OPTIMIZING ROTATING EQUIPMENT RELIABILITY AND INTEGRITY WITH DATA INSIGHTS

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Abstract - Unplanned downtime of critical refinery assets, such as motors, variable frequency drives and rotating equipment, can lead to major financial losses, operational disruptions and environmental harm. This paper introduces a practical framework to improve asset reliability and longevity through predictive analytics, condition-based maintenance and expert oversight. Focusing on operational efficiency and lifecycle management, the framework identifies early signs of wear, prevents equipment failures and supports data-driven decisions on maintenance, retrofits and replacements. The framework aligns with regulatory standards like the Ecodesign Sustainable Products Regulation and EU Energy Efficiency Directive, emphasizing longer equipment life, better resource use and reductions in Scope 1 and 2 emissions. By combining digital monitoring, edge-computed analytics and subject matter expertise, the framework keeps aging assets dependable and efficient – reducing lifecycle costs, enhancing reliability and supporting sustainability goals across refinery operations.

Index Terms – Predictive Maintenance, Condition Monitoring, Rotating Equipment, Asset Integrity, ESG Compliance, Sustainable Maintenance, Reliability Engineering, Digital Product Passport.

Note: The “framework” referenced throughout this paper describes a **governed predictive maintenance strategy** that uses a **closed-loop, analytics-driven maintenance framework**. It is validated using cross-industry scenario modeling rather than synthetic simulation. Its degradation patterns and response workflows are based on real-world observations across diverse industrial sectors, ensuring practical relevance and feasibility for field implementation.

I. INTRODUCTION

Rotating electrical assets and the motors and the variable frequency drives (VFDs) that control them, power essential refinery processes like crude distillation, catalytic cracking, hydrogen production and hydrocarbon transport. Asset failures can lead to severe disruptions, costing over USD 124,000 per incident and resulting in harmful emissions and flaring events from emergency shutdowns and restarts, as validated by recent industry research [1][2][12].

Despite their importance, many maintenance strategies are still reactive or based on fixed intervals. Time-Based Maintenance (TBM) schedules, based on fixed service intervals, often ignores actual asset condition, leading to premature or unnecessary servicing or missed failures. Condition-Based Maintenance (CBM) typically reacts to alarms without predicting future issues. Even Predictive Maintenance (PDM) systems that detect early anomalies often fail to connect diagnostic insights to maintenance actions or environmental goals.

Meanwhile, regulatory and financial expectations are shifting from qualitative maintenance records to machine-readable Environmental, Social and Governance (ESG) disclosures. Emerging EU regulations, including the Ecodesign for Sustainable Products Regulation (ESPR) with Digital Product Passport (DPP), and the EU Energy Efficiency Directive, require asset operators to trace and disclose durability, repairability, lifecycle energy performance and emissions [3][4][5]. Failure to comply risks financial penalties, regulatory restrictions, reputational damage and reduced access to green investment.

In this new environment, rotating equipment management must evolve beyond just a maintenance task; it must support risk management, financial mitigation, regulatory compliance and sustainability.

To meet these needs, this paper introduces a **governed predictive maintenance strategy (**referred throughout this paper as **the framework)**. The framework is a case-informed, six-layer predictive maintenance strategy that redefines asset lifecycle governance. It links early degradation detection, Subject Matter Expert (SME) validation, Computerized Maintenance Management System (CMMS) workflows and ESG-compliant maintenance actions.

Unlike conventional predictive systems focused primarily on fault detection, the framework integrates sensor data, hybrid analytics, structured SME validation, secondary diagnostics via lifetime expectation assessment and air gap inspections, CMMS task generation and ESG-aligned lifecycle tracking.

The framework improves equipment reliability and extends asset life, while cutting energy waste and maintenance costs. It closes the loop from early degradation detection to ESG-attributable task execution, supporting refinery goals for efficiency, transparency, resilience and carbon neutrality.

The strategy’s architecture is aligned with:

- ISO 13374-1 condition monitoring data structuring standards
- IEC 60300-3-11 dependability management practices
- ESPR Annex II
- EU Energy Efficiency Directive [3][4][6][7]

While the framework is not yet deployed in refineries, it is ready for pilot implementation. Its core components, such as stressor-based sensing, hybrid analytics, SME validation and ESG-aligned task governance, are individually proven in many industries. The framework combines these proven components into a single system designed for refinery needs while also being adaptable to other industries.

This paper explains the engineering challenges that led to the development of a **governed predictive maintenance strategy (the framework).** It describes how its closed-loop lifecycle management works and explores its potential impact on sustainability reporting, asset resilience, and regulatory compliance. It shows the links between stressor-based diagnostics to controlled execution, ESG goals and refinery resilience.

II. ROTATING EQUIPMENT DEGRADATION AND MAINTENANCE FAILURE

A. TEAM Stressor Landscape Driving Asset Degradation

Rotating electrical assets in refineries face complex operational and environmental stressors that degrade their mechanical, electrical and thermal performance over time. While individual degradation mechanisms are well-understood, their combined effects, especially under refinery-specific conditions, can significantly accelerate equipment failure.

The key degradation stressors are Thermal, Electrical, Ambient and Mechanical (TEAM).

Thermal stress results from repeated heating and cooling, leading to material expansion, bearing lubricant fatigue and component wear – especially in VFDs where it affects cooling fans, electrolytic capacitors, printed circuit board assemblies (PCBAs) and power semiconductor modules. Cooling fan degradation reduces thermal stability, capacitor aging accelerates DC ripple distortion, and PCBA and semiconductor degradation compromise control integrity and power conversion efficiency.

Electrical stress includes harmonic distortion, transient voltage spikes, load imbalance and partial discharge, all of which degrade motor winding insulation systems and power electronic components [1].

Ambient stress comes from refinery contaminants like sulfur, hydrocarbons and dust, which impair cooling and corrode materials.

Mechanical stress can be caused by electromagnetic vibration and mechanical vibration induced by unbalanced rotating masses, shaft misalignment, and foundation softness resulting in fatigue, excites structural resonances and risk of premature failure [1][2].

As shown in Fig. 1, environmental factors like ambient temperature and how the VFD is used, along with the thermal cycling experienced by insulated-gate bipolar transistor (IGBT) modules, significantly affect how quickly VFDs degrade and how urgently they need maintenance.

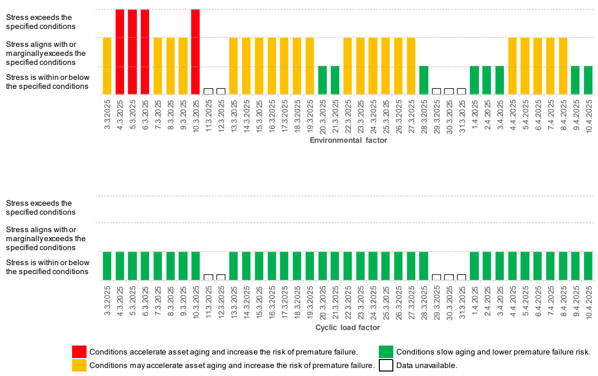

Fig 1. Environmental and cyclic factors influencing degradation and maintenance strategy in refinery VFD systems.

The overriding effect of these TEAM stressors erodes asset health, even for equipment designed to severe-duty specifications, underscoring the need for predictive and governed lifecycle management approaches.

B. Failure Modes and Degradation Mechanisms

TEAM stressors lead to well-documented failure modes in motors, generators and VFDs:

Thermal stress accelerates stator insulation aging and bearing lubricant degradation. In VFDs, cooling fans exhibit accelerated bearing fatigue at higher inlet air temperatures; electrolytic capacitors suffer capacitance loss and ESR increases, impairing voltage smoothing; PCBAs experience dielectric breakdown and control instability; and IGBT modules degrade under cyclic thermal loading, leading to junction instability and switching losses.

Electrical stress initiates partial discharge activity, surface currents, inter-turn shorts, ground faults and degradation of power electronics, including capacitor drying and IGBT gate instability [1].

Ambient stress causes cooling system inefficiency, pollution-induced copper corrosion, decline in insulation resistance, and insulation contamination.

Mechanical stress leads to bearing spalling, rotor vibration, shaft deformation, external forces acting on bearings and structural casing distortion. Electromagnetic forces also induce vibration and contribute to mechanical stress-related fatigue.

Whether occurring independently or interactively, these mechanisms define the main reasons for failure of refinery motors, generators and VFDs. Targeting these TEAM-aligned degradation pathways through structured sensing strategies and predictive diagnostics is fundamental to establishing resilient, durable and ESG-compliant asset management frameworks.

C. Product Variability and Failure Risk

Beyond external stresses, internal product variability, from manufacturing inconsistencies, material defects or commissioning issues, can cause premature failures, even under nominal operating conditions [1][2]. Failures fall into two categories:

Overstress: Instantaneous failure from a stress event, such as severe voltage transients or mechanical shocks that exceed an asset's designed strength.

Wear-out: Gradual degradation from prolonged exposure to sub-critical operating stresses.

In VFDs, variability in capacitor ESR degradation can contribute to early-stage failures, while IGBT substrate and chip solders are susceptible to thermal fatigue under cyclic loading, leading to progressive module degradation. Effective predictive maintenance systems must detect fast-acting overstress events and slow-progressing cumulative wear-out mechanisms to optimize maintenance timing and cost.

D. Gaps in Current Predictive Maintenance Models

Despite an advanced understanding of TEAM stressors and their degradation pathways, most refinery maintenance strategies remain reactive or only partially predictive.

Time-Based Maintenance (TBM): Use fixed service intervals, ignoring real-time stressor exposure and degradation dynamics, resulting in premature maintenance or undetected failure progression.

Condition-Based Maintenance (CBM): Responds to threshold-based alerts but lacks predictive forecasting and broader lifecycle integration.

Stressor-based models are more dynamic, adjusting preventive scheduling based on cumulative operating loads, such as internal and external temperature exposure, and enables basic Remaining Useful Life (RUL) trend estimation.

In contrast, classical CBM frameworks trigger interventions only when a threshold is exceeded and does not support RUL forecasting. As standalone methods, both TBM and CBM lack any secondary diagnostics and ESG lifecycle attribution, limiting their effectiveness for refinery ESG disclosure readiness and sustainable finance eligibility.

Fig. 2 shows how stressor-informed maintenance shifts from fixed intervals to degradation-driven actions, improving alignment with asset condition.

Fig 2. Transition from fixed-interval to stressor-informed maintenance logic, illustrating how predictive models shift refinery VFD maintenance timing based on real-world degradation exposure.

Even Predictive Maintenance (PDM) systems, though more advanced than CBM, often work in isolation, detecting anomalies without clear processes, SME validation or ESG metric attribution. Alarms set to avoid false positives can miss early warning signs, letting problems grow into disruptive events. As a result, valuable predictive insights are rarely used effectively across maintenance, risk or ESG reporting, limiting their overall impact.

E. The Need for Predictive Lifecycle Management

Studies show that in refineries motor and VFD failures are predictable weeks or months in advance using TEAM-based sensing and predictive analytics. Without a predictive lifecycle management infrastructure, operators face preventable production losses, emergency energy expenditures, regulatory non-compliance penalties and ESG non-compliance. Addressing this requires a shift from isolated anomaly detection to a governed predictive lifecycle model that includes:

Multimodal sensing, compliant with ISO 13374-1 condition monitoring standards [6], ensuring interoperable, traceable data.

Predictive analytics combining deterministic signal analysis with unsupervised learning techniques to detect complex, multivariate degradation patterns.

Structured SME validation through trigger–filter–review workflows, supported by secondary diagnostics to confirm asset health prior to maintenance intervention authorization.

Maintenance execution integrated with CMMS, generating machine-readable, ESG-attributable work orders aligned with digital product passport (DPP) standards [5].

Without full-loop integration, spanning early degradation detection, SME validation, governed maintenance execution and ESG metric attribution, predictive maintenance fails to deliver its full strategic potential. Operators continue to face escalating operational volatility, regulatory scrutiny and financial exposure.

By embedding stressor monitoring into maintenance processes, operators can reduce Scope 1 emissions via early intervention, optimize Scope 2 energy use, and meet requirements under the Ecodesign Sustainable Products Regulation (ESPR) Annex II and EU Energy Efficiency Directive.

Unchecked degradation not only leads to costly outages but also results in avoidable Scope 1 emissions from emergency flaring and Scope 2 inefficiencies due to harmonic distortion, control instability and bearing-related energy losses.

The next section introduces the actual architecture which comprises a six-layer predictive lifecycle governance framework, engineered to detect TEAM stressors, apply predictive analytics, guide SME-driven intervention and enable ESG-compliant maintenance execution.

III. ARCHITECTURE FOR GOVERNED PREDICTIVE MAINTENANCE

A. Layer 1: Multimodal Asset Sensing and Data Capture

The framework begins by capturing high-quality, multi-domain data from the rotating equipment, motors and VFDs using sensors tuned to the expected failure modes derived from the TEAM stressor analysis.

Thermal monitoring: Thermal sensors monitor stator windings, bearing housings, power semiconductors, and capacitors to detect overheating risks across both motors and VFDs. For motors, temperature rise over ambient and thermal cycling trends reveal insulation aging, lubricant degradation, and bearing fatigue. In VFDs, thermal excursions and gradient shifts indicate impaired cooling, fan degradation, and semiconductor stress. Deviations from thermal design baselines are used to forecast failure risk, enabling predictive interventions that preserve thermal integrity and extend lifecycle performance.

Electrical monitoring: Partial discharge sensors, (sensitive to electromagnetic emissions between 10 MHz to 1500 MHz) monitor insulation degradation in stator windings and terminal boxes. Power quality analysers (sampling rates exceeding 4 kHz) monitor Total Harmonic Distortion (THD), voltage imbalance, excitation drift, IGBT degradation and control instability.

Ambient monitoring: External temperature and humidity sensors quantify environmental loading on motors and VFDs. Elevated ambient temperatures reduce cooling margins and accelerate thermal aging, while high humidity increases the risk of condensation, insulation degradation, and corrosion. Deviations from environmental baselines are trended to assess stress exposure and guide derating decisions or preventive maintenance, supporting reliable operation under variable refinery conditions.

Mechanical monitoring: Tri-axial accelerometers, sampling at 6.6 kHz, and single-axis accelerometers, with a configurable sampling rate of up to 102 kHz, mounted at critical bearing and casing locations to track bearing issues, shaft misalignment, lost magnetic wedge and rotor unbalance. Oil condition sensors detect changes in viscosity, metallic particle counts and contamination ingress.

All sensor data is time-synchronized using a cloud-based reference clock. This allows cross-domain correlation during post-acquisition analysis. The data structure is formatted to ISO 13374-1 standards to ensure consistency and interoperability.

B. Layer 2: Signal Processing and Feature Extraction

Raw sensor data is processed in two stages, following ISO 13374-1 condition monitoring standards [6]. The first stage applies bandpass filtering using Hanning-windowed Finite Impulse Response (FIR) filters to isolate frequency bands linked to known fault signatures.

For bearing condition monitoring, the Early Shock Pulse Detection (ESPD) algorithm [9] analyzes high-frequency vibration data. It uses adaptive band splitting and signal segmentation to detect weak, periodic impacts from early-stage bearing defects. Fault indicators are based on impulse timing relative to shaft speed and the energy within resonance bands.

Motor shaft speed is estimated via frequency-domain interpolation of vibration and magnetometer signals, enabling accurate detection of mechanical issues like imbalance, misalignment and looseness.

Feature extraction is performed across three domains:

- **Time domain**: Root Mean Square (RMS), peak-to-peak, crest factor, kurtosis.
- **Frequency domain**: Fast Fourier Transform (FFT) harmonics, harmonic sidebands, THD.
- **Energy domain**: Spectral entropy, signal energy density.

For VFDs, features like THD percentage, odd/even harmonic ratios and negative sequence voltages are extracted to detect drive degradation and excitation instability. The framework also analyses oscillations and limit-approaching transients to anticipate dynamic faults like overcurrent, overspeed or over-/undervoltage trips.

All features are normalized against historical healthy baselines and enriched with metadata (e.g. motor frame size, drive type and duty cycle) to support adaptive anomaly detection.

C. Layer 3: Anomaly Detection and Remaining Useful Life Forecasting

The framework extracts features from time, frequency and energy domains, then uses predictive modeling to detect anomalies and estimate remaining Remaining Useful Life (RUL) under actual operating conditions.

It employs a hybrid analytics pipeline that combines unsupervised anomaly detection and RUL forecasting. The primary anomaly detection is optimized for high-dimensional, sparse industrial data, while One-Class Support Vector Machines (OCSVMs) [8] are used when asset operating profiles are available, allowing precise modelling of normal behavior.

Once the anomaly scores are obtained from the healthy training data, an anomaly score threshold τ_1 is derived using statistical features of the distribution. For selected input signals, in addition to anomaly score threshold, amplitude threshold τ_2 is identified from the training data.

For a data point to be considered anomalous, the following condition must be met

$$s_{in} > \tau_1 \text{ and } X_{in} > \tau_2 \qquad (1)$$

where s_{in} and X_{in} are the anomaly score and amplitude of the input data point.

A rolling window approach filters out transient anomalies, triggering alerts only for persistent deviations. RUL forecasting is applied to critical assets like VFDs using models trained on relevant degradation features including power quality indicators and cumulative thermal loading. Forecasts include 95% confidence intervals to support risk-based maintenance planning. While models are validated using emulated degradation data, real-world accuracy will be confirmed during pilot deployment.

D. Layer 4: Structured Subject Matter Expert (SME) Validation and Diagnostic Governance

While advanced analytics can detect early signs of failure, trusted decision-making demands human-in-the-loop expertise. The framework ensures this through a structured review by Subject Matter Experts (SMEs) for every predictive event. When an anomaly is detected or a RUL threshold is crossed, a diagnostic evidence packet is generated containing:

- Time-series plots of key features,
- FFT spectral overlays for vibration and THD profiles,
- Statistical deviations and trend indicators.

SMEs then conduct a three-stage assessment:

1. **Noise filtering**: Exclude false positives from transient disturbances.
2. **Fault diagnosis**: Match patterns with known failure signatures (e.g., ESPD-detected bearing defects or harmonic imbalance).
3. **Severity and urgency assessment**: Prioritize actions based on how fast the fault is progressing and the criticality of the asset.

This trigger–filter–review process ensures maintenance actions are based in risk and system importance.

Secondary diagnostics are used only when both data and expert judgement point to medium- or high-severity degradation issues. Air gap inspection is a non-invasive method that checks stator–rotor alignment and radial clearance in medium/high-voltage motors to detect rotor eccentricity, stator ovality and mechanical instability.

E. Layer 5: CMMS Integration and Governed Maintenance Execution

Once predictive events are validated, they are transferred into the CMMS as machine-readable work orders through a structured handoff process. Each work order includes:

- **Fault taxonomy codes** aligned to ISO 14224 failure mode classifications [7], enabling machine-readable traceability and asset-level maintenance hierarchy tracking,
- **Recommended actions**, such as bearing replacement or VFD tuning,
- **Asset-specific Bills of Materials (BOMs)** linked to predictive diagnostics,
- **Maintenance timing** based on RUL forecasts.

Each event remains traceable from initial anomaly to final work order, supporting audit compliance and data lineage integrity.

F. Layer 6: ESG Metric Attribution and Regulatory Compliance Readiness

Beyond operational improvements, the framework links predictive maintenance to ESG performance and compliance. Each intervention is mapped to:

- **Durability gains,** measured by increased Mean Time Between Failures (MTBF)
- **Scope 1 emissions reduction**, by preventing mechanical or electrical faults that could lead to flaring
- **Scope 2 energy savings**, from improved drive/motor efficiency and reduced harmonic losses
- **Repairability and transparency**, formatted for digital product passport (DPP) readiness [5][6].

The framework maintains a version-controlled ESG performance registry that records each event from anomaly detection to corrective action, aligned with EU Energy Efficiency Directive [4] and ESPR disclosure requirements. Data is exportable to EPREL 3.0 formats [5] to support sustainable finance reporting.

The ESG registry data structure and reporting scheme are detailed in Appendix A. Thus, the framework elevates predictive maintenance from an operational optimization tool to a strategic enabler of sustainability, compliance, and financial defensibility.

IV. SCENARIO-INFORMED VALIDATION AND KPI OUTCOMES

A. Case-to-Execution Workflow

The framework's readiness is validated using illustrated degradation scenarios based on real-world motor and VFD behavior from process industries. These workflows simulate asset behavior using synthetic fault conditions and stressor profiles to test the end-to-end maintenance process. The framework operates as a closed loop, from early anomaly detection through SME validation, governed secondary diagnostics and CMMS-driven work order execution. SMEs authorize secondary diagnostics only when needed, ensuring traceable and risk-aligned actions.

This scenario-informed method confirms that the framework's workflows are operationally ready, ESG-compliant, auditable and defensible against risk and sustainability benchmarks, prior to full-scale deployment.

B. Emulated Case Scenarios

1) *High-Voltage Synchronous Motor (Direct-On-Line Connection) Operating a Centrifugal Compressor:* The framework was evaluated using a 22 MW, 6.6 kV high-voltage synchronous motor model driving a reciprocating compressor in a refinery-like setting. The model included key stressors such as cyclic mechanical loads, pulsation forces, excitation system variations and environment contaminants.

The degradation scenario reflects concurrent bearing fatigue and excitation voltage instability, mirroring the typical mechanical–electrical fault coupling seen in centrifugal compressor.

Key degradation indicators included:

- 38% increase in vibration crest factor over baseline
- Growth of crankshaft-related harmonics in FFT analysis
- Excitation voltage deviations exceeding ±2% thresholds
- Early ESPD patterns pointing to localized bearing fatigue

Despite background noise and load fluctuations, the framework's analytics reliably detected these combined anomalies and predicted RUL with 95% confidence.

Structured SME validation was performed using compiled diagnostic evidence packets, including:

- Time-series vibration and excitation trend plots
- FFT overlays illustrating harmonic evolution
- Excitation voltage deviation tracking

Diagnostic data such as vibration trends, harmonic overlays and excitation deviation plots were reviewed by SMEs. Based on this, the following governed CMMS work orders were authorized: Time-series vibration and excitation trend plots,

- to confirm accelerated bearing degradation
- to assess rotor shaft alignment deviations

Once validated, predictive maintenance actions were initiated through CMMS workflows.

Maintenance Optimization Impact: Early detection, backed-up by SME-validated secondary diagnostics, enabled a condition-based maintenance strategy aligned with ISO 14224 [7] standards:

- **L1 (routine inspection)** and **L2 (minor corrective)** tasks were executed early
- Risk for **L3 (major corrective)** and **L4 (overhaul)** events was reduced
- Time-based maintenance (TBM) intervals were avoided

Because degradation was caught early and localized, the required L3+ intervention was completed without removing the rotor, reducing dismantling complexity, minimizing process disruption and shortening downtime from weeks to days.

This proactive approach avoided emergency shutdowns (contributing to Scope 1 emissions reduction) and improved energy efficiency (contributing to Scope 2 reductions) by preventing inefficient process cycling.

Lifecycle Extension and L4 Planning: Secondary diagnostics revealed early signs of stator winding thermal aging and rotor mechanical stability margin reduction. Although no critical winding defects were found, RUL analysis flagged medium-term degradation of the winding insulation.

In response, the team scheduled a proactive L4 motor reconditioning including stator rewinding and rotor refurbishment, during the next major plant maintenance outage. This early intervention avoided the risk of unplanned failures, prevented emergency shutdowns (eliminated Scope 1 emissions) and supported optimized resource planning, safer execution and lower maintenance costs. It also strengthened the framework's role as a strategic enabler of sustainable, resilient refinery operations.

2) *High-Voltage Induction Motor with Medium-Voltage Drive:* The framework was tested on a 3.3-kV, high-voltage induction motor paired with a medium-voltage VFD

operating a fluid catalytic cracking (FCC) air blower. The scenario reflects harmonic instability and power quality disturbances under partial-load variability.

Despite operational noise and THD escalation and negative sequence voltage drift emerging gradually, predictive analytics isolated key degradation trends including:

- Amplified vibration harmonics at 2× and 3× line frequency
- THD drift exceeding 8.1% operational limits
- Negative sequence voltage growth
- Slight power factor decline linked to harmonic distortion

To validate the predictions, SMEs reviewed diagnostic packets covering THD trends, voltage imbalance and vibration harmonics. Corrective actions were authorized based on SME-reviewed judgments:

C. *KPI Outcomes and ESG Impact*

The framework's predictive maintenance was evaluated through refinery-style emulations, with key operational ESG benefits summarized in in Table I.

TABLE I
KPI OUTCOMES AND ESG IMPACT FOR SCENARIO-INFORMED REFINERY CASE EMULATIONS

KPI	High-Voltage Synchronous Motor (Emulated)	High-Voltage Induction Motor (Emulated)	ESG Linkage
Predicted MTBF Improvement	+42%	+36%	ESPR Annex II durability compliance readiness
Predicted Normalized Energy Efficiency Gain	+0.1%	+4.9%	EU Energy Efficiency Directive
Predicted Scope 1 Emissions Avoidance	~23 tCO_2e	-	ESG Scope 1 emissions reporting readiness
Predicted Scope 2 Emissions Reduction	~101 tCO_2e/a	~13 tCO_2e/a	ESG Scope 2 emissions reduction validation
Repairability & and Traceability Readiness	DPP-compliant structures modeled	DPP-compliant structures modeled	ESPR Annex II reporting validation

Key Performance Indicators (KPI) Derivation Methodology: KPIs were derived from case-informed degradation modeling and predictive maintenance intervention scenarios.

- MTBF gains were calculated by comparing simulated failure rates before and after the framework's interventions
- Energy savings were derived from reduced harmonic losses, VFD optimization and effects of minimized mechanical losses
- Scope 1 emissions avoidance was based on preventing unplanned shutdowns and flaring
- Scope 2 emissions reductions were modeled using normalized grid emission factors
- Details are available in Appendix B.

Case-Specific ESG Contributions: In the High-Voltage Synchronous Motor case, ESG benefits stemmed from early mechanical fault detection, condition-based L3+ interventions without rotor removal, and pre-emptive L4 reconditioning These actions prevented emergency shutdowns (avoiding Scope 1 emissions) and substantially improved energy efficiency (Scope 2) by reducing mechanical and magnetic losses.

For the High-Voltage Induction Motor with Medium-Voltage Drive, the focus was on early identification of electrical issues like harmonic instability and voltage imbalance. ESG gains here came from Scope 2 efficiency improvements enabled by optimized VFD performance, without requiring mechanical secondary diagnostics.

Together, the two cases show the framework's ability to support both mechanical and electrical reliability strategies. Mechanical cases used lifetime assessments and air gap inspections for in-depth diagnostics, while electrical cases relied on SME-driven signal analysis. This flexibility supports tailored ESG reporting and reinforces operation resilience across diverse asset types.

D. *Summary of Case-Informed Validation*

The emulated case studies demonstrated the framework's ability to:

- Detect complex, multivariate degradation early, even under realistic refinery-like noise and variability conditions
- Accurately forecast RUL despite transient operational disturbances
- Use structured SME validation to ensure predictive insights are operationally credible
- Integrate predictive maintenance decisions directly into CMMS for risk-prioritized execution
- Quantify both performance and ESG benefits resulting from predictive interventions

The framework goes beyond flagging faults: it incorporates structured asset-specific diagnostics for motors. Lifetime assessments provides data-driven projections on bearing life and mechanical health using vibration trends, ESPD signatures and degradation modeling. Air gap inspection physically validates rotor-stator alignment by measuring air gap deviations and identifying early mechanical issues like shaft misalignment, rotor bow or stator ovalization.

These diagnostics are initiated only through SME approval and are tracked via governed CMMS work orders, ensuring traceable, risk-based and ESG-attributable maintenance actions. For VFDs, predictive decisions rely on expert validation of electrical anomalies (e,g, THD rise, negative sequence voltage drift and transient torque/speed behavior), without requiring mechanical inspections.

This dual-layer validation – analytics plus expert oversight – builds trust in RUL forecasts, reduces maintenance scheduling uncertainty and strengthens ESG compliance by linking maintenance to Scope 1 emissions avoidance and Scope 2 energy efficiency improvements.

These results are based entirely on case-informed models and SME-reviewed workflows; field deployment and real-world benchmarking are forthcoming and expected to further refine KPI accuracy.

V. STRATEGIC IMPLICATIONS FOR ESG ALIGNMENT AND INDUSTRIAL RESILIENCE

A. Strategic Role of Predictive Lifecycle Governance

Refineries face growing operational, environmental and regulatory demands. Traditional maintenance approaches, whether time-based or reactive, are no longer sufficient for ensuring reliable and sustainable operations. Predictive lifecycle governance, as offered by this type of framework, shifts asset management from fixed schedules to condition-validated, risk-informed and ESG-aligned maintenance strategies. By detecting failures earlier, enabling expert-validated decision and guided structured interventions, governed predictive maintenance becomes essential to achieving operational resilience and long-term performance.

B. ESG Alignment and Sustainable Finance Readiness

The framework aligns predictive maintenance with evolving ESG regulations. By tracking improvements in asset durability, reducing Scope 1 and Scope 2 emissions and ensuring repair traceability, the framework helps refineries meet ESPR Annex II requirements, EU Energy Efficiency Directive screening criteria and upcoming DPP disclosure rules.

Linking maintenance activities directly to ESG outcomes also enhances the refinery's qualification for sustainable finance opportunities, such as green bonds and ESG-focused investment assessments.

C. Operational Resilience and Industrial Risk Management

Failures of critical rotating equipment poses serious operational, financial and environmental risks, including production loss, regulatory fines, safety incidents and high Scope 1 emissions from emergency flaring. The framework mitigates these risks by delivering early warnings of equipment degradation, improving the accuracy of RUL forecasts and guiding SME-approved maintenance based on secondary diagnostic. This shift from reactive to predictive maintenance boosts refinery resilience, reduces unplanned downtime and supports reliable, sustainable operations in a tightening regulatory environment.

D. Roadmap to Field Deployment and Continuous Improvement

The framework is ready for immediate field deployment with initial pilots best focused on high-emission, high-criticality assets like VFD-driven process motors. These should be scheduled around plant outages, ESG reporting deadlines and digital readiness. Key performance indicators (KPIs) should include MTBF improvement, Scope 1 emissions reduction per unit and DPP data completeness.

As predictive maintenance expands across refinery asset fleets, ongoing operational learning will drive further optimization, extend asset lifecycles and embed ESG accountability into daily operations. The framework's predictive insights also inform strategic decisions, such as input factor adjustments, retrofit planning and targeted replacements. Early degradation detection and RUL forecasting help operators allocate resources, manage spare parts and schedule upgrades more effectively during planned outages. This proactive lifecycle planning further strengthens operational efficiency, reduces lifecycle costs and supports sustainable asset management practices aligned with ESPR and EU Energy Efficiency Directive frameworks.

The framework's scalable, closed-loop architecture supports broader deployment across refineries, petrochemical sites and industrial energy infrastructures, enabling resilient, sustainable and digitally traceable operations.

E. Summary of Strategic Value Proposition

Governed predictive maintenance has become a strategic imperative. The framework described here offers a scalable, structured approach that shifts refineries from reactive maintenance to predictive, ESG-aligned lifecycle management. By integrating advanced analytics, SME validation, CMMS workflows and ESG attribution, the framework bridges the gap between asset performance and sustainability objectives.

Predictive lifecycle governance is not just an operational enhancement, it is a strategic pillar for refinery competitiveness, resilience and leadership in a decarbonized, digitally accountable world.

The framework improves both operational expenditure (OPEX) and capital expenditure (CAPEX) by enabling early fault detection, optimizing L3+ condition-based interventions and planning proactive L4 overhauls. These actions reduce unplanned downtime, extend MTBF and defer major capital expenditures, lowering Total Cost of Ownership (TCO) while strengthening ESG performance and financial resilience.

The framework is a digitally traceable, ESG-qualifiable platform that connects predictive insights to auditable maintenance actions tied to emissions and durability metrics. It aligns executive, operational, sustainability and financial priorities:

- **Maintenance teams** benefit from longer MTBF and optimized maintenance execution
- **Operations teams** improve uptime and process stability
- **Sustainability teams** gain measurable Scope 1 and 2 emissions reductions aligned with ESPR and EU Energy Efficiency Directive
- **Finance teams** get improved asset utilization and sustainable financial readiness
- **Executive teams** strengthen license to operate via regulatory compliance and strategic ESG positioning

By closing the loop between predictive insight, governed execution and ESG impact, this framework positions refineries for long-term operational excellence and industrial transformation.

VI. CONCLUSIONS

The reliability and lifecycle performance of rotating electrical equipment are now central to operational continuity and ESG accountability in refineries. Traditional maintenance approaches, whether time-based, condition-based or predictive, often fall short in detecting complex, evolving degradation early enough to avoid unplanned failures, Scope 1 emissions and rising lifecycle costs.

At the same time, emerging regulatory frameworks like ESPR, EU Energy Efficiency Directive, and Digital Product Passport (DPP) demand traceable durability, repairability and ESG-aligned maintenance practices.

This mix of operational, regulatory and financial pressures raises a critical challenge: How can refineries predict, validate and govern maintenance in a way that supports resilience, reduces total lifecycle costs and meets sustainability reporting standards?

This paper introduces, as a solution, a **governed predictive maintenance strategy** that uses a **closed-loop, analytics-driven maintenance framework**. It is a framework that integrates multimodal sensing, hybrid analytics, SME validation, secondary diagnostics, CMMS generation and ESG-linked lifecycle metrics.

. Case-driven validation showed the ability to detect complex degradation early, forecast RUL with high confidence and deliver measurable gains in MTBF, Scope 1/2 emissions reduction, repairability and sustainable financial readiness. This framework bridges the critical gap between early fault detection and auditable, ESG-attributable maintenance execution, minimizing TCO while maximizing data-driven stewardship.

In a future shaped by carbon neutrality goals, transparency mandates and sustainable finance criteria, governed predictive maintenance is no longer optional. It is a strategic necessity.

Predictive reliability and integrity for sustainable maintenance across refineries and industrial sectors, they will redefine how asset reliability, sustainability and financial accountability come together in a digitally traceable, decarbonized future.

VII. REFERENCES

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VIII. NOMENCLATURE

VFD	Variable Frequency Drives
TBM	Time-Based Maintenance
CBM	Condition-Based Maintenance
PDM	Predictive Maintenance
EU	European Union
ESPR	Ecodesign for Sustainable Products Regulation
EPREL	European Product Registry for Energy Labelling
DPP	Digital Product Passport
CMMS	Computerized Maintenance Management System
SME	Subject Matter Expert
ESG	Environmental, Social, and Governance
TEAM	Thermal, Electrical, Ambient, and Mechanical stressors
IGBT	Insulated-Gate Bipolar Transistor
THD	Total Harmonic Distortion
FIR	Finite Impulse Response
ESPD	Early Shock Pulse Detection
RMS	Root Mean Square
FFT	Fast Fourier Transform
RUL	Remaining Useful Life
OCSVM	One-Class Support Vector Machines
MTBF	Mean Time Between Failures
OPEX	Operational Expenditure
CAPEX	Capital Expenditure
TCO	Total Cost of Ownership

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APPENDIX A

EXAMPLE DIGITAL PRODUCT PASSPORT (DPP) FOR A HIGH-EFFICIENCY MOTOR AND VARIABLE FREQUENCY DRIVE

Paper No. PCIC energy (will be assigned)

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Abstract - This appendix provides a completed example of a Digital Product Passport (DPP) for a typical industrial motor and variable frequency drive (VFD). It complies with the expected requirements under the Ecodesign for Sustainable Products Regulation (ESPR) and follows best practices for traceability, lifecycle management and sustainability reporting. This example DPP structure is aligned with ESPR Annex II.

TABLE A-I
SAMPLE CMMS WORK ORDER CLOSURE FORM — MOTOR AND VFD (UNIFIED TABLE)

Section	Field	Motor Example	VFD Example
Work Order Information	Work Order Number	XXX	XXX
	Asset ID	XXX	XXX
	Asset Name	XXX	XXX
	Serial Number	XXX	XXX
	Equipment Location	Pump Station 4, Line A	Pump Station 4, Line A
	Functional Location	PLANT-PS4-PUMP01	PLANT-PS4-VFD01
Work Details	Work Type	Corrective Maintenance	Corrective Maintenance
	Activity Performed	Bearing replacement, motor endshield inspection	Cooling fan replacement, firmware inspection
	Root Cause	Bearing wear due to lubrication failure	Overheating alarm; fan degradation
	Parts Replaced	Bearing Kit XXX	Cooling Fan Assembly XXX
	Service Instructions URL	https://new.abb.com/...	https://new.abb.com/...
	Labor Hours	4.5 hours	2.0 hours
	Technician(s)	X. XXX	X. XXX
Digital Product Passport (DPP) Data	DPP Version	v1.0	v1.0
	DPP Last Update Date	2025-03-15	2025-03-20
	DPP Repository Link	https://new.abb.com/...	https://new.abb.com/...
	Product Carbon Footprint (PCF)*	3.4 tCO_2e	2.1 tCO_2e
	Recyclability Rate (%)	96%	91%
	Repairability Score	8.5/10	7.8/10
	Compliance Declarations	CE Marked, RoHS Compliant, REACH Compliant	CE Marked, RoHS Compliant, REACH Compliant
	Digital Carrier Type	QR Code on Terminal Box Cover	QR Code on Label, RFID Embedded
Final Status	Asset Operational Status	Restored to Service	Restored to Service
	Next Scheduled Maintenance	6,000 running hours or 12 months	Firmware check at next service
	Additional Observations	Recommend enhanced lubrication monitoring	Recommend adding fan runtime monitoring
Sign-Off	Technician Name	X. XXX	Y. YYY
	Technician Sign-Off Date	2025-04-28	2025-04-28
	Supervisor Name	Y. YYY	Y. YYY
	Supervisor Sign-Off Date	2025-04-28	2025-04-28
	Supervisor Comments**	Repairs completed, DPP updated, ESPR compliance logged	Repairs completed, DPP updated, ESPR compliance logged

* PCF values estimated using component-level emission factors in accordance with ISO 14067.
** ESG fields logged in CMMS and linked to DPP repository for audit traceability.

APPENDIX B

KPI DERIVATION METHODOLOGY

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Abstract - This appendix presents a sample Digital Product Passport (DPP) for an industrial motor and VFD, structured aligned with the Ecodesign for Sustainable Products Regulation (ESPR). It illustrates how key maintenance events, repair actions, and ESG metrics – such as carbon footprint, repairability, and recyclability – can be digitally reported and linked to CMMS workflows.

BI. MEAN TIME BETWEEN FAILURES (MTBF) IMPROVEMENT CALCULATION

MTBF improvement was modeled as:

$$\Delta MTBF\ (\%) = \left(\frac{MTBF_{AFTER}}{MTBF_{BEFORE}} - 1\right) * 100 \quad (1)$$

where:

- $\Delta MTBF$ = Mean Time Between Failures improvement
- $MTBF_{BEFORE}$ = Simulated mean time between failures under conventional maintenance,
- $MTBF_{AFTER}$ = Simulated mean time between failures after framework activation.

Failure intervals were simulated based on degradation progression under TEAM stressor profiles.

BII. ENERGY EFFICIENCY GAIN CALCULATION

Energy efficiency improvement was modeled as:

$$\Delta\eta\ (\%) = \left(\frac{\eta_{AFTER} - \eta_{BEFORE}}{\eta_{BEFORE}}\right) * 100 \quad (2)$$

where:

- $\Delta\eta$ = Energy efficiency gain
- η_{BEFORE} = Simulated energy efficiency under conventional maintenance,
- η_{AFTER} = Simulated energy efficiency after framework activation.

Before and After efficiencies were estimated based on THD profiles, mechanical balancing improvements, and operational optimization impacts.

BIII. SCOPE 1 EMISSIONS AVOIDANCE ESTIMATION

Scope 1 emissions avoidance was estimated using:

$$CO_2e\ Avoidance\ (t) = N_{Avoided} * EF_{Shutdown} \quad (3)$$

(Note: Emission factor (45 tCO_2e/event) based on API RP 754 industry average for refinery emergency flaring events.)

where:

- $CO_2e\ Avoidance\ (t)$ = Emissions reduced by the energy efficiency action, expressed in metric tons CO_2e.
- $N_{Avoided}$ = Number of unplanned shutdowns avoided by predictive interventions,
- $EF_{Shutdown}$ = Average refinery flaring emissions per emergency shutdown, assumed at 45 tCOe per event, based on API Recommended Practice 754 [10].

BI. SCOPE 2 EMISSIONS REDUCTION ESTIMATION

Scope 2 emissions reductions were modeled as:

$$CO_2e\ Reduced\ (t) = \Delta E * EF_{Grid} \quad (4)$$

where:

- $CO_2e\ Reduced\ (t)$ = Emissions reduced through electricity savings relative to baseline, expressed in metric tons of CO_2 equivalent.
- ΔE = Annualized normalized energy savings (MWh/year),
- EF_{Grid} = Refinery grid carbon intensity, assumed at 500 kg CO_2/MWh, based on DOE [11].

BII. EXAMPLE KPI CALCULATIONS

1) Example KPI Calculations for Synchronous Motor Driven Rotating Equipment

MTBF Improvement Example:

- Baseline MTBF = 24 months
- Framework-enabled MTBF = 34 months

$$\Delta MTBF\ (\%) = \left(\frac{34}{24} - 1\right) * 100 = 41.7\%$$

Energy Efficiency Gain Example:

- Simulated energy efficiency under operation = 97.9%
- Simulated energy efficiency after framework activation = 98.0%

$$\Delta\eta\ (\%)\ \left(\frac{98.0 - 97.9}{97.9}\right) * 100 = \ 0.1\%$$

Scope 1 Emissions Avoidance Example:

- Shutdowns avoided = 0.5 events/year

- Flaring emission factor = 45 tCO_2e/event

$$CO_2e\ Avoidance\ (t) = 0.5 * 45 = 22.5\ tCO_2e$$

Scope 2 Emissions Reduction Example:

- Normalized energy savings = 201 MWh/year
- Grid CO_2 emission factor = 500 kg CO_2/MWh

$$CO_2e\ Reduced\ (t) = 201 * \frac{500}{1000} = 101\ tCO_2e/a$$

2) Example KPI Calculations for VFD Driven Rotating Equipment:

MTBF Improvement Example:

- Baseline MTBF = 20 months
- Framework-enabled MTBF = 27.2 months

(Note: Values derived from scenario-informed degradation emulation, not field data.)

$$\Delta MTBF\ (\%) = \left(\frac{27.2}{20} - 1\right) * 100 = 36{,}0\%$$

Energy Efficiency Gain Example:

- Simulated energy efficiency under operation = 88.0%
- Simulated energy efficiency after framework activation = 92.3%

$$\Delta\eta\ (\%)\ \left(\frac{92.3 - 88.0}{88.0}\right) * 100 = \ 4.9\%$$

Scope 2 Emissions Reduction Example:

- Normalized energy savings = 25 MWh/year
- Grid CO_2 emission factor = 500 kg CO_2/MWh

$$Scope\ 2\ Reduction\ (tCO_2e) = 25 * \frac{500}{1000} = 12.5\ tCO_2e/a$$

(Note: Scope 1 emissions avoidance is not directly modeled for VFD degradation events unless full drive failure leads to emergency shutdown.)

BIII. VITA

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