

Smart Maintenance: The Evolution of Machine's Response from Corrective to Predictive

Discover how to improve your
digital maintenance with Sound Anomaly Detection

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CHAPTER 1 — SMART MAINTENANCE

What is Smart Maintenance?

Smart maintenance describes learning-oriented, self-regulated, intelligent maintenance with the aim of maximising the technical and economic effectiveness of maintenance measures, taking into account the respective existing production system, through the use of digital applications.

Smart Maintenance –Der Weg vom Status quo zur Zielvision

Smart Maintenance, as being a part of Smart Factory, brings the cultural change to the maintenance process. Clash between traditional and modern mind-sets is reflected in trust gain over technology and data-driven approaches (for example referring to the dilemma of algorithm interpretability). As humans tend to make less precise and arguable reasoning, algorithms tend to achieve quite accurate answers for clearly defined questions, but without explanations for how the answer are derived. Achieving accuracy without losing transparency is costly, especially when in time context changes. Leaders are the one leveraging the trust, overseeing the change leading to Smart Maintenance, understand the performance potential, and ensuring that managers, engineers and technicians gain adequate knowledge and are not sensing any exclusion. Some required shifts in job profiles for connected factory reflecting Smart Maintenance will take place. Worker in the production will shift from carrying out production tasks, large share of manual tasks to exception handler in production line, operator in automated environment; maintenance expert will shift from trouble shooter and exception handler to overseer of predictive maintenance, planning and

steering based on data-driven analysis and quality specialist will shift from inspections of parts and control of quality standards to smart engineering of process and online control for quality issues.

As being part of Fourth Industrial Revolution, tending to automate processes and integrate data from physical to digital layer of manufacturing processes and back, digitalisation is becoming an advantage to the continuously changing market. By predicting equipment malfunctions and optimising resource management Smart Maintenance gives a solution to this ongoing problem. Its integration is developed in few phases:

- Understand the operations of maintenance activities, minutely understanding the manufacturing processes and the way equipment works.
- Collect and integrate data through:
 - Industrial IoT devices;
 - Robotics tools and autonomous robots;
 - Big Data analytics systems;
 - AI and Cognitive systems;
 - Augmented and Virtual Reality.

Data from industrial systems and equipment is collected, processed, analysed and transformed into conjoint form, connecting machines, making increased connectivity a new priority.

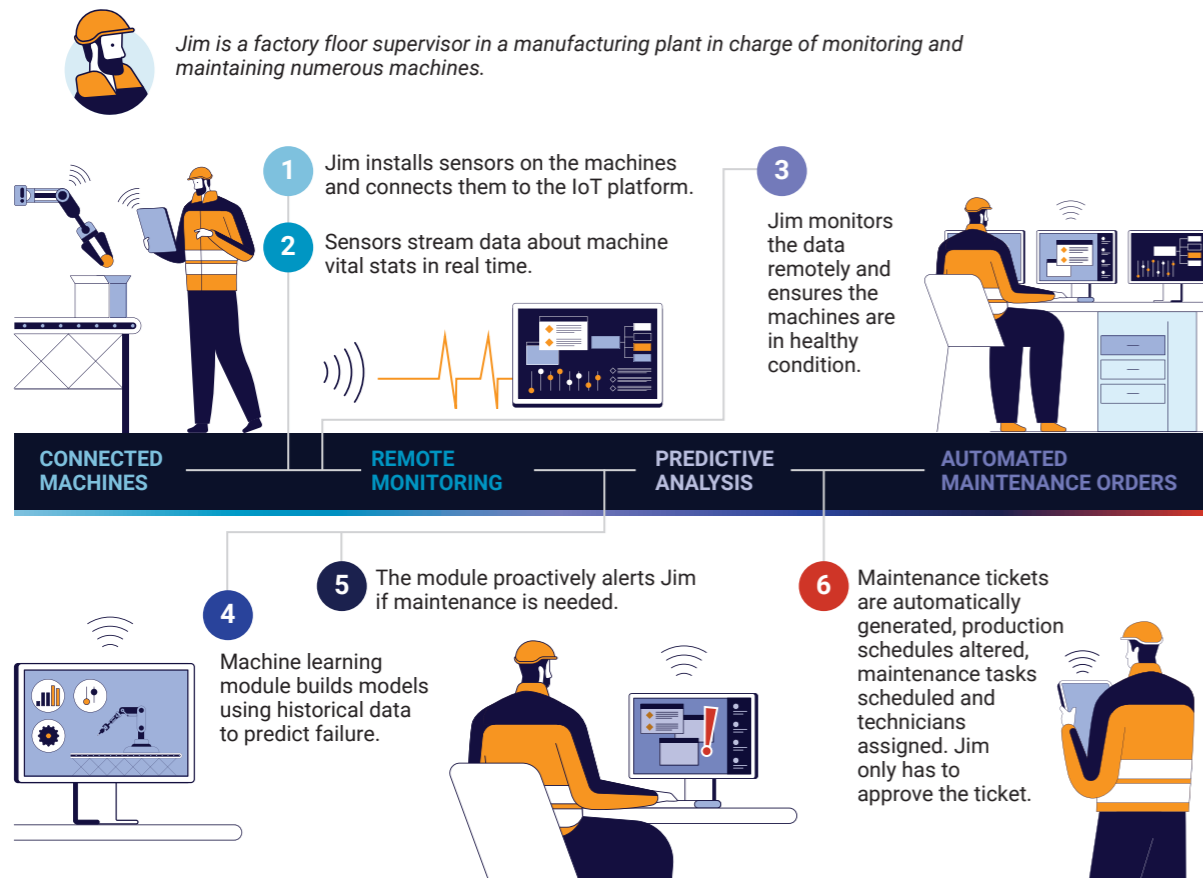
- Build an AI solution, by using existing or customized Machine Learning (ML) algorithms for anomaly detection and/or processes recognition, so remote monitoring, predictive maintenance and automated maintenance orders could go vital.

- Train the technicians to use the solution properly. Predictive maintenance enables planned maintenance, reducing the number of trained technicians and giving advantage in narrowed workforce scope.
- Implement and integrate the solution into operational processes, enabling reporting, alerting or taking actions. Trained technicians or autonomous robots are alerted in timely manner, having

full information about the maintenance problem, taking planned maintenance as a new way of operating.

Smart Maintenance is a key subject for industries like Telco (e.g. maintenance of the network infrastructures), Manufacturing (e.g. maintenance of elevators), Energy (e.g. production of electricity), Utility (e.g. water and gas), Transportation (maintenance of road and railway infrastructure) etc.

Figure 1. Predictive maintenance process



Source: Deloitte analysis, Deloitte University Press | dupress.deloitte.com

For designing Smart Maintenance, upgrading factories to Smart Factory, some principles should be fulfilled, such as:

(embedded computers interact with their environment via sensors and actuators).

- **Modularity** defined as the capability of system components to be separated and combined easily and rapidly. Modularity enables the real-time capability to allow the system to respond to changing customer requirements and to overcome internal system malfunctions.
- **Interoperability** defined as the ability to share technical information within system components. Standardized mechanical, electrical and communication information is essential for enhancing interoperability.
- **Decentralization** reflecting in decisions autonomously made in real time without violating the overall organizational goal. Decisions about ordinary matters are made on time, changing strategy and direction according to the change in business situations and environments
- **Virtualization** or Digital Twin refers to the creation of an artificial factory environment similar to the actual one, being able to monitor and simulate physical processes, enabling information transparency and the aggregation of sensor data.
- **Service orientation** as the idea that manufacturing industries will shift from selling products (selling them with almost no margin or profit) to selling products and services. Manufacturing industries will focus on outsourcing some of their processes and optimizing core ones, making maintenance the heart of this change.
- **Real-time capability (responsiveness)** as ability of the system to respond to changes on time, such as changes in customer requirements or the status of the internal production system (e.g., malfunctions and resource failures).

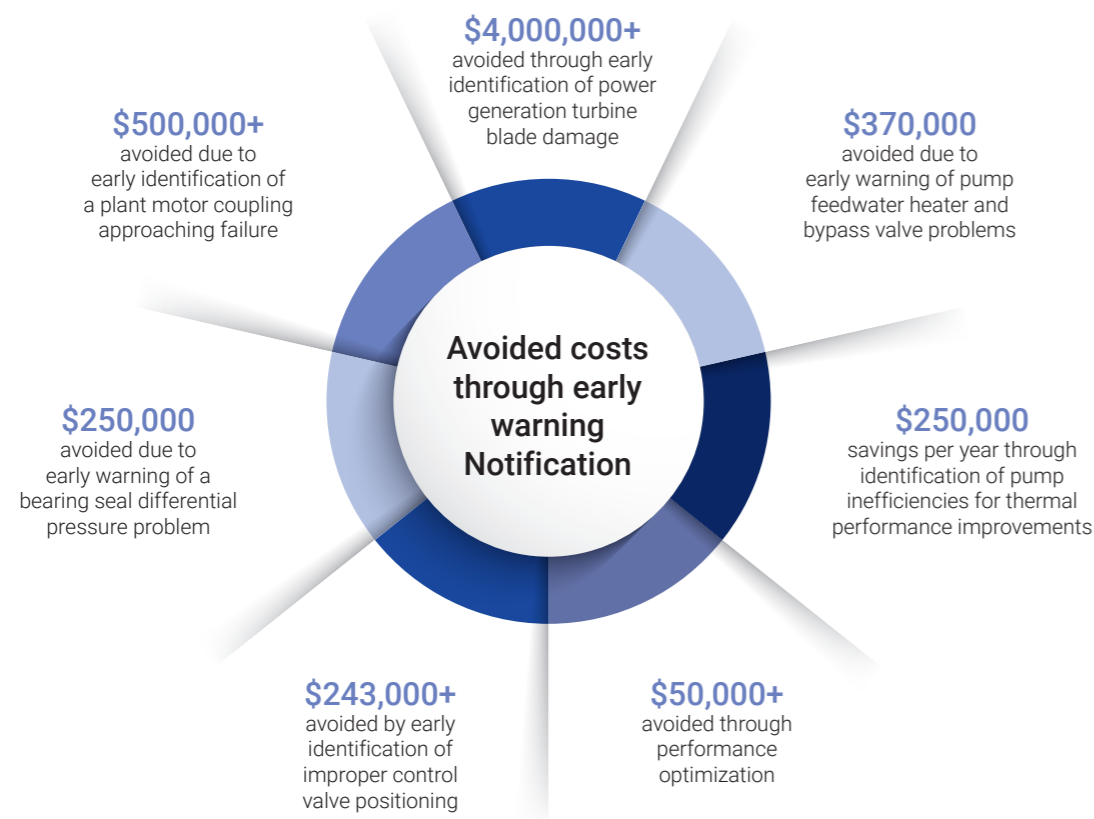
Main challenges

A field technician must quickly troubleshoot an onsite industrial asset, and is seeking a solution that combines a summary of the problem, including difficulty and time estimates; links to relevant manuals and necessary parts; additional

physical tools to resolve the problems and the current location of these tools; if the problem is difficult to resolve, additional support from people with the necessary expertise.

Paper-From Raw Data to Smart Manufacturing: AI and Semantic Web of Things for Industry 4.0

Figure 2. Avoided costs through early warning notification



Source: Aeva Brochure, Predictive Asset Analytics

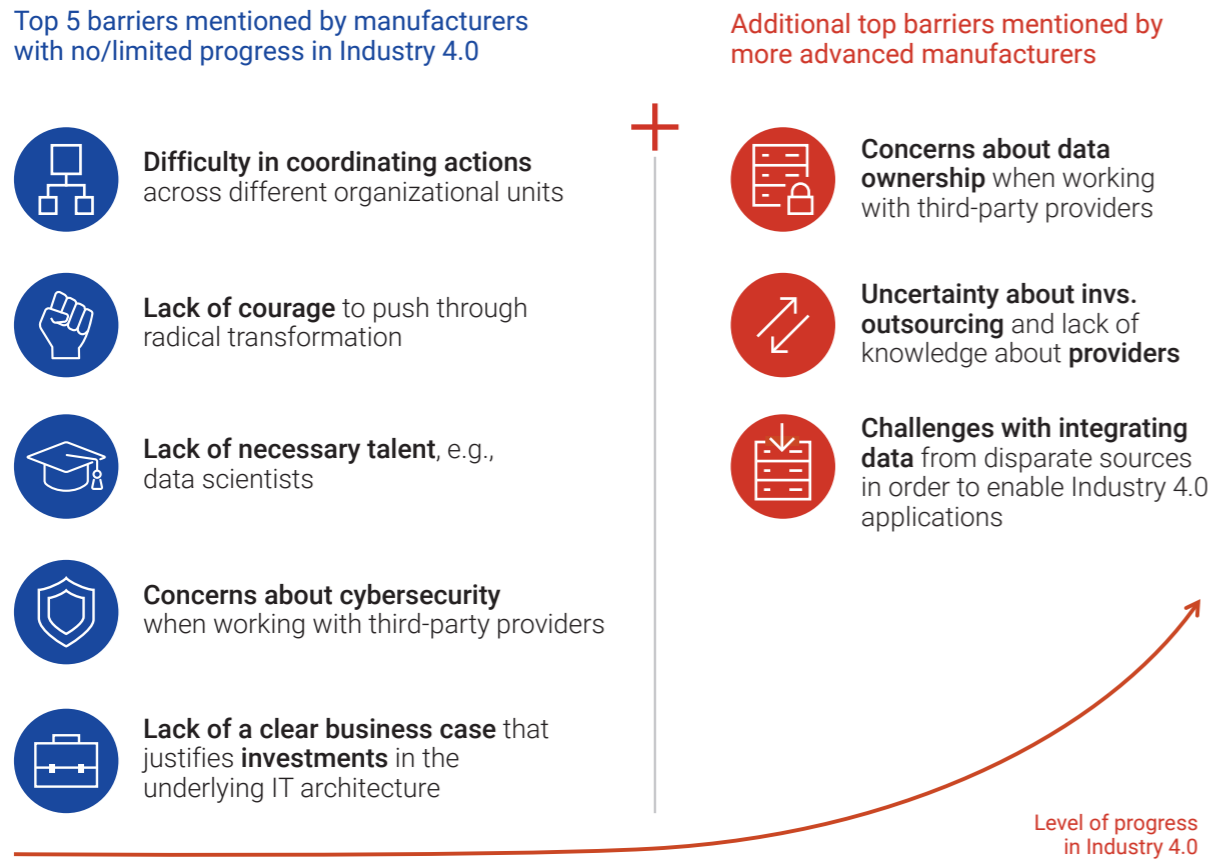
As systems change over time, improving the efficiency of equipment maintenance is becoming more challenging. This is especially evident when the complexity of operating processes and the volume of equipment is increasing while the workforce pool is waning. Depending on the industry unplanned machine downtime can cost manufacturers from 10,000 \$/hour to 3.5million \$/hour in lost production, without including negative impact on overall production and customer relationship. While smart maintenance promises to solve some of these issues, implementing it means overcoming some hurdles.

Increase profit by reducing costs of operations, increase efficiency by optimizing processes and reduce time of operations, prevent assets malfunction and reduce equipment downtime (predict ahead of time), optimize inventory management of spare parts and technician availability, optimize assets grid so reducing energy consumptions and CO₂ emission could be established, these are just some of the challenges of Smart Maintenance. The first obstacles in achieving such goals could be inadequate detailed technical knowledge about the equipment; assets could be remotely located or operating in very harsh environments (under water, on heights, very high temperature environments, and noisy environment); geographically dispersed assets are struggling to manage remote employees efficiently; spare parts acquisition takes too much time (call for additive manufacturing, if possible); selection of appropriate devices for data collection; legacy and disparate systems, leading to multiple visits and dissatisfied customers; incomplete, insufficient historical and current data or its poor quality, additional time and efforts needed for the cleansing and enrichment of the data; proven analytics and AI models etc. Even though, so many challenges exist in Smart Maintenance the companies are competing for time syncopation of

the solutions implementation. Understanding specific challenges from different industries definitely shortens the solution building. In Telecommunications, for example, inspections take place in substations once every month, taking a total of eight hours per inspection for a two-person team, this means 19,200 man-hours dedicated annually. In order to inspect 100 substations monthly, a total of 334 liters of gasoline is consumed by 5 different vehicles operating for this substation visits, having as a consequence 769 kg/CO₂ yearly emission. Still, with monthly inspections and current sensors installed the probability of asset malfunction is at around 6-8%, due to undetected situations. In the oil refinery following anomalies can signify major issues in the operations: high-temperature gas leakage, low-temperature gas leakage, deviations in rotor bearing, abnormal temperature increase, issues in pipe internal flow (cavitation, control valve noise, etc.). On the wind farms the aim is to reduce the turbine failure events, perform deep assessment of the energy production, forecast the wind-power production and, extremely important for electricity consumption-generation, balance in the distribution grid (which is the core challenge of smart grids). On the production line, anomaly detection on 20 different machines could take place in real-time, with multiple audio and video sensors, autonomous robots automatically taking action if any defect spotted, avoid any point of failure within the assembly line. Manufacturing companies struggle with short product life cycles, volatile demand and highly customized products, producing small batch sizes of a product, or even a single item, in a timely and cost-effective manner, so sufficient functionality, scalability, and connectivity could be met with the help of customers and suppliers.

More generally, 6 out of 10 manufacturers struggle in implementing Industry 4.0 applications/ strategies and some of the implementation barriers are mentioned below.

Figure 3. Manufacturers need to overcome major implementation barriers, of which some are more relevant for advanced players



Source: McKinsey Industry 4.0 Global Expert Survey 2016

What is AI?

Artificial intelligence (AI) is a term that covers a wide range of technologies from statistical analysis, to machine learning, deep learning or even meta-heuristics. There is no generally accepted strict definition of AI but there are some characteristics that all AI programs share. First and foremost is the ability to learn from data. All artificial intelligence is built upon a large quantity of data that has been curated, to some degree, in order to exemplify the final goals of the program.

This data is used by the AI to train until it achieves a satisfactory level of performance on a series of tests. After crossing the performance threshold training is stopped and the AI no longer learns. In the second phase, known as the inference stage, the AI is exposed to new real-world data and uses what it has learned to output conclusions. The second characteristic of AI is that the output is statistical. This means the AI will always return a result with a certain confidence level. The system must be designed to interpret the output by taking into account the confidence level and set the appropriate thresholds. While this may seem like a disadvantage at first glance, in practice it means the AI can deal with situations of varying levels of certainty. The ability to deal with approximate data inputs or uncertain data is the third characteristic commonly shared by all AI systems. Exactly how tolerant an AI can be varies from case to case but in general it is enough to grant AI systems a significant advantage over traditional rule-based systems. If the incoming data remains within the same parameters the AI will continue to function at the same performance level. However, there is

currently no production AI that can continue learning while it is operating. All the learning has to be finalized in the training phase of creating the AI.

Since the process of building an AI depends on having large quantities of data this also imposes a series of unique project management challenges. First of these is collecting, cleaning and labelling the data. This can't be overlooked since it often implies a significant cost and specialized software tools. Usually, human experts are required to label the data accurately and a data scientist is needed for correct data management. One can never have too much good data so an aim is to collect as much as possible without compromising quality. The second unique challenge appears during training. Not only this process requires a lot of processing power, but in order for the training phase to be successful the model architecture and the parameters have to be tuned. This is a looping process that requires many iterations until the AI performs as intended. It's for this reason that slippage must be taken into account during the project planning phases.

While AI may seem challenging, it is a rapidly maturing field and there are enough procedures, products and expertise on the market to eliminate any difficulties often encountered when tackling it. The advantages it brings are immense. Not only does AI reduce costs and accelerates the time to market, but in many cases it provides solutions that would never have been possible to implement using other techniques. In the long term, proper data governance also provides a competitive advantage as deployed AIs can be configured to collect new data. No AI is capable of continuous learning but all the new data it collects can be used to manually build future versions.

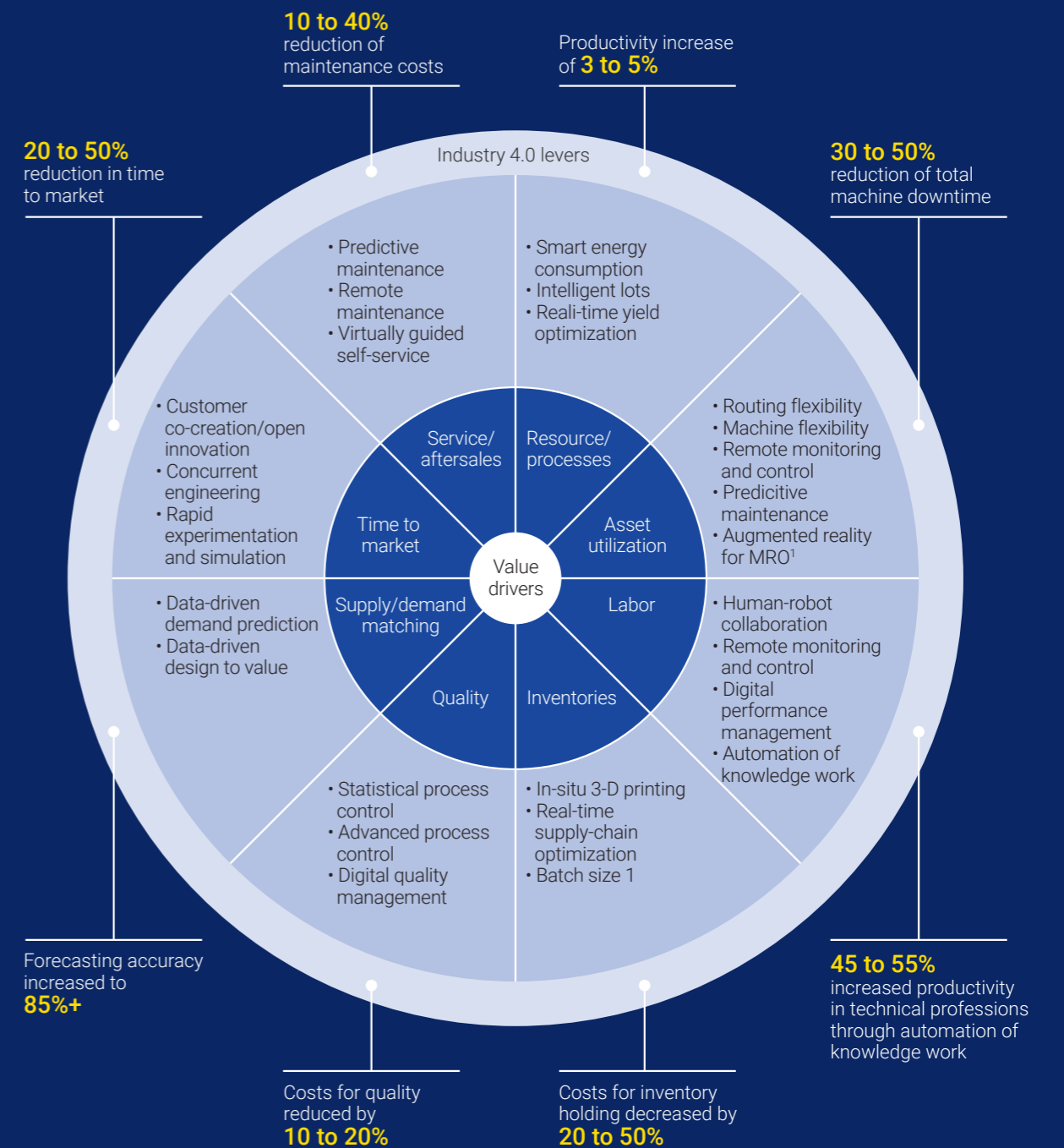
Benefits of implementing AI in Smart Maintenance

A large chemical manufacturer is actively deploying connected technologies with significant interest in predictive asset analytics. The company is proactively looking to reinforce its leading position in asset and process management by adopting digital technologies in its 'Future of Automation' program. A pilot implementation of predictive capabilities for one asset class, extruders, resulted in 80 percent reduction of unplanned downtime and cost savings of around \$300,000 per asset. Now the company is expanding this capability to other critical equipment across multiple facilities.

Deloitte Insights <https://www2.deloitte.com/us/en/insights/focus/industry-4-0/using-predictive-technologies-for-asset-maintenance.html>

AI can leverage great efficiency potentials in Smart Maintenance. Gathering data from multiple sources, like Industrial Internet of Things (IIoT) sensor data, historical data, processes and customer data, asset usage data, location data, weather data, etc., increases system connectivity. Using this large quality data pool, synthesized with AI on edge devices or cloud-based Machine Learning (ML), real time reports, alerts, analysis and decision making is enabled. Direct benefits of ML are rapid model development, adaptable to different asset families, scalable across the entire plant, flexible deployment approaches and model selection. With natural language processing recall of answers, in context, and analysis of human readable text for clues, insights and evidence is possible. Automated model building and infinite learning gives AI the opportunity to watch data and derive rules, to incorporate human feedback to strengthen or dismiss conclusions, automatically learn from feedback and enlarge the volume of data, to improve accuracy, capability and insight. Deep Learning and reasoning algorithms could even more improve accuracy, learn complex patterns and scale efficiently (high speed, large data implementations). Powerful visualization with evidential insights provides transparency and evidence about what the AI based system is learning and proposing, presenting data elegantly with friendly interface and easy feedback. Those systems are offering knowledge to technicians and engineers about health and performance of the equipment; forecasting failures so equipment maintenance and repairs could be planned, avoiding costly downtime; increasing control, safety, reliability and security; monitoring process quality (ensuring compliance with maintenance-relevant standards), cycle time and energy consumption; even virtually assisting humans in case of failure or better configuring complex processes network.

Figure 4. The McKinsey Digital Compass maps Industry 4.0 levers to the 8 main value drivers



¹ Maintenance, repair, and operations.

Source: *Industry 4.0: How to navigate digitization of the manufacturing sector*, McKinsey Digital, 2015

McKinsey looked at 8 main value drivers in maintenance, repair and operations, explicitly showing the benefits of Industry 4.0 involvement. Other companies, like Deloitte, also recognize that predictive maintenance can reduce the maintenance planning time by 20-50%, diminish total maintenance costs by 5-10% and increase equipment uptime and availability by 10-20%. NTT DATA successfully deployed Weaver solution for utility with more than 1,300 substations and more than 40,000 km of network, in Japan for TEPCO, the largest electricity company in the country. The solution reduced on-site visits by 50%, decrease vehicle fleet and carbon footprint – more than 100 tons of CO₂ per a year and the probability of failures derived from failure to

detect malfunctions was reduced from 43% to 10%. With Google Glass and Skylight enterprise software from Upskill, Boeing cut its wiring production time by 25% and reduced error rates effectively to zero.

New-generation AI is capable of analyzing audio, video and sound data. Therefore, designing Smart Factories with Smart Maintenance implementation is just one portion in technology pace. Smart Mobility, Smart Grid, Smart Logistics, Smart Homes and Smart Buildings are also part of Industry 4.0 environment. Process automation is rapidly leading industrial change by removing repetition, improving precision and efficiency, allowing more creative thinking and acting.

Figure 5. Top 5 Predictive Maintenance start-ups impacting Industry 4.0. The Heat Map illustrates the geographical distribution of 5 out of 135 predictive maintenance start-ups disrupting Industry 4.0



Source: StartUs Insights, June 2019

According to StartUS INSIGTS research in June 2019 there were 135 start-ups in Predictive Maintenance and 222 Predictive Maintenance solutions impacting the energy industry.

Industry 4.0 revolution is pushing maintenance to evolve faster, bringing more innovative solutions to the beneficiaries.

Drawbacks of AI in the maintenance process

As with any innovation, AI presents a unique set of challenges during implementation. Most of these revolve around the need to provide large amounts of data for training. Organizations have long struggled with good data management practices that would ideally allow them interactively gather and analyse information at scale over time.

Some machinery might be decades old, with maintenance records stored in obsolete formats or with no digital interfaces. Such data can't be simply discarded as it is often invaluable for the construction of an accurate AI model. Therefore, implementers of AI maintenance have to be ready to customize their data ingestion protocols and procedure to accommodate the customer side. It should be noted that not all maintenance information is documented. Often times, key individuals might be the only ones with specific knowledge about the operation and defects of key machinery. These individuals can be cooped to perform expert data labelling in order to improve the AI training.

When existing data sources are insufficient, it is necessary to engage in a concentrated data collection effort. Custom IoT devices have to be deployed on functioning

machinery to digitize outputs and provide extra sensory information. The advantage is that the IoT devices can become part of the overall maintenance strategy. For example a smart camera that reads the analog gauges of machinery while also recording all the nearby sounds might enable early detection of faults that were previously responsible for costly breakdowns. A reliable AI model can spot patterns that were not apparent to human operators and the cost savings can far outweigh the initial costs of IoT development and deployment.

Even a well-trained AI with a reliable interfaces to the real world might still encounter a final pitfall: bias. Depending on the goals set for training, an AI can end up favouring triggering maintenance interventions too early or too late in order to optimize the targeted KPIs. A biased AI might even trigger false alarms leading to shutdowns of critical equipment and considerable financial costs. This might seem obvious but it's easy to introduce such biases when failing to predict true failures can have catastrophic results. A good balance must be found through rigorous analysis and testing. Therefore an AI smart maintenance solution can't be considered a "set and forget" solution. A long term collaboration between the client and the implementer ensures a continuous alignment between how the solution functions and the customer goals.



CHAPTER 2 – S.A.D. IN MAINTENANCE

What is S.A.D.?

Industrial units suffer damage due to continuous usage and the normal wear and tear. Such damages need to be detected early to prevent further escalation and losses. The data in this domain is usually referred to as sensor data because it is recorded using different sensors and collected for analysis. Anomaly detection techniques have been extensively applied in this domain to detect such damages.

<http://cucis.ece.northwestern.edu/projects/DMS/publications/AnomalyDetection.pdf>

Sound Anomaly Detection is an anomaly detection technique aiming to identify if the sound coming from target machine is related to normal or anomalous behavior of the equipment. Automatically detecting failure is crucial for Smart Maintenance, for building (AI)-based factory automation. Real time detection of machine failure, by recording its sounds, may be useful for machine condition monitoring.

Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior. The goal is to be able to identify data deviation from what is considered normal, expected or likely in terms of the data probability distribution, or the shape and amplitude of a signal in time series. Anomaly detection finds extensive use in a wide variety of applications such as fraud detection for credit cards (anomalies in credit card transaction data could indicate credit card or identity theft), insurance or health care (an anomalous MRI image may indicate presence of malignant tumors), intrusion detection for cyber-security, fault detection in safety critical systems (anomalous readings from a space craft sensor could signify a fault in some component of the space craft), and military surveillance for enemy



activities, etc. Various disciplines such as statistics, process control, signal processing, machine learning, data mining, information theory, spectral theory have enriched anomaly detection technique for solving specific problems depended on nature of the data (sound, image or video), availability of labelled data (normal or anomalous), type of anomalies to be detected and classified (intrusion detection, fraud detection, fault/damage detection, medical Informatics, etc.), the characteristics of data (existence of labels, number and types of data attributes, data volume) and the expected output (label or score, need for result interpretability).

In industry, damage detection is of interest for Smart Maintenance. Fault detection in mechanical units and structural defect detection are two domains of damage detection applications. First one monitors performance of industrial components such as oil flow in pipelines, ship engine, gas turbine, elevator, escalator, air conditioner or other mechanical components and detect defects which might occur due to wear and tear or other unforeseen circumstances. Former domain refers to system health management, detection is associated to anomalies in structures, e.g., cracks in beams, strains in airframes, defects in component painting process, oil leak bleeding, consumption or oil level changes, meter reading, etc. Data (binary, discrete, continuous, audio, video, etc.) collected real time from network of sensors, usually connected to the internet (IoT), is in the streaming mode. If this data is in audio format then Sound Anomaly Detection (S.A.D.) technique is performed. Machine-operating sound is used to prevent accidents and/or mechanical failures by detecting sounds that do not normally occur. Previously, system health checking and maintenance happened only in two cases: when a complaint is made or during a regular check scheduled every few months. In the latter case, it was common for the inspector or walk around the machine room and listen for abnormal sounds. These two approaches can cause small problems to eventually become big and costly, since damages are only found after they have already occurred. For instance, the cost of replacing a damaged motor fan can be around \$50K dollars. Also, shortage of skilled workers has become a serious issue that necessitates an automated system for continuous monitoring of machinery sounds. Now, as S.A.D. has been developed, real time predictions are attainable, maximizing uptime of machines. Preventive measures, anomaly confirmation and automatically issued repair work orders, required to be taken as soon as an anomaly occurs.

S.A.D. implementation

In many cases a visual inspection cannot capture the true condition of the surveilled entity. A pump suffering from a small leakage, a slide rail that has no grease or a fan undergoing voltage changes might appear intact when inspected visually but when monitored acoustically, reveal its actual condition through distinct sound patterns. Further, acoustic monitoring has the advantage of comparably cheap and easily deployable hardware. The early detection of malfunctioning machinery with a reliable acoustic anomaly detection system can prevent greater damages and reduce repair expenses.

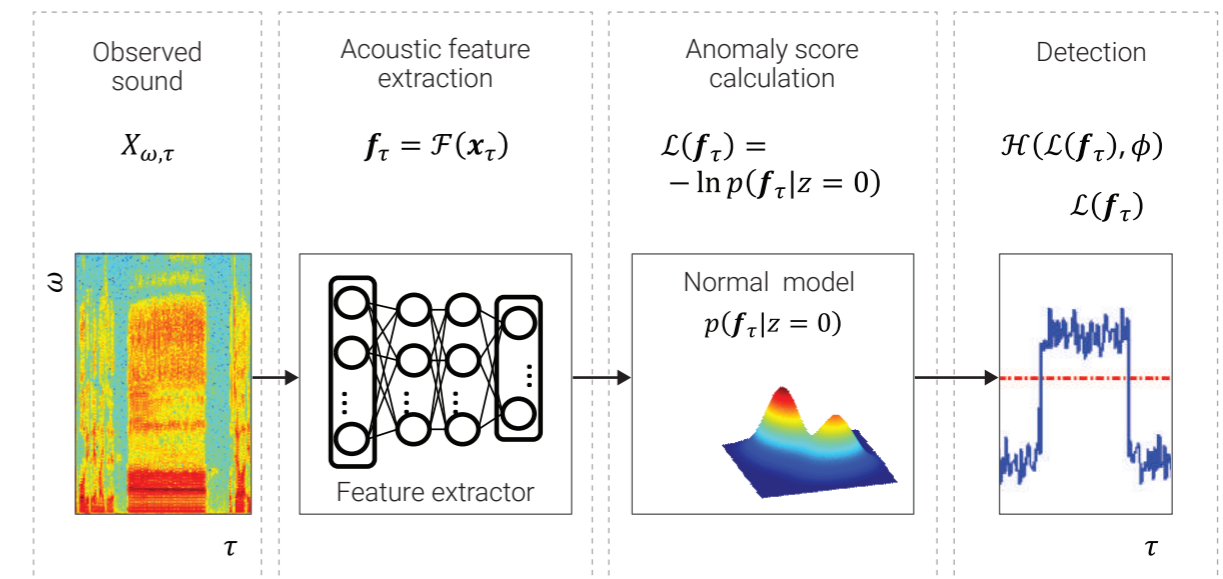
<https://www.researchgate.net/publication/341998250>
Acoustic Anomaly Detection for Machine Sounds based on Image Transfer Learning, Robert Müller, Fabian Ritz, Steffen Illium and Claudia Linnhoff-Popien Mobile and Distributed Systems Group, LMU Munich

In a noisy industrial environment, where various sensors are deployed, it is difficult to clearly distinguish normal instances from anomalous ones, as the boundary between the two is usually imprecise and could evolve over time, especially if missing sequences occur. As a consequence, most of the existing anomaly detection techniques solve a specific problem. Furthermore, anomalies are often rare events, so data collection would be time consuming or impossible (for

instance damaging on purpose the equipment). Consequently, labelled data for model training and validation are either unavailable or severely imbalanced in favour of normal instances. Semi-supervised or unsupervised learning is more frequently used than supervised learning where labelled instances for normal as well as anomaly class coexist. In a semi-supervised approach, labels exist only for the normal class. Any unlabelled instances that are nearby in terms of distribution, are assumed to have the same label as the labelled instances. In unsupervised learning approach, the only assumption is that a very small fraction of the overall data is anomalous data or that anomalies lie far away from most data instances or in low-density regions. The model is actually trained to learn the normal behaviour of a system and as the output giving anomaly score, ranked list of anomalies, choosing to either analyse top few anomalies or use a cut-off threshold (domain specific threshold or parameter dependent one) to select the anomalies or a label (normal or anomalous) to each test instance. It is, for instance, essential to extract a set of informative acoustic features, which provides a small anomaly score for normal sound and large anomaly score for anomalous sound.

Various algorithms with different computational efficiency and detection efficacy are available for S.A.D. depending on field of application. Examples of anomaly detection techniques used for fault detection in mechanical units: Parametric Statistical Modeling, Non-parametric Statistical Modeling, Neural Networks, Spectral and Rule Based Systems.

Figure 6. Procedure of anomaly sound detection based on outlier detection



Source: <https://www.erasip.org/Proceedings/Eusipco/Eusipco2017/papers/1570341166.pdf>

Benefits of S.A.D. in the maintenance process

When a crack occurs due to wear or deterioration of the mold used for presswork, the required machining precision cannot be obtained and leads to the generation of defective products. In addition, if presswork is continued without noticing the crack, it is possible that fragments may fly about causing injury to the operator. Although large cracks can be confirmed with visual inspections, shatter cracks are difficult to ascertain visually, and presswork may go on without the cracks being noticed. Therefore, a sound collecting microphone was attached to a metal rod and a mechanism was built to detect the presence or absence of cracks.

Source: <https://www.oki.com/en/otr/2017/n230/pdf/otr-230-R09.pdf>

The available data volume has been continuously growing over the recent years. For instance, as pointed on the picture, the report from NVIDIA shows huge amounts of data collected by Oil and gas companies. Processes are becoming massive, prompt, more complex and customized. Great pursuance for automation is driving the course of the industry. Regardless of this urge, sound anomaly detection is still underrepresented. Due to the decrease in IoT gadgets pricing, rising development of ML algorithms and release of publicly available datasets the situation is gradually improving.

As mentioned in presswork example, malfunction could be hard to spot on site, crash of one component could lead to malfunction of another, making not only the production, but also the security endangered. With S.A.D. automation the risk management is improved, avoiding security issues, unplanned downtime, costs in the production and

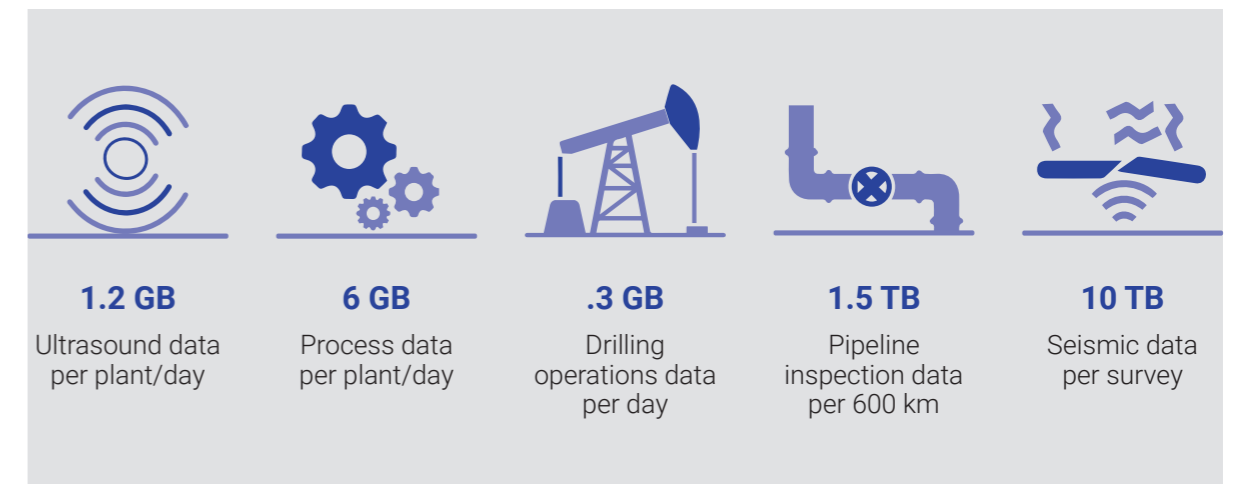
maintenance. Unplanned machine outages could cause losses of 5% to 20% of income due to lost in productivity. Real time monitoring of large number and vast variety of machines is the main virtue of AI and IoT capabilities in maintenance. Difficulties in identifying alert rules (processes are too complex, and dynamic, lack of experienced workers, time-consuming to educate them, variations in judgment with different workers) and alert fatigue (large volume of data or machinery that needs to be monitored, threshold-based analysis of individual sensors does not communicate the full picture of the equipment performance) could be easily avoided. Also, remote or allocated assets and machinery in dangerous or harsh environments where maintenance is impossible or expensive could be avoided.

S.A.D. sensors, compared to the vibration sensors for example, has few advantages such as:

- completely wireless;
- easy installation into already existing equipment - though sound comes out of the machine there for direct access to the motor or generation is not needed;
- portability - though sensors do not need to be directly attached to the motor there for portable sensor solution could be built and the collection of the data from more than one machine is much easier and less time consuming.

S.A.D. can merge gathered data and help translate it into actionable insights. Detecting early potential failure, making information easy visually accessible by showing machine status and real time alerts, in order for suitable and timely actions could take place in real time, improves decision-making. S.A.D. has easy implementation, instantly saving costs and increasing failure detection.

Figure 7. NVIDIA reporting the huge amount of data collected by Oil and Gas



Source: NVIDIA, AI: Fuelling new efficiencies in Oil and Gas

CHAPTER 3 – NTT DATA S.A.D. TECHNOLOGY

What is NTT DATA S.A.D. technology?

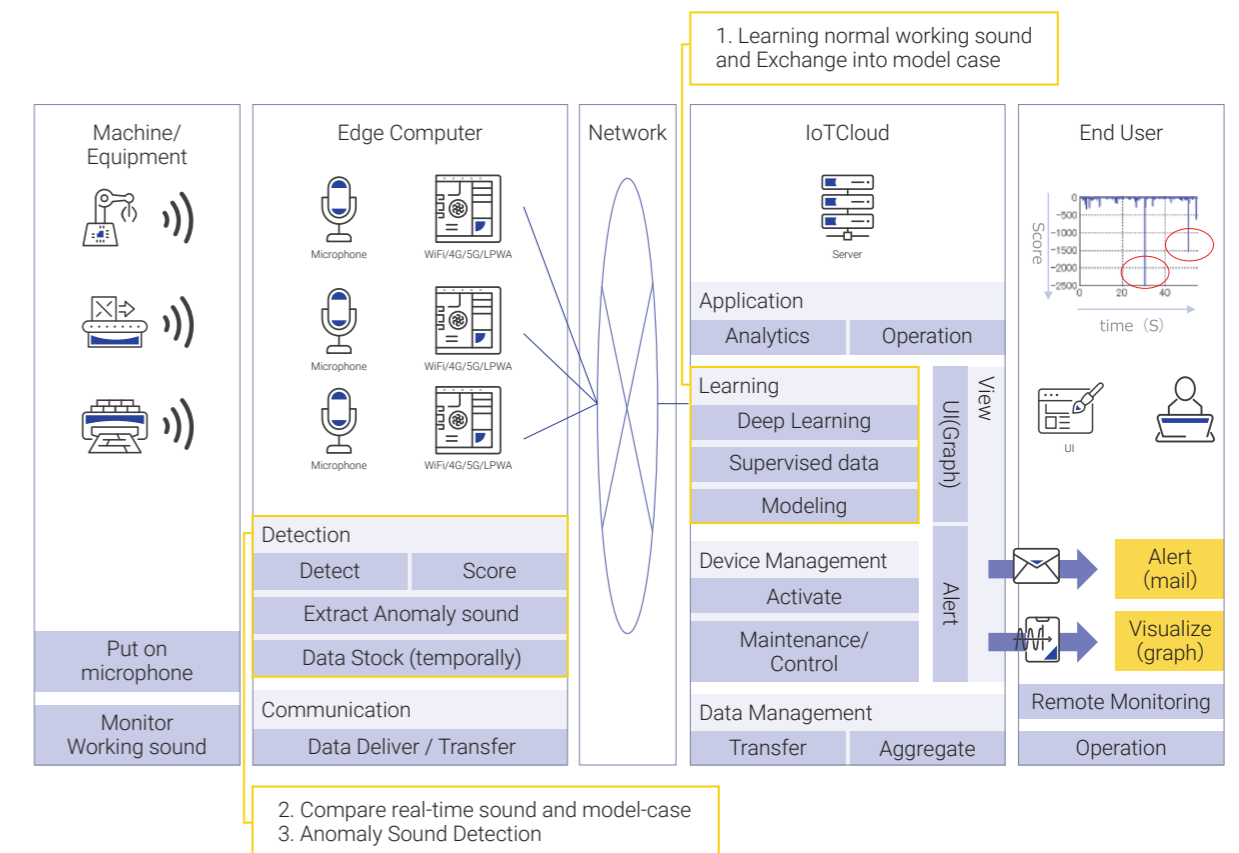
Abnormal sound data is difficult to collect, it rarely occurs and that sound could have various patterns. Sound Abnormality Detection (S.A.D.) system, offered by NTT DATA, using technology developed by NTT Media Intelligence Laboratories detects anomaly sound by training only with normal operating sound of machines in factories.

S.A.D. solution enables detection of abnormal sound by using unsupervised deep learning techniques developed by NTT DATA, obtaining acoustic features for the machine automatically (the state of the machine is identified as having an anomaly when the measured deviation from the normal state exceeds a predefined threshold).

The solution also captures sounds from the target source in noisy environment, using "Intelligent microphone technology" developed by NTT DATA. Environment noise is suppressed, Suppression Technology with microphone array, resulting with cleared and emphasized operating sound. This technology improves the performance of sound recognition. Also, using cloud based model, on-line remote monitoring is provided, enabling real-time process analysis giving timely abnormal sound detection.

The system is built to grow wiser while running, by additionally learning mis-detected sounds. In some cases an actual abnormal sound cannot be detected, additional training (registered abnormal sound training) using the undetected abnormal sound will provide a more robust detection system. Conversely, if a normal sound is erroneously detected as abnormal, the error can be avoided with additional training (registered normal sound training) using the erroneously detected normal sound. Training model created using normal sound generated by multiple machines in multiple factories (multi-domain training), can be used with small amount of normal sounds collected on the new machine of interest to create Domain Adaptive Training Model. This model is

Figure 8. Sound Abnormality Detection system implementation



useful when creating a training model for multiple factories because it requires only a small amount of normal sounds.

By using these registered abnormal sound detection functions and by collecting more

normal sounds over long time to improve the accuracy of the training model, continuous improvement in accuracy can be expected, resulting with high, **more than 90%, accurate system.**

Where could we use it and why?

Collecting and analyzing sound for Predictive Maintenance, in After Service domain, by environment data sensing is a key component of NTT DATA S.A.D. technology. Target devices for Predictive Maintenance are huge and special ordered machine (e.g) processing machine for ship engine, gas turbine and FA robot. The microphones are attached to the machines and S.A.D. solution provides their working-status and alerts if any abnormal sound occurs.

For Predictive Maintenance beside operation sound analysis, facility operation log data analysis and maintenance work log data analysis are done in parallel to accomplish better predictions. Additionally, remote monitoring, as a part of Remote Maintenance, is possible on building equipment (e.g.) elevator, escalator, air conditioner, pump and generator.

Existing maintenance processes have issues connected to the quality of maintenance process, non-efficiency in routine work and accident risk by missing fault sign. S.A.D. technology improves maintenance efficiency, quality and rapidness by using AI analysis in the factory or infrastructure equipment. Improvements in equipment operation rate and reduction in costs validate the value of NTT DATA S.A.D. technology.

An example of successful industrial implementation of S.A.D. technology comes from a company which produces electric motors.

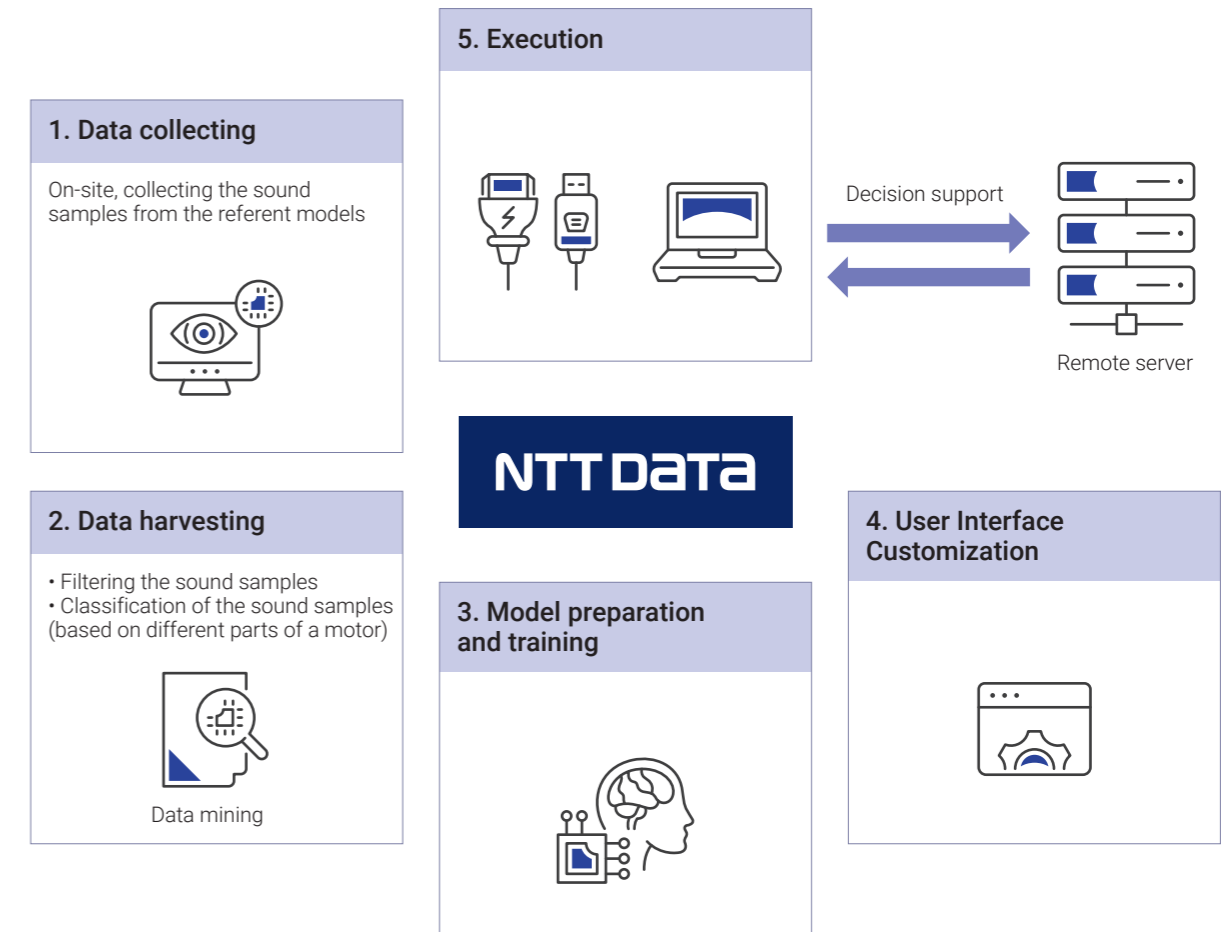
Figure 9. Setting up a microphone close to sound source to collect sounds.



The potential of using S.A.D. for the product validation improvement and automation was identified by NTT DATA, for solving the existing issues:

- The produced brush-type and brushless DC motors have been validated manually, meaning that experienced engineers can determine the malfunctioning motor by its sound;
- There is no automated validation;
- There is no a possibility of prediction of the malfunctioning;
- There is no classification of the malfunctioning parts;
- For every DC motor type, there is a 'golden sample' which is used as a referent model.

Figure 10. High level overview of the S.A.D. system implementation with particular client



NTT DATA S.A.D. implementation

Implementing the solution step by step with verifying the validity is given in the table below.

Table 1. Flowchart of the process for introducing the S.A.D. system

| | DECISION TO IMPLEMENT | OFFLINE PoC | ONLINE PoC | ADVANCE AND FULL-SCALE OPERATION |
|------------|---|---|---|---|
| OBJECTIVES | Check if the abnormal sound system corresponds to the customer's requests | Verification of the analysis effectiveness in specific environment | Effectiveness verification considering the actual use-case environment | Full – scale operation and maintenance |
| TO DO | <ul style="list-style-type: none"> • Checklist (Create a list) • Hearing sheet (Customer's request) • Decision | <ul style="list-style-type: none"> • Sound collection • Training • Detection accuracy check • Finishing | <ul style="list-style-type: none"> • Sound collection • Training • Detection accuracy check • Prepare for operation • Operation • Maintenance • Finishing/picking up equipment | <ul style="list-style-type: none"> • Sound collection • Training • Detection accuracy check • Prepare for operation • Operation • Maintenance • Finishing/picking up equipment |

In the Decision to Implement phase there is a checklist to determine whether to install the S.A.D. system according to the environment or machine condition before starting the Offline Proof of Concept (PoC) phase. If the S.A.D. system is applicable, clarification of the S.A.D. system usage is expected. Since each customer has different business needs, it is important to make optimal proposals that match the customer's needs. For example, abnormal sounds can be detected in real time with the system, but some customers only need it once a month.

In the Offline PoC and Online PoC phases it is verified the effectiveness of the system and identifying operational issues.

Before introducing the system to the customer's environment, a training model is created using the normal sounds recorded in the customer's site, including the operating sounds of the machine to be inspected. Unlike the actual abnormal sound of the machine to be inspected, Pseudo Abnormal Sound refers an abnormal sound generated or recorded in advance. This sound is used to improve the accuracy of

Table 2. Steps in the process of introducing the S.A.D. system

| NO | STEP | TASK | SUMMARY |
|----|-------------------------------|--|---|
| 1 | Sound Collection | Checking variation of sound and hearing of abnormal sound data | Classify the type of sound to be normal from the sound recorded at the site. Conduct interviews with customers as necessary. |
| | | Recording policy decision and experiment (Microphone arrangement, etc.) plan | Prepare an experiment plan from the hearing sheets and customer information, etc. |
| | | Preparing Equipment | Check the stock, purchase the missing equipment, and send the equipment to the customer when all the equipment is ready. |
| | | Setting | Set the recording equipment based on the experimental plan. |
| | | Recording | Record the operating sound generated when the machine to be inspected is in a normal state using the recording equipment. |
| | | Collect sound data | Collect the sound data that accomplishes the task, save it on computer or other devices to bring back. |
| 2 | Training | Collecting information for data analysis | Conduct hearings with the customer to find the approximate time of the sound to be labeled in data analysis. |
| | | Data analysis | Analyze and label a time zone usable to operating sound generated when the machine to be inspected is in a normal state from the sounds recorded on the customer's site. |
| | | Create training data | Conduct data cleansing by extracting data from data recorded on the customer's site and labeled with an available time zone in the data analysis process to create operating sound data generated when the machine to be inspected is in a normal state for training. |
| | | Create a training model | Create a training model using the operating sound training data generated when the machine to be inspected is in a normal state, created in the previous step. |
| | | Calculate thresholds | Calculate three proposed thresholds of "tight", "Normal" and "loose", using a tool based on the training model created in the previous step. |
| 3 | Detection Accuracy Evaluation | Create Normal Sound for Evaluation | Create a Normal Sound for Evaluation by extracting an appropriate part of the collected sound data. |
| | | Create Mixed Sound | Create a Pseudo Abnormal Mixed Sound using pseudo abnormal sounds and normal sounds for training by trimming, labeling, data cleansing, and data augmentation as needed. |
| | | Detection Simulation | Evaluate the created training model using normal sounds for training manipulated as described in previous step, Pseudo Abnormal Mixed Sounds (Abnormal Sounds) and proposed thresholds. |
| | | Detection Result Analysis | Analyze the statistics output from the detection simulation. |
| | | Reporting | Prepare documents for reporting to the customer based on the evaluation results. |
| 4 | Finishing | Finishing | Coordinating with customers to conclude the case and support for the equipment and collect unnecessary equipment. |

the training model and to evaluate the accuracy of the system. Pseudo Abnormal Sounds are preinstalled when the system is installed. Offline PoC aims to confirm the accuracy of the detection of the training model using test data created with actual sounds or Pseudo Abnormal Sounds, and to report the analysis results to the customer. Offline PoC has four steps described in the table above.

In the Online PoC phase, all steps from sound collection to detection are performed. This is a preliminary verification before the full-scale operation. In this phase, customers will experience the effectiveness of the system by using the same functions as in the full-scale operation, and consider whether to move to the

full-scale operation. Unlike the Offline PoC, it is necessary to respond to misdetection, overlooking, and aging of the machine to be inspected due to long-term use, and to address the tasks such as backup of daily accumulated data and maintenance of this system.

After the PoC, when the system is used for the actual production purposes, the system will be implemented in full-scale operation. Operations are basically the same as those in the Online PoC, but there are additional tasks such as domain application considering multiple locations or collateral quality.

Actors involved in the process of S.A.D. technology implementation are defined as following:

Table 3. Actors involved in the introduction of the S.A.D. system

| ACTOR | DESCRIPTION |
|--------------------|--|
| Proposer | Proposes the system to customer. |
| PoC Operator | Operates the entire processes from collected sounds, training, evaluation and report in the Offline PoC or Online PoC. |
| System Constructor | Constructs the system in the customer's environment. |
| Machine Inspector | Monitors whether machine to be inspected is normal or abnormal using the system (Do not set parameters for abnormal sound detection.) |
| System Operator | Controls the parameters of abnormal sound detection of the system to maintain the quality of detection results. (This operation may be done by a user company or by a consultant.) |
| System Maintainer | Checks if this system is operating normally, and checks system logs during maintenance work. |

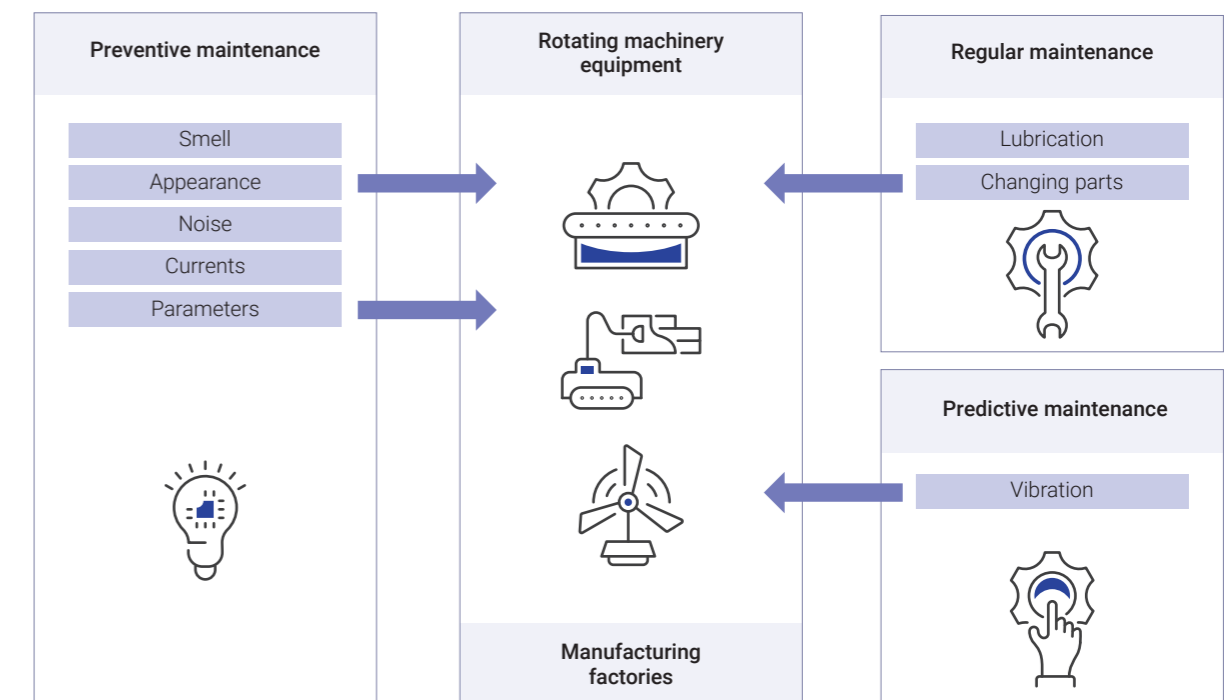
Data collection and implementation of more integrated solution

Industrial fans play a critical role in manufacturing facilities, and a sudden shutdown of critical fans can cause significant disruptions. Ensuring early, effective, and accurate detection of fan malfunctions first requires confirming the characteristics of anomalies resulting

from initial damage to rotating machinery. In addition, sensing and detection must rely on the use of sensors and sensing characteristics appropriate to various operational abnormalities.

Hindawi Journal of Sensors, Research Article Design and Implementation of Acoustic Sensing System for Online Early Fault Detection in Industrial Fans

Figure 11. The maintenance category of rotating machinery

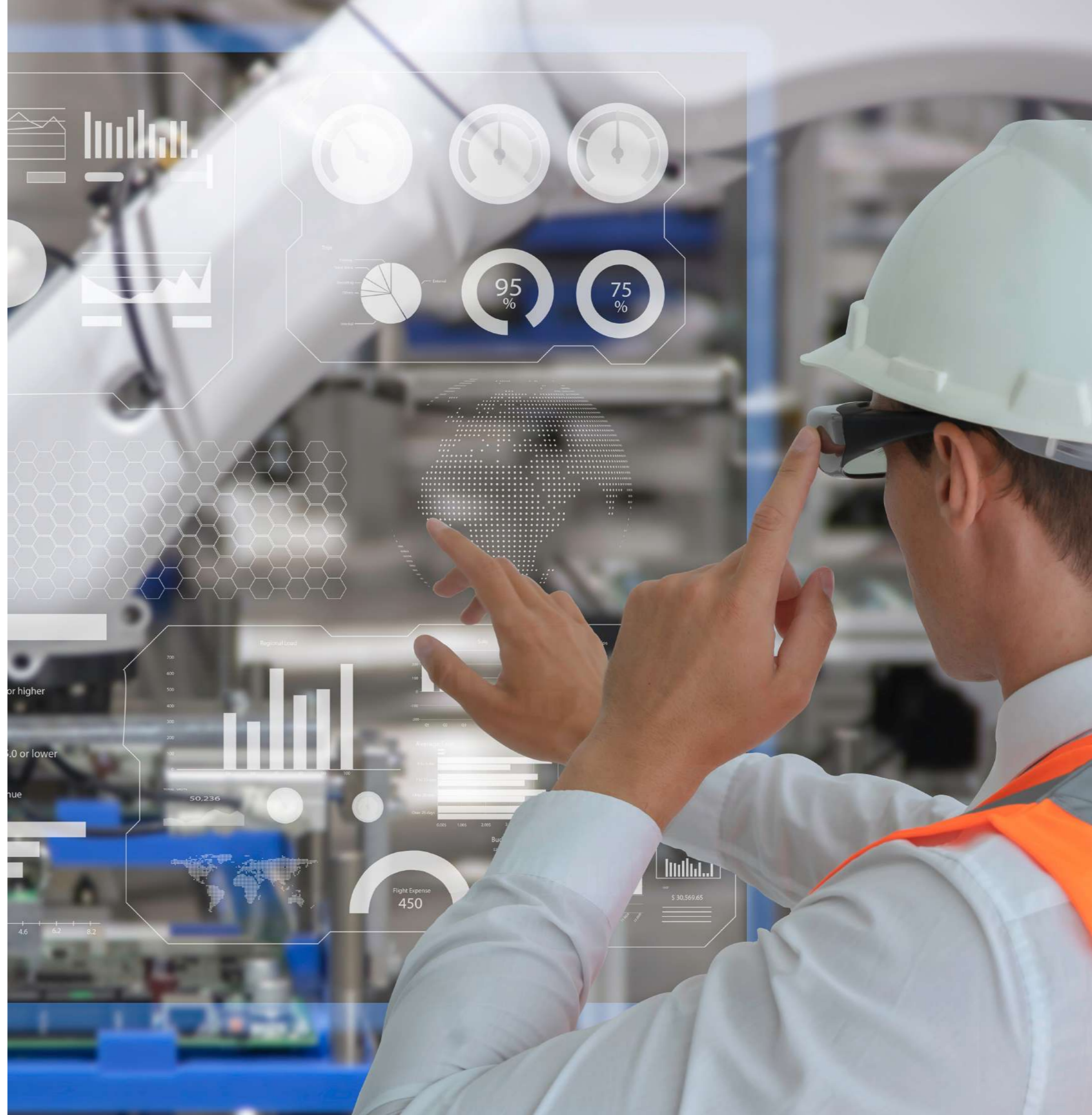


Source: <https://doi.org/10.1155/2018/4105208>

Industrial fans are used to remove exhaust emissions, ventilate, compress air, and drive air-conditioning systems. They operate continuously for long durations, and improper assembly or maintenance can result in malfunctions (bearing failures, looseness, shaft cracks, poor balance, misalignment, and resonance). Problems in rotating machinery are typically indicated by the presence of abnormal vibration, noise, or temperature. Maintenance of this rotating machinery relies on the integration of various sensors (accelerometers detecting vibration anomalies, microphones detecting sound anomalies, cameras or thermal cameras detecting visual or thermal anomalies) to provide real-time data on equipment conditions. Combining audio and images could enhance perception in any industrial environment, with a more constant and accurate surveillance of assets across the grid. Predictive maintenance and equipment diagnosis could be performed on any equipment, not by monitoring only sound, but also monitoring control panels, meter readings, detecting unknown objects, using drones for inspecting facilities on heights, etc. Even wider, various IoT devices could capture the diverse types of data:

- Mechanical data produced by different mechanical stress like pressures, fretting movement, fluctuating stress, tensile stress, residual and applied stress;
- Thermal data in low-voltage systems (control cabinets and electrical components), medium-voltage systems (electricity generators and transformers) or in high-voltage systems (power transformers and insulators);
- Environmental data produced by reaction of materials to aggressive environments;
- Radiation exposure data when equipment is impacted by ultraviolet light, sunlight and ionizing radiation.

All of the above can be then transmitted to an anomaly detection system that could compare collected data with historical patterns and detect the changes. By combining sound anomaly detection technology with other information a more robust and efficient smart maintenance system is obtained.



CHAPTER 4 – KEY TAKEAWAYS

Roadmap of the process


Smart Maintenance Roadmap represents the core knowledge that supports companies in their own transformation of their maintenance organization. It starts with a common understanding of the company's objectives for smart maintenance. Defining common goal for all stakeholders involved (in addition to maintenance, for example, management, production, quality, logistics, etc.) and accepting upcoming changes can be done in early stages. It is necessary to determine at which point in the transformation process for smart maintenance the company is currently. A cyclical consideration of the following four steps helps to actively and purposefully shape the path to smart maintenance:

- Development of a common understanding of goals;
- Regular determination of one's own position in the smart maintenance transformation process;
- Deriving and sorting the development steps in an individual roadmap;
- Implementation of the next development steps on the basis of the previously completed "homework".

Development paths are determined, paying attention to the different relationships (technical, organizational or cultural) and the next concrete development steps derived.

The Smart Maintenance Roadmap is presented based on the six design fields and the six maturity levels in the next table:

Figure 12. Smart Maintenance roadmap

| |  COMPUTERIZATION |  CONNECTIVITY |  VISIBILITY |  TRANSPARENCY |  PREDICTIVE ABILITY |  ADAPTABILITY |
|--------------------------|--|---|---|---|---|---|
| Joint Planning | Separate (manual) Planning in silos | Common, static Planning across silos | Joint planning in real time with Target / actual comparison | Data-based Planning optimization | Forecast-based Planning | Automatic, dynamic Planning |
| Availability orientation | Capture the Events | Determination more relevant Key figures | Key figures in real time | Effective relationship between Measures and Key figures | Scenario forecast based on Measures and Key figures | Automatic decision based on Key figures |
| Flexibility | Static resource optimization in silos | Static resource optimization | Resource availability and allocation in real time | Needs-based allocation of resources | Scenario forecast of the resource allocation | Automatic Resource optimization |
| Knowledge management | Digital Service reports | Global Plant history | Digital twin a system with Real-time data | Digital solution catalog and procedural instructions | Automatic generation, prioritized proposed solutions | Automatic provisioning of necessary information |
| Spare parts management | Digitized information in silos | Integrated spare parts system / Master data management | Spare parts stocks Network in real time | Risk-oriented Spare parts stocking | Optimized spare parts requirements in the network (3D printing) | Autonomous, dynamic procurement |
| Value contribution | Capture the direct Maintenance costs | Output-related Accounting (Unit cost) | Digital shadow of the Value contribution over the Organisation | Scenario analysis based on the Value contribution | Scenario forecast based on the Value contribution | Automatic Decision based on of the Value contribution |

Source: Smart Maintenance – Der Weg vom Status quo zur Zielvision, acatech STUDIE; English: Smart Maintenance - The path from the status quo to the target vision

Each maturity level and design principle represents added value for the organizations and contributes to the ability change more quickly and more objectively.

- **Computerization**
Company's employees are supported by data processing systems.
- **Connectivity**
Data processing systems are linked to one another and have the ability to map end-to-end processes.
- **Visibility**
Companies can make data-based decisions because their company has a digital shadow.
- **Transparency**
Factual relationships within the company can be analysed retrospectively and used for tactical or strategic adjustments.
- **Predictability**
Future scenarios can be examined and decision options can be evaluated.
- **Adaptability**
Company's systems reacts independently to changed influencing factors and adapts to them.
- **Joint planning**
Targeted information logistics is the core of Smart Maintenance. Ensures that decisions can be made faster based on data. These advantages arise when coordinating with other departments and when planning orders and measures. The joint planning of maintenance and production, as well as possibly adjacent processes, offers the potential to use flexible production space as efficiently as possible and to minimize downtimes necessary for maintenance.
- **Availability orientation**
Smart Maintenance is adapting to the availability of the technical assets, as

the production in real time requires, and to the ability to guarantee the needs-based availability of production in the long term. It offers condition monitoring using modern sensor technology enabling high-frequency monitoring of conditions, faster detection of malfunctions and the ability to react to them more quickly with the right measures. Building on this, predictive maintenance can be used to prevent unplanned downtime and thus also increase availability in line with existing requirements. With increasing availability, other factors such as performance, productivity or quality improve.

- **Flexibility**
In order to meet the increasingly complex requirements of a smart factory, Smart maintenance must be able to react to unexpected events in the shortest timely manner. Short-term change in the production program, as a result of special customer requests, can occur requiring flexible adaptation of the maintenance program. To achieve this high flexibility, smart maintenance need to fulfil the availability of sufficiently qualified and experienced maintenance personnel as well as the spare parts or tools required for the orders.
- **Knowledge management**
The social transformation towards a knowledge society with all its implications has made knowledge the central success factor of every company. Technical service and maintenance are often carried out on complex and highly individual machines and systems and therefore very individual expert knowledge is required. Networking and digitization offers the potential to absorb efficiently knowledge of individual employees of a company and make it accessible. The current difficulty lies in the high level of manual effort that has to be carried out to generate context in the available content.

- **Spare parts management**
Missing spare parts can lead to considerable delays in eliminating malfunctions. With smart maintenance, consumption can be better predicted. With 3D printing, for example, an optimization of spare parts and a shortening of their procurement time can be realized. Also decentralized value-added networks can be set up and processes can be optimized with autonomous transport systems.
- **Value contribution**
In Smart Maintenance, maintenance is understood as a value-adding partner which goes beyond the mere provision of needs-based availability of technical assets. In addition to avoiding direct and indirect maintenance costs, efficient and effective maintenance contributes to an increase in productivity and quality. It ensures a balanced workforce of employees and secures important, implicit domain knowledge for the company. The added value of smart maintenance is therefore an important factor in maintaining and even expanding the competitiveness of manufacturing companies.

Final word

Maintenance becomes smarter by adapting:

- Data collection with Smart sensors;
- Big data, cloud (sharing product service and factory functions) and edge computing for online monitoring and control of the system in real time using diagnostic and reactive decision-making and online data analysis by transferring customer requirements to products and investigating manufacturability using existing resource or outsourcing services;
- Standard and secure communication using standardized communication protocol (information can be reordered, enriched, and saved in the integration layer);
- Modular and decentralized control architecture, standard supply infrastructure for connecting system components to all supply layers;
- Modular machine tools or workstations for the flexibility of machines and workstations to be reconfigured and multi-skilled workforce for performing several types of tasks, including decision making, supervision, maintenance, programming or performing a manual assembly or process;
- Reconfigurable fixture for adjustability of a fixture to hold set(s) of parts or products and reconfigurable tools for the capability of tools to be used indifferent tasks (i.e., tightening different sizes of bolts).

Implementing such strategy the system becomes collaborative, capable of sharing meaningful information, aiming to accomplish system goals. Also it becomes able to recover from disturbances without or with minimal human intervention in near real-time, increasing its heal ability. As a result maximization of equipment uptime, reliability and availability, reduction of costs, elimination of risks and optimization of operational efficiency brings the core value to this change.

Conclusion

The ongoing global change, pushing the digital transformation to industry 4.0, reflects the launch of new services, new process innovations or other innovative solutions, tackling existing pressure on costs and prices. Therefore, we believe AI will be integral to all future smart maintenance endeavors. Missing such opportunities might prove disastrous, as companies will not be able to follow the pace. Providing relevant data at any time and from anywhere, generating new insights using big data processing and AI to support decision-making is a core advantage in the global market. The use and integration of exponential technologies needs to be gradual but steady. In such ways that companies are enabled to flexibly adjust to customers' needs, increasing customers' satisfaction, as well as to customize product cycles, without disturbing internal or external processes. Companies need to develop new specialist skills in the areas of analytics and efficient data management and put new business processes in place according to the insights generated.

The traditional maintenance and reliability professionals have the primary goal of improving

asset availability and performance. Additionally, maximizing equipment uptime, minimizing unplanned equipment downtime, identifying potential failures, increasing connectivity and better managing maintenance outsourcing even further challenge the maintenance operation. While learning is the key to sustainable organizational development, there is a clear need to bring in additional AI specialists and data scientists to complement the knowledge and experience already present in maintenance teams. The effective analysis, assessment and application of the data collected from machines and sensors is what makes maintenance smarter and all these goals possible. It also improves operational safety, work processes and servicing. Transparency makes development and production processes more efficient offering substantial operational cost reductions. Maintenance work can be carried out in a true needs-oriented manner, creating long-term competitive advantages in both reliability and price. The new generation of intelligent maintenance systems, driven by big data analysis and advanced diagnostics, are already guiding automated predictive innovation towards the ideal of zero-failure activity.

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