Applying Generative AI methods to make possible Predictive Maintenance and Estimate Remaining Useful Life (RUL)

A Data-Driven Approach to Fault Detection

Content

Introduction:

- Traditional vs generative AI
- Developing application of generative AI methods to make possible predictive maintenance and estimate remaining userful life (RUL).

Methodology:

- Data Preprocessing (cleaning, scaling).
- Exploratory Analysis (trends, correlations).
- Statistical and ML-Based Anomaly Detection, Evaluation and Insights Generation
- Tools Used: Python, Autoencoders, Statistical Tests

Results & Discussion:

- Predictive Maintenance Model Outcomes; Significant anomalies detected in value_TEMP and value_ACC.
- Extract actionable insights from pump sensor data, from Analyzed: 5 key sensor features over time.

Conclusion:

- Recommendations: Integrate findings into predictive maintenance systems

References:

- Generative adversarial networks for data augmentation in machine fault diagnosis, Siyu Shao, Pu Wang, and Rugjang Yan, April 2019: https://www.sciencedirect.com/science/article/abs/pii/S0166361518305657

Traditional vs Generative AI

Traditional AI: Relies on explicit programming and predefined rules for specific tasks. Based on historical patterns in data, predicts outcomes for specific use cases (e.g., numeric predictions)

Generative AI: Uses machine learning techniques to autonomously create new content based on learned patterns and data. Understands context and generates novel human-like content (e.g., text, code, music, audio, video, data, etc.)

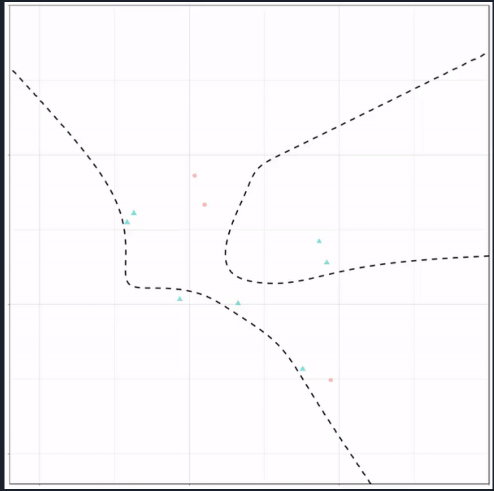
Images
- Gemeni
- Image Creator

Text
- ChatGPT
- DALL-E

Videos
- Stable diffusion
- Runway

Other Media
- Anyword
- Jasper

Example "Copilot": Generative artificial intelligence (AI) is a type of AI that generates images, text, videos, and other media in response to inputted prompts.

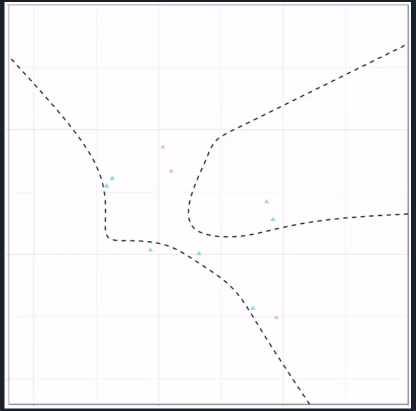


Limitations of Traditional AI Approaches

- Traditional AI Implementation
  - Can predict machine failure or abnormal behavior in advance
  - Depends on past historical failure patterns for self-learning
- Scarcity of Historical Failure Scenarios
  - Makes model development harder
  - Challenges in implementing predictive maintenance solutions in real-time
- Insufficient Data on Past Failures
  - Hinders development of accurate prediction models
  - Renders predictive maintenance solutions ineffective in real-time
- Challenges in Developing Reliable Models
  - Difficulty in generalizing well to new situations

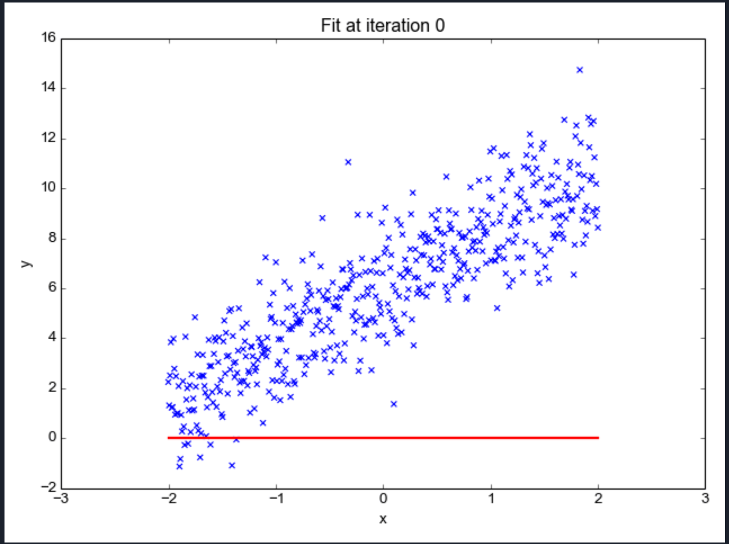
Generative AI for Predictive Maintenance

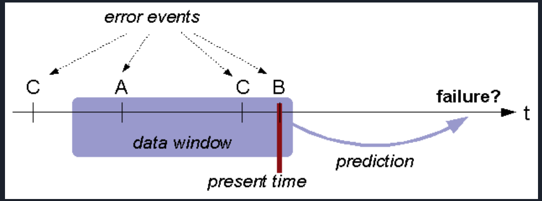
- Advancement in AI for Predictive Maintenance
  - Recent AI advancements enable predictive maintenance across industries
- Generative AI Algorithms
  - Capable of mimicking near-real time instances
  - Generate various operational anomaly instances
- Combining AI Techniques
  - Solves challenges in predictive maintenance



Challenges in Machine Failure Prediction

- Factors in Machine Failure
  - Various factors can cause machine failures
  - Failure types and modes vary over time
- Data Collection and Analysis Challenges
  - Difficulty in collecting and analyzing failure data
  - Current methods struggle to predict remaining useful life
- Degradation Due to Failures
  - Equipment can degrade significantly from single or multiple failures
  - Identifying the right point of degradation is challenging



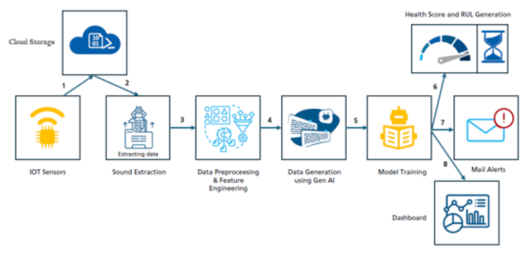


[Animated Visualizations of Machine Learning Algorithms (davpinto.github.io)]

Application Implementation- Crude Oil Transfer Pumps

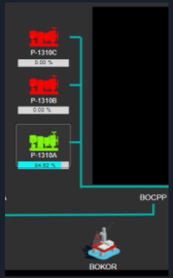
Scope

- Implementation Scope
  - Predictive maintenance for Upstream equipment
  - Focus on Crude Oil Transfer Pumps
  - Covering critical failure modes
- Generative AI Algorithm
  - Creates anomaly instances
  - Feeds data to predictive maintenance solution
  - Enhances model health
- Remaining Useful Life (RUL)
  - Estimates RUL of the machine in advance



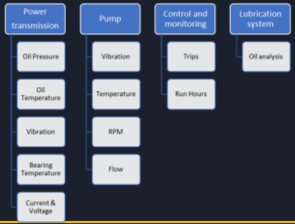
Data Applied

- Data Collection from PI System
  - Gathering operational data
  - Analyzing collected data
  - Making predictions based on data
- Focus on Critical Components
  - Identifying key components of Crude Oil Transfer Pumps
  - Prioritizing the most critical components



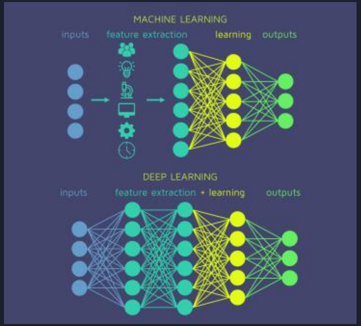
Equipment Failures

- Most common cause of failure
  - Regular Wear and Tear
  - Cavitation
  - Pressure Pulsations
  - Excessive Radial or Axial Thrust
  - Suction and Discharge Recirculation
- Mechanical Failures
  - Bearing Failure
  - Seal Failure
  - Gear Box Failures
  - Lubrication Failure
  - Excessive Vibrations
- Improper Use or Operator Error
  - Human factor failures, including operator errors



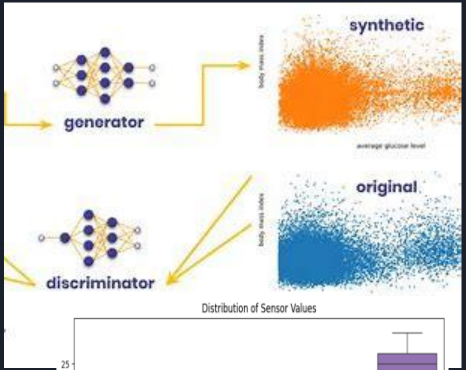
Data & Model

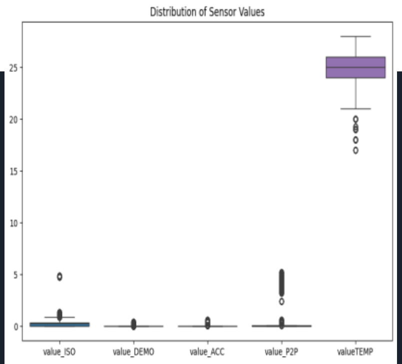
- Development and Testing Framework
  - Leverages generative adversarial networks (GANs)
  - Utilizes variational autoencoders (VAEs)
- Modeling Complex Dynamics
  - Focus on upstream equipment
  - Handles nonlinear dynamics
- Generating Realistic Synthetic Data
  - Used for training purposes
  - Used for testing purposes
- Validation of Framework
  - Case study on upstream production system
  - Real-world data from offshore



Feature Extraction

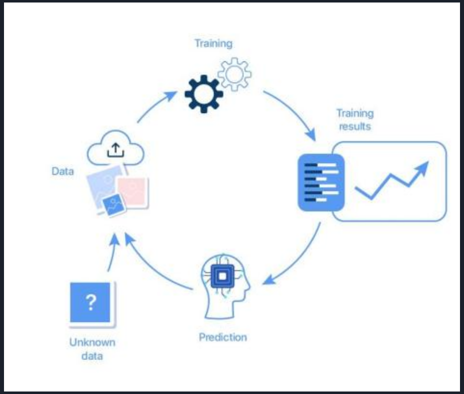
- Data Consumption by Analytics Team
  - Data is analyzed extensively
  - Exploratory data analysis is performed
- Feature Engineering
  - Team uses domain understanding
  - Creates tailored features
  - Aims to provide better insights





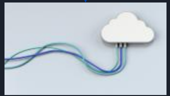
Model Training and Testing

- Model Finalization
  - Selecting a suitable model for the task
- Data Utilization
  - Using prepared data for training the model
- Performance Testing
  - Testing the trained model with unseen data
  - Evaluating model performance
- Model Finalization or Iteration
  - If results are satisfactory, finalize the model
  - If not, return to feature engineering for improvements



Stage 1: Data Acquisition

- Data Acquisition Stage
- Sensors deployed at the equipment
- Collect real-time data
- Store data in the local database (DB)
- Data types collected
    - Pressure
    - Temperature
    - Oil flow
    - Vibration

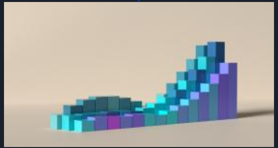


Stage 2: Cloud-based IoT Hub

- Cloud-based IoT Hub
    - Used for storing and processing data
- Data Transformation and Storage
    - Data is transformed and stored in cloud storage
    - Stored at year, month, day, and hour granularity
- Hourly JSON Files
    - Contains sensor values at second level

Stage 3: Data Processing and Model Inferencing

- Data Consumption in Azure Data Bricks
    - Data stored in Blob Storage is utilized
    - Used for pre-processing and model inferencing
- Auto Encoder Model
    - Trained on historical data
    - Deployed for inferencing
- Anomaly Detection
    - Model flags any anomalous points detected



Stage 4: Dashboard

- Cloud-Based Email Delivery
    - Used for sending email alerts
    - Alerts triggered by anomaly detection during inferencing
- Anomaly Score Distribution
    - Shows the distribution of anomaly scores over time
- Equipment Health Score
    - Indicates the overall health of the equipment
- Contribution Plot
    - Displays the contribution of different factors
- Historical Breakdown Data
    - Provides a historical view of the data

Crude Oil Transfer Pumps

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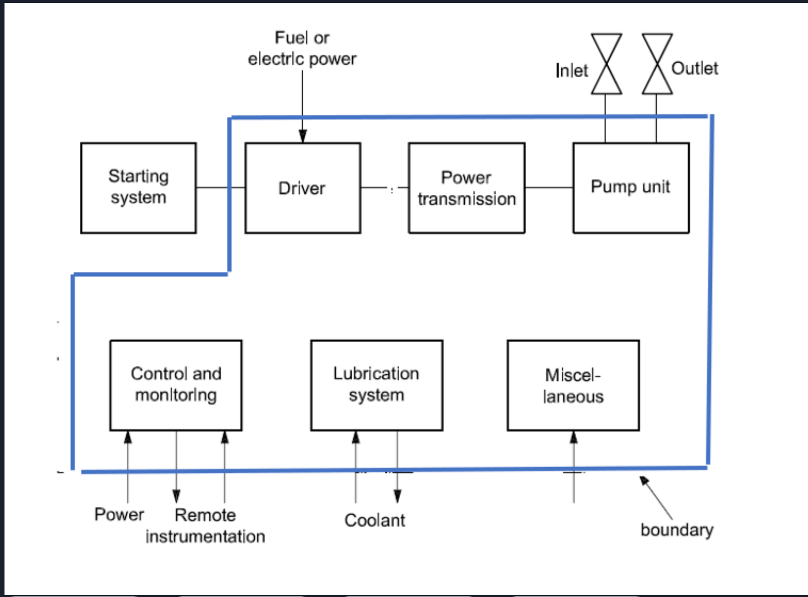

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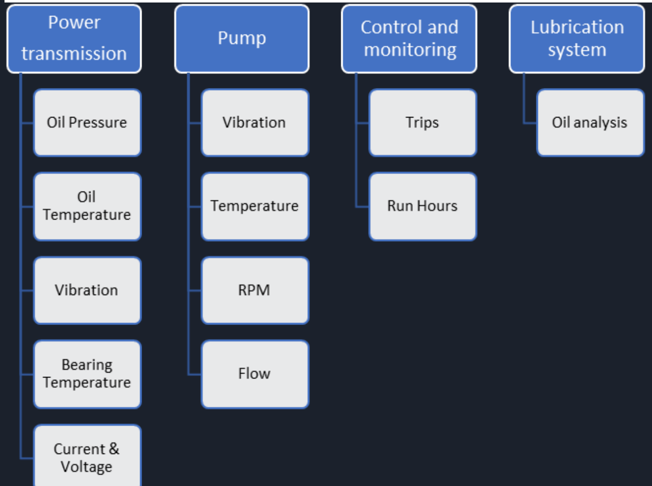
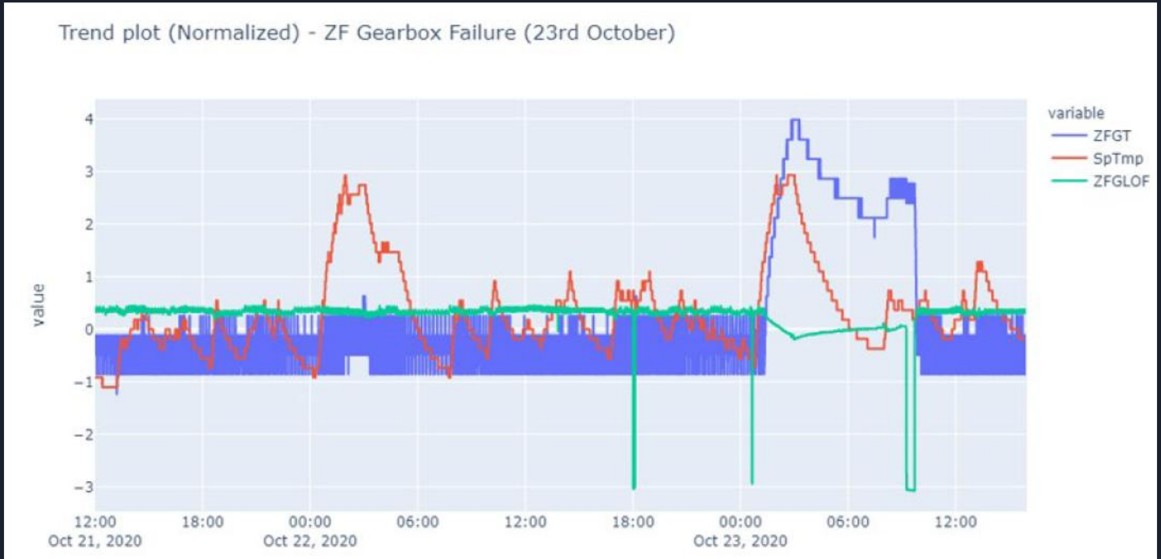
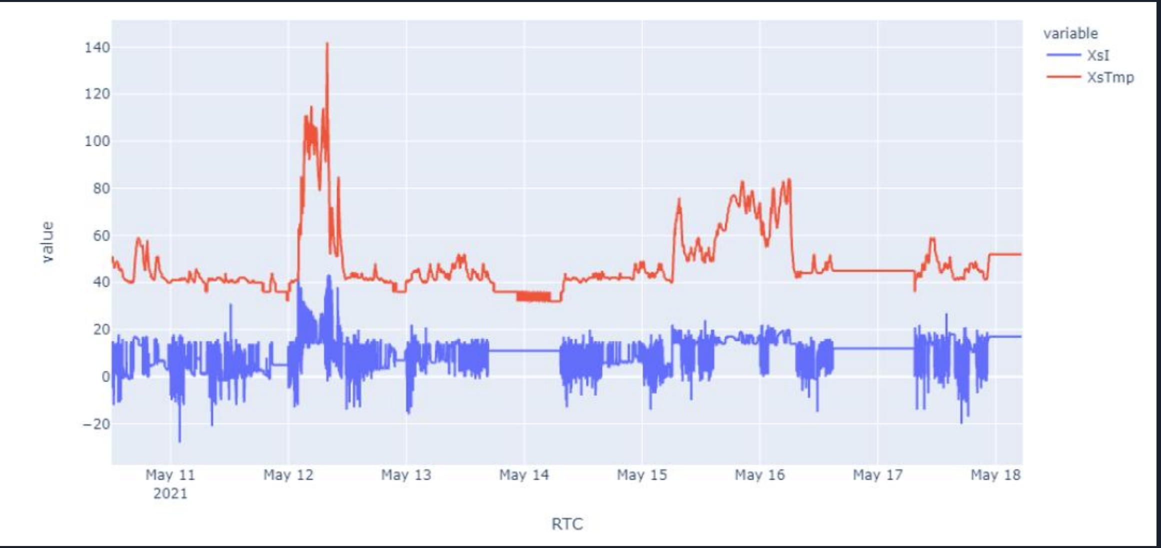


Example 1: Gearbox Temperature and Lubrication



- Gearbox Temperature Increase
  - Observed 8 hours before failure
  - Significant rise noted
- Reduced Lubrication Oil Flow
  - Observed alongside temperature increase
  - Contributes to failure indication
- Trend Plot Analysis
  - Normalized values show correlation
  - Temperature rise and oil flow reduction linked to failure
- Machine Status Information
  - Temperature increase during running state
- Failure Date

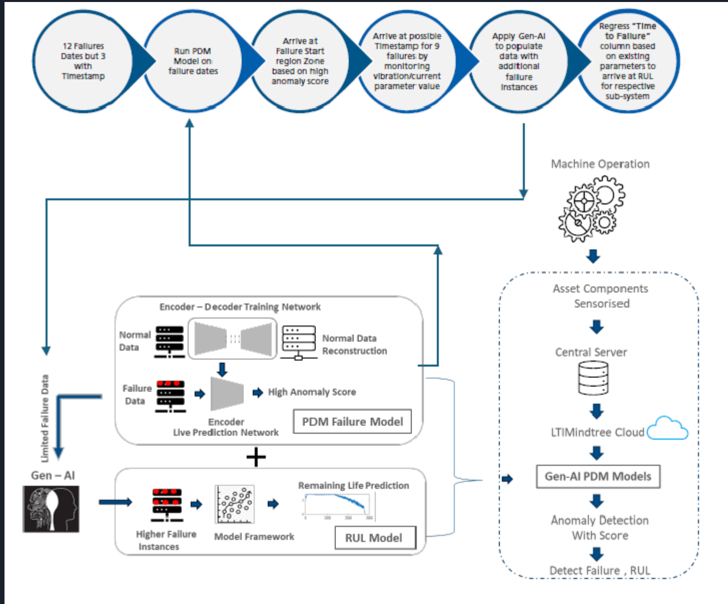
Example 2: Motor Temperature and Current



- Sudden Increase in Motor Temperature and Current
  - Observed 8 hours before failure on 12th May
  - Similar trend for Motor current during the same period
- Machine Status Information
  - Temperature and current started increasing during running state
  - Continued to rise till 9:00 AM
  - Machine went under maintenance at 9:00 AM
- Significant Indicators for Breakdown
  - Current and temperature of the Motor
  - Indicators for the breakdown on 12th May 2021

Predicting the Remaining Useful Life (RUL) of the machine

- Stage 1: From 12 failure data points out of which only 3 had the exact failure timestamp.
- Stage 2: Employ the above trained PdM (Predictive Maintenance Model) model on these data to discover the most probable timestamp when the failure could have happened. The timestamp corresponding to the highest anomaly score could be the most probable failure time. Based on this approach now we have the failure timestamp for 12 points.
- Stage 3: Now we use the generative AI technique to generate the synthetic failure data, taking the original 12 data points from above as the base reference to generate the data.
- Stage 4: Now after the data generation, we have sufficient data to train our regression model taking the required features to estimate the Remaining Useful Life (RUL).



Predictive Maintenance Model

- Auto Encoder Model Deployment
  - Trained on strictly non-anomalous data
  - Objective: flag abnormal behavior deviating from training data
- Anomaly Score as Breakdown Indicator
  - Model's residue used as the anomaly score
  - Score within threshold: not flagged
  - Score beyond permissible range: flagged

- Early Detection:
- The lube oil flow and gearbox temperature disturbances are picked by the model
- 6 hours before the breakdown (at 03:00 AM).

- Required Improvements and Systems
  - Additional subsystems with IoT data for better failure estimates and RULs
  - Incorporate a digital twin of the CNC machine using complete IoT system data
  - Standardize the model with more historical failure instances
  - Port model to edge server for faster failure detection using On-premises technologies

Conclusion

The recent advancement in AI has opened the door to predictive maintenance

- ✓ Generative AI algorithms are capable of mimicking near-real time instances based on few samples observed and able to generate various operational anomaly instances.
- ✓ In this application scope, the predictive maintenance solution is being implemented for Upstream equipment Crude Oil Transfer Pumps and to cover critical failure modes.
- ✓ A Gen AI algorithm will be applied to create anomaly instances and then feeds this data to the predictive maintenance solution to bolster the model health.
- ✓ In addition, this serves to estimate the Remaining Useful Life (RUL) of the COTP in advance.