Predictive Maintenance of Industrial Equipment
Using Air Borne Sound
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How to better predict and avoid unplanned downtime of Industrial Equipment?

By having less unplanned outages we aim to reduce the cost associated with manual periodic maintenance.
Introduction

Solution Overview

Acoustic condition monitoring via airborne sound analysis in conjunction with advanced signal processing and machine learning methods has proved to be a powerful tool for early detection of machinery breakdown. It allows timely detection of anomalies, which results in more efficient and cost-effective maintenance. It also provides a simple and effective method to retrofit to existing plants and environments where this could otherwise be costly.

Key Objectives

- Provide an approach to build a repeatable core using Air Borne Sound for Predictive Maintenance of Industrial Equipment across industries and customers.
  - an edge model for all local processing of the data and decision making without moving the data to the cloud that requires centralised processing.
  - a master model that is more generic, more robust and learns from multiple edge models. The learnings from n machines can be then applied to n+1 machine.
- Propose an approach to build a rich library of Anomaly Sound Datasets of Industrial Machines (Labelled data with various Failure Modes)
- Propose a reference architecture for the Hardware with Installation Specification
SAP holds more than 80% market share in Mining and Oil & Gas as well as significant market share in other asset intensive industries. The SAP Maintenance solution is widespread across customers that run SAP as the core ERP. Globally we estimate that a 2% saving in maintenance costs across the top 40 miners would yield a 13.4 Bil dollar saving to the industry. The resulting production increase that would result from a 1% higher asset availability is estimated to yield 38 Bil USD in incremental revenue for our customers.

The proposed solution can be integrated to the existing ERP solution and help provide a more compelling reason to consider extending the current SAP portfolio to include SAP Predictive Maintenance. Moreover because of its market dominance as a trusted system of record it makes SAP a logical choice as a service partner to look at the federated learning concept. Many of our customers run plants that are several years old and the concept of air-born sound coupled with structural sound means that it is relatively easy to retrofit to existing plants where sensorisation may not practically make sense or would be very expensive. This coupled with the ability to use federated learning to accelerate the machine learning process would be appealing to customers running older equipment.

SAP also has a solid track record of being an organization that respects and can enforce data privacy. The federated learning approach ensures that the data is not transmitted from the edge to the cloud, but the machine learning models which are deployed at the edge are transferring the learning to the primary system (deployed in cloud). This effectively segregates the data while allowing the learning to be transferred across organisations.
Multi sensor array

An audio signal is a complex signal composed of multiple ‘single-frequency sound waves’ which travel together as a disturbance (pressure-change) in the medium. When sound is recorded we only capture the resultant amplitudes of those multiple waves. Fourier Transform is a mathematical concept that can decompose a signal into its constituent frequencies. Fourier transform does not just give the frequencies present in the signal, it also gives the magnitude of each frequency present in the signal.
Multi sensor array

Once the signal is broken back into its clean state it can be analysed for failure patterns. In the same way we would resolve a single machine with a single sound sensor.
Fraunhofer Sound Engineering Expertise

SAP & Fraunhofer research collaboration

Detection faulty gearing mechanism parts

- End-of-Line testing for automotive
- Analysis of spindle sound
Spectrogram

Sound

Federated Learning

Inference

Normal

Defect
POC: Federated Architecture

In this demo

Theoretical architectural behavior:

1. **Local training**: All active clients locally compute training gradients or parameters and send locally trained ML parameters to the server;

2. **Model Aggregating**: The server performs secure aggregation over the uploaded parameters from N clients without learning local information

3. **Parameters Broadcasting**: The server broadcasts the aggregated parameters to the N clients

4. **Model Updating**: All clients update their respective models with the aggregated parameters and test the performance of the updated models.

5. **Repeat**
Federated Learning

In this demo

Goal: Simulate Federated Learning → Federated Averaging for Aggregation Method

Algorithm 1: FedAvg
1: Initialize global model $\Omega$
2: while termination criteria not met do
3: Select round clients, $S_i \subseteq S$, $|S_i| = C \cdot |S|$ 
4: for each client $s_i \in S_i$, in parallel do
5: Download model $\Omega_k \leftarrow \Omega$
6: Perform local SGD, $\Omega_k \leftarrow \text{SGD}(\Omega_k, D_k, \eta)$
7: Upload $\Omega_k$ to server
8: end for
9: for $i \leftarrow 1$ to $|S|$ do
10: Average layer, $\Omega_i \leftarrow \frac{1}{|S|} \sum_{k=1}^{K} |D_k| \cdot \Omega_k$
11: end for
12: end while

Test Result

<table>
<thead>
<tr>
<th>Device</th>
<th>Local Performance</th>
<th>Global Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AUC</td>
<td>Accuracy</td>
</tr>
<tr>
<td>Device 1</td>
<td>91.8%</td>
<td>98.1%</td>
</tr>
<tr>
<td>Device 2</td>
<td>98.7%</td>
<td>99.6%</td>
</tr>
</tbody>
</table>

Algorithm 2: FedAdam
1: Initialize global model $\Omega$, $M \leftarrow 0$, $V \leftarrow 0$
2: while termination criteria not met do
3: Select round clients, $S_i \subseteq S$, $|S_i| = C \cdot |S|$ 
4: for each client $s_i \in S_i$, in parallel do
5: Download model $\Omega_k \leftarrow \Omega$, $M_k \leftarrow M$, $V_k \leftarrow V$
6: Perform local Adam SGD,
7: $\Omega_k, M_k, V_k \leftarrow \text{Adam}(\Omega_k, M_k, V_k, D_k)$
8: Upload $\Omega_k, M_k, V_k$ to server
9: end for
10: for $i \leftarrow 1$ to $|S|$ do
11: Average layer, $\Omega_i \leftarrow \frac{1}{|S|} \sum_{k=1}^{K} |D_k| \cdot \Omega_k$
12: Average 1st moments, $M_i \leftarrow \frac{1}{|S|} \sum_{k=1}^{K} |D_k| \cdot M_k$
13: Average 2nd moments, $V_i \leftarrow \frac{1}{|S|} \sum_{k=1}^{K} |D_k| \cdot V_k$
14: end for
15: end while
Predictive Maintenance of Industrial Equipment using Airborne Sound
High Level technical POC Setup

SAP Predictive Asset Insights
Apply Machine Learning Process

Machine Learning Engine
- Configure Model
- Train Model
- Evaluate Model
- Score Model
- Feedback

Analysis Tools
- Remaining Useful Life
- Anomaly Score
- Health Status
- 30 days  25

Data Processing in Compliance with GDPR
Fraunhofer IDMT
Local Data Recording
Secure Data Transfer

Illustrative Machine
Detail Microphone
Detail Microphone
Ambient Microphone

Data Processing in Compliance with GDPR
Next Step
For real dataset

Robust Anomaly Detection Model for raw data:
• Semi-Supervised Approach: AnoGAN
• Unsupervised Approach: CNN-AE model (latest result: Accuracy: 70+%)  

Federated Learning:
• Communication cost: In the federated networks, the communication between massive number of devices can be slower than local computation. Up and down time is unclear
• System Stability: local devices variability (CPU memory, GPU sizes), network connection (5G, WIFI) and battery level.
• Aggregator Model: The standard approach is federated averaging and federated SGD. Currently there is no robust approach that can suitable for any situations.
Approach, Current Status
Scope: Federated Learning and Air Borne Sound for Predictive Maintenance of Industrial Equipment

Part of the POC using Hitachi Dataset