DATA-DRIVEN INSIGHTS FOR INDUCTION MOTOR CONDITION MONITORING

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Abstract – Effective condition monitoring of electric motors plays a pivotal role in ensuring the reliability and performance of various industrial processes.
This paper presents a comprehensive methodology for real-time monitoring of internal thermal and loading behavior within electric induction motors, employing pattern recognition & matching techniques. The approach outlined leverages data-driven insights to assess the health and performance of electric motors in a proactive manner.
The paper defines an approach utilizing conventional sensors, relay data, and advanced pattern recognition & matching algorithms for predictive maintenance, minimizing downtime and optimizing operational efficiency.

Index Terms — Induction Motors, Digitalization, IED, Machine Learning, Data Analytics, Algorithm Development, Abnormal Behaviors, Predictive Maintenance

I. INTRODUCTION

Traditional Electric Motors Management relies on Preventive Maintenance (PM), primarily guided by manufacturer's recommendations, international standards, and operators' experience. PM routines encompass not only maintenance tasks like cleaning, parts replacement, and oil refill, but also a set of electrical and mechanical tests to evaluate the motor's condition.

Intelligent Electronic Devices (IED) monitor various parameters such as currents, voltage, power, winding and bearing temperatures, vibrations, ensuring equipment safety. While these real-time data are vital for protecting the motor, they primarily identify specific failures or anomalies without structured analytics for predictive failure detection or improved machine operations.

Trending and analyzing electrical parameters from IED, along with mechanical and process data from the Equipment Unit Control Panel (UCP) and/or Distributed Control System (DCS), provide a powerful tool for operators in their day-to-day work.

In the realm of industrial operations, effective monitoring of electric motors is crucial. Ensuring their optimal health not only minimizes downtime but also aligns with industry goals of reducing emissions through electrification.

While smart sensors offer undeniable benefits [1], the methodology presented for real-time monitoring to identify abnormal behaviors and areas for operational improvement solely depends on IED and DCS/UCP data. This approach, depending on device and automation network characteristics and availability, minimizes costs and simplifies system complexities.

Employing advanced pattern recognition & matching techniques as anomaly detection algorithms, the method uses real time data to proactively assess electric motor health and performance. By identifying abnormal behaviors, it enables predictive maintenance, reducing unplanned downtime and optimizing operational efficiency.

II. SYSTEM ARCHITECTURE FOR DATA ACQUISITION

Several architectures are accessible for data acquisition, accomplished through an automation serial network connecting the mentioned devices/systems to a dedicated server functioning as a data hub [2].

IEDs can be connected in switchboard architectures in STAR configuration, Ring, Multiple-Ring, Redundant (HSR or PRP), etc. as briefly illustrated in Fig. 1. An exemplar of the overall architecture, including IED, DCS and UCP is displayed in Fig. 2.

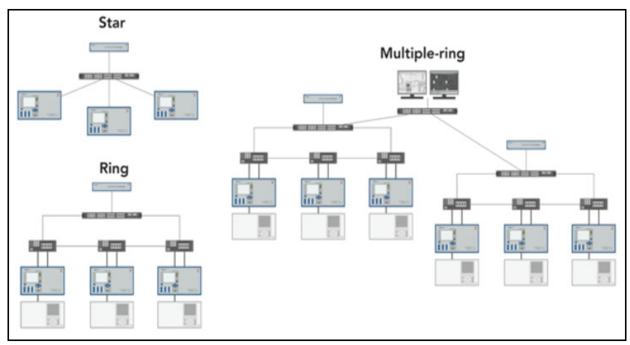

Fig. 1 Typical network topologies

While this paper introduces the foundational concepts of system architectures for data acquisition, it refrains from delving into detailed specifications or configurations, leaving further exploration to be pursued as indicated in reference [2].

III. MOTOR CONDITION MONITORING – MOTOR MODELS

A. *Thermal Model*

The Thermal Model facilitates the detection of abnormal thermal conditions by analyzing data related to motor currents (ILs), winding temperatures (WDG_Ts), and calculated thermal load (THML). Motor currents and thermal load are acquired from IED, while winding temperatures can be sourced from either the IED (as displayed in Fig.3) or the UCP/DCS.

THML acts as the supervised and primary parameter for overload protection (ANSI Code 49) [3]. The IED computes THML by considering true RMS and negative-sequence currents, along with heating and cooling time constants. The heating up of the motor is determined by the square value of the load current. However, in case of unbalanced phase currents, the negative-sequence current also causes additional heating. Protection based on both current components helps avoid abnormal motor heating. The thermal load is influenced by various operational situations and phase current levels [4].

The multidimensional scatter plot (Fig. 4) represents the data and aids in identifying the healthy zone and several failure modes, such as:

1) *Motor High/Very High Temperature:* Triggered when a winding temperature exceeds defined alarm limits. This condition may be associated with an overload state, insufficient/failed motor cooling systems or internal overheating/hot spots. Operators are alerted to prevent motor failure, with machine shutdown recommended based on motor loading.

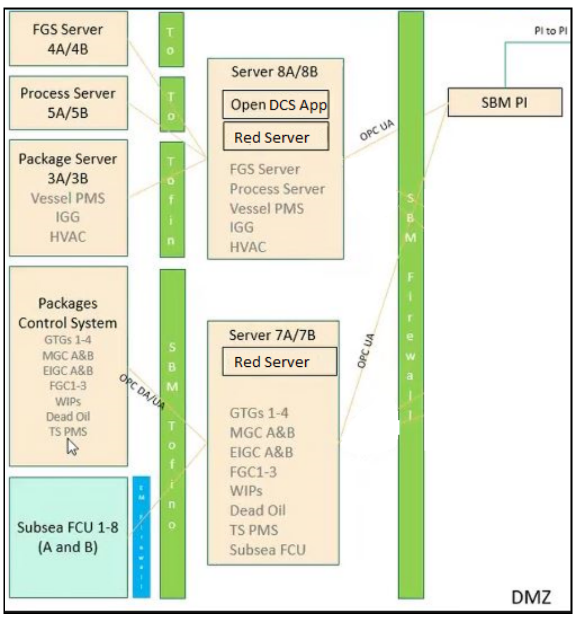

Fig. 2 Example of overall architecture philosophy

2) *Motor High Thermal Load:* Activated when the thermal load surpasses defined alarm limits. This failure mode may indicate motor overload conditions, prompting operators to prevent motor trips.

3) *Motor Abnormal Thermal Behavior:* Activated when, given a thermal load value, one of the winding temperatures exceeds the recognized healthy range. This condition could relate to cooling issues or internal overheating/hot spots, sometimes even high ambient temperature. Operators are alerted to investigate the causes of deviation.

4) *Abnormal Instrument Readings:* Evident when one of the winding temperatures falls below the recognized healthy range. Additionally, this condition arises when the temperature difference between phases exceeds 30%. If this condition is contemporary with the abnormal thermal behavior area, both modes are triggered.

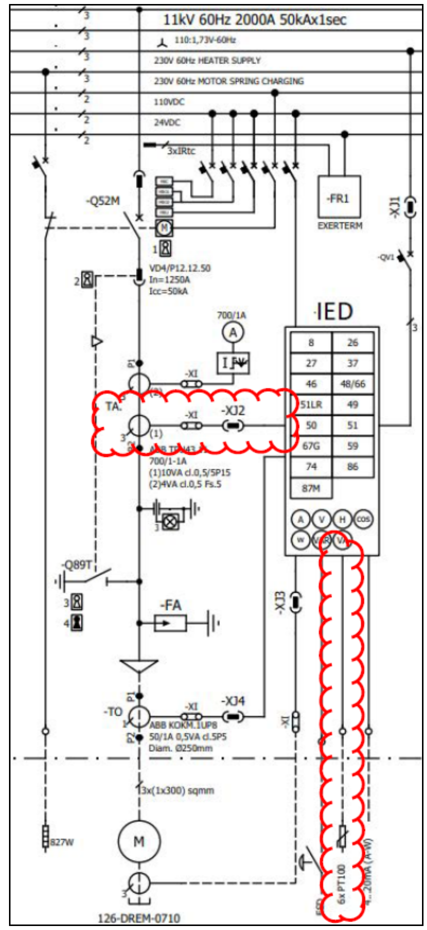

Fig. 3 Motor starter typical scheme

The healthy range or “normal behavior” is determined based on the observations made during the training phase. The model learns to recognize these normal patterns within the collected data.

The developed learning algorithm involves the integration of multiple prediction and regression models throughout its training period. This period is algorithmically initiated once deviations in the motor's operational points converge toward the optimal operating point within predetermined thresholds. Subsequently, the delineation of the healthy range is centered around the anticipated area, expanded by additional margins as determined by Subject Matter Experts (SMEs). Drawing from an analysis of over 120 monitored HV motors, the standard training duration spans approximately 2000 to 2200 running hours, inclusive of 3 inrushes minimum, while maintaining individual temperature deviations below 5% under specific thermal loads.

Algorithm's functionality includes the filtration of irregular signals, such as spikes, through a comprehensive analysis of signal densities. Illustrated in Fig. 5 to 7 are density plots correlating the three phases winding temperatures with the thermal loading, within the specified period displayed in Fig. 4.

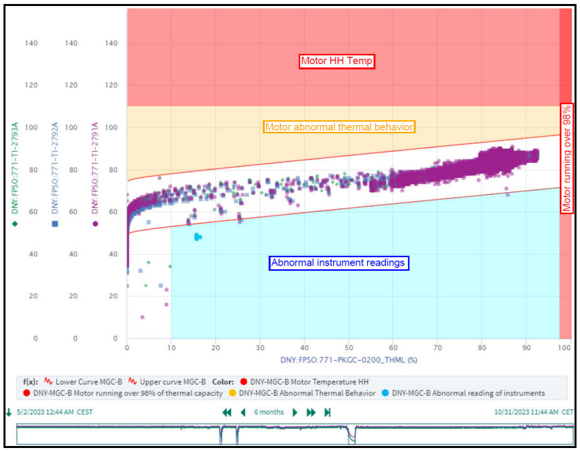

Fig. 4 Winding Temperatures vs THML scatter plot

Besides, the algorithm is equipped to assess unsynchronized data. When input signal sampling occurs within a predefined range (e.g., 20 seconds in the current model), the algorithm synchronizes THML values through linear interpolation. Any data points exceeding the specified sampling period are disregarded. However, it should be noted that this aspect poses a limitation during motor inrush, rendering the presented model not always reliable for analyses during such periods.

B. Loading Model

While the thermal model is universally applicable to all induction motors, irrespective of the driven load, the proposed loading model specifically caters to pumps and compressors with limitations.

The Loading Model detects possible abnormal loading conditions by analyzing data related to motor absorbed power (P), suction and delivery pressures (Pr-s and Pr-d), fluid flow and inlet temperature (FF and FT). Motor absorbed power is directly sourced from IED, while other parameters are acquired from the UCP or DCS, as depicted in Fig. 8 [5]. Loading is calculated by the algorithm as the product of fluid flow and differential pressure (dP = Pr-d – Pr-s). At specific intervals of inlet Fluid Temperature (FT), motor absorbed power and calculated loading are presented on multidimensional scatter plots (Fig. 9), aiding in identifying the healthy zone and potential areas of anomaly, such as:

1) *Motor Excessive Loading:* Activated when power exceeds the healthy range for a given loading value. This condition may be linked to mechanical issues, decreased efficiency, instrument failures, or specific machinery issues (e.g., surge, internal recycling, change in gas composition for compressors [7] and cavitation for pumps [8]).

2) *Motor Under-Loading:* Evident when power falls below the recognized healthy range. This condition may relate to abnormal instrument readings or failures.

The determination of the healthy range or 'normal behavior' is based on observations during the training phase. The model learns to recognize normal patterns within collected data.

The developed learning algorithm integrates multiple prediction and regression models throughout its training period. This training period, algorithmically initiated by dividing samples into data-pools based on inlet flow temperature, is defined by Gas Compression System SMEs.

Data groups are processed as deviations in the motor's operational points converge toward the optimal operating point. The healthy range is centered around the anticipated area, expanded by additional margins as determined by Subject Matter Experts (Electrical and Gas System SMEs). Drawing from an analysis of 18 monitored gas compressors and water pumps drives by HV motors, the standard training duration spans approximately 2000 running hours.

The algorithm automatically excludes data during machine starting and in recirculation mode. It includes the filtration of irregular signals, such as spikes, through a comprehensive analysis of signal densities. Fig. 10 illustrates density plots correlating absorbed power and loading (P vs dP*FF) within the specified period indicated in Fig. 9.

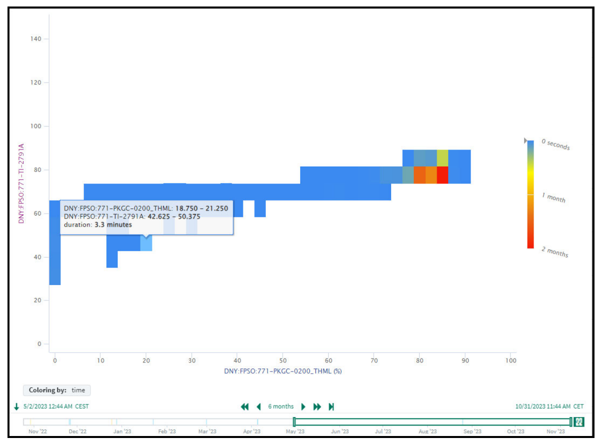

Fig. 5 Winding 1 Temperatures vs THML density plot

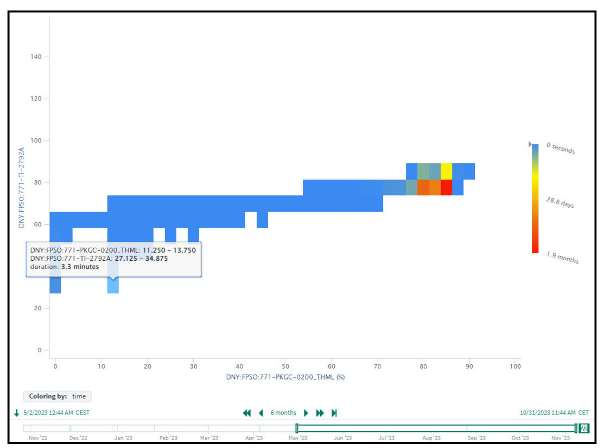

Fig. 6 Winding 2 Temperatures vs THML density plot

Additionally, the algorithm assesses unsynchronized data. When input signal sampling occurs within a predefined range (e.g., 1 minute in the current model), the algorithm synchronizes Loading values through linear interpolation, disregarding any data points exceeding the specified sampling period.

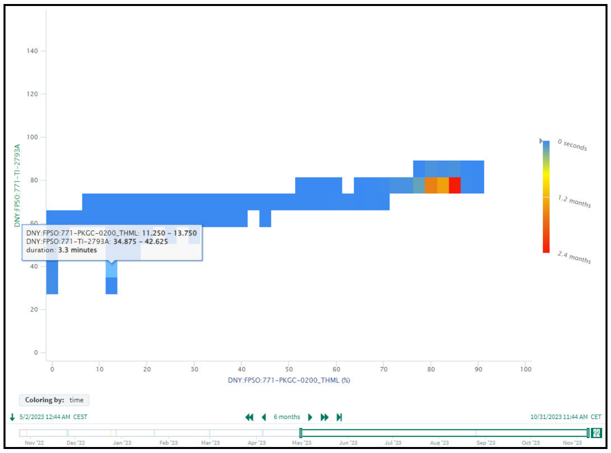

Fig. 7 Winding 3 Temperatures vs THML density plot

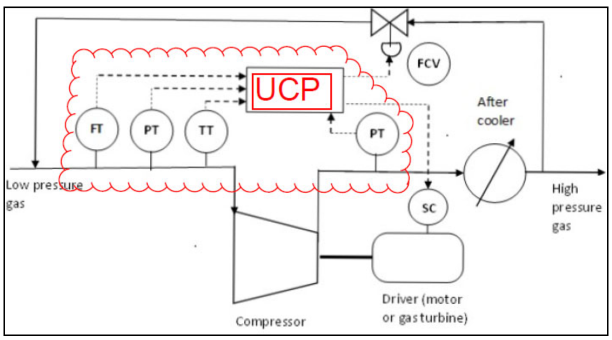

Fig. 8 Simplified PID for compressor[1]

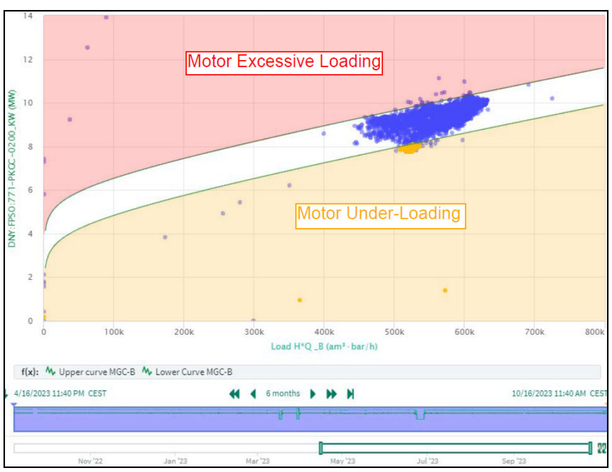

Fig. 9 Motor absorbed power vs Loading at fixed FT scatter plot

IV. SELECTED DEMONSTRATIVE CASES

This section elucidates chosen illustrative instances that exemplify the pragmatic application of thermal and loading models for induction motors driving main gas compressors and water injection pumps in operational Floating Production Storage and Offloading (FPSO) units. These cases afford valuable insights into the efficacy and practical utility of the implemented models, thereby elucidating their influence on operational performance and reliability.

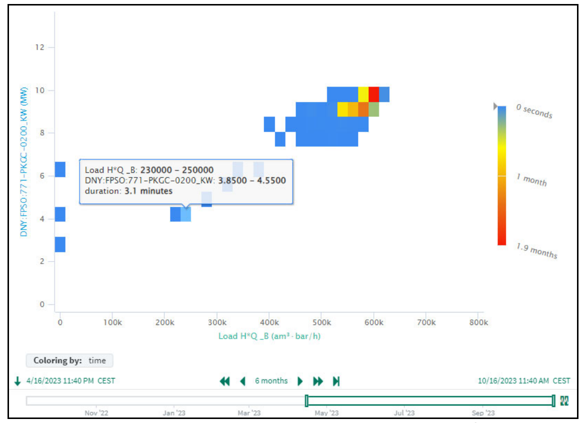

Fig. 10 Motor absorbed power vs Loading at fixed FT density plot

A. *Thermal Abnormal Behavior*

For Motor Very High Temperature and Motor High Thermal Load (set at 98%) conditions, the notification is instantaneous upon occurrence. Conversely, for other instances such as abnormal thermal behavior and abnormal instrument readings, the notification is dispatched via email either upon the condition's cessation or one hour after activation.

Fig. 11 depicts the primary instance of abnormal thermal behavior for a main gas compressor, illustrated in a multidimensional scatter plot filtered for the specific condition. A remote investigation revealed a temporary cooler malfunction, distinguished by elevated cooling medium temperatures, consequently hindering operational efficiency.

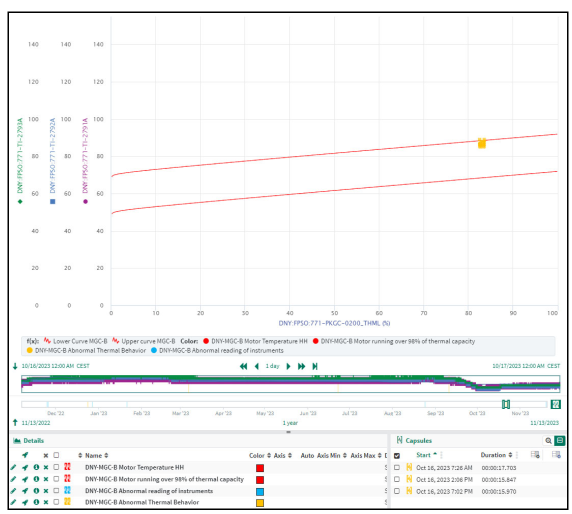

Fig. 11 Case-1 Abnormal Thermal Behavior – multidimensional scatter plot

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[1] Legend: FT Flow Transmitter, PT Pressure Transmitter, TT Temperature Transmitter, FCV Flow Control Valve, SC Speed Controller

Another distinct case, related to a different gas compressor motor, illustrated in Fig. 12, displays an abnormal thermal condition triggered by momentary overload. Despite the acceptable thermal loading level, the time-plot analysis depicted in Fig. 13 indicates a slower increase of thermal load compared to temperatures, suggesting an incorrect heating time constant in the Intelligent Electronic Device (IED). Corrective action involved fine-tuning the protection 49 settings.

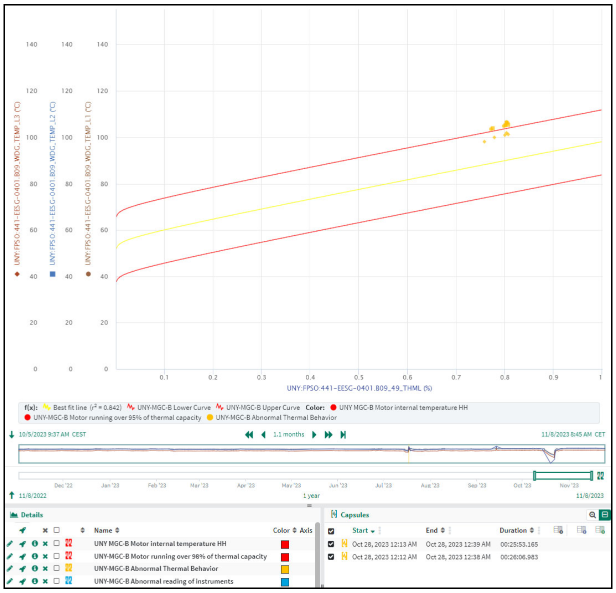

Fig. 12 Case-2 Abnormal Thermal Behavior – multidimensional scatter plot

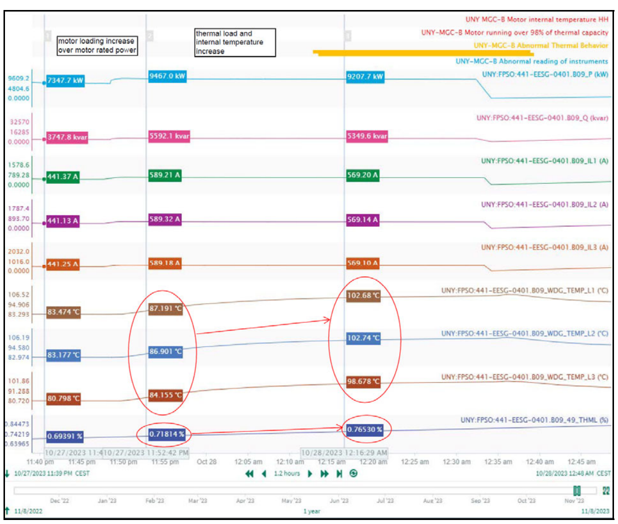

Fig. 13 Case-2 Abnormal Thermal Behavior – time plot

B. *Motor Excessive Loading*

While the UCP diligently monitors mechanical parameters (vibrations, temperatures, and process parameters), providing alarms and trip signals as needed, the proposed model proves instrumental in evaluating package efficiency.

Figure 14 illustrates a case of increased loading in a water injection pump motor through a multidimensional scatter plot. Trends reveal a gradual load increase over a one-year period, attributed to the reduced efficiency of the pump.

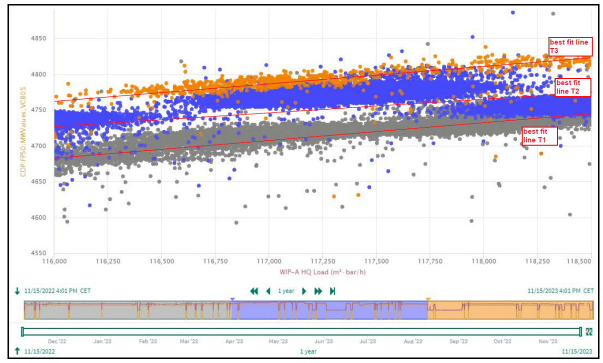

Fig. 14 Motor excessive loading due to reduced compressor efficiency – multidimensional scatter plot

Distinct colors and associated lines represent different trimesters of the year (gray for T1, blue for T2, and orange for T3). It is discernible that there is an approximate 1.97% increase in absorbed power over the last year. This data has been utilized as supporting information for the pump performance monitoring tool.

V. METHOD EVALUATION AND FUTURE IMPROVEMENTS

The deployed method has unequivocally proven its efficacy in real-time identification and resolution of operational anomalies. This success is particularly evident in its ability to facilitate proactive maintenance by autonomously generating Work Orders based on real-time data, thereby optimizing operational efficiency and prolonging the lifespan of critical components.

Additionally, the method plays a fundamental role in incident troubleshooting, promptly identifying issues like abnormal thermal behavior and motor excessive loading.

However, it is essential to acknowledge certain limitations. The thermal model, while generally robust, exhibits reduced reliability in capturing short/fast transients, necessitating ongoing refinement for improved responsiveness and accuracy.

Similarly, the present mechanical model is confined to efficiency assessment, prompting the need for expansion to involve a larger spectrum of mechanical and process data. To address this, ongoing efforts involve integrating the mechanical model into the machinery model owned by the mechanical department. This integration aims to leverage additional data, including vibrations and temperatures, to provide a more comprehensive evaluation of motor health.

In the realm of thermal modeling, ongoing enhancements are actively being pursued. The algorithm is currently undergoing refinement with the inclusion of motor cooling and ambient temperature parameters into its framework. Simultaneously, the introduction of new dimensions for pattern recognition and the integration of machine learning algorithms are in progress, offering the potential for more nuanced insights into motor behavior. These advancements aim to streamline remote investigation tasks and enhance the system's responsiveness, ensuring a faster and more effective response to operational needs. A noteworthy initiative involves the creation of a unique induction motor intelligent integrity and surveillance tool. This tool extends beyond electrical models, incorporating innovative analytics like disturbance recorders analysis (Comtrade DFT – Discrete Fourier Transform – analysis) to refine diagnostic capabilities and enhance predictive accuracy.

These ongoing developments are aimed at solidifying the method's position as an advanced, adaptive system adept at navigating the complexities of operational technology. Through continual refinement and expansion, the method is poised to persist in its role as a cutting-edge solution for the dynamic challenges inherent in the operational landscape, offering a holistic approach to motor health and performance monitoring.

VI. CONCLUSION

The methodology presented in this paper offers a comprehensive framework for real-time monitoring of induction motor health and performance. By leveraging data-driven insights and advanced pattern recognition techniques, the approach enables proactive maintenance, minimizes downtime, and optimizes operational efficiency. The thermal and loading models discussed demonstrate the efficacy of the system in identifying abnormal behaviors and potential areas of improvement. Through selected demonstrative cases, the practical utility of the implemented models in operational scenarios, such as Floating Production Storage and Offloading (FPSO) units, has been highlighted.

While the deployed method has proven effective in real-time anomaly identification and resolution, certain limitations exist, particularly regarding the responsiveness and accuracy of capturing short/fast transients in the thermal model. Ongoing efforts are directed towards refining the algorithms and expanding the scope of mechanical modeling to incorporate a wider range of mechanical and process data. Future improvements aim to enhance the system's responsiveness and diagnostic capabilities through the integration of machine learning algorithms and innovative analytics.

VII. ACKNOWLEDGEMENT

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IX. VITA

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