*NF (Mat G)*
Vibration	1	1	2
Current	2	2	2
Thermography	2	1	2
Acoustic	2	1	1
Flux	2	1	2

Table 11. Ease of application score matrix E, F, G (motor + load side)

Matrix operations:

The basic methodology adopted here is to get a scoring matrix dependent on faults themselves which is the basis of a technique selection. Then to get a single score for each technique, all the values in a row are added technique-wise. Now the weights of each factor can be multiplied by individual matrices for getting a final score of individual techniques.

[A]: Motor side fault detectability score matrix for common techniques.

[B]: Load side fault detectability score matrix for common techniques.

[C]: Motor side faults priority score matrix

[D]: Load side faults priority score matrix

[E]: Cost score matrix for common techniques.

[F]: Ease of data collection score matrix for common techniques.

[G]: Noise factor score matrix for common techniques.

Step 1:

All rows of [A] are multiplied by [C], and all rows of [B] are multiplied by [D], let's call these [A1] and [B1].

[A1] = {[Fault detection] x [Fault priority]} score matrix on motor side for common motor faults.

$$[A1] = \begin{bmatrix} A_{1,1} * C_{1,1} & A_{1,2} * C_{1,2} & A_{1,3} * C_{1,3} \\ A_{2,1} * C_{2,1} & A_{2,2} * C_{2,2} & A_{2,3} * C_{2,3} \\ A_{3,1} * C_{3,1} & A_{3,2} * C_{3,2} & A_{3,3} * C_{3,3} \\ A_{4,1} * C_{4,1} & A_{4,2} * C_{4,2} & A_{4,3} * C_{4,3} \\ A_{5,1} * C_{5,1} & A_{5,2} * C_{5,2} & A_{5,3} * C_{5,3} \end{bmatrix}$$

$$[A1] = \begin{bmatrix} 2 & 2 & 1 \\ 1 & 4 & 2 \\ 1 & 2 & 1 \\ 1 & 0 & 1 \\ 0 & 4 & 2 \end{bmatrix}$$

[B1] = {[Fault detection] x [Fault priority]} score matrix on load side for common load machine faults.

$$[B1] = \begin{bmatrix} B_{1,1} * D_{1,1} & B_{1,2} * D_{1,2} & B_{1,3} * D_{1,3} \\ B_{2,1} * D_{2,1} & B_{2,2} * D_{2,2} & B_{2,3} * D_{2,3} \\ B_{3,1} * D_{3,1} & B_{3,2} * D_{3,2} & B_{3,3} * D_{3,3} \\ B_{4,1} * D_{4,1} & B_{4,2} * D_{4,2} & B_{4,3} * D_{4,3} \\ B_{5,1} * D_{5,1} & B_{5,2} * D_{5,2} & B_{5,3} * D_{5,3} \end{bmatrix}$$

$$[B1] = \begin{bmatrix} 2 & 4 & 2 & 2 & 2 \\ 0 & 2 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 2 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Step 2:

Calculate row summation of [A1] and [B1] separately

MFDFP: Motor fault detection and fault priority.

LFDFP: Load fault detection and fault priority.

[MFDFP] = Combination score for each technique on the motor side.

$$[MFDFP] = \begin{bmatrix} 2 & 2 & 1 \\ 1 & 4 & 2 \\ 1 & 2 & 1 \\ 1 & 0 & 1 \\ 0 & 4 & 2 \end{bmatrix} = \begin{bmatrix} 5 \\ 7 \\ 4 \\ 2 \\ 6 \end{bmatrix}$$

[LFDFP] = Combination score for each technique on the load side.

$$[LFDFP] = \begin{bmatrix} 2 & 4 & 2 & 2 & 2 \\ 0 & 2 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 2 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 12 \\ 3 \\ 1 \\ 5 \\ 0 \end{bmatrix}$$

Step 3:

Weightage is assigned to each factor:

WM: Fault detection and priority on the motor side.

WL: Fault detection and priority on the load side.

WC: Cost to implement the technique on the asset.

WD: Ease of data collection.

WN: Noise factor associated with a technique.

MCDM matrix is made using techniques, criteria, and weights assigned to all the criteria and is presented in Table 12. As all the values have a different range they are normalized as shown in Table 13.

Weights	WM	WL	WC	WD	WN
Techniques/ Criteria	MFDFP	LFDFP	Cost	EDC	NF
Vibration	5	12	1	1	2
Current	7	3	2	2	2
Thermography	4	1	2	1	2
Acoustic	2	5	2	1	1
Flux	6	0	2	1	2

Table 12. MCDM matrix

Weights	WM	WL	WC	WD	WN
Techniques/ Criteria	MFDFP	LFDFP	Cost	EDC	NF
Vibration	0.714	1	0.5	0.5	1
Current	1	0.25	1	1	1
Thermography	0.571	0.083	1	0.5	1
Acoustic	0.285	0.416	1	0.5	0.5
Flux	0.857	0	1	0.5	1

Table 13. Normalized MCDM matrix

TAS scores are calculated by multiplying weights with their respective criteria values in the normalized MCDM matrix, shown in Table 14. Both mechanical, as well as electrical faults, can happen in an industrial asset. As evident from Section 2, motors side electrical faults are prioritized. Load-side mechanical faults are significant. TCJS Technique combination justification score concerning combinations consisting of best techniques in detecting mechanical as well as electrical faults together. TCJS scores are presented in Table 15 with their normalized values.

Techniques	**TAS by MCDM**
Vibration	WM x 0.714 + WL x 1 + WC x 0.5 + WD x 0.5 + WN x 1
Current	WM x 1 + WL x 0.25 + WC x 1 + WD x 1 + WN x 1
Thermography	WM x 0.571 + WL x 0.0833 + WC x 1 + WD x 0.5 + WN x 1
Acoustic	WM x 0.285 + WL x 0.416 + WC x 1 + WD x 0.5 + WN x 0.5
Flux	WM x 0.857 + WL x 0 + WC x 1 + WD x 0.5 + WN x 1

Table 14. TAS scores for each technique

Technique combinations	**TCJS**	**Normalized (NTCJS)**
Vibration + Current	2	1
Vibration + Flux	2	1
Vibration + Thermal	1	0.5
Current + Acoustic	2	1
Acoustic + Flux	2	1
Thermal + Acoustic	1	0.5
Thermal + Flux	1	0.5
Current + Flux	1	0.5
Current + Thermal	1	0.5

Table 15. TCJS values for technique combinations

Step 4:

The obtained TAS scores are added corresponding to technique combinations and then multiplied by their respective normalized values of TCJS to calculate the final TCAS values as shown in Table 16.

Score description for TCJS:

1: Technique combinations not consisting of best techniques from both mechanical and electrical faults category.

2: Technique combinations containing best or alternative best techniques one from mechanical and the other from the electrical category of faults. Refer to Table 8.

Technique Combination	Technique Combination Asset Score TCAS = [TAS1+TAS2] x NTCJS
Vibration + Current	[TAS (Vibration) + TAS (Current)] x 1
Vibration + Flux	[TAS (Vibration) + TAS (Flux)] x 1
Vibration + Thermal	[TAS (Vibration) + TAS (Thermal)] x 0.5
Current + Acoustic	[TAS (Current) + TAS (Acoustic)] x 1
Acoustic + Flux	[TAS (Acoustic) + TAS (Flux)] x 1
Thermal + Acoustic	[TAS (Thermal) + TAS (Acoustic)] x 0.5
Thermal + Flux	[TAS (Thermal) + TAS (Flux)] x 0.5
Current + Flux	[TAS (Current) + TAS (Flux)] x 0.5
Current + Thermal	[TAS (Current) + TAS (Thermal)] x 0.5

Table 16. TCAS scores for technique combinations

TCAS Score is based application of technique combination package for the complete system (motor + load) considering critical faults detection, ease of application, cost, ease of data collection, and noise sensitivity with taking into account the main focus of the implementing CM technique is to detect both mechanical as well as electrical faults. The location of sensors and how easily the data can be collected are taken into consideration. Sensors are combined in a solution like smart sensors packages for online monitoring of critical systems. It is easy to collect data from one location and better if the engineer does not have to visit the site for that purpose. All these factors are taken into consideration for making the final rankings. The expert team can be consulted to carefully choose the weights and find the best technique combinations for their asset. Each asset has its criticality and needs fault monitoring systems which can be best understood by the experts in that field.

There are different kinds of assets with different needs like equipment cost, space, and downtime cost, therefore generally a single technique is not sufficient to fulfill the needs of CM. To eliminate such shortcomings, a combination of sensors has to be used. Also evident from MCDM score values shown in Figure 20 to Figure 24, when independent techniques are compared to technique combinations. Assets can be classified into 3 different categories such as critical, sub-critical, and non-critical. All these systems have different factors which are considered by industries like cost, downtime, effectiveness, ease of implementation, complexity, external factors, shutdown cost, and maintenance strategy. (Bellini et al., 2008; Guoji et al., 2014; Henriquez et al., 2014; Schütze et al., 2018; Shin & Lee, 2015; Trajin et al., 2010; Uddin et al., 2014; Zhang et al., 2012).

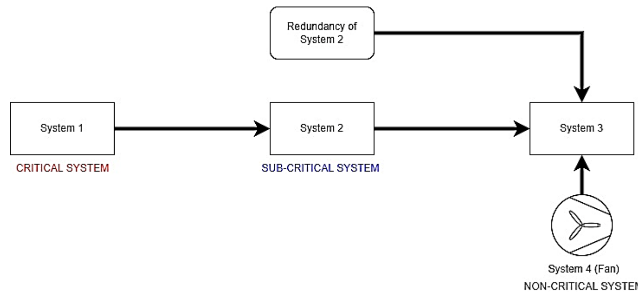

Figure 19. Example of system criticalities on an assembly line (Critical, Sub-critical, non-critical)

Figure 19. Example of system criticalities on an assembly line (Critical, Sub-critical, non-critical) shows an example of different system criticalities. System 1 is referred to as a critical system because if it fails the whole system shuts down, so low downtime is essential and the best techniques have to be adopted. System 2 is sub-critical because it has a redundancy that can be used while the system is in maintenance but not for a long time. System 4 is non-critical because even if it fails the production is still smooth but can reduce efficiency, so cost-effective techniques have to be chosen.

According to literature and expert opinion the weights for critical, sub-critical, and non-critical assets in some industrial sectors like oil refinery, chemical plants, power generation, water applications, material handling, agriculture, manufacturing and packaging are mentioned in Table 17. In critical systems, the main focus is to protect the system and prevent any fatal failures which are responsible for shutdowns. 70 % of weightage is given to motor and load fault detection and fault priority criteria, other criteria are of lower priority in this type of system. Sub-critical systems are given 50 % weightage to fault detection and priority and 40 % to cost as these systems usually have redundancies that can operate for some time if these systems are under maintenance. A balance between cost and quality of CM is usually maintained. Non-critical systems can usually be shut down or can be replaced if failed, their failure has a very low effect on the whole system. Cost criteria have the highest weightage in these systems at 70%. (Al-Najjar, 1999, 2000, 2007, 2012; Al-Najjar & Alsyouf, 2003; Maletič et al., 2015)

With the given weights from expert opinion, TCAS scores of all the possible technique combinations were obtained for critical, sub-critical, and non-critical assets as shown in Table 18 to Table 20. The best combinations suitable to an industry can be chosen according to the ranking of the technique based on the criticality of the asset.

Criticality/ Weights	Critical	Sub-Critical	Non-Critical
WM	35 % (0.35)	25 % (0.25)	10 % (0.10)
WL	35 % (0.35)	25 % (0.25)	10 % (0.10)
WC	10 % (0.10)	40 % (0.40)	70 % (0.7)
WD	10 % (0.10)	5 % (0.05)	5 % (0.05)
WN	10 % (0.10)	5 % (0.05)	5 % (0.05)

Table 17. Weightages of each factor for different system criticalities by expert opinion

Technique combinations	TCAS	Rank
Vibration + Current	1.5375	1
Vibration + Flux	1.35	2
Current + Acoustic	1.183333333	3
Acoustic + Flux	0.995833333	4
Current + Flux	0.64375	5
Vibration + Thermal	0.639583333	6
Current + Thermal	0.608333333	7
Thermal + Flux	0.514583333	8
Thermal + Acoustic	0.4625	9

Table 18. Technique combination ranking for Critical systems

Technique combinations	TCAS	Rank
Vibration + Current	1.516071429	1
Current + Acoustic	1.438095238	2
Vibration + Flux	1.392857143	3
Acoustic + Flux	1.314880952	4
Current + Flux	0.750892857	5
Current + Thermal	0.725595238	6
Vibration + Thermal	0.671130952	7
Thermal + Flux	0.663988095	8
Thermal + Acoustic	0.632142857	9

Table 19. Technique combination ranking for Sub-critical systems

Technique combinations	TCAS	Rank
Current + Acoustic	1.745238095	1
Acoustic + Flux	1.680952381	2
Vibration + Current	1.521428571	3
Vibration + Flux	1.457142857	4
Current + Flux	0.892857143	5
Current + Thermal	0.882738095	6
Thermal + Flux	0.850595238	7
Thermal + Acoustic	0.830357143	8
Vibration + Thermal	0.718452381	9

Table 20. Technique combination ranking for Non-critical systems

From the obtained TCAS scores for different asset criticalities, the top 3 techniques were chosen as shown in Table 21. Only the best technique is recommended for critical assets. It is well evident from Section 2 that vibration and current are the best techniques for mechanical and electrical faults. Acoustic which is the best alternative for vibration made a pretty good combination with current and flux which was the best alternative for current made an appreciable combination with vibration to obtain the top 3 positions in sub-critical and non-critical assets.

Criticality	Ranking	Technique Combination
Critical	1	Vibration + Current
Sub-Critical	1	Vibration + Current
	2	Acoustic + Current
	3	Vibration + Flux
Non-Critical	1	Acoustic + Current
	2	Acoustic + Flux
	3	Vibration + Current

Table 21. Recommended technique combinations for different criticalities

Technique comparison charts when each technique is used independently and when it is used with other techniques are shown in Figure 20 to Figure 24. To compare the combinations with independent techniques, TAS values (MCDM values) of both techniques are added and a percentage increase in the score is evaluated with respect to the base technique. For comparison, the case of critical assets is considered as having the most weightage towards the quality of fault detection.

As evident from the given chart technique combinations are more effective concerning rotating machinery where both mechanical, as well as electrical faults, are present with other criteria and difficulties.

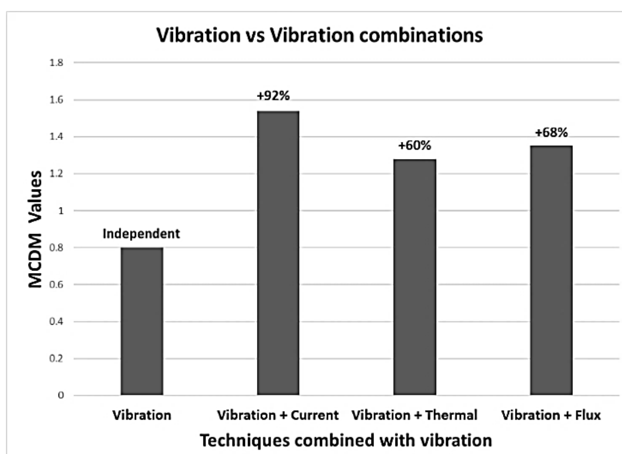

Figure 20. Percentage improvement when vibration is combined with other techniques in critical assets

When a single technique is used for both motor and load sides only a single category of faults can be detected as evident from Table 5 and Table 6. For example, if vibration monitoring is used on both sides and the winding fault in the motor the whole system will be shut down without any fault indicator.

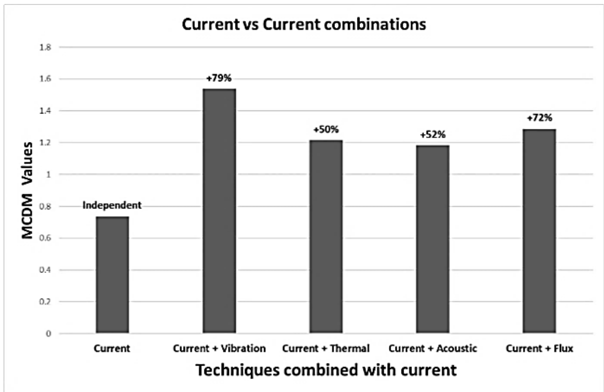

Figure 21. Percentage improvement when current is combined with other techniques in critical assets

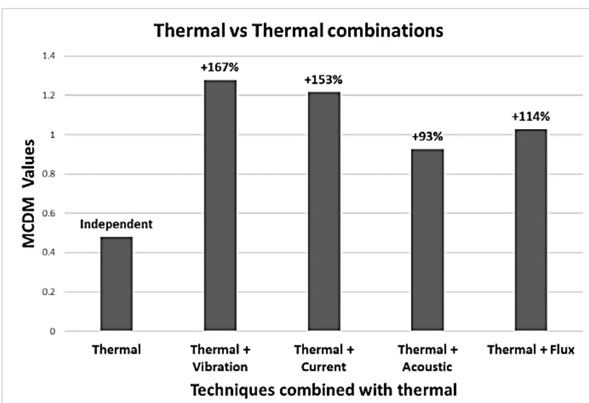

Figure 22. Percentage improvement when thermal is combined with other techniques in critical assets

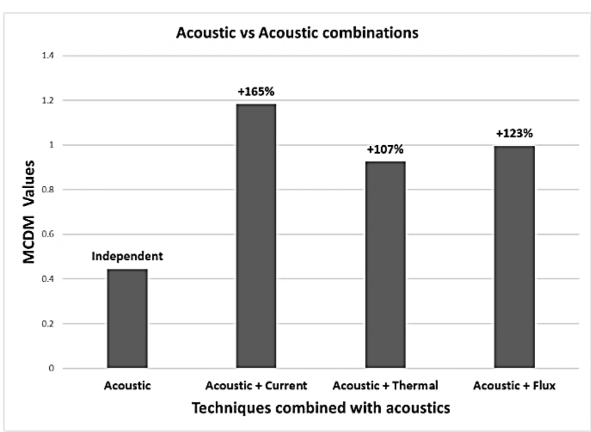

Figure 23. Percentage improvement when acoustic is combined with other techniques in critical assets

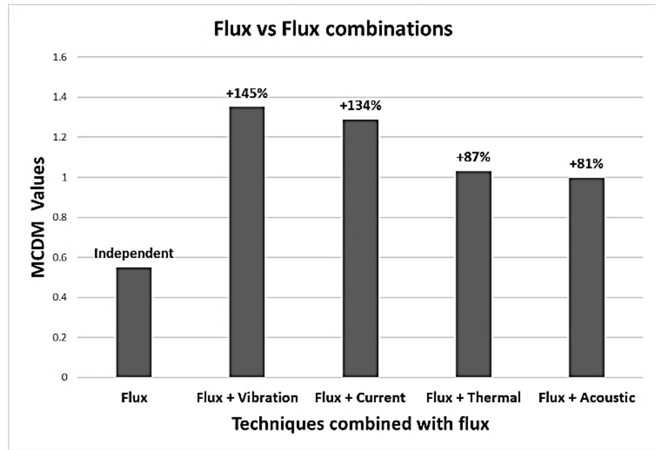

Figure 24. Percentage improvement when the flux is combined with other techniques in critical assets

The best combinations can be effectively used in industries for health monitoring of complete assets (motor + load). The combination of Vibration-acoustic was eliminated by careful observation that both detect similar faults. Industries that do not want to spend much on CM for non-critical assets, can adopt the recommended technique for specified industries or in similar applications as per expert opinion. Industries willing to spend some money on sub-critical assets can adopt recommended combinations for cost-effective monitoring. For critical applications, the main objective is to reduce downtime, vibration-current combination which got the best TCAS score is recommended. Implementation of recommended techniques will surely help in the maintenance of rotating machinery while also saving a lot of time that goes towards unplanned maintenance. Costs associated with shutdowns and machinery costs can be saved with the recommended technique combinations for specific needs.

Figure 25 shows a typical implementation system for CM of rotating machinery. A multi-sensor package will transfer the machine data to DAQ which then will be converted from an analog signal to digital, and directly send by serial communication. Binary signals can be stored in a large quantity in small databases and then can be sent using Industrial Internet of Things (IIOT) technology which will be uploaded to the cloud. Information will be downloaded and decrypted to its original form by DAQ software. Original information like vibration data, temperature, sound, flux, and current which is recorded from MCC Panel (Machine Control Centre) will be analyzed by the Fault Detection Model. If there is any unusual behavior or fault it will be immediately reported to the maintenance engineer, and steps will be taken to correct the problem.

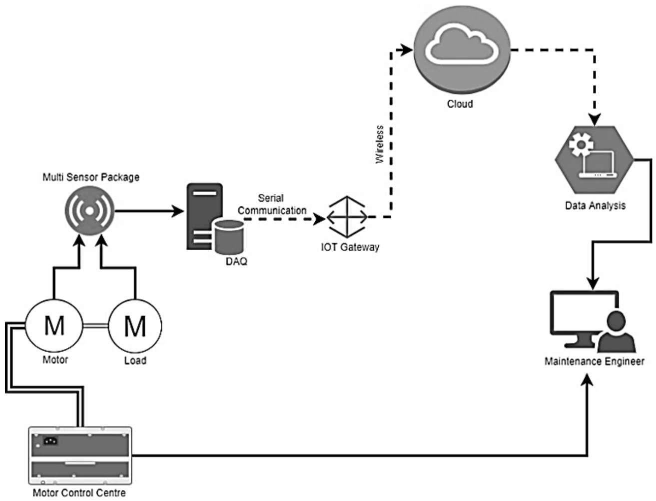

Figure 25. Typical wireless CM setup for continuous monitoring using IIOT for rotating machinery

Figure 26 shows typical multiple DAQ systems connected to a chassis controller if there is a need for a large amount of sensor data to be collected in an industry, a realization of industry 4.0 (Duan et al., 2018; Goman et al., 2019; Ichwana et al., 2020; Peng et al., 2018).

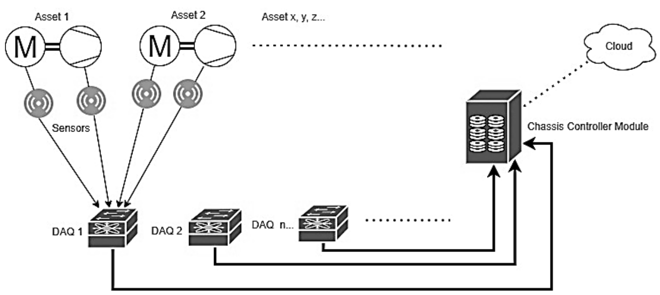

Figure 26. Typical multi-rotating machinery with multiple DAQ setup

Concluding thoughts are given in section (IV).

4. CONCLUSION

It is evident from the techniques and scores that the best techniques of CM are vibration for mechanical faults diagnosis and current for electrical faults diagnosis. But it is not practical to implement these in every scenario. Industries consider cost and other factors into account for diagnostic setup and if the diagnostic system will cost more than the asset cost, the industry will not even implement CM in the first place. This paper tries to solve that problem by giving them the flexibility to choose a suitable combination of techniques for different levels of sophistication. As per industrial needs expert opinion could be taken for deciding the weights for given criteria and final scores can be obtained from the mentioned methodology. A set of weights were obtained from industrial experts for critical, sub-critical, and non-critical assets in some industries. Recommended combinations can be used by industries and in similar applications. Factors like cost, noise, criticality, multiple fault category justification, and ease of data collection are already considered in the methodology so that the results can be directly applied to real-time rotating machinery. A comparison is also shown when a technique is implemented independently and when it is combined with other techniques to help understand the advantages of combining techniques. Also, a suitable wireless setup is suggested, considering the latest advancements in technology for remote monitoring of rotating machinery.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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