Whitepaper

Predictive Maintenance & Remaining Useful Life (RUL) Estimation using Generative AI Techniques

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Introduction

Maintenance of heavy machinery is one of the most critical factors for any manufacturing process simply due to the fact of keeping the run-time high with optimum operational efficiency. Maintenance engineers are critically involved in various scheduled maintenance based on work orders scheduled in daily operations. Preventive, corrective, pre-determined, condition-based, and reactive are the different types of maintenance work orders that are usually maintained. However, with the advent of IoT (Internet of Things) sensors and algorithms, along with cutting-edge technology, many organizations are adopting predictive maintenance to identify the maintenance needs in advance. In addition, with next-gen AI (Artificial Intelligence) techniques it is possible to estimate the operational machine life in advance.

Problem statement

In manufacturing operations, various factors may be involved in a machine failure. The type and mode of failures varies from time-to-time. In failure scenarios there may be only a few live examples of these various mode failures. At times there can be instances where not a single failure has been observed so far.

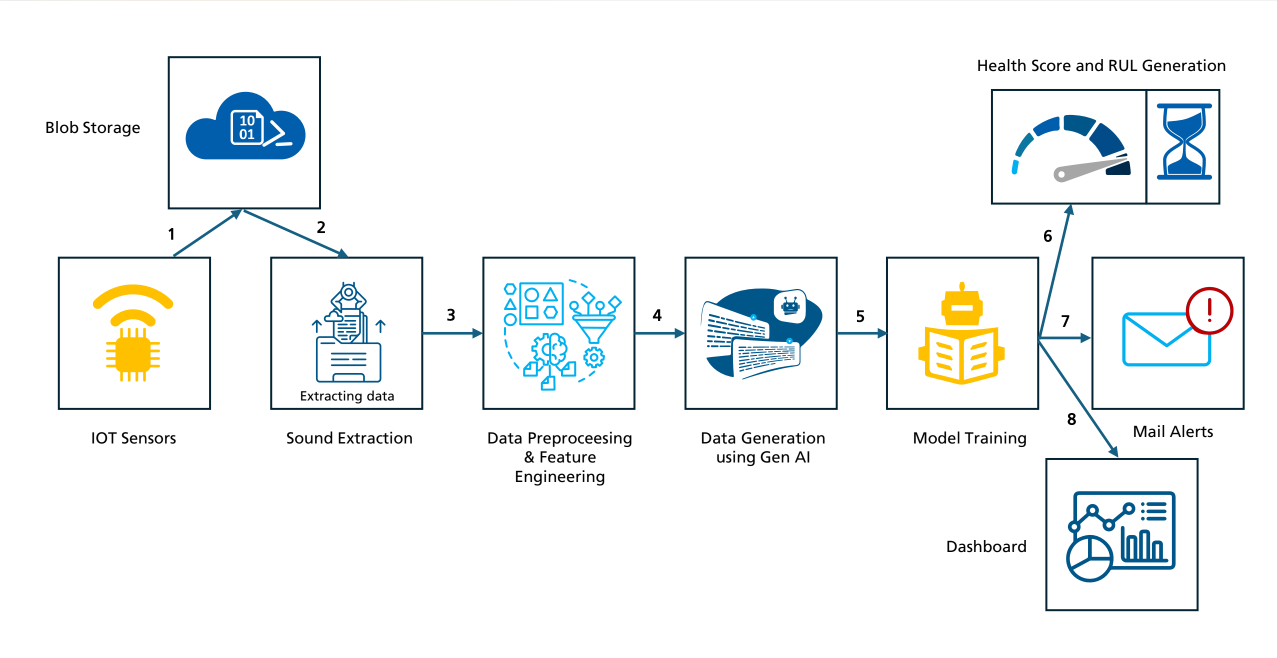
Even traditional AI implementation approach could be adopted to predict machine failure or abnormal behavior in advance, but AI is dependent on the past historical failure patterns for its self-learning. However, scarcity of historical failure scenarios makes the model development harder and challenging in implementing predictive maintenance solutions in real-time environments.

The lack of sufficient data on past failures hinders the development of accurate prediction models, rendering predictive maintenance solutions ineffective in real-time environments. This makes it challenging to develop reliable models that can generalize well to new situations.

Solution outline

The recent advancement in AI has opened the door to predictive maintenance across industries. Generative AI algorithms are capable of mimicking near-real time instances based on few samples observed and able to generate various operational anomaly instances. Combining these two AI techniques helps us to solve the above challenges.

In this scope, the predictive maintenance solution is being implemented for Gantry Drilling Machine for one of the reputed boilers manufacturers in Asia. There have been very limited failure instances not covering all types of failure mode. A Gen AI algorithm is 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 machine in advance.



In-depth solution overview

Failure in heavy-duty machinery, be it any mechanical or electrical failure, results in a huge loss to the operating company. These breakdowns result in higher repair costs, production downtime, as well as health and safety implications for workers, and affects the production and delivery of services.

The primary reasons that lead to such failures could be:

- Regular wear and tear:

  It is the most common cause of failure. Prolonged utilization of machinery will ultimately result in deterioration and exhaustion, commonly referred to as 'metal fatigue.' If neglected, the consequences of wear and tear can be devastating.

- Lack of predictive maintenance or condition monitoring:

  By leveraging real-time machine performance data, advanced algorithms can rapidly identify impending issues and alert you well in advance, affording you the opportunity to address potential problems before they evolve into major breakdowns.

These tailored and accurate analyses provide insightful predictions regarding when a possible equipment failure is likely to occur, empowering you to take proactive measures and prevent costly downtime.

- **Improper use or operator error:**

  Human factor failures, including operator errors caused by distractions, poor decision-making, or deviations from established processes, can lead to a wide range of issues, ranging from temporary operational downtime to serious safety incidents.
  Out of the above outlined points, this paper majorly focuses on point number two concerning predictive maintenance of machinery in Industry 4.0.

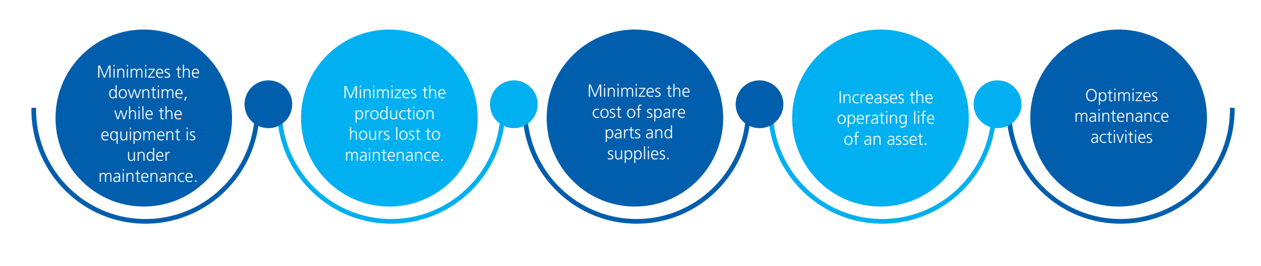
- **What is Predictive Maintenance of Industry Equipment?:**

  - Implementing predictive maintenance allows organizations to proactively monitor equipment performance in real-time, forecast potential machine failures, and address issues before they cause downtime. This approach helps prolong the lifespan of assets, which can fluctuate based on maintenance frequencies. By adopting predictive maintenance, organizations can reduce the likelihood of unexpected breakdowns, decrease repair costs, and improve overall efficiency.

  - Predictive maintenance uses condition monitoring using the real-time data it gains with Industrial Internet of Things (IIoT) sensors, and this is considered a critical element of the industry 4.0 revolution.

  - In this manner, it monitors operations dynamically and detects possible future errors and regulates them before any repercussions. Predictive maintenance drives you to the future by catching potential problems in any early-stage or discovering the symptoms that may subsequently cause more defects down the line. It helps industries with decision-making and real-time monitoring. Furthermore, it helps regulate the machine's life, physical conditions, and work efficiency.

  - Here are some of the main advantages of predictive maintenance. It:

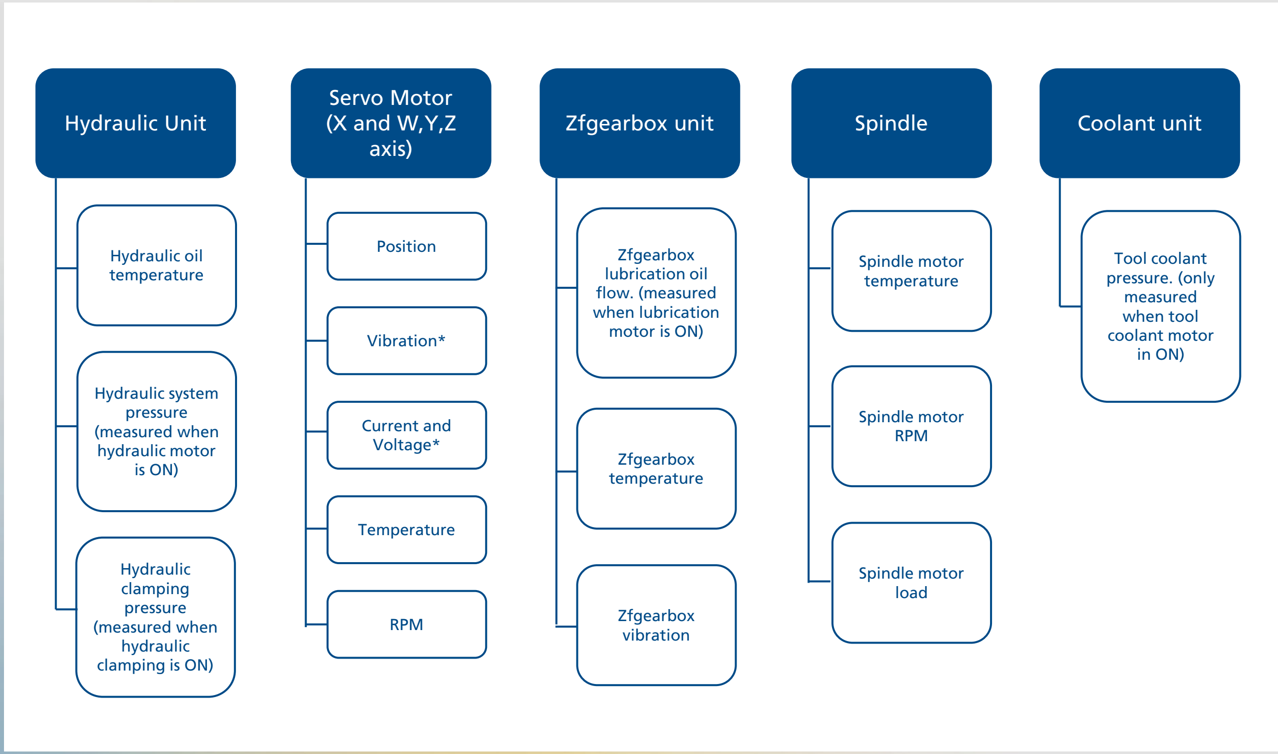


- **Machine and equipment in focus:**

  For our use case we would consider the predictive maintenance activity for the gantry drilling machine by fixing sensors at different positions for data collection and then analyzing the data and making predictions on it.

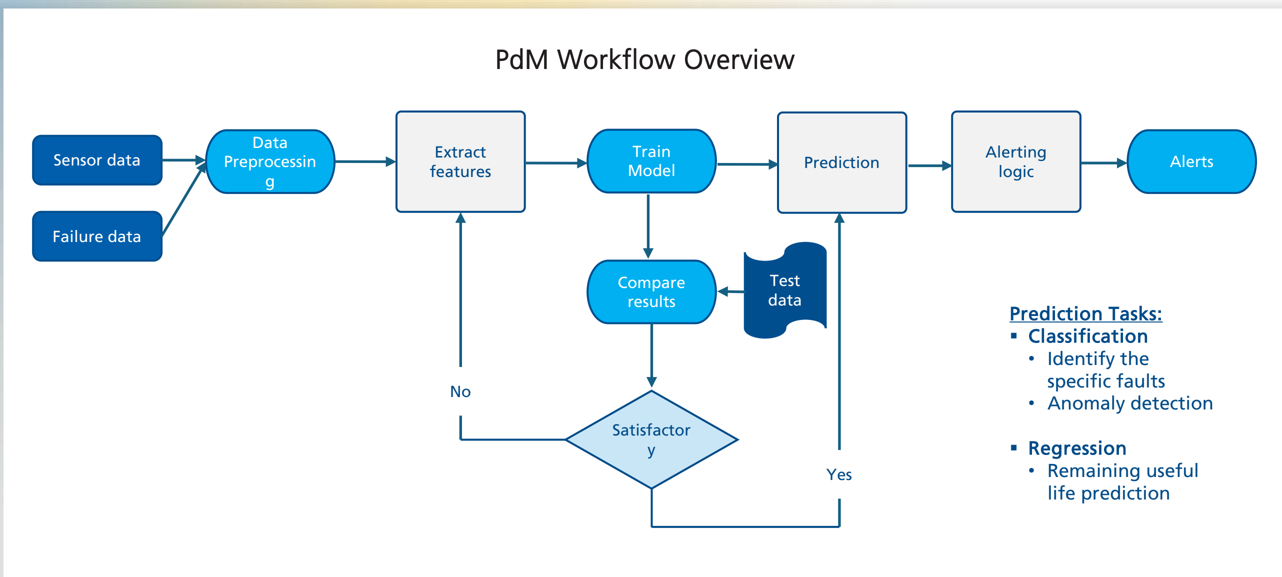
Of all the components of the drilling machine (as shown in the below image) we will focus on the following two most critical components:

- ZF Gearbox.
- X-axis servo motor.



- **PdM solution workflow and architectural design:**

  The diagram below outlines the workflow which has been implemented for this specific PdM solution.



- Data collection:

  We have sensors for different equipment parts that continuously collect the data (both normal and anomalous) and store them in the appropriate databases.

- Data pre-processing:

  The data collected is then processed and converted in a format to be used for further processing.

- Feature extraction:

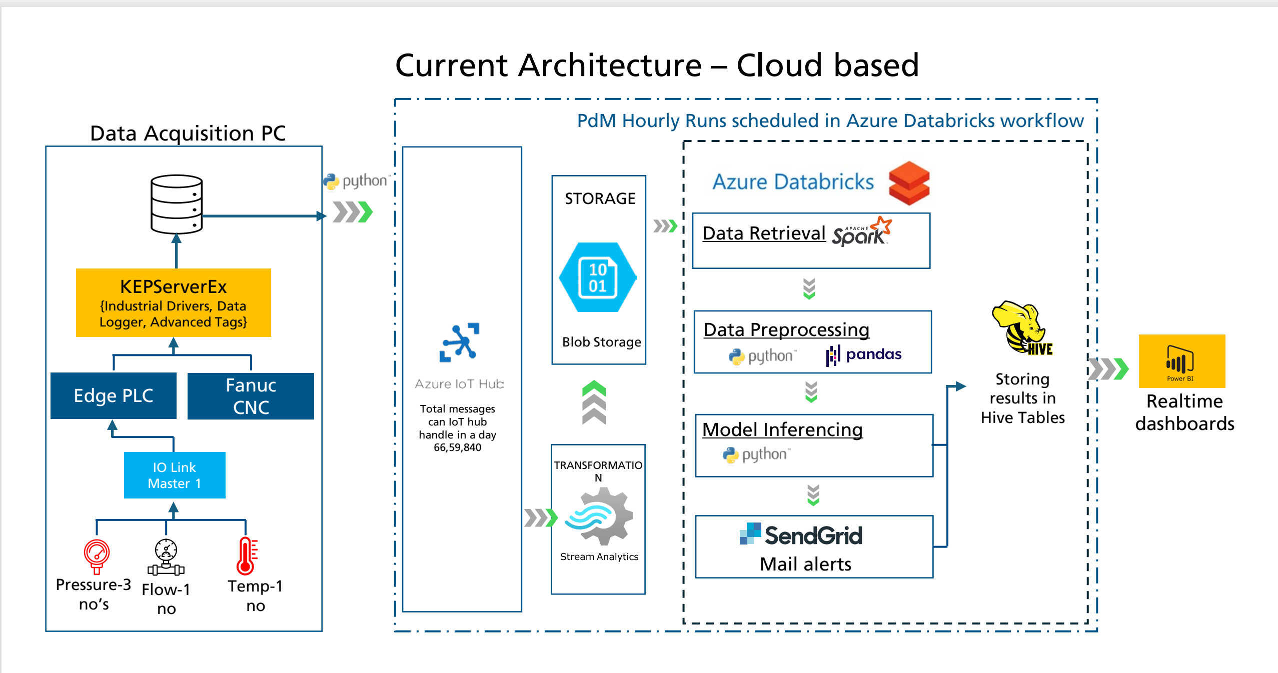
  Next, this data is consumed by the analytics team for analysis and to perform extensive exploratory data analysis and feature engineering on it. With their domain understanding, the team makes tailored features which could give better insights.

- Model training and testing:

  A suitable model is finalized, and the prepared data is then used for model training. Subsequently, the trained model is tested to check the performance with unseen data in order to identify how well it performs. If it produces satisfactory results, we finalize the model or we go back to the phase of feature engineering for improved feature derivation and data pre-processing.

- Inferencing:

  In this phase the real-time data collected by sensors for the past one hour is passed through the deployed model to do the inferencing. If any anomalous points are found by the model, then they are immediately flagged, and alerts are generated and passed on to the responsible members.



The following stages illustrate how the data is gathered, consumed, and inferred for any anomaly.

- Stage 1:

  In the data acquisition stage, the sensors deployed at the equipment collect real-time data and store it in the local database (DB). Data related to pressure, temperature, oil flow, vibration, etc. is collected and stored.

- Stage 2:

  The Azure IoT Hub is used to store and process data. The data is then transformed and stored in the Blob storage at a year, month, day, and hour granularity. Each hourly Json file contains the sensors values at second level.

- Stage 3:

  The data stored in the Blob Storage is then consumed in the Azure Data Bricks for pre-processing and model inferencing. An Auto Encoder model is trained on historical data and is deployed for inferencing. Any anomalous point detected by the model is flagged.

- Stage 4:

  Then SendGrid is employed for sending e-mail alerts for any anomaly detected while inferencing.

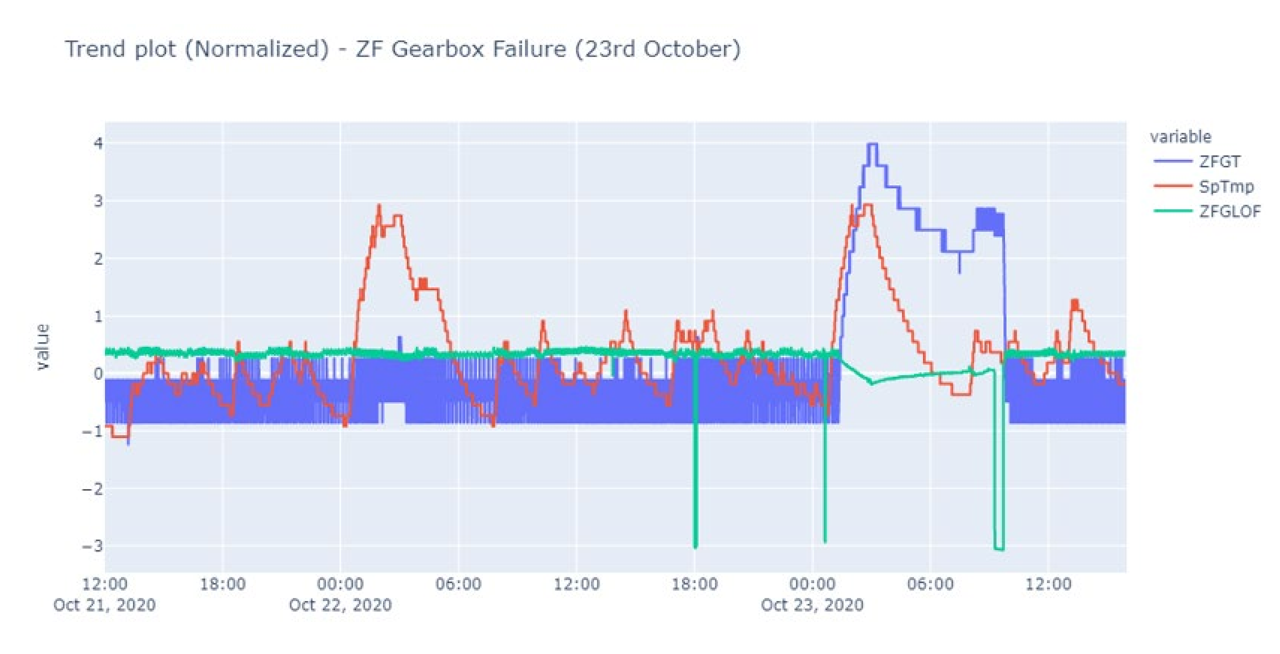
- Stage 5:

  In the final stage all the data is depicted in the Power BI dashboard. We show the Anomaly score distribution over time, Equipment Health score, Contribution Plot, and the Historical Break down data.

▪ Failure data analysis prior to model building

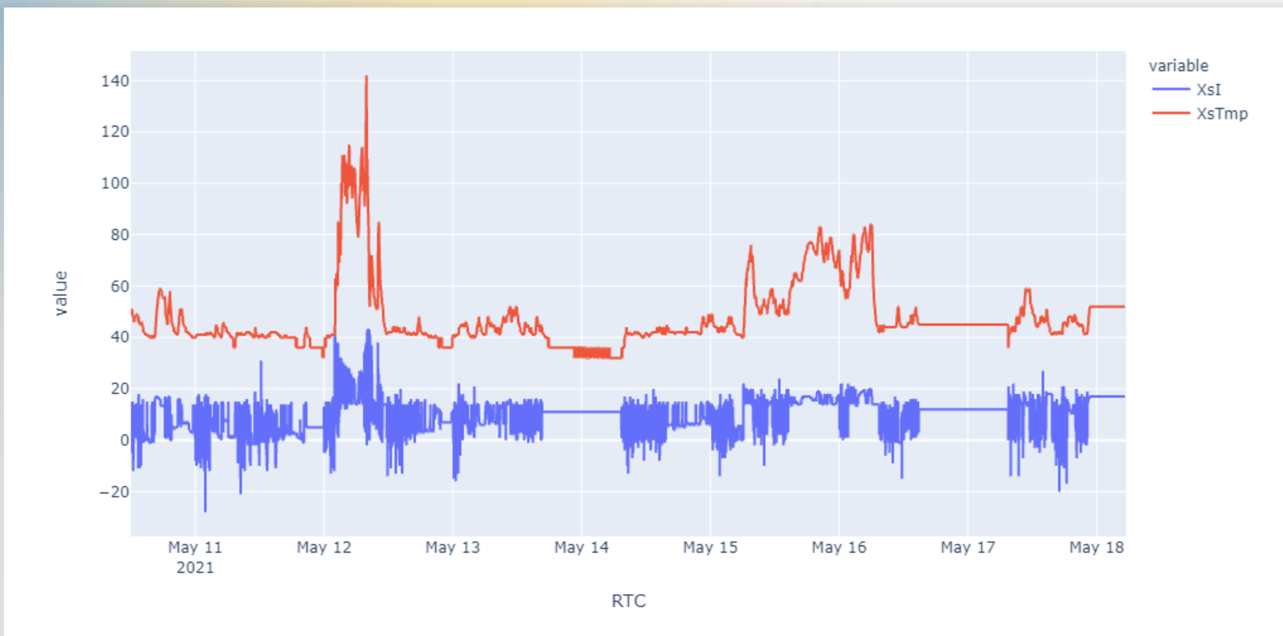
At the initial stage, we received the data for the different machine components (breakdown + normal operation data). We analyzed the break own data in depth to identify patterns for the parameters like temperature, lube oil flow, vibration, etc. A very prominent observation was that a couple of hours before the breakdown was likely to occur, the parameter values started fluctuating in an abnormal way and the trend is very clearly visible as compared to the normal equipment behavior.

Here are some of the examples where the trend analysis for different parameters was done for the failures:



Observations:

- The increase in the spindle and gearbox temperature along with reduced lubrication oil flow observed for the period 8 hours before failure on the specific date.
- The trend plot with the normalized values for the parameters shows that the rise in gearbox temperature is a significant indicator for failure when coupled with the lower lubrication oil flow.
- The machine status information shows that the temperature of the ZF Gearbox started increasing during the running state and continued to rise till 9:00 AM till the machine went under maintenance.
- Hence, the temperature of the ZF Gearbox can be considered a significant indicator for the breakdown that occurred on 23rd October.



Observations:

- The sudden increase in the XS servo motor temperature and current observed 8 hours before the failure on 12th May.
- A similar trend was observed for XS servo motor current during the same period.
- The machine status information shows that the temperature current started increasing during the running state and continued to rise till 9:00 AM till the machine went under maintenance.

Hence, the current and temperature of the XS servo motor can be considered significant indicators for the breakdown that occurred on 12th May 2021.

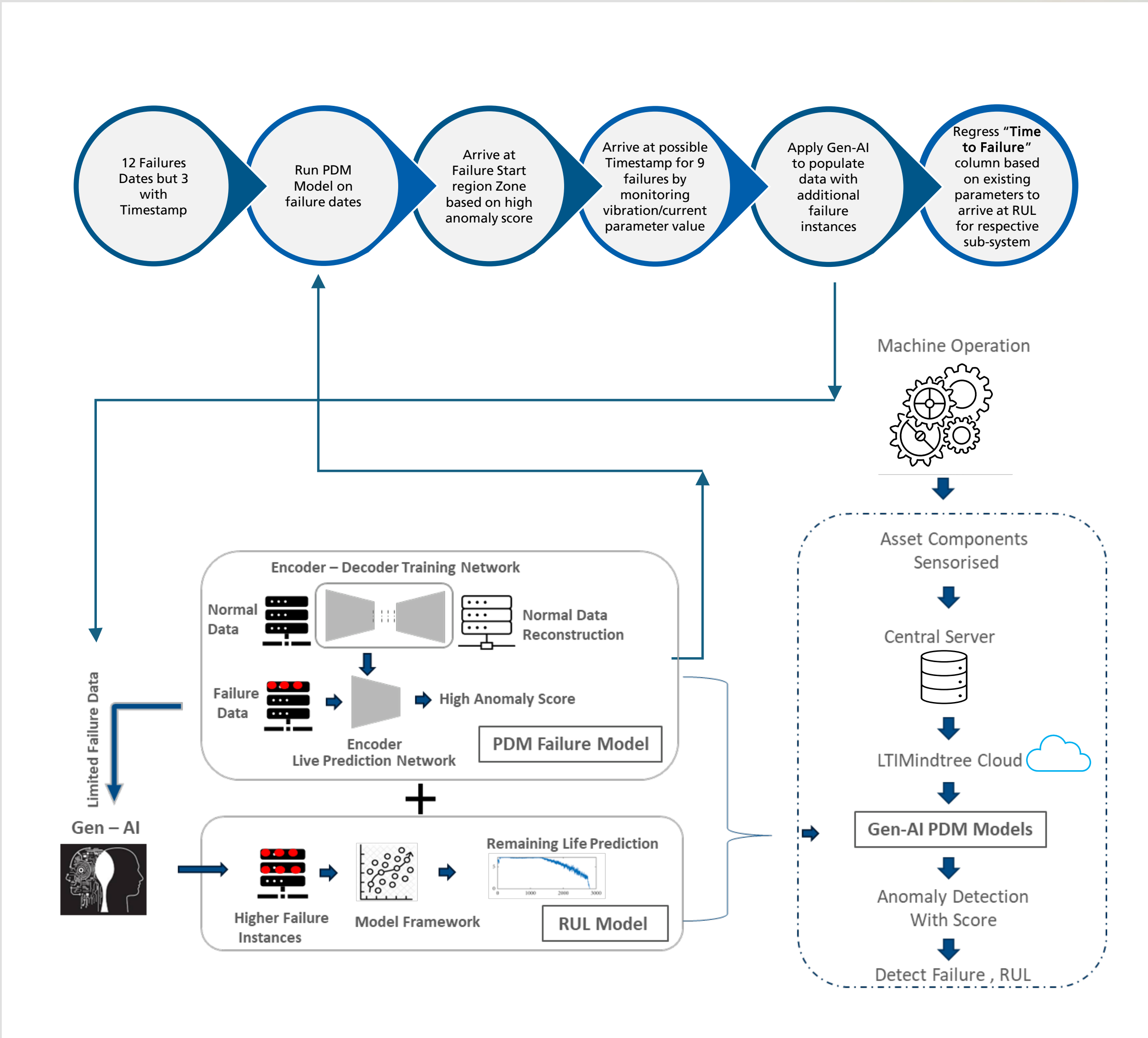
- **Predicting the Remaining Useful Life (RUL) of the machine**

  In predictive maintenance, estimating the remaining useful life (RUL) of machines is critical to scheduling maintenance, optimizing efficiency, and avoiding unexpected downtime. RUL refers to the amount of time a machine is expected to function before requiring repair or replacement. By considering RUL, engineers can plan maintenance activities, maximize operating efficiency, and prevent unforeseen stoppages. Therefore, accurately estimating RUL is a primary objective in predictive maintenance programs.

  So, to develop a model which could predict the RUL or Time to Failure of the equipment we would need higher samples of failure data to accurately model the behavior.

However, typically this does not hold for real-world industrial scenarios as a mechanical system under operation will be in the normal state for most of its lifetime, while fault states are rare. It is an expensive and challenging affair to gather an ample amount of fault data when the system traverses through the short duration of faulty state conditions.
So, to solve the issue of data unavailability, this paper suggests the use of novel generative AI techniques to use the existing anomalous data and generate synthetic data mimicking the fault conditions which can be further used by the model to regress the RUL.

The following workflow clearly explains the steps we intend to take to generate synthetic data and to build an RUL model.



- Stage 1:

  Initially from our original dataset, we had 12 failure data points out of which only 3 had the exact failure timestamp.

- Stage 2:

  We then 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:

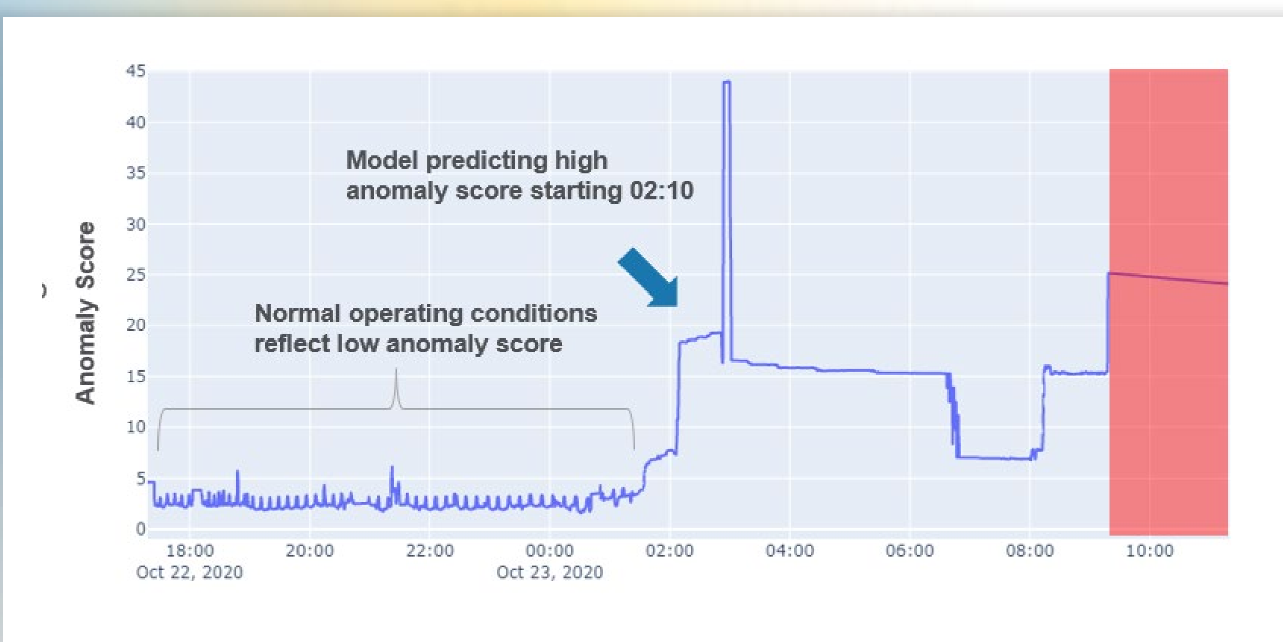
  Now after the data generation, we have sufficient data to train our regression model taking the required features to estimate the Remaining Useful Life (RUL).

Predictive Maintenance Model Outcomes

- Breakdown prediction by the deployed model

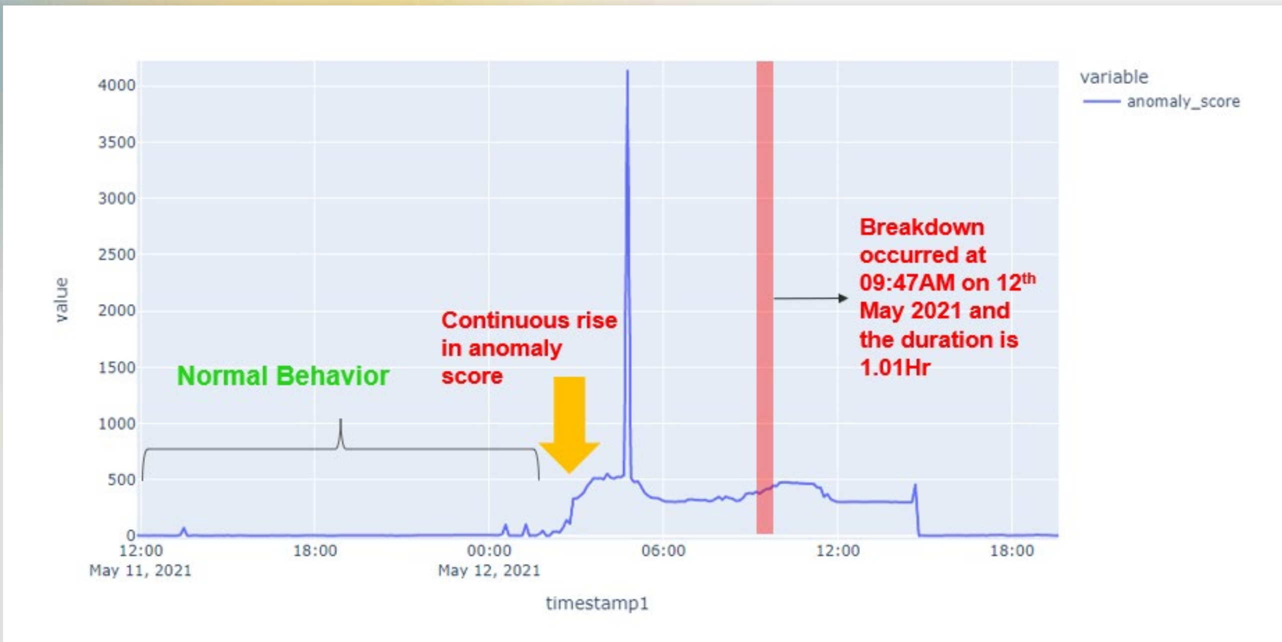
  As mentioned earlier, we have deployed an Auto Encoder model which was trained on strictly non-anomalous data. The objective behind this approach was, (as there were very few instances of the breakdown scenarios present) to train the model on the normal data and let it pick and flag any abnormal behavior which digresses from what it was trained on.

  So, we choose the model's residue also known as the "Anomaly Score" as an indicator of the breakdown. While doing the inferencing, if the anomaly score lies within a threshold, then it is not flagged. However, if the score goes beyond the permissible range, then those are flagged by the model.



Observations:

- The lube oil flow and gearbox temperature disturbances are picked by the model 6 hours before the breakdown (at 03:00 AM).
- Time stamp for the breakdown: 09:25 AM to 12:45 PM.



Observations:

- The continuous trend of rise in anomaly score started around 02:40 AM on 12th May 2021, seven hours prior to the breakdown.
- The anomaly score spiked above 4000 around 04:45 AM on 12th May, five hours prior to breakdown.

Our Point of View and Opinion

- Additional subsystems with IoT data can help in improving the model outcome with better failure instance estimates and RULs.
- If available, the complete IoT system data can be used to incorporate a digital twin of the entire CNC machine.
- The model can be standardized with more historical failure instances, which can be replicated and generalized in the future for any similar kind of CNC machine.
- The model can be ported to the edge server and deployment can be leveraged using On-premises technologies (OT) for faster turnaround on failure detections (wherever cloud deployment is not feasible).

Use case studies

In addition to the above scenarios, we can further extend the PdM solution to other areas as well where it can generate value for the end user. Here are some of the examples:

- The above approach of the PdM can be replicated for other industries or equipment as well, following a similar approach provided. We have enough operational technology available for the same.
- Taking the available data, we can use that for forecasting the other parameters like the temperature of the equipment, vibration, etc.

Business Use Cases

- The PdM models provide maintenance staff with timely alarms and information about the state of the equipment. They can take preventive measures, even before the breakdown happens. The PdM system also strives to optimize maintenance schedules by contemplating anticipated health conditions, operational demands, and financial considerations, for ensuring the minimum production disruption possible. The live model has successfully detected and saved a catastrophic machine failure at customer end, as acknowledged by the key-stakeholders.

Conclusion

In addition to the above scenarios, we can further extend the PdM solution to other areas as well where it can generate value for the end user. Here are some of the examples:

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\

Author Profiles

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Jayaharan C J is a digital transformation expert in IIOT, Industry 4.0 and plant floor to business floor (IT/OT) integration. With 24 + years of experience in diverse industry verticals, he has executed sustainability projects like Green H2 plants, large drinking water asset management, manufacturing predictive data analytics projects along with process optimization solutions for various process industries.

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Vishwanathan has 26+ years of experience across geographies, expertise in the field of Business Intelligence, Data Warehousing, Artificial Intelligence, Machine Learning, Deep Learning and Data Sciences. He is a technology leader, technical author, storyteller, AI strategist, and trainer.

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Somsuvra is a committed and passionate data scientist with 15+ years of experience, 13+ in the field of Analytics and Data Science. He has worked across diverse domains such as CPG, Retail & Manufacturing, Energy, etc. He has been engaged in developing solutions for various computer vision and image processing-based products and projects.

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Swagat is a Data Science Professional with 8+ years of IT experience having worked in multiple domains like Insurance, Healthcare and Manufacturing. He has experience in developing different NLP solutions and cloud-based experience with Azure.

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Rounaq is an IT professional with 5+ years of experience in R&D in the field of Artificial Intelligence, Machine Learning, Deep Learning and Computer Vision. He has an interest in computer vision and social graph-based algorithms. He is currently engaged in developing solutions for various data science projects.