Hitachi High-Tech

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# Reliable Industrial Insight

## A Pathway to Predictive maintenance

Cheaper, faster and instantly – that's the rhythm in industry and especially when it comes to producing goods. That is supposed to be achieved factories, always being up and running. To keep the system running, a sophisticated maintenance regime is required, only stopping machines when absolutely necessary. Wasting productive time with too many inspection activities or running into failures are no option. Data collection and analytics are identified as key enablers to realize and ensure such reliable production system. Predictive maintenance (PdM) – the estimate of a machine's future health condition and its risk for failure in order to plan maintenance activities – becomes the key tool for profitable machine operations. However, with PdM, new skills, tools and methods have to be introduced.

*Hitachi High Technologies* in collaboration with *Flutura* present in this Whitepaper a proven pathway to realize PdM for machine user and machine manufacturer alike. We will look into particular maintenance regimes with their individual scopes and outline the benefits of PdM in comparison. The five step approach to realize PdM are introduced and its outcome shown in an industrial use case.

## Promise of data analytics – Benefits of PdM

The market of industrial analytics is forecasted to grow significantly for providers and users within the next years. Among different applications, PdM and plant optimization are most promising. On its own, PdM might reach USD 4.9 bn. by 2021[1].

The origin of the demand for such solution is that machines will fail over time - some earlier, other later. Wearing of components, machine misuse, design flaws and off-specs. raw materials are common causes for machine breakdown. These result in unplanned downtimes. The resulting reduction in machine availability is countered by maintenance operations such as inspection, overhaul or repair in case of an actual failure.

All these activities aim to reduce unplanned downtime by introducing planned machine downtime. The mean time between failures (MTBF) is supposed to decrease. That results in more reliable machines, makes production planning easier and helps to improve

1 https://www.marketsandmarkets.com/PressReleases/operational-predictive-maintenance.asp

delivery reliability. However, in the worst case, downtime and effort for inspection outweigh losses due to breakdown, hence not decreasing non-productive time (NPT). Eventually, the goal has to be to avoid any machine downtime in the first place – planned as well as unplanned!

In a perfect world, machines would not break down and perform always flawless. As this is unrealistic, the next best thing is to know in advance with 100 % confidence when a breakdown will occur in advance and how the machine can be recovered. Achieving such plannable state of operation in manufacturing is the promise of predictive analytics.

The development of the different maintenance regimes started with

- reactive maintenance: Run into failure and repair) and
- preventive maintenance: Continuous inspection and regularly scheduled

repair. This regime advanced towards

- condition based maintenance: Reacting on performance parameters to issues repair activities) and finally
- PdM: estimate the time of breakdown in the future to schedule repair activities.

Reactive Maintenance
Preventive Maintenance

| | Condition based Maintenance | | Preditive Maintenance | |
|---|---|---|---|---|
| | Vistual inspection | Remote condtion monitoring | Statistical based | Stohastic based |
| Screening | Visual inspection/ | Integrated, connected sensors | Integrated, connected sensors | Integrated, connected sensors |
| Monitoring | Periodical physical inspection | online | online | online |
| IT infrastructure | On premise | on premise,<br>in cloud | on premise<br>in cloud | on premise<br>in cloud |
| Real-time monitoring | No | Yes | Yes | Yes |
| Combination of data sources | No | Yes | Yes | Yes |
| Real time analytics | No | No | Statistical analytics | Stohastical analytics |
| Maintenance trigger | If measurment of value or feature shows crictical characteristics | If monitoring shows crictical characteristics | When calculated health score reaches critical value | When failire risk is above threshold |
| Required skills | Experienced craftman or inspector | Trained inspector | Relaiability engineer | Relaiability engineer, data sciencetist |

*Figure 1 Characteristics of Maintenance Regimes*

PdM implies the reduction of the overall maintenance effort. Inspection is realized in parallel to productive operations, preferable by automatically monitoring critical parameters via sensors. If a potential failure is detected, its root-cause can be determined and counter measures initiated. For such analysis, historical data and live data is utilized. Repair and exchange of worn parts is only done, when actually required, utilizing the full usefulness of individual parts – the so called remaining useful lifetime (RUL).

When maintenance activities are scheduled, the should be performed fast and complete. With a known root-cause, the right spare parts can be made available just in time on the repair site. That helps to reduce spare part inventory and lead time for spare parts in case of a breakdown.

Even if something unpredictable happened, a so called Black Swan event, data analytics can help to identify efficient ways to mitigate its consequences. For detected and unpredictable failures, the mean time to recover (MTTR) can be reduced significantly.

## PdM Realization Path for Machine Users and Manufacturers

Predicting the future events is rather tough and difficult to archive – especially if high confidence levels are desired. Besides fully avoiding maintenance, prediction is the most ambiguous target, which is seen to come with high effort and investment. That doesn’t have to be the case as the path towards prediction provides several achievable benefits such as continuously increase the understanding of machines behavior and processes and work towards PdM.

How that pathway looks like, depends on who is initiating it. Manufacturer and users of machines vary in their slightly business cases and models, access to machine functions, and understanding of specific applications.

With detailed understanding of their specific application und use cases, machine users are experts in how machines have to be operated to manufacturer their products. Their production facilities feature machines and their components from various vendors. Such are assembly lines and machining shops, for example in automotive industry. These machines typically constitute of standard components like servo motors, compressors,

pumps and all kind of sensors. Nevertheless, the resulting machines are frequently custom designs for special purposes. A system integrator installs these machines in the production facility.

For machine users can the **business case** be described as endeavor to improve direct cost and performance situation. Even with technical availabilities close to 100%, PdM helps to reduce costs in the form of less yet focused maintenance activities. Regular physical inspections can be shifted towards digital monitoring of machine components.

For high investment machinery manufacturers, PdM becomes a lucrative service offer towards their customers. Systems such as container ships, die casting or forging facilities, and oil drilling units consists of multiple components of a sometimes very high technological level. The deep, technical knowledge of the manufacturers puts them in the position to create sophisticated digital services. The full access to existing functions and possibility to introduce future function of the equipment provides the technical foundation to create valid service offers.

The **business case** for machine manufacturers follow the idea of creating a value offer for their customers to improve the customers' cost and usage performance. Despite the fact of detailed equipment knowledge, manufacturers lack daily work experience on how the equipment is utilized. Knowledge about the specific application at a customer might require collaboration with that customer.

1. **Collecting**: Before starting to tap machine controllers and install new sensors, a general classification of equipment of the machines under consideration have to be conducted. The collection of physical readings over time, for example energy consumption, oil/pneumatic pressure, temperature and vibration.
   Collection of event data, such as change of machine state (startup, idle, operational, breakdown), and reports of maintenance, repair and overhaul (MRO) activities are gradually digitalized, interlinked and made available. Time series, incorporating different data sources, reveal very often formerly unknown issues within the equipment and their operations. The **Cerebra Analytical Twin** enables to consistently store the machine related data by mapping general machine types and instantiating these for specific machines.

2. **Visualization**: With the data made available online, nominal equipment conditions can be formulated. These conditions are based on sensor reading with respect to machine state. The deviation of key parameters against such nominal conditions in the sense of threshold monitoring provide a good initial indicator for anomalies and equipment issues. The **Cerebra Visualization** and **Pre-Diagnostics Studio** help to setup dashboards and alarms.

3. **Understanding and Model Building**: Detailed analyzing of collected data and reports for specific events by analyzing data from multiple equipment to identify interdependencies and root causes for unintended behavior, like unplanned equipment downtime. Establishing models to predict specific equipment conditions. Integrate prediction of equipment condition into MRO activities to reduce unplanned and planned downtimes. With pre-developed **Cerebra Nano-Apps** for specific components, such as motors, pumps and valves, that process can be significantly shortened.

4. **Integration into operations:** With the approach of gradually digitalizing the production equipment, the Prove of Value can be checked continuously in each project phase. However, that value should be more that machine insight – it has to be reflected in cost and performance improvements. An integration into daily operations ensures, that monitoring results are used and informed decisions are made in manufacturing.

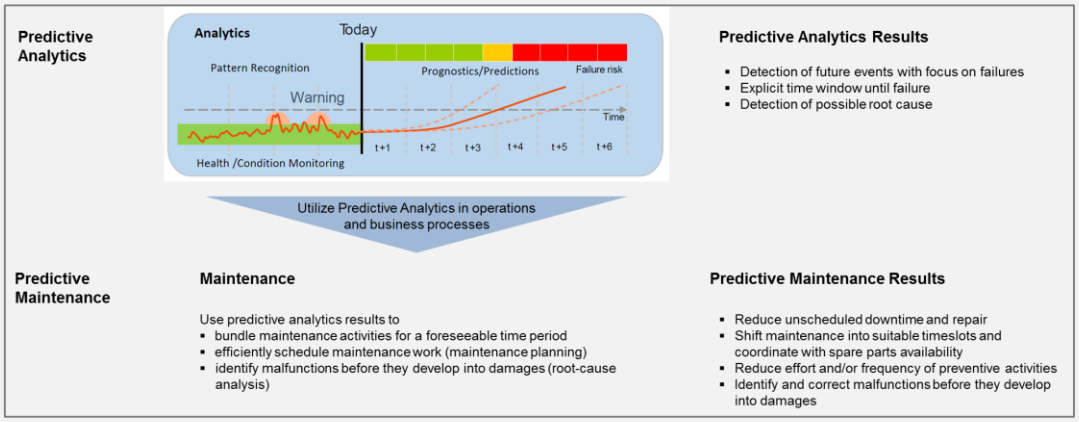


*Figure 2 From analytics to maintenance*

For machine users, the **challenges** of such approach and especially for are number of machines and deep access to these machines. Getting all relevant machines from different vendors, their components and eventually external sensors connected in proper time requires a proper strategy or significant manpower. Various communication protocols and interfaces complicate the integration process. Detailed machine functions with raw sensor readings is looked deep within the machine controller and difficult or sometimes not at all, accessible by the machine operator. The direct discussion with the original machine manufacturers might help to open up the black box for data access.

Model building for different types of machines and their processes can result in a severer effort to build individual mathematical models to monitor and eventually predict machine conditions. Templates on how to handle typical machine components help to ease the integration procedure.

For machine manufacturers, the main **challenges** of such approach are effort of formulating reliable mathematical models. Real live data is not always available, but the collaboration with existing customer might help. Networked devices, collected data and even the calculated results alone do not add any value. Only if the analytics results are fed back into the operations and meaningful activities to harness the benefits.

Customer confidence in the prediction results is as important as the fact, that a service offer might include a liability commitment regarding the predicted results. The validation

on a customers' running system can provide performance clarity for all involved stakeholders.

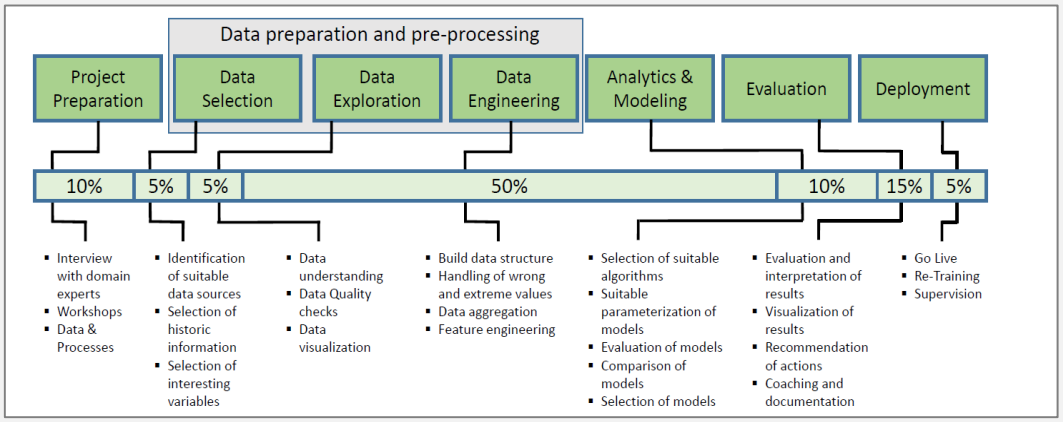


*Figure 3 Data – source and challenge for analytics*

## Monitoring of Early Production Skids for Oil & Gas Industry

The above mentioned approach was followed for the case of a leading multi-million-dollar for surface technology and services in the US oil & gas industry. We helped reimagine the user journey of a leading upstream equipment manufacturer through Cerebra. The company largely engages in the designing, manufacturing, and marketing of technologically sophisticated systems and products for the oil and gas industry.

Focus of this case study have been Early Production Skids (EPS), used in the separation of oil, gas and water. Being located close to the digging site, such equipment is supposed to run 24/7 in rather remote places. The **initial problems** were too many signals to process, no existing equipment diagnostics, no detailed sensor intelligence and a manual monitoring process. Such manual screening tended to miss anomalies and critical developments in the equipment performance and health condition.

In **consequence**, severe downtime with negative effect on project profitability occurred. Delay in corrective measures lead to damages and loss with missed signals and

decrease in productivity.

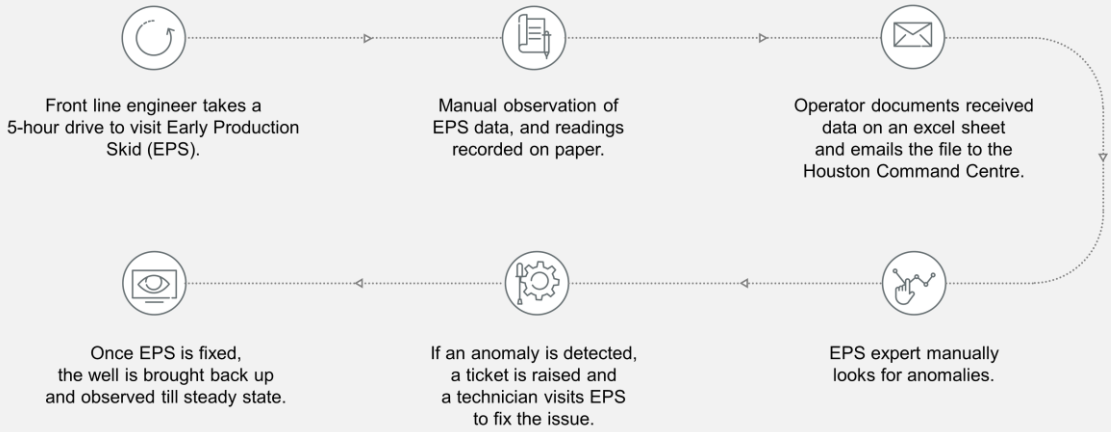


*Figure 4 Initial process of anomaly detection and removal*

By digitalizing the data intake from EPSs and combining it with the easy to configure platform CEREBRA, the Customer process could be improved significantly. The detection of anomalies invisible to human eye and interpretation of thousands of sensors, emitting millions of data points, was automated. Real-time detection of anomalies became possible, before it is too late. With AI-powered automation of alerts, real-time updates, and timely notifications help the customer to manage several thousand machines all over the country to manage maintenance activities in a centralized and efficient manner.

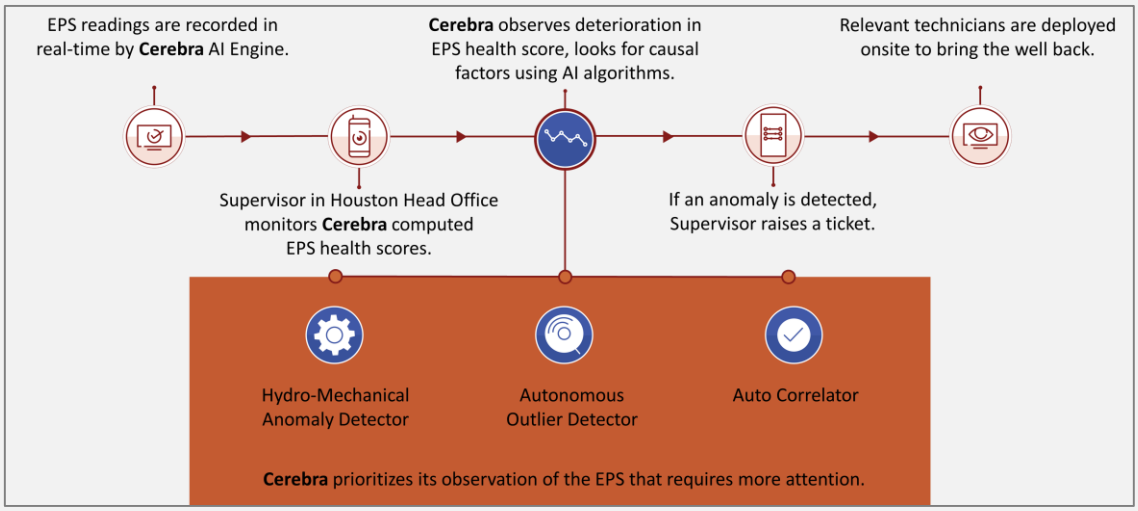


*Figure 5 Improved process for Machine Monitoring*

In the reworked process, the EPS readings are recorded in real-time. A supervisor in the Huston Head Office monitors all machines remotely. With Cerebra apps, the health score is calculated for each individual EPS. Cerebra observes deterioration in EPS health scores, looks for causal factors using AI algorithm. Aggregated and condensed into a dashboard, the critical EPSs are high-lighted, whenever their heath score drops in a critical fashion. If an anomaly is detected, supervisor raises ticket. Local technicians are deployed onsite to bring the hardware back on track.

The Non-Productive Time all EPSs could be improved by responding to missed anomalies. That includes

- 99.7% Reduction in anomaly detection latency,
- 23% Reduction in Non-Productive Time (in 12 months) and
- 17% Increase in project profitability.

## Swift Start with Continuous Improvement

To utilize the promise of PdM – downtime and cost reduction, improved reliability, etc. –, starting from scratch might take a while. With an existing platform and customizable apps for monitoring, visualization and analytics, a start becomes easy and first results available in no-time. Within days, machines are connected and within few weeks, a first prototype is made available. The Prove of Value within live equipment can be established by incorporating decision makers and operational personal alike. In collaboration of data scientists with experienced machine operators and maintainers, a health score can be formulated, monitoring and its future trend be predicted. The integration in shop floor and field operations is customized to the customers' requirements and situation in order to minimize the entry barriers and boost worker acceptance. ,

## About Hitachi High Technologies GmbH

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## About Flutura Decision Sciences and Analytics Ltd.

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