Whitepaper

PREDICTIVE ANALYTICS (PdA) SOLUTION

AI/ML Driven PdA Solution for Early Detection of Asset Failure

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UP TO

5%

KBR's predictive analytics solution enhances equipment availability to help clients avoid unplanned shutdowns and maintain peak performance

Solution Overview

The Predictive Analytics solution is designed to enhance the reliability, efficiency, and longevity of refinery assets through the power of advanced data analytics, artificial intelligence (AI), and machine learning (ML). This solution enables refineries to move from traditional reactive maintenance strategies to a proactive, data-driven approach, allowing for early detection of potential asset failures, optimized maintenance schedules, and overall process optimization.

WITH PdA, WE CAN

The Predictive Analytics (PdA) for Asset Performance Management solution offers refineries a transformative approach to asset management, driving operational excellence and reducing costs. By leveraging AI and machine learning to predict failures, optimize maintenance, and extend asset life, refineries can improve their overall performance, safety, and profitability. This data-driven solution not only enhances day-to-day operations but also supports long-term strategic goals, positioning refineries for greater sustainability and competitiveness in an increasingly dynamic industry.

Key benefits

1 **Minimized Downtime:** Predictive models monitor asset health in real-time, providing early warnings of potential failures. This proactive minimizes unplanned downtime, ensuring continuous refinery operations and reducing production disruptions.

2 **Optimized Maintenance Costs:** By predicting asset failures and prioritizing maintenance tasks based on asset condition, the solution helps refineries allocate resources efficiently, reducing unnecessary maintenance and lowering overall operational costs

3 **Extended Asset Lifespan:** AI and ML models analyze operational data enables timely interventions and extending life cycle of critical equipment, such as pumps, compressors, and turbines.

4 **Improved Operations Efficiency:** Continuous monitoring and predictive insights allow for optimized operating conditions, improving energy efficiency, throughout and overall performance across refinery processes.

5 **Data-Driven Decision Making:** Predictive analytics provide refinery managers with actionable insights, supporting better decision-making regarding maintenance, capital investments, and resource allocation, ultimately leading to improved asset management and a higher return on investment (ROI)

6 **Enhanced Safety & Compliance:** Early identification of equipment failures and deviations in operational conditions enhances refinery safety by preventing accidents, reducing risks, and ensuring regulatory compliance.

AI/ML based machine learning algorithms enable earlier detection of abnormal conditions compared to traditional limit-based methods

KEY TECHNOLOGY PILLARS

KBR's predictive analytics (PdA) solution has a strong foundation of the following technology pillars:

Real-time Monitoring

IoT-enabled sensors and instrument tags in process historian database capture continuous data from refinery assets, feeding into AI/ML models for real-time performance analysis.

Advanced AI/ML Algorithms

These algorithms process historical and real-time data to predict failures, optimize maintenance schedules, and enhance operational strategies.

Seamless Integration

The solution integrates smoothly with existing refinery systems such as process historian, SCADA, CMMS, ERP platforms, ensuring cohesive data flow and actionable insight

Cloud-based Platform

The cloud infrastructure enables scalable data storage, processing, and analysis, while ensuring security and ease of access.

PdA facilitates necessary decision support mechanism for maintenance scheduling in an automated manner

Solution Features

Asset Health Monitoring

Continuously monitors the condition of critical assets using real-time and historical data, enabling early detection of anomalies and degradation trends

Failure Prediction and Root Cause Analysis

Utilizes advanced machine learning models to predict potential equipment failures and identify their underlying causes, helping to reduce unplanned downtime and extend asset life.

Real-Time Alerts and Notifications

Automatically generates timely alerts and notifications when anomalies or thresholds are detected, ensuring swift response and preventive action by maintenance teams.

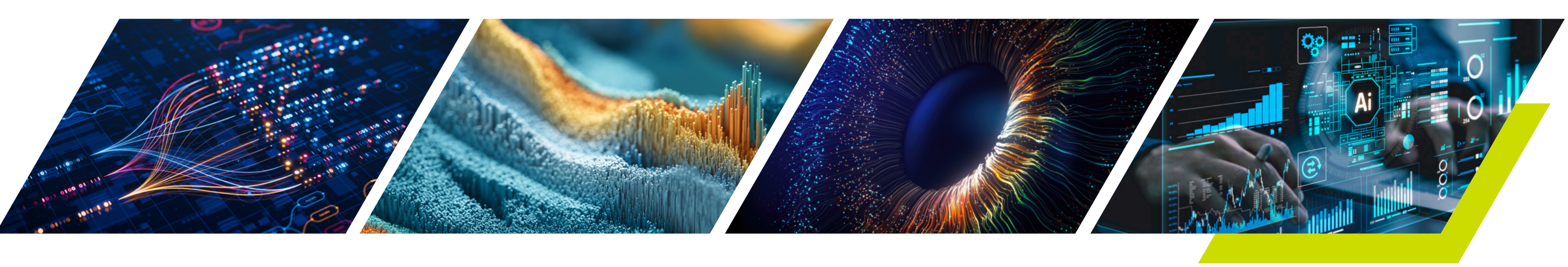
Anomaly Investigation Workflow Management

Enables users to manage the investigation process for detected anomalies, including the ability to add comments, track progress, and document findings. All investigations are securely stored for future reference, promoting knowledge retention and continuous improvement.

Data-Driven Decision Making

Empowers stakeholders with actionable insights through interactive dashboards and reports, supporting strategic planning, resource allocation, and performance optimization.

These core features of the PdA solution leverage AI/ML algorithms to optimize maintenance schedules and enhance operational efficiency



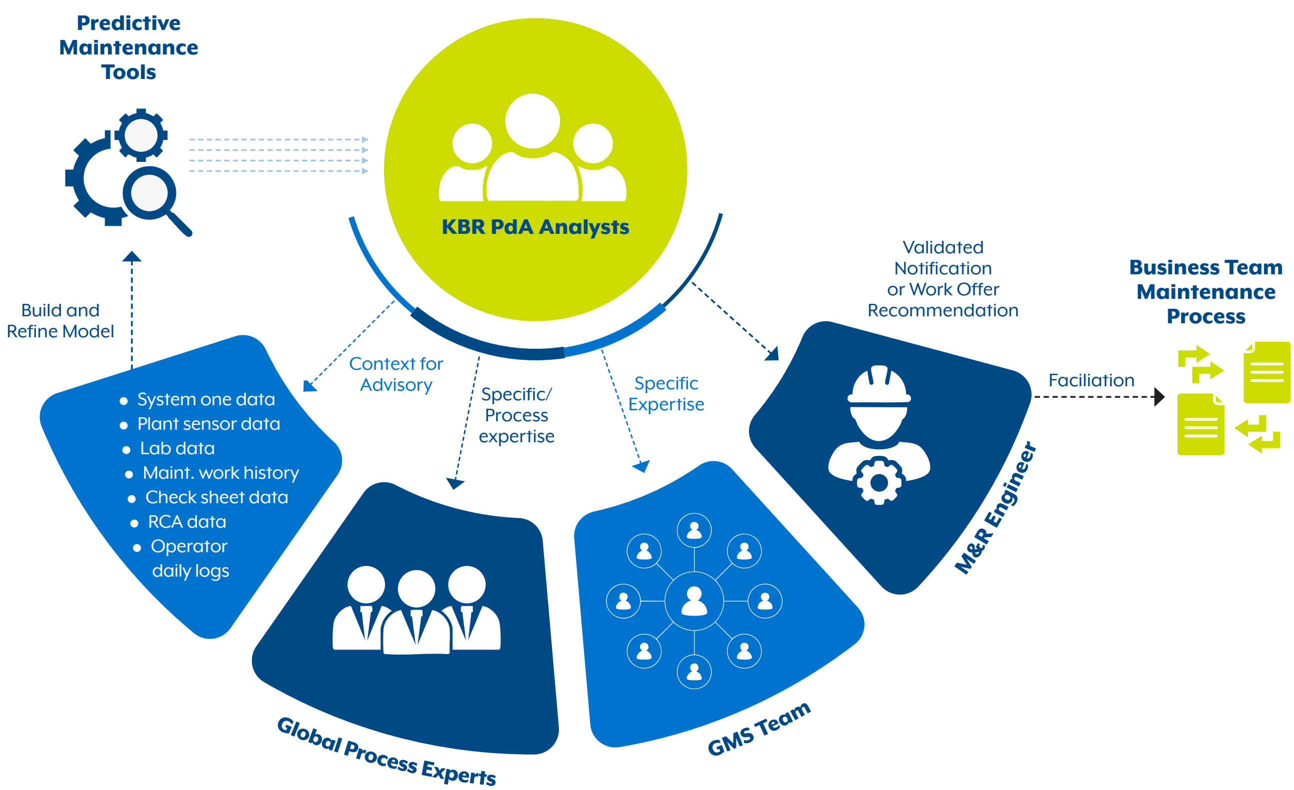
KBR's maintenence, process and reliability experts work together to deliver high performance results

Why KBR?

With KBR’s extensive maintenance and process expertise, customers gain more than just a technology provider — they gain a strategic partner committed to optimizing asset reliability, reducing costs, & enhancing operational performance.

KBR's domain knowledge ensures the AI/ML solution are tailored to align seamlessly with customers' operational environments, making them highly effective and practical for real-world challenges. Once the model development phase is complete, the PdA analysts take a hands-on approach during the evaluation period. They monitor and analyze model performance in live operational scenarios, assessing its accuracy, reliability, and effectiveness in detecting anomalies. Throughout this process, the analysts collaborate with KBR’s global network of process and maintenance experts, leveraging their decades of experience to fine-tune the models. This iterative process ensures that models adapt to the specific operational conditions of the customer’s environment while reducing false anomalies and increasing actionable insights. KBR’s unique feedback loop plays a pivotal role in refining the models, addressing edge cases, and identifying patterns that may not be immediately apparent.

FULL CYCLE METHODOLOGY

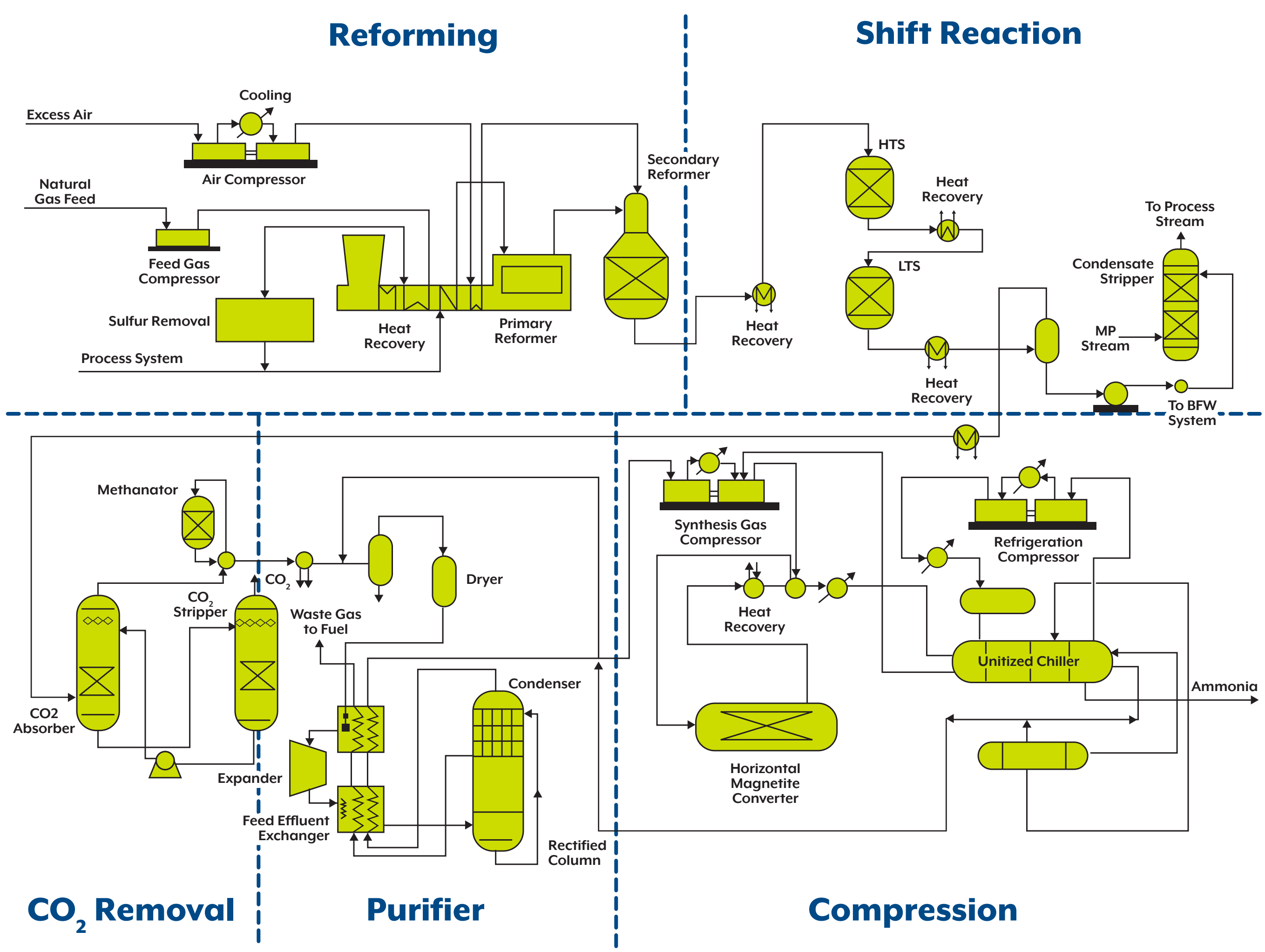


Once the models demonstrate consistent and satisfactory outcomes, they are transitioned to the customer for operational use. KBR provides comprehensive handover training and support, ensuring customers are equipped to manage and benefit from the models independently.

KBR's full-cycle methodology, combining cutting-edge AI/ML technology with in-house expertise in model training, operational fine-tuning, and post-implementation support, sets it apart as the preferred partner for AI/ML-based predictive analytics solutions. By delivering solutions that are reliable, actionable, and deeply rooted in industry knowledge, KBR empowers customers to proactively manage their assets, minimize risks, and drive long-term value.

System by System Approach

Implementing a system-based model using a system-by-system approach for predictive analytics in asset health monitoring involves breaking down the overall



system into individual components and developing tailored solutions for each. KBR's "System by System" approach integrates equipment with the broader system, ensuring predictive analytics are not performed in isolation. This holistic view enables more accurate feature selection by understanding the relationships between individual components and the entire system, improving anomaly detection and minimizing the cascading impacts across processes.

We integrate the data of different equipment in the system, creating a comprehensive and multidimensional training data set. This holistic approach ensures that the models capture the complexities of interconnected equipment and detect anomalies that may not be evident in isolated equipment data.

Comprehensive FMEA Knowledgebase

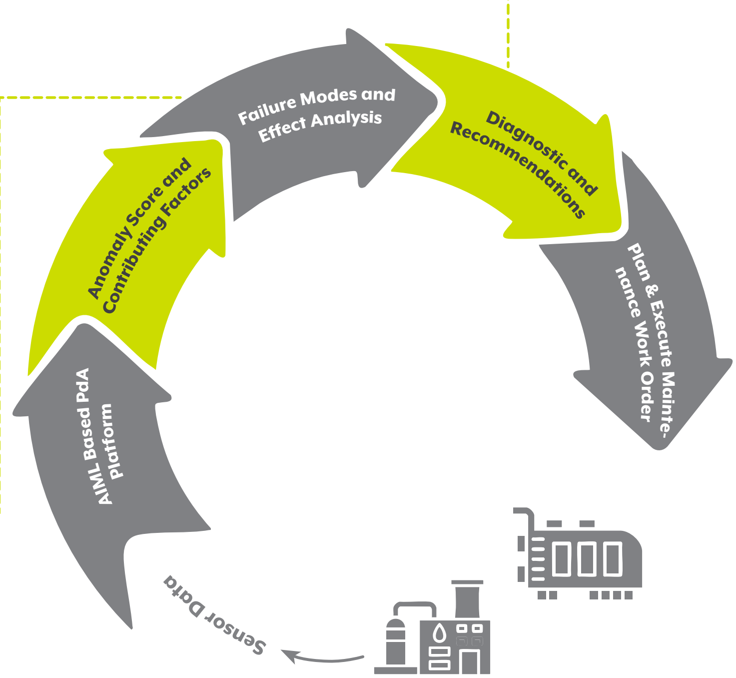
KBR's ready-to-use FMEA knowledgebase is built on a deep understanding of equipment operations under various circumstances. With extensive coverage of failure modes across various industries, our customers can easily leverage this robust resource to proactively identify and prevent equipment failures, ensuring improved reliability and performance.

FMEA KNOWLEDGE BASE

Cause	Recommendation_1	Recommendation_2
Vibration Anomaly	Perform detailed spectrum analysis & confirm problem	Repair / Replace the bearing
Process Anomaly	Analyze process trends	Adjust process parameters/Minimize process deviations
Seal Anomaly	Inspect, repair / replace the seal laybrinth	
Filter Anomaly	Analyze Lube Oil Pressure and Temperature	Check Lube Oil Filter DP

Sensors/Tags	Vibration Anomaly	Process Anomaly	Seal Anomaly	Filter Anomaly
Vibration Sensors	1	0	0	0
Process Tags	0	1	0	0
Seal Pressure Tags	0	0	1	0
Filter DP Tag	0	0	0	1

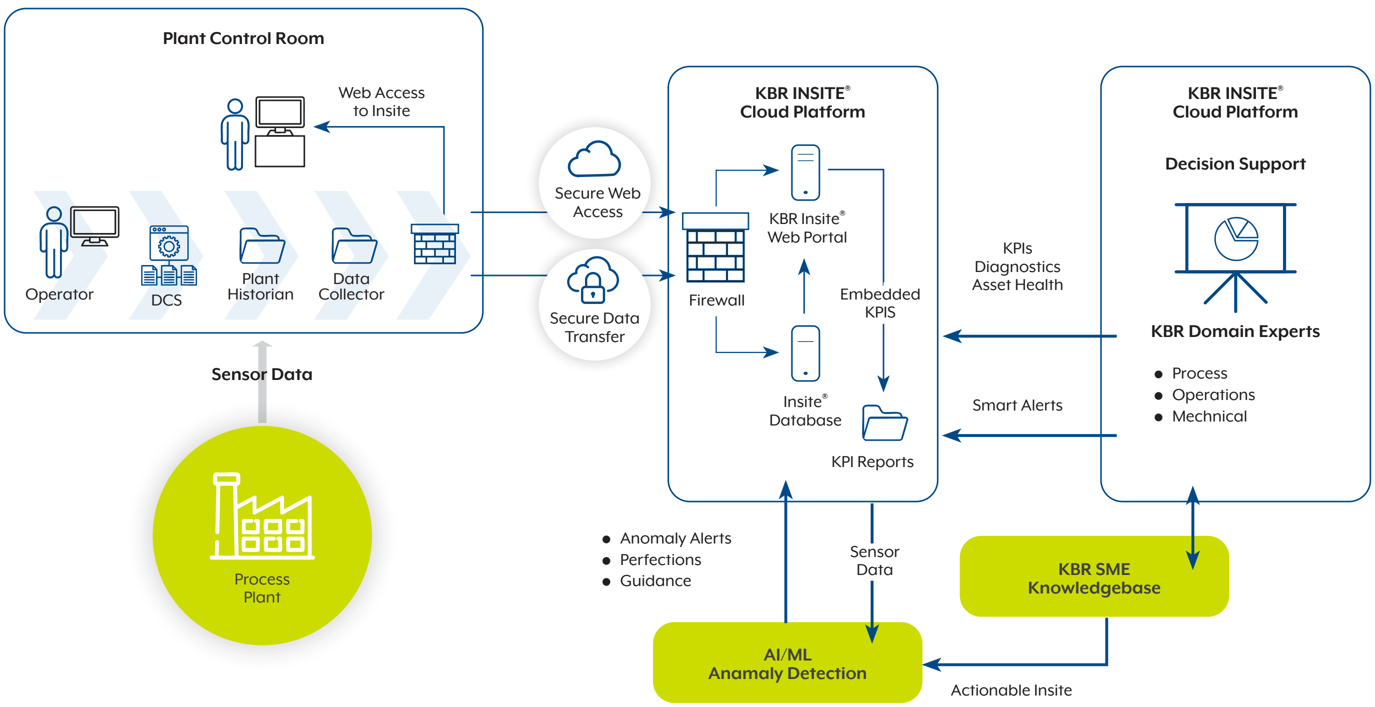
Cause	Severity	Occurrence	Detectability	RPN
Vibration Anomaly	8	1	6	48
Process Anomaly	4	3	9	108
Seal Anomaly	8	1	6	48
Filter Anomaly	8	2	9	144



Solution Details

Designing a predictive analytics solution architecture for a refinery involves integrating various components to ensure efficient data collection, processing, analysis, and actionable insights. Typical architecture of AIML based PdA solution is as follows:

SOLUTION ARCHITECTURE



AI and Machine Learning
- Anomaly Detection
- Contribution Factors
- Root Cause Analysis
- Predictife Models
- Prescriptive Guidance

Asset Performance
- Catalyst
- Reformer
- Reactors
- Compressors
- Heat Exchangers

Operational Excellence
- Plant Uptime
- Production
- Energy Efficiency
- Emissions
- Life-cycle Reliablity

AI/ML Model Design

The design of an AI/ML model for asset health anomaly detection focuses on identifying deviations or irregular patterns in the performance of assets (e.g., pumps, motors, turbines) in a refinery or industrial setting. By analyzing real-time and historical sensor data, the model can detect potential faults, wear, or operational inefficiencies before they lead to asset failures. This approach enables predictive maintenance and optimized resource allocation. The following are the steps used in AIML model building:

Data Collection & Preprocessing

Input Data: The model requires sensor data collected from various assets, such as vibration, temperature, pressure, flow rate, motor current, and other operational parameters. Data may come from IoT sensors, SCADA systems, and PLCs.

Lube Oil
- Header Press
- Supply Temp
- Return Temp
- Filter DP

Radial Bearings
- Bearing Temp
- Bearing Vib

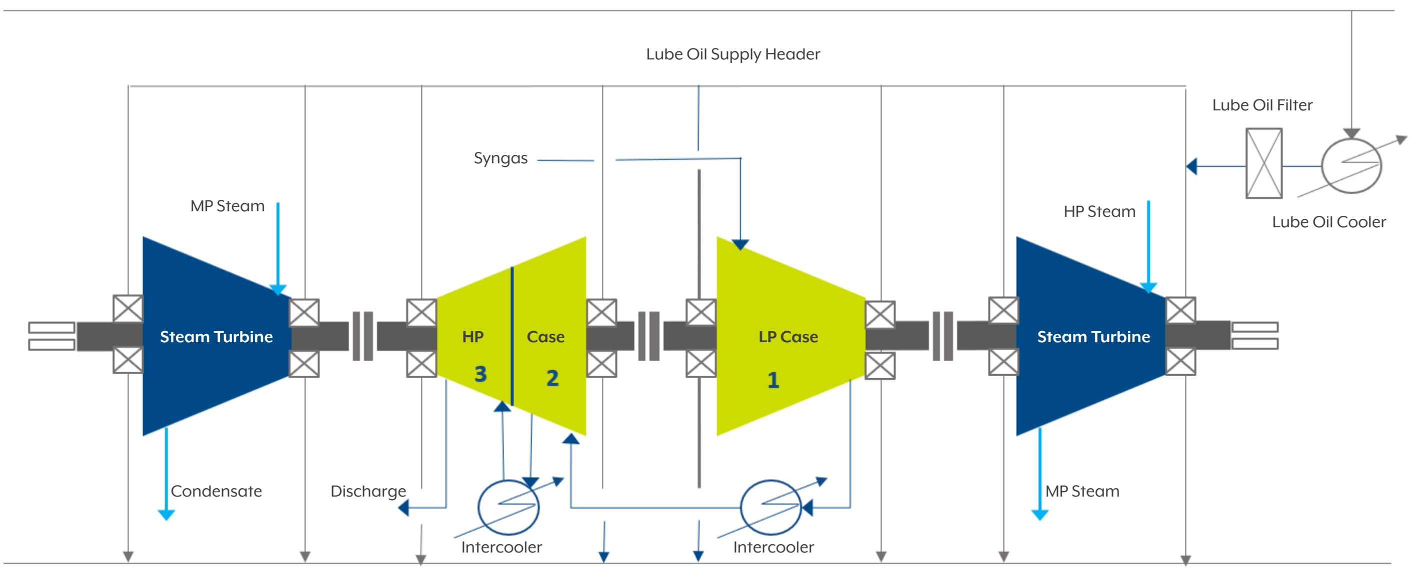
Thrust Bearing
- Axial Disp
- Bearing Temp

Steam Turbines
- RPM
- I/L F, P, T
- O/L F, P, T
- Seal Press

LP and HP Case
- Suct F, P, T
- Interstage P, T
- Disch P, T
- Air Filter DP
- Antisurge Valve OP

Intercoolers
- CW Sup/Ret Temp
- SyngasI/O Temp

AIR COMPRESSION SYSTEM



FAULT COVERAGE: Bearing Failures | Coupling Failures | Rotor Failures | Seal Failures | Filter Choking | Intercooler Fouling | Process Abnormalities

Data Preprocessing:

- **Cleaning:** Handle missing or noisy data (e.g., outliers, inconsistent sensor readings).
- **Normalization:** Scale sensor data to a common range to improve model convergence.
- **Feature Engineering:** Derive features such as rolling averages, trends, rate of change, etc., to capture the underlying patterns of asset performance.
- **Data Labelling:** Label the data with “normal” or “anomalous” behaviour, ideally based on historical failure data or expert input.

Feature Selection

Relevant Features: Identify the most important features for detecting anomalies, such as:

- **Vibration levels** (e.g., abnormal vibrations indicating potential bearing issues)
- **Temperature** (e.g., overheating indicating pump failure)
- **Pressure** (e.g., pressure drops or spikes indicating blockages or leaks)
- **Motor current** (e.g., fluctuations indicating mechanical inefficiencies)

Correlation Analysis: Perform statistical tests and correlation analysis to identify which features most significantly impact asset performance and help in distinguishing anomalies.

Model Selection & Design

Algorithm Selection: Choose appropriate AI/ML models based on the complexity of the data and the nature of anomalies.

- **Supervised Learning:** If labelled data is available, models like Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) can be used for classification (normal vs. anomalous).
- **Unsupervised Learning:** If labelled data is limited, unsupervised learning methods such as Autoencoders (neural networks) are useful for detecting novel anomalies based on data distribution.
- **Semi-supervised Learning:** A hybrid approach, where a small amount of labelled data is augmented with large volumes of unlabelled data, can also be effective (e.g., using clustering algorithms such as K-Means with manual labelling of outliers).

Analyzing real-time and historical asset data enables early identification of faults, wear, and operational inefficiencies leading to significant cost savings

Leveraging AI and ML algorithms can uncover patterns, predict failures to improve asset reliability and efficiency

Model Training & Evaluation

Training: Split the dataset into training and test sets. Train the model on historical data (e.g., normal and faulty behaviour).

Cross-Validation: Use k-fold cross-validation to assess model performance and avoid overfitting, ensuring the model generalizes well to new, unseen data.

Metrics: Evaluate the model using standard metrics:

- **Precision and Recall:** For detecting anomalies accurately without false positives (precision) and missing actual anomalies (recall).
- **F1-Score:** Balances precision and recall for overall detection performance.
- **Training and Validation Loss,** Model accuracy to determine the difference between predicted and actual data.

Anomaly Detection & Threshold Setting

Anomaly Scoring: Once the model is trained, it assigns an anomaly score to each data point, representing how much it deviates from the expected behaviour. Higher scores indicate more likely anomalies.

Thresholding: Set a threshold for what constitutes an anomaly. This can be a fixed value (e.g., above a certain score) or dynamic (e.g., based on standard deviations from historical data). Fine-tuning the threshold helps balance between detecting all anomalies and reducing false positives.

Real-Time Monitoring & Alerts

Deployment: Once the model is deployed, it continuously monitors incoming data from refinery assets in real time.

Alert System: If an anomaly score exceeds the set threshold, the system triggers alerts. Alerts can be routed to maintenance teams with relevant contextual information, such as which asset is affected, potential failure modes, and recommended actions.

Visualization: A dashboard or control centre displays real-time health status, trends, and detected anomalies, allowing operators to visualize asset performance and make data-driven decisions.

Continuous Learning & Model Updates

Model Retraining: The model should be periodically retrained with new data to adapt to changing operational conditions. This is especially important in dynamic environments where asset performance patterns may evolve over time.

Feedback Loop: Integrate a feedback mechanism where maintenance personnel can provide feedback on false positives/negatives, allowing the system to refine its predictions.

Asset Sensor Data

- Vibration Data
- Process Data (Temprature, Presuure, Flowrates)
- Current/Voltage
- RPM
- Lube oil analiysis

Asset Maintenance History

- Failure History
- Operational Logs
- Downtime Logs
- Repair and Replacement Data

Environment and Operational Context

- Production Load
- Environmental Conditions
- Maintenance Schedules
- Operating Modes

Quality Data

- Online Analyzers
- Lab Samples Analysis

Data Requirements

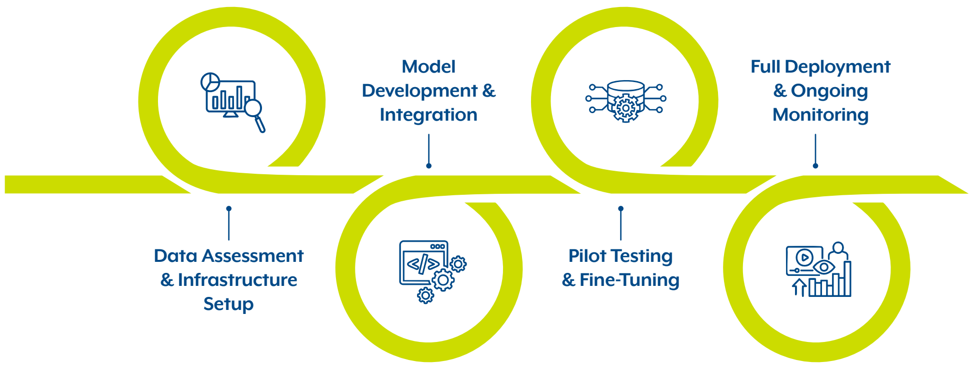
To effectively design and deploy an AI/ML model for asset health anomaly detection, a comprehensive data strategy is essential. The success of the anomaly detection model depends on the quality, quantity, and variety of the data used for training, testing, and real-time predictions. Building an AIML model for asset health anomaly detection in a refinery requires diverse datasets that include sensor data, historical maintenance logs, environmental data, operational context, and feedback from real-time operations. By leveraging these datasets,

Effective anomaly detection is based on the quality, quantity, and variety of data used for training, testing, and prediction

the AI/ML model can effectively detect anomalies, predict failures, and optimize maintenance strategies, resulting in reduced downtime and improved asset management. Below are few datasets required to implement AI/ML model:

Implementation Phases

The implementation of AIML based PdA solution will be carried out in four phases to ensure successful delivery. Typical timelines for pilot implementation take one to three months depending on the complexity of the project. The implementation phases are as follows:



Phase 1 – Data Assessment & Infrastructure Setup

- Conduct a comprehensive assessment of the current asset management system and define data sources.
- Set up IoT sensors, data infrastructure, and cloud platform for seamless data flow and processing.

Phase 2 – Model Development & Integration

- Develop AI/ML models based on historical asset data and operational parameters.
- Integrate the predictive analytics platform with existing asset management systems (EAM, CMMS).

Phase 3 – Pilot Testing & Fine-Tuning

- Deploy the predictive analytics solution in a pilot environment and test it with real-time data.
- Fine-tune models for better accuracy and ensure the solution aligns with operational needs.

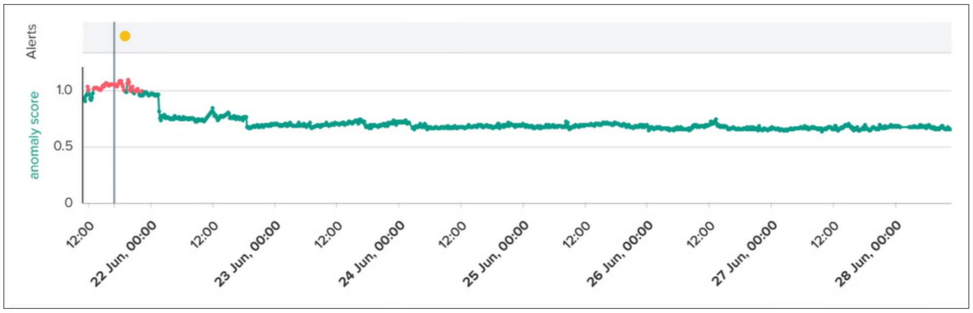
Phase 4 – Full Deployment & Ongoing Monitoring

- Scale the solution across the entire asset portfolio.
- Continuously monitor system performance, update models, and provide ongoing support.

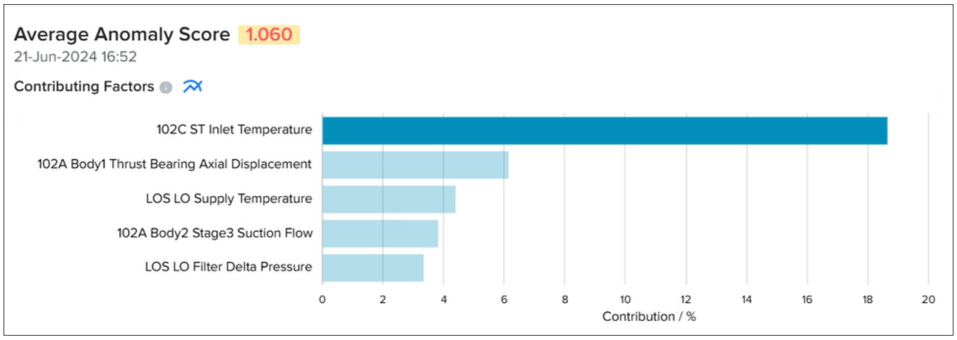
Case Studies

Analyzing Air Compressor for Leading Fertilizer Industry

Problem: Steam turbine efficiency declined after the plant startup and continued to operate at a lower efficiency even after the plant had stabilized.



Solution/Analysis: The delivered AI/ML model for the air compression system successfully identified a process anomaly, pinpointing a drop in steam inlet temperature as the root cause. The model promptly alerted the user, enabling swift corrective action.

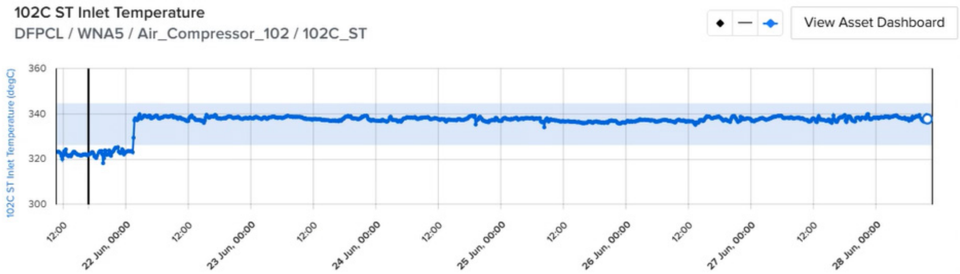


Details

For the detected anomalies, the AI/ML model identified key contributing factors, including:

- Steam inlet temperature to the turbine
- Steam outlet temperature from the turbine

Operators discovered that a manual valve on the steam drum had been closed, leading to the flow of saturated steam to the turbine. After reopening the valve, the steam turbine efficiency improved significantly.



Analyzing Syngas Compressor for Top Fertilizer Company

Problem

The synthesis gas compressor (103-J) experienced an unexpected trip due to high radial bearing temperature.

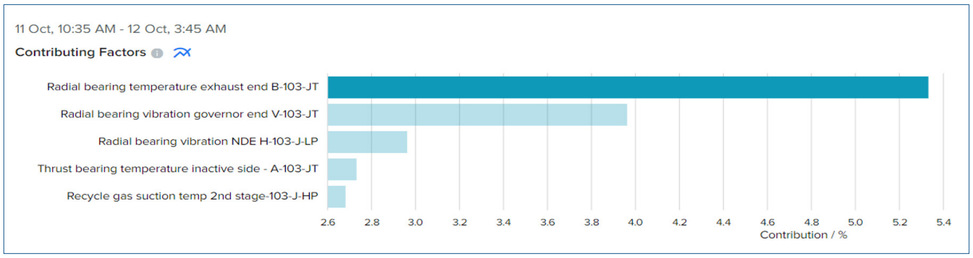
Solution/Analysis

The AI/ML model pilot for the SynGas compressor, utilizing multivariate analysis, detected the process anomaly early and alerted the user. The anomaly score began to rise significantly two weeks before the trip, highlighting ability to provide critical lead time for corrective action.

Details

For the identified anomalies, the AI/ML model highlighted the following key contributing factors:

- Turbine radial bearing exhaust end temperature
- Turbine radial bearing governor end vibration
- Turbine thrust bearing temperature (inactive side).



ALERT		CAUSES 1	RECOMMENDATIONS 2
Event	event alert for analytic: uc-ana-103-j-r2 & model: 103-j-r2	• The bearing wear will lead to excessive vibrations, high bearing temprature and will untimately lead to turbine trip. May include failure modes related to shaft and	• Perform detailed spectrum analysis & confirm problem • Repair/Replace the bearing
Severity	Warning		

Converter (105-D) Analysis for Reputed Fertilizer Company in Europe

Problem

The plant experienced a shutdown due to a rapidly increasing pressure drop across the 105-D converter.

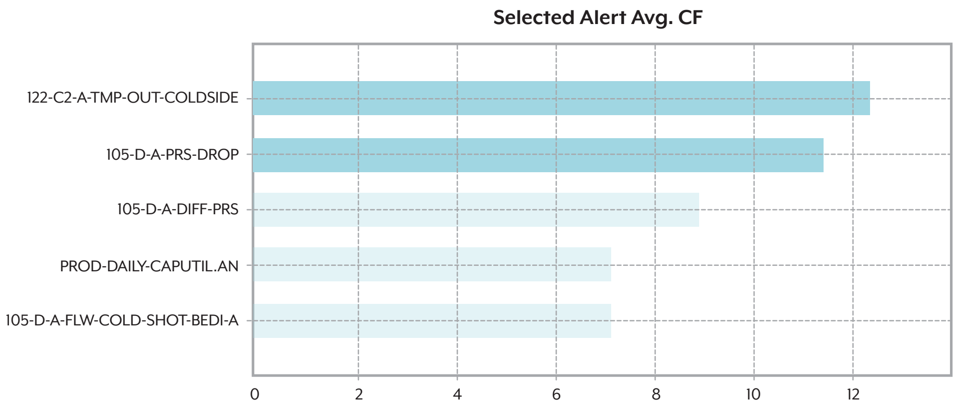
Solution/Analysis

An AI/ML test model, leveraging advanced multivariate analysis, was developed specifically for the 105-D converter, utilizing data collected over the entire year to identify underlying issues.

Details

In analyzing the anomalies, the AI/ML model pinpointed several major contributing factors:

- An obstruction or resistance to flow within the converter, causing a gradual increase in delta pressure.
- Inadequate reactions occurring within the beds, resulting in significant changes to the temperature profile.
- Furthermore, after the trip, several parameters exhibited drastic shifts from their normal operating ranges. This comprehensive analysis underscores the AI/ML model's ability to detect critical issues and provide insights that can prevent future shutdowns



Unlock the full potential of refinery operations, through AI/ML-powered predictive analytics and transition from reactive asset management to a proactive, data-driven strategy.

Enhanced Asset Reliability and Efficiency: AI and ML technologies enable proactive monitoring of refinery equipment, reducing unplanned downtime and extending asset lifespans.

Advanced Predictive Maintenance Strategy: The solution replaces reactive maintenance with intelligent forecasting, allowing early detection of potential failures and precise intervention planning.

Operational Optimization and Cost Reduction: Data-driven insights support smarter decision-making, streamline workflows, and deliver sustained cost savings across refinery operations.

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