Grid Solutions

Advanced Analytics and Managed Services

POWERNODE MOTOR HEALTH MANAGEMENT

GE Vernova's HVDC technology powers a densely populated South Korean city

Whitepaper

GE VERNOVA

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ABSTRACT

Electric motors comprise a significant part of industrial load. They often control critical industrial processes, and any unplanned downtime could result in huge losses. There are many solutions that monitor the health of the motors, but most require additional sensors and have limitations in detecting motor faults when they are subjected to oscillations of the load. GE Vernova Grid Solutions has launched a new solution, PowerNode – Motor Health Management (MHM), that monitors the health of the motors and detects faults at an early stage of development. The solution leverages the electric protection relays as sensors to collect the motor data, analyse the data, and provide valuable analytics. The advanced algorithms use physics-based features along with machine learning techniques to detect faults even when the motor is subjected to load oscillations. The MHM solution is available as an on-premise solution or as a managed service securely hosted in the cloud. The cloud solution is most suitable for monitoring a fleet of motors. GE Vernova Managed Service helps the customers in interpreting the analytics and take right decision to avoid unplanned motor outages.

1. INTRODUCTION

1.1 NEED FOR MOTOR HEALTH MONITORING

Electrical machines play a vital role for the modern industrial world. The impact of unplanned downtime due to the breakage of these electrical motors is estimated to be more than $30 billion USD each year.[1]

GE Vernova's expertise in electric motor protection with more than 100 years of engineering experience with motors, generators, and control equipment, brings physics-based analytics and advanced machine learning algorithms together into the PowerNode – Motor Health Management (MHM) solution. It detects evolving faults within the electrical motors, helps identify future issues, and supports customers to avoid failures or resolve faults in advance, thus reducing unplanned downtime.

Traditional techniques for implementing predictive analytics are based on installing new sensors which add cost and new potential failure points. The data stored in SCADAs/historians is not suitable for predictive analytics due to low sampling rates. GE Vernova's IEDs provide high frequency/resolution data and hence no additional sensors are required.

The MHM solution also supports non-GE Vernova IEDs, but an evaluation will need to be carried out to confirm the suitability of the IED.

1.2 COMMON FAULTS IN MOTORS

The following is a brief list of the different failure modes and their physical descriptions.

1.2.1 Bearing Faults

The bearing faults considered here are specific to rolling element bearings. Rolling element bearings are one of the most widely used elements in machines, and their failure is one of the most frequent reasons for machine breakdown.

Mechanical vibrations in the bearings create airgap variations that in turn convert into current pulsations at frequencies different from the natural frequencies of the bearings, which are used for fault detection. The MHM solution detects two types of bearing faults.

Point defects: Bearing defects that occur at single localized points are called point defects. A point defect causes airgap movement and frictional load torque oscillation at characteristic frequencies.

- Outer Race Defect: Localized single point defects on the outer race way such as spalling and brinelling in which material is displaced or upset.
- Inner Race Defect: Localized single point defects on the inner race way such as spalling and brinelling in which material is displaced or upset.

Generalized roughness: If the bearing is degraded or becomes rough over a larger area then the defect is termed as generalized roughness. This type of defect causes airgap and frictional load torque oscillation in a broader frequency range.

1.2.2 Insulation

Insulation degradation refers to the aging of insulation due to several factors like thermal, mechanical, electrical, and environmental. The insulation between the winding turns and the insulation between the turn to ground are prone to degradation and, over time, develop into a turn-to-turn fault or turn-to-ground fault. Different stages of insulation damage can be detected.

Shorted turns describe the stage when insulation degrades and forms a direct short (very low impedance) between adjacent turns of a phase winding or between turns of two different phase windings. Stator turn faults result in impedance unbalance between the phases which will result in increased negative sequence in the motor current. This is used for detection of the fault.

1.2.3 Broken Rotor Bars

A major cause for rotor bar or end ring failure is frequent load variations or start stops which create more stress on rotor circuit. A partially damaged rotor bar will result in increased current flow at adjacent bars leading to their failure, as well as uneven heat distribution in the rotor. In addition, a completely broken bar can lift off from its slot and rub against stator, resulting in severe mechanical or winding failures. A breakage of the rotor bar results in unbalance in the rotor circuit, creating a negative revolving field in the rotor which modulates stator current and appear as sidebands in motor current. This can be used for their detection. MHM analytics uses a modified algorithm which uses a demodulated signal derived from motor current to eliminate leakage and resolution related issues associated with common broken bar detection techniques using Electrical Signature Analysis (ESA).

1.2.4 Mechanical Faults

Mixed Eccentricity: Eccentricity in the motor is caused primarily by the misalignment of the stator and/or rotor axes and the centre of rotation. Eccentricity creates airgap variations that in turn result in winding inductance variations which are then reflected on to the currents, detectable as sidebands at the rotational frequency in the frequency spectrum of motor current. The frequency spectrum of the currents, or demodulated signals derived from currents, can hence be used to detect this fault. There are three types of eccentricity faults:

- Static eccentricity – Rotor centre and centre of rotation coincide but different from the stator centre.
- Dynamic eccentricity – Stator centre and centre of rotation coincide but different from the rotor centre.
- Mixed eccentricity – Stator centre, rotor centre and centre of rotation do not coincide.

MHM Services algorithms are designed to detect mixed eccentricity faults. Growth of any form of eccentricity can also be detected as there is always a small amount of mixed eccentricity in all machines.

Bent Rotor Shaft: A bent rotor shaft is a mechanical deformation of the rotor shaft resulting in airgap variations. This is similar to the mixed eccentricity of the airgap which can be detected using the eccentricity algorithm.

1.2.5 Electrical Supply

- **Voltage Total Harmonic Distortion (THD):** MHM Services monitor machine voltage THD. Increased voltage THD can result in increased torque ripple and losses in the machine.
- **Positive & Negative Sequence Voltage:** MHM Services monitor machine negative sequence voltage. Increased negative sequence voltage causes torque ripple at multiples of the fundamental frequency and increases motor losses.
- **Positive & Negative Sequence Current:** MHM Services monitor machine negative sequence current. Increased negative sequence current causes torque ripple at multiples of the fundamental frequency and increases motor losses.
- **Current Harmonics:** MHM Services monitor the harmonic spectrum of motor current. A deviation of current spectrum of motor current from baseline indicates some developing faults in the system.

2. MOTOR APPLICATIONS

2.1 CLASSIFICATION OF MOTOR LOADS

Industrial motors are used for different applications and, depending on the application, the load torque oscillations vary. The table below gives typical motor applications in industries and corresponding intensity of load torque oscillations.

TYPE OF APPLICATION	INDUSTRY	LOAD TORQUE OSCILLATIONS
Crushers, Grinders	Power plants, Metal	High
Mills (Metal industry)	Metal	High
Reciprocating Compressors	O&G, Plastics	High
Pumps, (near low flow op. conditions), slurry pumps	Most Industries (pumps), mining (slurry pumps)	High
Conveyors	Most Industries	Medium
Blowers/Fans/Centrifugal Compressors	Most Industries	Low
Hydraulic Press	Automobile	High

Figure 1. Classification of motor applications based on load type

2.2 LIMITATION OF MOST EXISTING ANALYTICS

Load torque oscillations result in frequency modulations of the electrical parameters such as current, voltage and power. Most of the existing ESA algorithms are sensitive to these modulations, resulting in the reduced performance of the algorithms.

Torque oscillations (in cases like coal crushers, steel rolling mills, etc.) are random and stochastic in nature. They cause the electrical signal spectral content to jump around in a randomly modulated way and hence physics-based features experience the following distortions:

a. The additional spectral power due to faults may be spread out across a wider frequency region than is being currently explored.

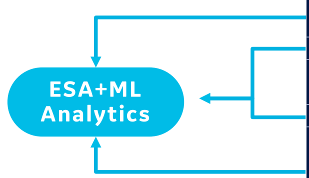
b. The spectral content might change from time to time in a random fashion.

c. Noise floor may be increasing and time-varying in nature.

3. MHM SOLUTIONS

The MHM solution addresses the gaps in existing motor health monitoring solutions using a combination of advanced physics-based algorithms and machine learning techniques.

MHM uses advanced algorithms that combine the physics-based features with machine learning techniques to detect motor faults such as broken rotor bar (BRB), stator inter-turn fault, bearing faults and mechanical faults like eccentricity, bent rotor shaft, foundation looseness, and misalignment under load oscillations. The algorithms were validated in the lab using purpose-built setups and by means of field trials. The motors were subjected to load torques with varying frequencies and amplitudes to simulate the load torque oscillations. Tests were carried out on both healthy and faulty motors, and the algorithms performed very well in detecting the defects at an early stage. The table below summarizes the faults detected by the MHM solution.



		Motor Technology	
		IND	SM
Bearing Faults	Outer Race Defect	●	●
	Inner Race Defect	●	●
Insulation	Stator Intern-turn short*	●	●
Temperature	Bearing Temperature	●	●
	Stator Temperature	●	●
BRB	Broken Rotor Bar	●	
Mechanical	Mixed Eccentricity	●	●
	Bent Rotor Shaft	●	●
	Foundation Looseness	●	●
	Misalignment	●	●
Thermal	Thermal Capacity Used	●	●
Electrical Supply	Currrent & Voltage THD*	●	●
	>0 & <0 Sequence Current & Voltage	●	●
	Power Factor Monitoring*	●	●
	Current & Voltage Harmonics*	●	●
	Motor Start Monitoring	●	●

IND: Induction Machines SM: Synchronous Machines

*Voltage Required

List of failure modes based on latest GE relay's technology for LV & MV motors

ESA+ML analytics are included in the standard set and other analytics are provided as optional based on relay capabilities

For third party relays, an evaluation will need to be carried out

Figure 2. Motor analytics

More details are given in the next section.

3.1 SOLUTION ARCHITECTURE

GE Vernova's MHM Services help to increase uptime and reduce OPEX by implementing prognostics-based equipment insights. The buyer provides the remote connectivity and accessibility that enables this connection.

MHM Services provide real-time equipment health information. On-site and cloud-based monitoring elements monitor the equipment and provide an Equipment Health Dashboard. The solution provides detailed insight into alarms, escalating them to GE Vernova's experienced data analysts, subject matter experts and service engineers who provide recommendations for action.

The figure below depicts the overall connectivity architecture of the system. In the following paragraphs, each of the integrating elements is described in more detail.

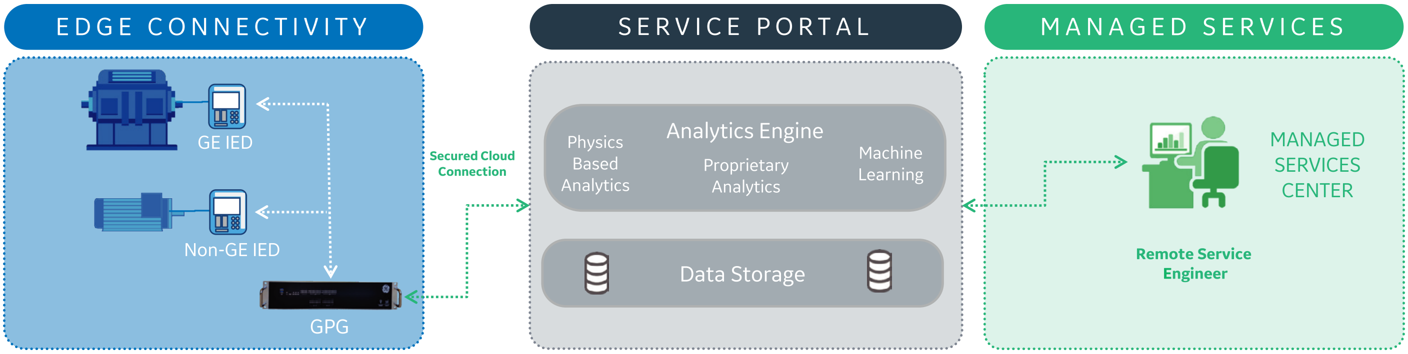


Figure 3. MHM solution architecture

The fast-reacting protection function of the IEDs continuously monitor the raw signals of current and voltage and analyse the status of the machine. When acting as edge devices, the IEDs also take periodic snapshots of high-frequency data and upload them to the cloud platform through the GPG Gateway hardware platform.

A Secure IPsec tunnel is established between the GPG and the GE Vernova cloud where the analytics engine, data storage and service portal are hosted in a secure environment. GPG uploads the machine operating data from the plant to the GE Vernova cloud for remote monitoring and diagnostics. The secure tunnel also enables the remote access of GPG from the GE Vernova network for troubleshooting and upgrades.

Exporting the data to the cloud platform ensures that the analytics applied to the raw data is always the latest version, as GE Vernova continuously updates the algorithms based on experience.

An on-premises version of the solution is also available for the customers who have in-house expertise to analyse the alarms and take appropriate maintenance actions.

3.2 ANOMALY DETECTION TECHNIQUE

Machine learning techniques are extensively used in asset condition monitoring. In most of the cases, real life failure data is not widely available to apply supervised learning techniques. Unsupervised learning techniques like clustering are proven to be effective for anomaly detection in such cases. The following sections explain the application of this method for motor health condition monitoring.

3.2.1 Feature Sets

The performance of an asset depends on multiple factors such as its design, operating conditions, loading pattern on the asset, age of the asset, etc. Typically, a set of features characterize a fault, and the variations in these features distinguish the healthy state of an asset from the faulty state. Often, the degree of variations in the values of the feature sets changes from one asset to the other and it is difficult to come up with a common set of boundary values that separate healthy and faulty states for all assets. Each asset is taken through an initial baselining phase prior to monitoring.

3.2.2 Anomaly Detection

The measured data from the asset is processed in frequency domain to construct feature sets relevant to different faults. The number of features is typically more than one for any fault, and we have a multi-dimensional feature space. In this feature space, the boundaries of the baseline cluster are modelled, and a probabilistic measure is computed as to how far from baseline any test condition lies. This approach is called anomaly detection. The test condition pertains to the asset during its monitoring phase. An overview of this principle is given in the figure below.

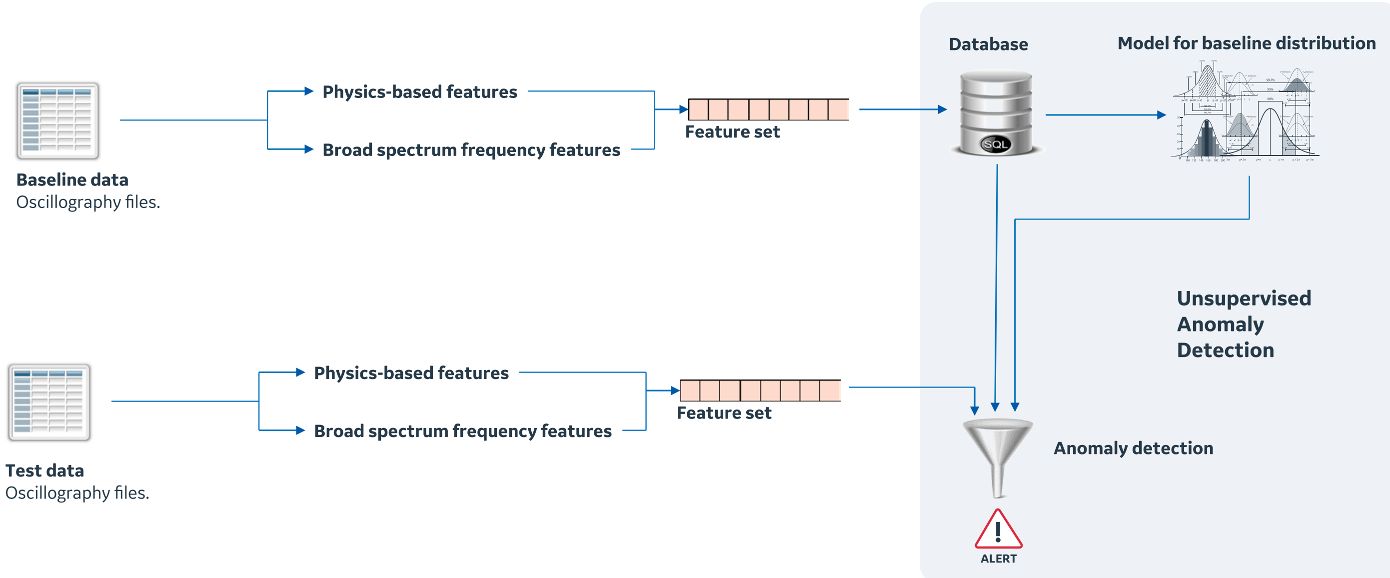


Figure 4. Anomaly detection principle

3.2.3 Algorithmic Approach

A set of thresholds is defined for each type of fault based on the data processed during the baseline phase. During the monitoring phase, a test cluster is considered and a set of scores known as Silhouette scores are computed based on the average distance of the test cluster from its k nearest neighbours (k-NN). The occurrence and severity of the fault can be predicted based on the value of the computed scores in comparison with the thresholds. The severity of the fault is defined in two levels, attention needed and critical stage. The algorithm is explained in the figure below.

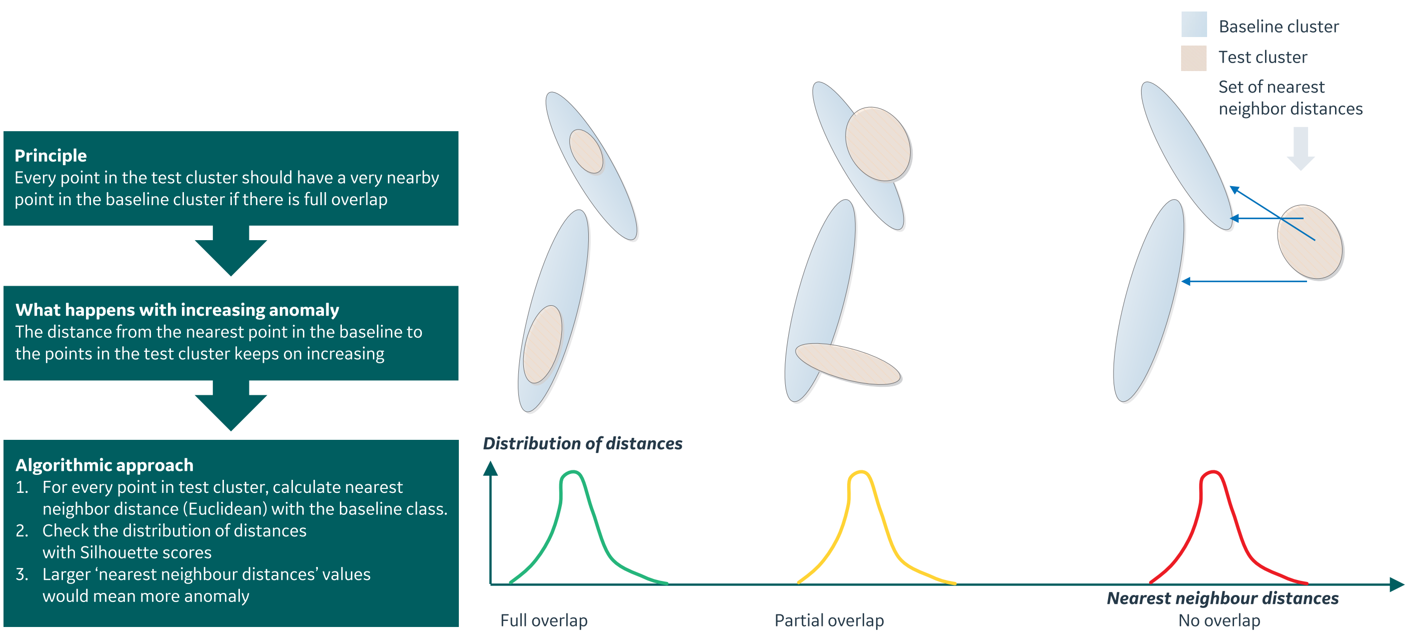


Figure 5. Fault detection algorithm approach

3.3 FAULT DETECTION IMPLEMENTATION

The fault detection solution is implemented using the technique explained in the previous section. The solution approach has the following key steps.

1. Feature selection and construction of feature sets
2. Data quality checks
3. Baselining the motor health
4. Monitoring the motor health and alerting

3.3.1 Feature Selection for Various Faults

A distinct feature set is used to detect each type of fault mentioned earlier. The feature set is constructed from the high-frequency time series data captured by the relays.

3.3.1.1 Broken Rotor Bar

Fast Fourier Transform (FFT) of instantaneous real power and reactive power signals is considered for detecting broken rotor bar faults. The corresponding energies of the signals delP and delQ are computed in a specific frequency range.

The trend of the ratio of the energies delQ and delP helps to distinctly identify if the motor has a broken rotor bar under load conditions. The following figure depicts the trend under the conditions of no load oscillation and load oscillation. MHM solution identifies the BRB fault and sends alerts.

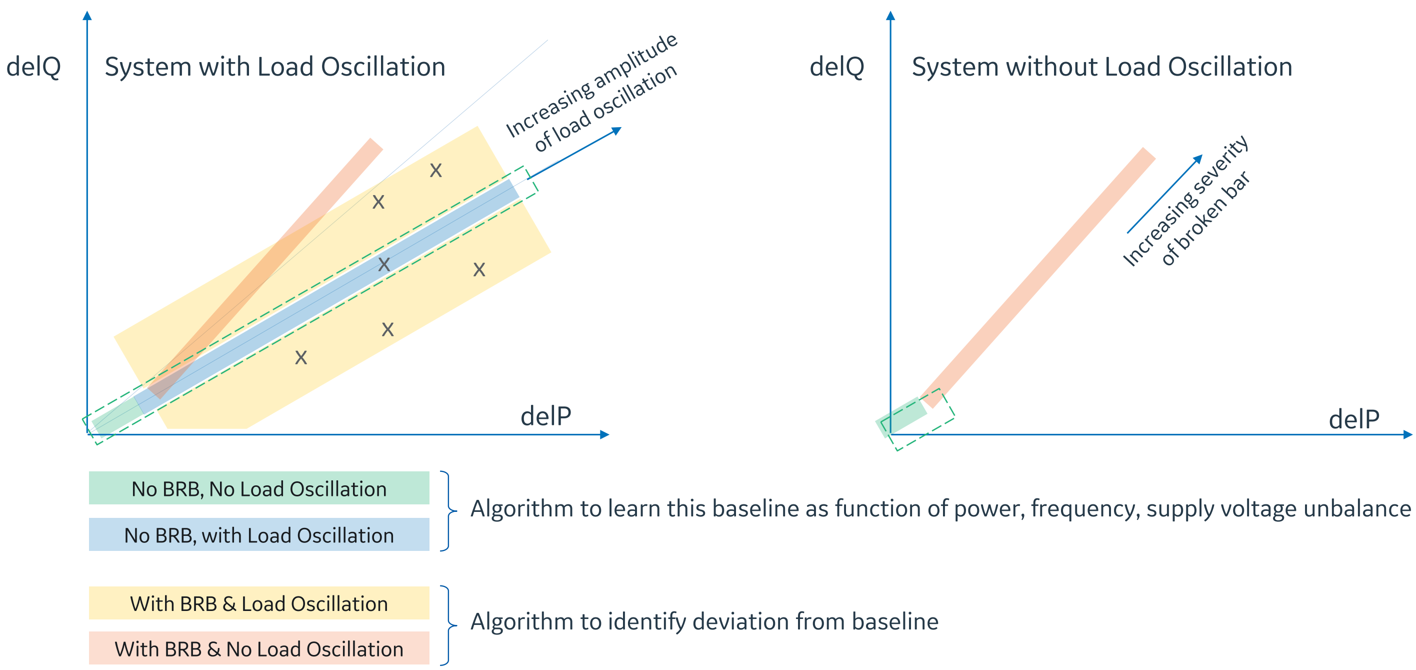


Figure 6. Broken rotor bar fault detection principle

3.3.1.2 Mechanical Faults

Both the positive and negative frequency components of the complex current signal FFT are considered for mechanical fault detection. It is observed that the load torque oscillation is present only in the positive frequency side of the FFT and not on the negative frequency side as shown in Figure 7. The increase in the amplitude of the feature because of a mechanical fault appears on both the frequency sides of the FFT. Hence, the energies in several frequency bands in the negative frequency side of the FFT of the complex current signal is considered for detecting the mechanical faults.

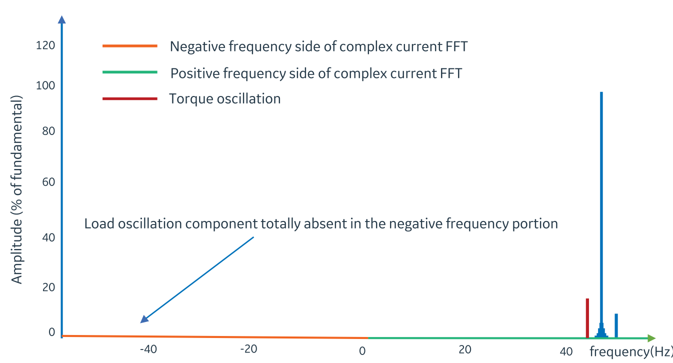


Figure 7. Mechanical fault detection principle

3.3.1.3 Stator Inter-turn Fault

The basic physics of fault detection is based on the increased unbalance between 3-phase windings of the machine when the fault is developed in one of the phase windings. This will change the cross-coupled impedance Z_{np} (negative to positive sequence impedance) of the machine. The fault index used here is the ratio of cross-coupled (Z_{np}) to positive sequence impedance (Z_{pp}) which can be calculated from the measured voltages and current as below.

$$FI = \frac{Z_{np}}{Z_{pp}} = \left| \frac{V_n - Z_{nn} I_n}{V_{p\text{-}rated}} \right|$$

Z_{pp} = Positive sequence impedance
Z_{np} = Cross-coupled negative-to-positive sequence impedance
V_n = Measured negative sequence voltage phasor
I_n = Measured negative sequence current phasor
V_{p_rated} = Rated positive sequence voltage of the machine
Z_{nn} = Complex negative sequence impedance of the machine

For VFD machines:

$$FI = \frac{Z_{np}}{Z_{pp}} = \left| \frac{V_n - Z_{nn} I_n}{V_{p\text{-}rated}} \right|$$

V_{p_rated} = Rated positive sequence voltage of the machine at rated frequency

The above method of computing the fault index has the following advantages

- Applicable to induction and synchronous motor – Grid or VFD fed
- Less sensitive to load, supply unbalance variation, and frequency
- Less motor-to-motor variation

3.3.1.4 Bearing Faults

Energies in the squared current signal over a specified range of frequencies in the FFT spectrum are used for detecting bearing faults. A wide range of frequencies is considered for bearing fault detection under load oscillations and no load oscillations. The range includes outer race, inner race and ball defect characteristic frequencies. The outer race, inner race and ball defect factors vary based on the bearing geometry and motor parameters.

The characteristic fault frequencies $f_{bearing}$ for the different bearing faults that depend on the bearing geometry and rotational frequency are given as:

$$f_{bearing} \begin{cases} \text{Outer raceaway: } f_o = \frac{N_b}{2} f_r \left(1 - \frac{D_b}{D_c} \cos ß\right) \\ \text{Inner raceaway: } f_i = \frac{N_b}{2} f_r \left(1 + \frac{D_b}{D_c} \cos ß\right) \\ \text{Ball: } f_b = \frac{D_c}{D_b} f_r \left(1 - \frac{D_b^2}{D_c^2} \cos^2 ß\right) \end{cases}$$

The amplitude of the feature at fault frequency increases when there is a bearing fault as shown in Figure 8.

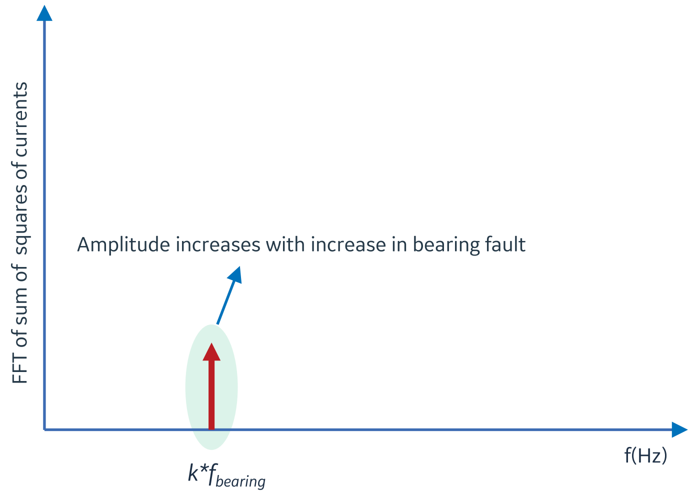


Figure 8. Bearing fault frequency for the signal I²

3.3.2 Data Quality Checks

For successful working of the motor diagnostics algorithms, the machine should operate relatively steadily, meaning there is only limited variation in load, frequency, or input voltage. If any transient above a particular limit is observed, then that data is filtered and not passed to the fault detection algorithm for calculating the fault index.

3.3.3 Baselining

In the baselining phase, several data files are processed, and feature sets are derived based on the feature definitions mentioned in the previous section. This data is used to populate a statistical model. The model output is a set of thresholds which is saved for use during the monitoring stage. Typically, the motor is taken through an initial baselining phase, and then the motor will transition into a monitoring and alerting phase.

As the operating conditions of the motor change over a wide range, data binning techniques are used to improve the accuracy of the model.

3.3.4 Monitoring and Alerting

During the monitoring phase, the data captured through the relays is processed, and the feature sets are constructed and then sent to the model. The computed scores or fault indices are compared with the threshold values saved during the baselining phase. The health of the motor is predicted as per these values. Typically, there are two levels of thresholds defined for any fault: low-level threshold represents attention needed stage and high-level threshold represents critical stage. Respective alerts are generated whenever the fault index crosses these thresholds.

3.3.5 Extensive Validation

Initially the algorithms were validated in the lab on setups that were specifically built for the purpose. Validation of the algorithms was done on motors that were healthy and then on the motors having specific faults. Both DOL and VFD-fed motors were considered. The motor was subjected to oscillating loads whose amplitude and frequency were varied. In addition, the operating conditions such as percentage load current, frequency and voltage unbalance were monitored during the tests.

The algorithms were able to detect the healthy or faulty condition of the motor with an accuracy level greater than 90 percent for all the faults considered.

4. FLEET MANAGEMENT

The solution is available as two variants, a cloud-based version and an on-premise version. The cloud-based version is capable of managing a fleet of motors with additional insights and better performance by applying big-data analytics.

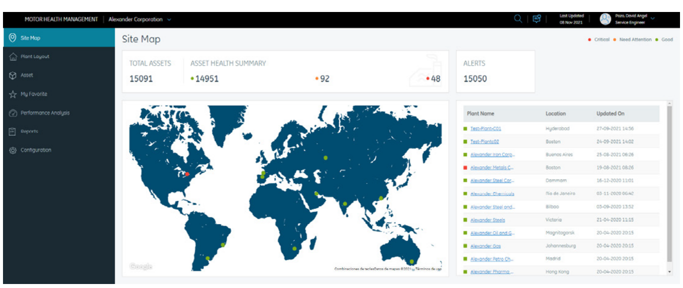
The motor data gathered is stored in a highly secure environment in the cloud. Additionally, a cluster or a group of motors is identified during the baseline period based on the combination of motor type, condition during the baseline phase, year of manufacturing, load application, and other parameters. This type of clustering helps in optimizing the frequency of data retrieval from the relays and in fine tuning the thresholds used during the alerting phase.

5. MANAGED SERVICES

5.1 PORTAL

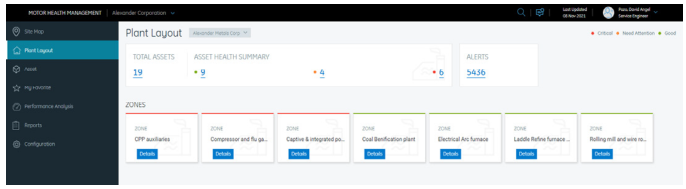
The MHM portal provides a comprehensive view of the health of the motors starting from a site-level view and going up to a specific fault in a motor. The health analytics are displayed as visual dashboards for the different levels. A few dashboards are given below.

1. **Site Map:** Overview of the location of all monitored sites and assets of a company. Locations with an asset with potential issues will be highlighted in **orange** or **red**.



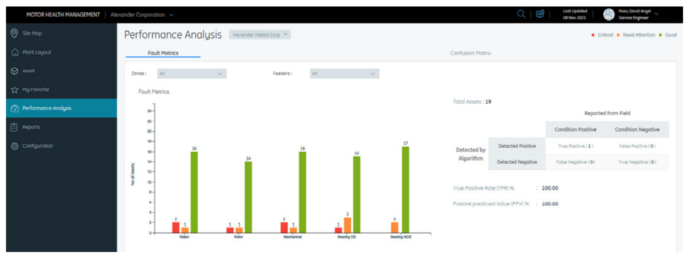
Data displayed in the chart are for the purpose of illustration only

2. **Plant Layout:** Navigating to a specific site will show the asset status organized in up to 4 hierarchical levels to easily locate a specific asset. e.g.:
   a) Plant Zones/Areas b) Voltage Level
   c) Switchboard Name d) Asset List



Data displayed in the chart are for the purpose of illustration only

3. **Asset List:** Provides asset data and health status information. From this list, we can access the asset details by clicking on the "View" link.



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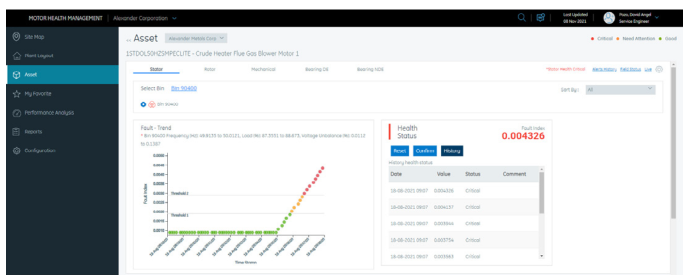
4. **Asset Details:** Overview of actual and historical data for each asset and failure type. This information is mainly relevant to our team of experts to validate a potential motor failure.



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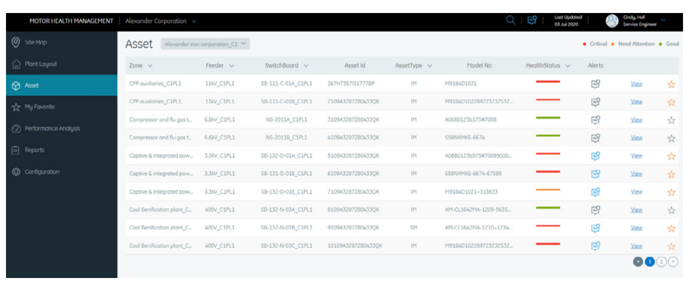
5. **Performance Analytics:** A set of dashboards that displays the status of the assets by failure type and a confusion matrix that displays the failure detection accuracy.



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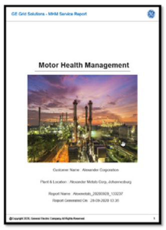
5.2 REPORTS

MHM provides detailed reports that can be downloaded from the portal. The motor health analytics are sliced and diced into easily comprehendible charts for the users. The fault trend charts offer deep insights into the motor performance.

Reports: *Periodic report (e.g. monthly, quartely) that includes overview of all monitored assets for given site.*



Report includes:

- Health Summary dashboards
- Asset Alerts table for reporting period
- Plat-level fault distribution
- Fault trend charts for selected motors
- Motor expert's conclusions

5.3 THREE LEVELS OF SERVICES

The Managed Services Centre studies all potential failures detected by the service portal.2 A team of experts perform three main actions:

Service 1: Review and validate the incipient failure of the motor. Prepare and send recommendations of actions to be taken by the site maintenance team to address the problem.

Service 2: Support the site maintenance team to investigate and correct the problem.

Service 3: If failures are missed or incorrectly detected, the managed service team performs an investigation and modifications of motor parameters and/or performs enhancements to the failure detection algorithm to increase failure detectability.

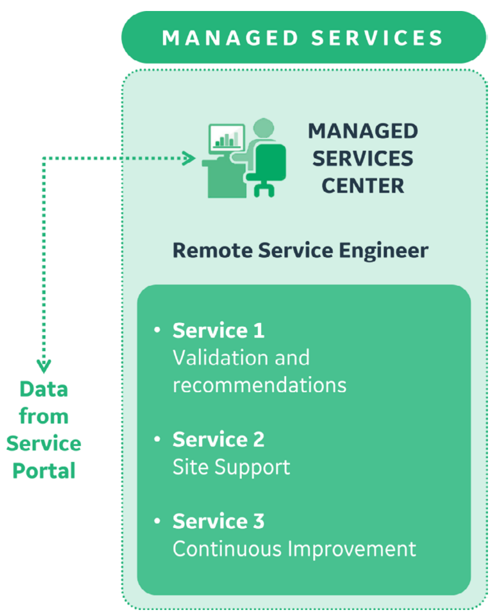


Figure 9. Managed Services levels

Electrical motors operate under different load conditions depending on the application. A continuous improvement process can adapt failure detection to specific operating conditions.

6. REFERENCES

1. Sergio Dominguez, Luke Solomon, Simon Baggott, Stuart Gray, Andrew Ireland, Electrical Rotating Machine APM Overview
2. https://www.gegridsolutions.com/powerd/catalog/powernode-motor-health-mngt.htm

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