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Advanced sensor-based maintenance in real-world exemplary cases

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ABSTRACT

Collecting complex information on the status of machinery is the enabler for advanced maintenance activities, and one of the main players in this process is the sensor. This paper describes modern maintenance strategies that lead to Condition-Based Maintenance. This paper discusses the sensors that can be used to support maintenance, as of different categories, spanning from common off-the-shelf sensors, to specialized sensors monitoring very specific characteristics, and to virtual sensors. This paper also presents four different real-world examples of project pilots that make use of the described sensors and draws a comparison between them. In particular, each scenario has unique characteristics requiring different families of sensors, but on the other hand provides similar characteristics on other aspects.

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Condition-based maintenance; predictive maintenance; virtual sensors; use cases; demonstrators; pilots

1. Introduction

The development of new materials and sensor technologies that enable the production of more cost-effective sensors (with still adequate reliability) and the simultaneous increase of processing power of relatively cheap processors have dramatically increased the interest to use these kinds of devices in the support of maintenance and maintenance services. The advances in industrial electronics are the leading forces for the fourth industrial revolution. While most factories have traditionally made heavy use of electronics and information technology to automate production (third industrial evolution), the novel paradigm aims at maximizing the benefits of information by integrating multiple data sources and by ubiquitous access to the information itself [1]. It is expected that this, in turn, will enable the introduction of the Condition-Based Maintenance (CBM) strategy, i.e. maintenance is carried out when it is needed, instead of based on pre-defined schedules or when the production machinery stops working.

When the new technology is used in an ideal way, the measured data can be used to automate diagnosis, whose results can be passed to the Computerised Maintenance Management System (CMMS) for managing the maintenance work orders and spare parts supply [2]. Naturally, the introduction of all of this is a demanding task, but the most important new aspect is the availability of reliable data anywhere where it is

needed through the internet. Consequently, companies that so far have only been selling production equipment for global markets can now also offer maintenance services for their products. This in turn will mean more stable income for them, which does not vary only based on sales, and at the same time a new possibility for their customers to concentrate on production of their own products instead of worrying about the availability of the production equipment.

Building a CBM service platform was the goal of the MANTIS Project [3], which was a European initiative that aimed at enabling novel maintenance strategies of industrial machinery pertaining to different industries. The project was focused on the real-world application of the developed techniques, and its pilots were centred on machines whose design was adapted for the inclusion of novel maintenance techniques. In this sense, the pilots were the testing ground for the innovative functionalities of the CBM service platform architecture and for its future exploitation in the industrial world.

Productive 4.0 [4] is a European project that aims to foster the digitization of the manufacturing industry, and one of its technological pillars is the servitization of all communication between involved devices, which can span from cyber-physical systems (CPS) to servers in the cloud. The Productive 4.0's middleware is instrumental in facilitating secure data collection from sensors used in CBM platforms.

This paper focuses on the sensors that are of interest to CBM project pilots. An analysis is drawn between different pilots, to expose how they are technically different but can still benefit from CBM and advanced sensing techniques in general.

In Section 2, the paper defines what CBM is by building over other maintenance strategies and describes how it is enabled by sensing activities. Section 3 delves into an analysis of sensors as pertaining to off the shelf, custom and virtual sensor categories. Section 4 showcases the application of sensing techniques to maintenance in real pilots. Section 5 discusses the differences and commonalities between the pilots and draws some conclusions on the topic at hand.

2. Background information

This section introduces concepts related to advanced maintenance, to drive the discussion on the rest of the paper, and provides insights on related work and the projects that have investigated CBM and the sensors enabling it. A list of the abbreviations used in the paper is reported in Table 1.

2.1. Supporting concepts in manufacturing maintenance

As stated in [5], maintenance is a strategic activity aimed to assure the operation reliability and/or a certain degree of continuity of equipment and/or processes where this equipment is installed while ensuring the safety of people that are part of it. Moreover, it is globally recognized that maintenance play a fundamental role in the whole lifecycle of an asset from its installation passing through operational stage and decomposition stage [6]. It is clear that maintenance is becoming, more and more, involved into the decision-making process (operational and strategic decisions) related to the

asset acquisition, design, operation, customer satisfaction and sustainability within the enterprise as confirmed in [6]. Therefore, maintenance activities and procedures are always on high pressure from the top management levels of companies to guarantee cost reductions in terms of money and time of the intervention before the equipment lose performance within a threshold [7]. Several policies and strategies for maintenance have been defined, developed and adopted in the past: (i) Corrective Maintenance (CM); (ii) Preventive Maintenance (PM) and (iii) Condition-Based Maintenance (CBM). These policies and strategies are strictly linked to the technological progress in the recent years and reflect the growing need for companies to be competitive [8].

CM also called Run-to-failure and reactive maintenance can be described as a fire-fight approach, meaning that the production equipment is only replaced or repaired after it breaks. It has the advantage of minimizing manpower to keep things running. Disadvantages reside in large levels of scrap, unpredictable production capacity and high overall maintenance costs.

PM, which includes both time and usage-based maintenance, relies on periodic maintenance execution that can range from equipment lubrication to replacement. Maintenance tasks are performed based on specific periods of time, amount of machine usage (number of working hours) and/or mean time to failure (MTTF) statistics. This approach requires production stoppages for maintenance, but it improves equipment lifetime and it reduces malfunction probability [9]. Due to the periodic aspect of the policy, the replacement of equipment may occur prematurely as well as failures can occur [10].

CBM relies on continuous equipment condition monitoring by means of physical measurements (e.g. temperature, vibration, noise, lubrication, corrosion) [11], as well as offline analysis and modelling of the degradation profiles for remaining useful life (RUL) estimation with current measurements. When these measurements reach a certain level, preventive maintenance is applied. In this sense, maintenance only happens based on the need when a certain threshold is reached. As a matter of fact: *“PM is a philosophy or attitude that, uses the actual operating condition of plant equipment and systems to optimize the total plant operation”* [12]. Therefore, CBM did not emerge to replace CM and PM, but as an additional tool to improve them. CBM includes different actions, from system design phase, workmanship, scheduling and maintenance procedures, to the usage of communication technologies, feedback information and optimization techniques [13], to investigate the root causes of the problems, and dealing with them before problems occur.

The successful implementation of CBM strategies strictly depends on the availability of an efficient and

Table 1. The following abbreviations are used in this manuscript.

AE	Acoustic Emission
BLE	Bluetooth Low Energy
CBM	Condition-Based Maintenance
CM	Corrective Maintenance
CMMS	Computerised Maintenance Management System
CNC	Computer Numerical Controller
CPS	Cyber-Physical Systems
DB	Database
ERP	Enterprise Resource Planning
HMI	Human Machine Interface
IMU	Inertial Measurement Unit
MAS	Multi-Agent System
MTTF	Mean Time to Failure
PAPM	Periodic and Automatic Periodic Monitoring
PM	Preventive Maintenance
PRS	Philips Remote Service
RUL	Remaining Useful Life
SM	Spot Measurement
SOA	Service-Oriented Architecture

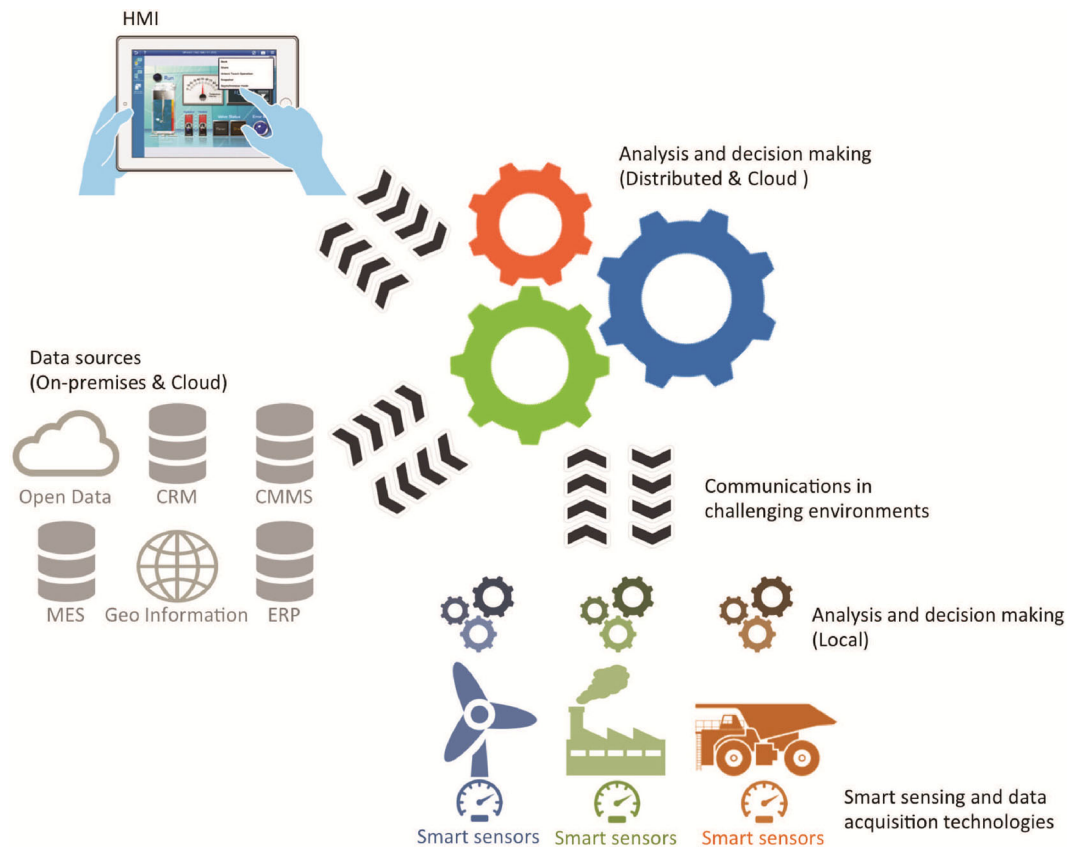


Figure 1. Key technologies for CBM.

effective monitoring infrastructure that can gather relevant operational data from the machine/equipment and combine and analyse these data to identify possible breakdowns and their root causes. Therefore, a CBM service platform should have distributed processing chains, which distill raw data into knowledge, while minimizing bandwidth usage. These platforms need to include key technologies such as (see Figure 1): Smart sensors, actuators and CPS; Robust communication systems for harsh environments; Distributed machine learning for data validation and decision-making; Cloud-based processing, analytics and data availability; and Human Machine Interfaces to visualize information. In particular, the foundation of such a platform is the sensing capability, which is bestowed into sensors and has the responsibility of nourishing the system with vital information from equipment and processes. In fact, CBM relies on item/equipment constant condition monitoring and evaluation to avoid machine failures.

2.2. Related work

The analysis of the State of the Art highlighted that in the last decade several research and prototyping actions, initiatives and efforts have been developed addressing the digitalization of the manufacturing sector in Europe, the USA and Asia [14–17]. Putting the light on Europe, the pervasive digitalization of the

industry – driven by technological breakthroughs – is opening new opportunities for industry to become more efficient and effective while ensuring enhanced and improved processes, production systems and operations. If from one side, the digital transformation is putting maintenance into great pressure – due to the great impact it has on production quality, quantity, costs and final customer satisfaction – from the other side, it is triggering the development of new and more effective and efficient maintenance activities, procedures and practices [6]. In particular, the following technological areas are expected to trigger the transformation of the maintenance management concepts, philosophies, policies, strategies and practices (extracted from [18]):

- ICT solutions for factory floor and physical world inclusion: to deliver all the necessary mechanisms to facilitate the connection and the information sharing between physical assets (such as machinery, robots, production lines, etc.) and between physical assets and back-end systems;
- ICT solutions for the next generation data storage and information mining: to deliver all the necessary mechanisms for data extraction, data transformation and loading for allowing the connection of business intelligence tools for data mining, stream processing, knowledge discovery for supporting the decision-making process;

- ICT solutions for implementing high-performance and services platforms: to deliver a distributed ecosystem of services and related applications for the provisioning of customized functionalities;
- ICT solutions for modelling and simulation: to deliver dedicated modelling and simulation tools to describe the dynamics and predict the behaviour of the physical assets;
- Collaborative and decentralized application architectures and development tools: to deliver highly decentralized solutions that facilitate the integration of maximum information from monitoring, life cycle management and enterprise resource planning (ERP) applications in a common maintenance-oriented application platform.

With this in mind, several EU founded projects can be selected and analysed to provide a vision of the digital transformation of the European industry while highlighting the importance of the analysis of the data provided by sensors for the assessment of the equipment status. The selected projects are: FP7-PRIME [19], FP7- SELF-LEARNING [20], H2020-PROPHESY [21], H2020-PERFORM [22], H2020-GOODMAN [23], ARTEMIS-Arrowhead [24], ECSEL-MANTIS [3], ECSEL-Productive 4.0 [4].

Most of the research work is related to the implementation of CBM solutions mainly targeted the implementation of CPS-based systems thus, focused on the following main principles adapted from [25,26], namely:

- (1) abstraction and architectures;
- (2) decentralization, modularity and composability;
- (3) interoperability;
- (4) real-time capability;
- (5) interconnected data and data analytics/processing.

As an example, the PRIME and GOODMAN projects mainly used the Multi-Agent System (MAS) technology and cloud technologies to deliver a distributed architecture made up of agents. The proposed architectures provided virtualized functions for ensuring the monitoring and control of physical assets, i.e. the extraction, transmission and loading of sensor information for the derivation of production decisions and the control of production processes. The Self-Learning, Arrowhead, PERFORM and PROPHESY projects mainly used Service-Oriented Architecture (SOA) technologies and approaches for building distributed architectures made up of smart and intelligent components that expose services. Similarly to MANTIS and Productive 4.0, these projects rely on the Arrowhead for implementing CPS-based solutions, i.e. to enable the implementation of an interoperable and integrable framework that facilitates the data collection, data analysis and processing.

It can be noticed that the main focus and common ground between the considered actions is: (1) the extraction of the data from the environment by using a sensing layer used by CPS; (2) the faults/anomalies detection from the data available from sensors and (3) the diagnosis of the causes of these faults/anomalies.

Other works such as [27] consider to create a control loop using collected data, for example to mitigate machining vibrations to both improve the result of the production process and increase the lifetime of the machine. On the contrary, in the context of this paper, the main idea is to provide insights regarding the sensing layer and study how it enables CBM in different domains of application.

The problem of monitoring numerous concurrent activities is considered in [28], where a software-sensor-based activity-time and performance measurement system is proposed. Here, fixture sensors and an indoor positioning system data were merged with product-relevant information, to allow a real-time connection between operator performance and varying production.

In [29], sensor fusion for dynamic object tracking is used. Measurements from several sensors are used to increase accuracy and give more reliable and robust estimates. There, sensor measurements are combined at various levels (raw data, state vector, decision level). In [30], some findings are presented about monitoring a channel hydrodynamic behaviour by means of sensors based on imaging and ultrasound.

In this landscape, the demand of intelligent sensors and sensor systems as the key enabler of enhanced flexibility, adaptability, configurability and agility in production processes has been fully recognized, as also confirmed in [31,32]. However, most of the solutions and designs provided by research projects are still underestimating the impact that the choice of sensor systems has on situational control and decisions. As a result, the presented research shows how different domains and application scenarios prefer specific sensing layers with unique characteristics.

Preliminary research activities [33] have laid the groundwork for the present work, by defining the main categories for sensors used in CBM and by briefly describing some of the pilots that are analysed in this paper. Anyway, there is the need to provide more information regarding the topic at hand, both in terms of characterizing the sensorization (i.e. adding sensors in a device, to allow for online data collection regarding its status) of CBM-supported systems, by discussing the problem of sensor ageing, which plagues hardware sensors deployed in harsh environments such as factories, by providing more details regarding how CBM is enabled by sensors in the pilots, and by presenting the pilot on the monitoring of wind turbines, which shows the application of off-the-shelf sensors for a very specific – but effective – monitoring strategy.

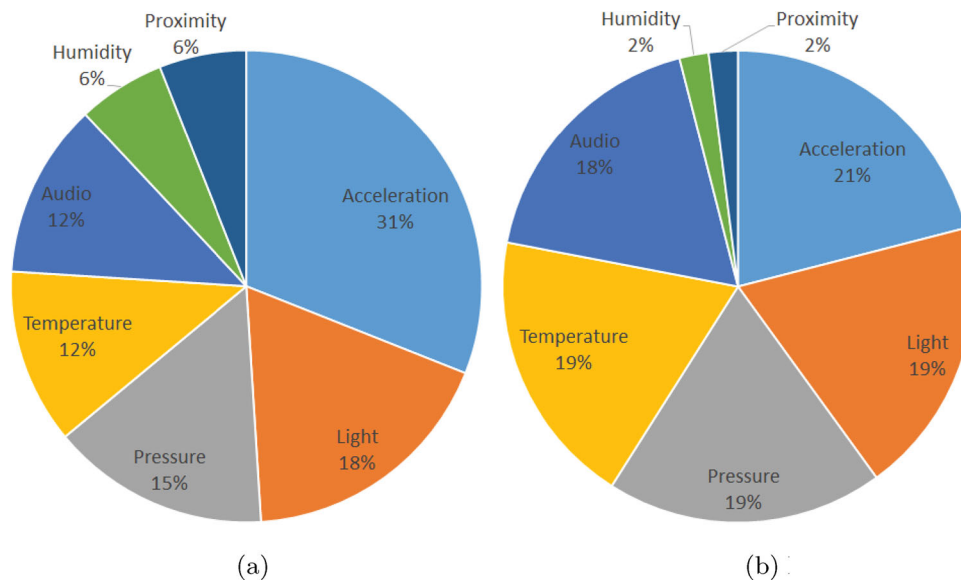


Figure 2. Distribution of sensor types: (a) distribution by applications and (b) distribution by nodes.

3. Sensors for machine maintenance

Sensors for advanced maintenance operations can be classified into a number of ways. While focusing on real-world pilots, this paper differentiates the sensors as common off-the-shelf sensors (Section 3.1), custom sensors that are created for specific maintenance applications (Section 3.2) and virtual (software) sensors (Section 3.4). Moreover, Section 3.3 deals with ageing issues that are relevant for off-the-shelf and custom sensors.

3.1. Off-the-shelf sensors

According to [34] that examined more than 300 devices in 12 different applications, one can observe two distributions of sensor types, i.e. by application usability and nodes availability (see Figure 2). In addition, seven sensor types were identified as the most common sensors: temperature, acceleration, light, force, audio, humidity and proximity. The analysis also considers that most sensor nodes offer multiple physical data sources (e.g. pressure, light and temperature).

The effect of temperature can be noticed on materials (solids or fluids) and components. These effects can have a significant impact on operation of machines by causing increased wear, hydraulic systems degradation, materials expansion, etc. Proper temperature sensing allows for the continuous analysis of temperature variation and/or its stability. For example, scanning bearing housing on motors can prevent major failures. Monitoring the temperature of fluids is useful, as some properties of fluids degrade with increased temperature.

Mechanical systems are composed of many moving parts that deteriorate over time and generate vibration. Therefore, collecting acceleration data allows early detection of rolling element bearing faults, gear wear, etc.

Measuring the pressure of pumps can reveal their physical changes. Operating conditions, such as fluid type, temperature, and speed affect the pressure, and if the pressure goes outside a given range, there is the possibility of damaging parts. Moreover, pressure variation can lead to cavitation (creation of vapour cavities in a fluid), which can potentially lead to material damage [35]. Cavitation can be sensed either by means of pressure or vibration or acoustic emission or sound measurement.

The usage of light sensors may include the detection of material cracks and object detection. By placing an object between a light source and a light sensor, cracks can be detected by the amount of light that goes through the object. Moreover, if a shadow is formed on the light sensor, it can indicate the presence of an object in a certain area, such as a person near a cutting machine, and thus shutdown the machine for safety reasons.

Sound monitoring is strongly related to vibration sensors. While vibration sensors register the motion of the component they are rigidly attached to, microphones listen to a component. Microphones are in some cases used to monitor bearings and gearboxes.

Monitoring the percentage of humidity in a certain environment can be useful, as for example, high levels of humidity in an injection moulding process line can add moisture to resins, causing improper moulding of produced parts. The accumulation of moisture in gearboxes can lead to gearbox corrosion, reduced efficiency and breakdown.

Proximity sensors can be used to measure the displacement of parts, improper presence of objects and vibration in rotational components. In case of non-contact measurement, with the sonar or infrared light emission it is possible to detect the presence of objects in the observed area.



Figure 3. Torque sensor.

3.2. Custom sensors

Many other kinds of sensors can be found in specific applications. Usually, these sensors are not mass produced, their structure presents a high degree of customization, and they retrieve very specific environmental data. Among the plethora of the custom sensors, there are sensors capable of performing crack detection, torque measurement, analyse wear of material and retrieve oil status [36].

The early detection of cracks allows the prevention of fracture failures. These cracks can be produced by applied stress concentration, excessive stress over time, overload, defective assembly or environmental conditions. Crack detection (through non-destructive methods) can be performed using different techniques such as radiography, ultrasonic and shearography [37], penetrating liquid [38], magnetic particle inspection [39].

Several sensing techniques can be applied to estimate or compute torque. Through components speed, it is possible to calculate torque and torque brake; an alternative method is using pressure sensors to correlate with the torque brake [40]. Other custom sensors (Figure 3) can target deviation of torque, brake torque and friction values from the normal values, since they can detect shaft misalignment or the presence of wear particles, which in turn are predictors for equipment malfunction.

Another type of custom sensor is the oil sensor. Oil sensors can be divided into different groups based on the data under measurement, such as oil condition, oil temperature and oil pressure. Oil condition sensors have the capability to detect ferrous particles, water, viscosity changes, etc. [41]. Oil condition monitoring allows the detection of lubricant related engine wear and lubricant quality degradation, among other problems [42]. Early problem detection leads to on-time,

preventive adjustments that reduce machinery downtime.

3.3. Sensor ageing

Whether off-the-shelf (Section 3.1) or custom sensors (Section 3.2) are used, they must be robust and built in such a way that they withstand the rigours of industrial environments. All electronic devices have limitations and real sensors are no exception. In many cases, right away after being bought, off-the-shelf sensors are unable to fulfil the requirements in CBM monitoring. Hence, there is often a need for the optimization of sensors for specific conditions, and particularly for the use in harsh environments. A reasonable solution to this problem can be the right choice of a suitable sensor technology together with the implementation of an appropriate measurement (monitoring) strategy. Furthermore, an important aspect of sensor application in system maintenance is ageing. Sensor characteristics are degraded with time and for this reason they should be monitored as well.

Several studies show that the key sensor characteristics (e.g. the offset and the functional sensitivity) normally change to some extent in the course of time [43–46]. Operation in harsh environmental conditions (high temperature, aggressive medium, location, frequency and intensity of loadings) certainly accelerates the ageing rate of sensors. The ageing manifests in deterioration of material and the defects in the sensing structure influencing the reliability of the sensor readings.

While physical systems and their working environment are continuously monitored by a range of sensors, resulting in massive amounts of data, we need to consider the sensor ageing and need to have some measures

to mitigate time ageing in order to correctly interpret the data.

Non-negligible ageing of the sensors should also be taken into account when selecting the sensing components for CBM monitoring. One can improve the reliability of the sensor readings by introducing redundant sensing hardware into the system, but such solutions may not always be feasible due to cost and space constraints. Therefore, it is important to consider sensor's characteristics degradation over time and for this reason they should be monitored as well. Besides the proper selection of the sensing components, this might also include the proper interpretation of sensor data.

The problem of monitoring the sensor's performance has been considered by many authors. One solution is an approach based on capturing dynamic characteristics of the sensor within the sensor readings separately from those of the monitored system [47], which enables tracking of key dynamic indicators of the sensor and statistically assess the significance of their changes. In [48], the authors discuss three different methods for the sensors' conditions monitoring based on their own measurements which are able to detect deterioration/failures of the sensor parts in time for their replacement. Alternatively, a possible solution can be an implementation of virtual sensors.

3.4. Virtual sensors

The virtual sensor is a technology used to retrieve more effective and accurate information from collected data [49,50]. Virtual sensors make use of readings collected either by multiple networks or from a single sensor. Data are combined from multiple sources (e.g. temperature, humidity, CO₂) and process models are applied to compute new outputs, based not only on current sensor values but also on its time series.

The Virtual Sensor Architecture, whose view is represented in Figure 4, can retrieve sensor data either in an *event-based* acquisition, meaning that physical sensors will make the data available (generate events) when certain conditions are met; or in a *time-based* fashion, where the virtual sensor will periodically inquire the physical sensors for new data. This step is accomplished in the *Acquisition Method* module. The *Aggregation Functions* module has the task of applying common mathematical functions (e.g. temperature average of different sensors in a same room) or complex models (e.g. wear prediction model). The entity/user managing the virtual sensor has the capability (through the *Dynamic Configurator* module) to change threshold parameters used to generate outputs or to change signal evaluation parameters. Configuration parameters are kept in the *Virtual Sensor Parameters* module and are used by the *Signal(s) Evaluation* module to perform an analysis of the results achieved in the *Aggregation*

Functions module. Finally, similar to the *Acquisition Method*, the *Response Method* module is able to generate the virtual sensor output, by the same two common paradigms, i.e. through events or in a time-based manner.

Virtual sensors are used in different areas, such as computer science, construction, chemistry and transportation systems. In computer science, virtual sensors (i.e. programs) hide hardware components from upper-level applications. They offer consistent and reconfigurable information and are easier to maintain and upgrade than real sensors. A virtual sensor example in a construction site is to determine if a crane has exceeded its capacity. Using physical sensors to monitor angle and wind speed, calculations can be performed by virtual sensors to evaluate instant working safety [51]. Another example is the usage of virtual sensors in chemistry, in applications that control air quality, leaks and danger of an explosion. The combined usage of temperature and gas concentration raw data, allows the production of virtual sensor outputs that discriminate between H₂, CO and humidity. An example regarding transportation is based on the Washington State's Traffic Management System [52], where a virtual sensor was developed that relied on real-time data from road sensors, to predict traffic on roads that do not have real sensors. Both virtual and real sensing data are provided to the Transportation Department.

4. Use cases

This section presents four pilots in which the usage of CBM can facilitate maintenance interventions, cost reduction, equipments lifetime, and in general provide added value to the industrial process. With respect to a traditional remote maintenance scenario, and most previous work, the main objective of a CBM system is not only to monitor an asset but also to infer its current and future condition and take decisions in its maintenance, by means of leveraging multiple data sources and advanced data analysis to distill all collected data into high-level information leading to informed decisions.

The four pilots were built in the context of the MANTIS project [3], and all of them feature real-world factories and installation. Therefore, the use cases provide a connection between the role that CBM is supposed to hold, and what is actually happening in real installations as technology evolves and our economy and society change with it. The first pilot (Section 4.1) exploits the composition of data from off-the-shelf sensors, the second one (Section 4.2) focuses on the use of custom sensors, the third one (Section 4.3) features virtual sensors, and the fourth one (Section 4.4) uses a set of sensors deployed dynamically by using a robotic platform.

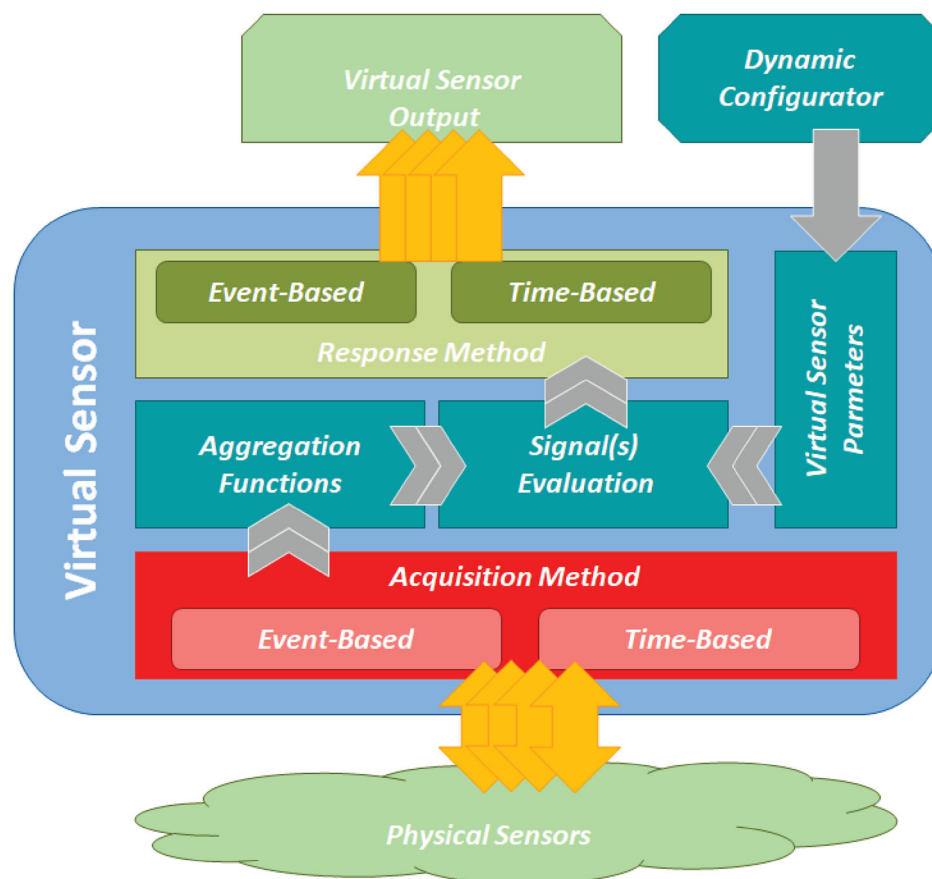


Figure 4. View on the virtual sensor architecture.

4.1. Monitoring of a sheet metal bender

The Sheet Metal Bender pilot [53], whose architecture is represented in Figure 5 involves detection, prediction and diagnosis of malfunctions in a sheet metal bender machine that pertains to the Greenbender family, manufactured and commercialized by ADIRA (see Figure 6). The machine is able to exert a force up to 2200 kN using 2 electric motors of 7.5 kW each, and it is able to bend metal with high precision. Moreover, the Greenbender is able to save energy by the order of 65% (95% while in stand-by mode, 45% when operating) with respect to similar equipment, and it is aligned in this sense with the European directive EcoDesign (2005/32/CE).

The use case considers two scenarios. In the first scenario, a malfunction in a component raises the need for the replacement of component(s), and the goal of the work is to allow the monitoring subsystem to detect a potential failure in the industrial process, perform proper analysis, and communicate the replacement operation that must be implemented. The second scenario aims to predict machine failures before they occur, by means of applying machine learning techniques to data collected from the sensors.

Data are collected from sensors used for the automation of the machine, which existed previously to the MANTIS project and gathered by the Computer

Numerical Controller (CNC) of the machine, and from two new sets of sensors, an oil sensor and two accelerometers.

A sensor responding to the Custom Sensors category (see Section 3.2) monitors the oil that lubricates the machine's hydraulic circuits, both in terms of its temperature and its quality, being the latter related with presence of contaminators like water, particles, glycol and other impurities in the oil.

The system that analyses the oil consists of two parts, the sensor unit (Hydac Sensor AS1008), and the data acquisition and computation board. The sensor reads temperature from -25 to 100 °C, and saturation from 0% to 100%. Both signals are reported using a 4–20 mA interface. The data acquisition/computation module receives the signals, convert them and exports the data through an analogical voltage signal with a range from 0 V to 10 V to the machine's CNC. The CNC digitalizes and sends the data through a communication middleware to the cloud for storage and processing, the latter being the comparison with custom thresholds.

Two accelerometers (highlighted in Figure 6) pertaining to the off-the-shelf category (Section 3.1) monitor the blade that performs the bending of the metal sheet, both in terms of its movement, and the vibration patterns caused by the hydraulics. In fact, the vibratory pattern can be related to the condition of the machine's

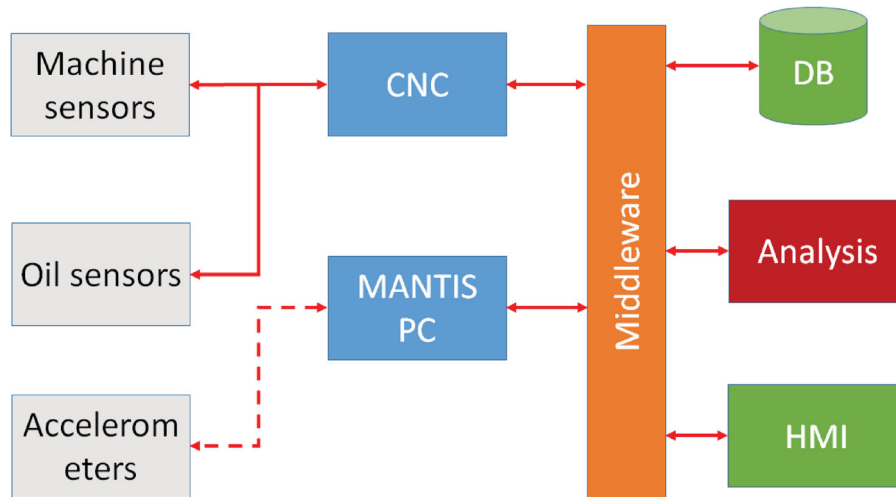


Figure 5. Monitoring architecture for metal sheet bender.



Figure 6. Frontal view of the machine with two Inertial Measurement Units (IMUs).

bending motors, and the collected data can thus be used to perform CBM of the machine. Data are sent to the cloud for storage and processing, and machine learning is used to learn vibration patterns and detect outliers, from which CBM can predict failures. For example, if the hydraulic pistons are starting to malfunction due to the existence of particles in the oil, a different vibration pattern can be detected.

The sensors are based on the Arduino 101 platform that provides a 3-axis accelerometer with a maximum amplitude range of 8g, and are battery-powered in order to ease components' installation. For this specific pilot, the sensors were configured for a lower measurement range (0g to 2g) to attain a better accuracy.

The MANTIS-PC is a Raspberry Pi 3 Model B that acts as a Bluetooth Low Energy (BLE) server, a

data-converter, a middleware client, and provides a simple User Interface to inspect the data as they are collected. The MANTIS-PC uses a server-side JavaScript program built over Node.js and the noble library to collect values from both sensors with a period of 30 milliseconds, and sends them to cloud through the Middleware component, which is based on the AMQP [54] protocol. The cloud hosts the components to store the data (Database, or DB), to analyse them (Analysis) and to interact with the user (Human Machine Interface or HMI). The simple HMI presented by the MANTIS-PC (Figure 7) uses a server-side/client-side JavaScript based on Node.js to send warnings to management personnel. The interface is based on the *Highcharts* library, and it enjoys its “full-responsiveness” capabilities.



Figure 7. Simple Human Machine Interface (HMI).



Figure 8. A stamping press machine.

4.2. Press machine maintenance

A stamping press (Figure 8) is a metal working machine used to shape or cut metal by deforming it with a die. This use case focuses on press machine maintenance, monitored continuously by a broad and diverse range of intelligent sensors that keep track of its operational conditions.

A mechanical press, during its active lifetime, might be capable of giving more than 40 million strokes applying forces of the order of $2000Tn$, insofar as it is used – and maintained – appropriately. The machine under study belongs to Fagor Arrasate, whose customers demand products with high quality and availability. These latter characteristics are in contrast with the production downtime caused by unnecessary maintenance and repair operations. Therefore, based on

financial studies, it was decided to incorporate cyber-physical systems in the most critical components, to facilitate CBM activities in order to provide high availability but without extensive unnecessary maintenance operations, besides reducing malfunction chances and improving lifetime.

CBM activities in this use case enabled by a cloud service platform, which makes use of data captured continuously, monitored, transmitted, stored and analysed by intelligent sensors responding to the Custom Sensor category (see Section 3.2). In particular, two applications collect data from multiple data sources related to press structural health, crank forces and wear-ing of gears and bushings.

A first application is focused on structural health monitoring by means of an early detection of cracks/

fissures in the press' head and caps, which enables to prevent damaging fracture failures caused by press' damping and stress concentration in certain parts of the structure. Both crack gauges and conductive inks are being used, the last allowing higher surface measurements. In the latter case, ink is spread on the surface of the monitored component, and the current passing through the ink is measured and compared with a threshold. The rationale is that cracks on the target make the ink break and thus increase the resistivity of the circuit. A key factor for an optimized application is to thoroughly choose and deposit a proper insulating layer, by means of flexibility, among other facts, as the crack needs to be naturally transferred up to the ink layer, behaving likewise.

The second application is represented in Figure 9, and it implies the sensorization of a gear shaft. A shaft-adapted wireless sensor node [55] comprises a transducer (torque oriented gauges), a signal conditioning front-end and a wireless microcontroller, the latter allowing a local preprocessing and treatment of the collected data. Two software approaches are implemented. In the first one, a finite iteration based auto-zeroing algorithm is applied, which configures the proper gain and offset values for the system, taking into account gauge's signal and measured signal feedback, thus enhancing system's dynamic range and avoiding signal saturation. In the second one, digital data are retrieved and preprocessed, reducing the payload by means of averaging. These data are transmitted to a gateway based on the Beagle Bone platform via a custom industrial protocol, since standard ones either lack of deterministic features (e.g. IEE802.15.4) or scalability (e.g. IEEE 802.15.1). Moreover, widespread industrial solutions (e.g. ISA 100.11a) do not provide tools for guaranteeing sampling synchronization, which is critical for certain applications, therefore a TDMA MAC has been placed on top of the physical layer and specific synchronization elements have been added for obtaining synchronized *analogue digital converter* conversions in nodes [56]. Finally, the necessary calculations to obtain torque values (Nm) are done in a computer connected to the gateway.

The fact that the sensor has to be applied in a rotatory and shaky shaft (working at approximately 88 rpm) implies, on one hand, the need to develop a robust housing architecture and housing to protect it from vibrations and lubrication oiliness [57]. Regarding the electrical domain, a proper isolation from electromagnetic interference is needed, protecting the most sensitive signals and components, by means of dedicated filtering configurations, passive elements additions or shielding. On the other hand, a power friendly approach must be considered, such that the wireless sensor can work without external grid power. Current design allows a finite duration of the measurement process, as the system is powered with a small Li-Ion

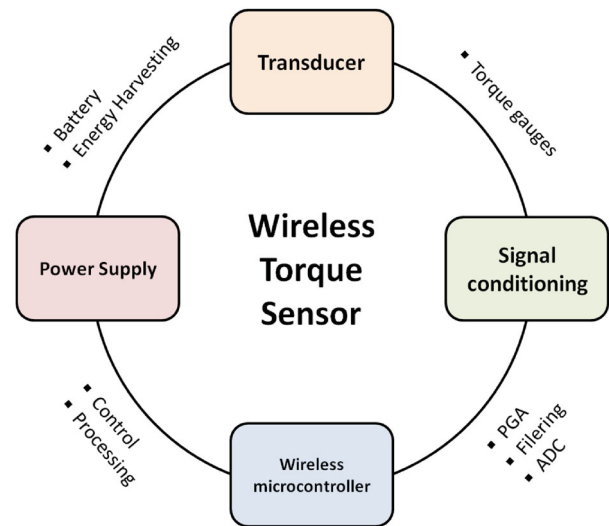


Figure 9. Wireless torque sensor node block diagram.

battery. Thus supplementary solutions such as wireless power or energy harvesting are under analysis. In fact, this latter approach is of interest in this scenario, where multiple energy sources are available, such as vibrations, temperature and radio frequency noise. The key factor is a good matching between the available energy source [58] in such scenario and the most suitable harvesting technology for it, in order to scale an optimize harvesting solution. Once that is defined, a well-suited low power energy acquisition, storage and management unit is needed, which controls the systems power supply or support efficiently.

4.3. Maintenance of medical devices

Modern medical devices have a large number of embedded sensors, and in this use case CBM is applied to advanced medical devices from Philips that can perform non-invasive patient diagnosis. Installed sensors cover the complete range of off-the-shelf sensor type (Section 3.1), and data are distilled into more advanced information by means of virtual sensors (Section 3.4). The hardware sensor solution under development is a stand-alone sensor box, the e-Alert controller, that can autonomously monitor environmental conditions of the medical device, and that can generate electronic notifications to different users of the medical device. The e-Alert controller (Figure 10) is based on a Raspberry Pi platform, and it can sample connected sensors, for example, temperature sensors, humidity sensors, magnetic field sensors. These sensors are connected to an interface box (max 8 sensors per interface box), and the interface box is connected to one of the inputs of the e-Alert controller box. Multiple interface boxes can be daisy-chained. This provides a scalable sensor platform that can be tailored for the specific device under monitoring.



Figure 10. e-Alert controller box to monitor environmental conditions in a medical device.

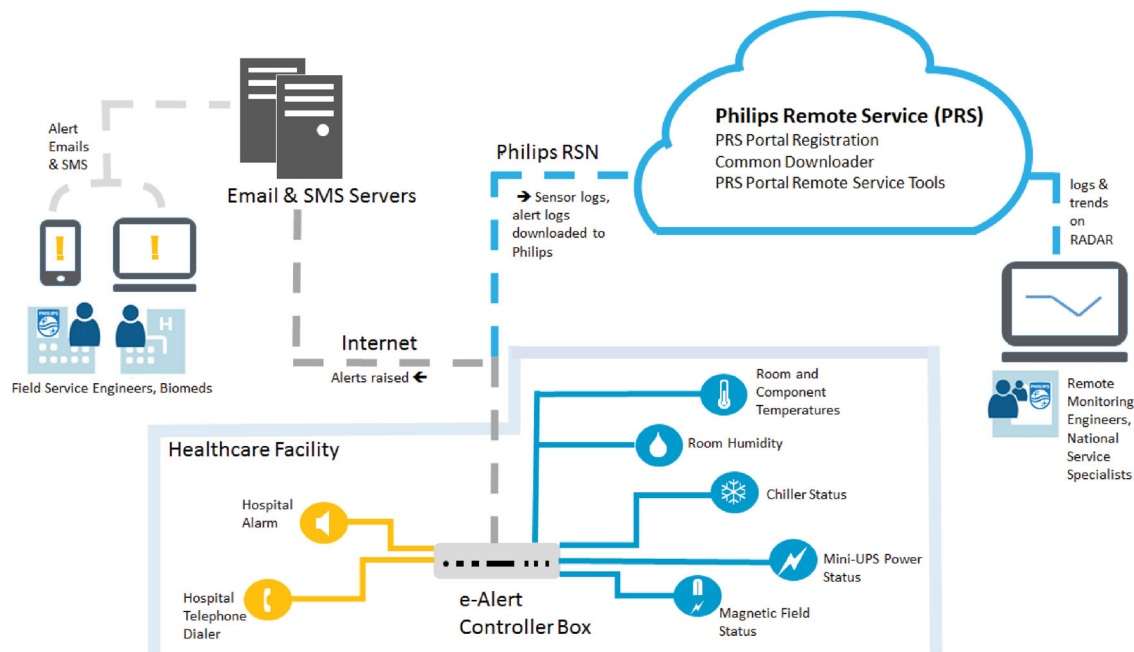


Figure 11. Sensor context diagram.

The e-Alert controller box acquires sensor values once per minute and checks these values against configured thresholds. To avoid false positives, a sensor value must be out-of-spec for a number of consecutive samples before an alert is raised. If a sensor value remains out of the configured threshold, the e-Alert controller box sends an Email or SMS alert to configured alert receivers.

The e-Alert controller software is represented in Figure 11. It provides a web-based user interface to configure sensors, thresholds, Email/SMS server and Email/SMS receivers. The e-Alert controller is connected to the hospital network and, through its IT infrastructure, healthcare facility staff can access the user interface of the e-Alert controller. This user interface provides capabilities to view the history of sensor values when root cause analysis is required after an alert. Moreover, the user interface allows to reconfigure the e-Alert controller, for example for its alert thresholds, and to update its embedded software.

The e-Alert controller also provides a capability to interface with the medical device manufacturer. For this purpose, connectivity to Philips Remote Service (PRS) can be configured. With this interface, sensor values can

be aggregated and statistically analysed by the manufacturer. This enables the manufacturer to determine an operational profile, specific to that medical device. This information can be used to fine-tune the configured alert thresholds for that specific device to keep the medical device in optimal operational conditions. The benefits from the CBM strategy can easily be seen, since the device is life critical. It is not acceptable that devices would fail when in use as it is not financially possible to have redundancy, and moving of patients to another hospital might not be possible, and thus it is of the utmost importance to minimize devices' downtime.

A web-based portal (Figure 12) was developed to access the e-Alert data. This portal provides access to the complete history of sensor data for each of the e-Alert controllers, which are connected to the PRS. Furthermore, the portal is used to review the connectivity status; this enables the manufacturer to restore the connectivity to support the CBM strategy.

One of the scenarios considers to obtain operational profiles of the medical device to fine-tune the configured alert thresholds. For example, temperature sensor data from 20 e-Alert controllers, covering 2 different magnet types, has been analysed. For a period of 6

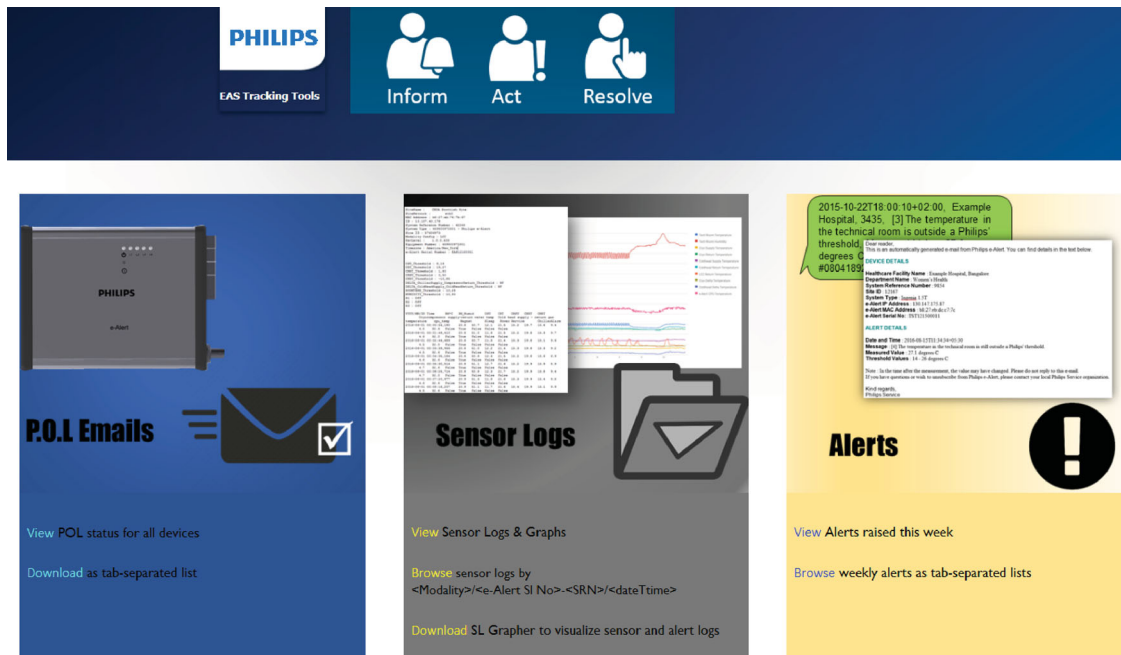


Figure 12. e-Alert controller data portal.

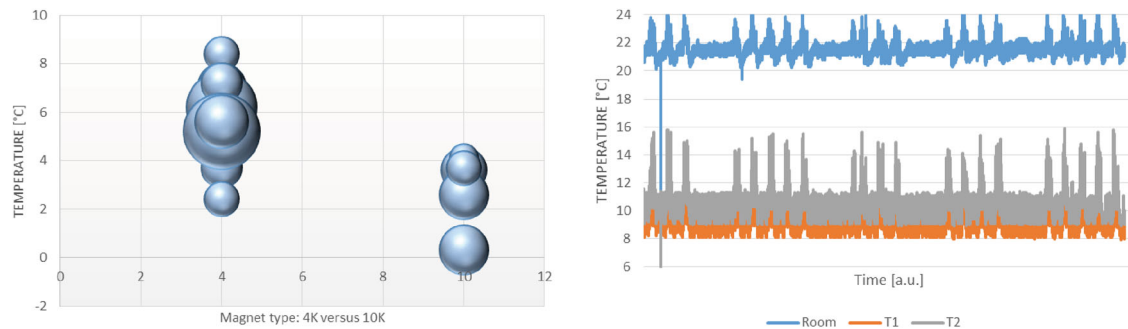


Figure 13. Temperature distribution and classification (left) and temperature correlations (right).

months, the average temperature and its variance has been calculated (see left side of Figure 13). Each centre of a bubble is the average temperature whereas the radius is the variance. Each bubble represents one e-Alert controller. From this analysis, it has become clear that the alert levels can be magnet-type specific.

Another analysed scenario aimed to check the correlation between sensor values. For that purpose, 30 days of temperature sensor data (named T1, T2, Room) has been analysed, see right side of Figure 13. Here, it is observed that there is a correlation between these temperatures. Consequently, the e-Alert controller can issue three (different) alerts, even in case of a single failure mode. Knowledge about such correlations can be used to avoid duplicate alerts and further optimize PM. This correlation was observed for multiple e-Alert sensors, but not for all of them. This indicates that there are other, yet unknown, mechanisms or local environmental conditions that may lead to this correlation.

4.4. Monitoring of a wind turbine

The status of a wind turbine, represented in Figure 14, can be monitored by means of a set of Acoustic



Figure 14. Wind turbine area of interest.

Emission sensors (AE) placed on the tower next to its joint with the nacelle. The sensors are of off-the-shelf kind (Section 3.1) and were added in the context of the MANTIS project execution.

The monitoring process is represented in Figure 15. Typically, all rotary equipment produces an acoustic signature (Acoustic Emission) that propagates through the material. The purpose of the presented technique

is, by means of AE sensors, to acquire those signals, process them and compare them over time to verify the structural health of the wind turbine. The wind turbine structural noise is the basis for the degradation analysis. Such noise is composed by the contribution of each wind turbine rotary components, the mechanical forces generated by the blades movement, and wind.

During the normal operation of the turbine, all the components are rotating and producing fairly constant and stable signals. Those are treated as benchmark signals and considered as background or Gaussian white noise. If a malfunction occurs and one of the rotary components is permanently damaged, the acoustic signature would change. It is possible to identify three main different structural changes: (a) degradation of the bearings/gearbox that increases the friction forces applied on the rotary shaft and reduces the power transmission ratio while producing higher floor levels of noise. (b) Shaft and/or bearing misalignment, which produces periodic acoustic signal patterns that can be detected and analysed. (c) Mechanical cracks, which generate new frequency harmonics, can be visualized as spikes outstanding from the regular noise.

To undertake the signal processing, the signals are amplified and their mean levels are removed before being acquired by an analogue digital converter. The pre-amplifiers are installed as close as possible to the acoustic emission sensors in order to improve the signal noise ratio. The analogue digital converter is connected directly to a PC used to run the signal processing algorithms and export the signal to be further processed.

The condition monitoring system implements two different measurement strategies. The Periodic and

Automatic Periodic Monitoring (PAPM) strategy considers that the monitoring subsystem is permanently installed and attached on the top part of the wind turbine tower, and the monitoring process is periodically executed according to the schedule previously defined by the end user. The Spot Measurement (SM) strategy considers that the measurement process is executed whenever the end user requests it, disregarding the previously defined schedule; this implies the interaction with the end user, but on the other hand it allows executing multiple measurement when a problem is expected.

The actual inspection is undertaken by means of a robotic platform able to climb up to the area of interest using magnetic adhesion. Once the position has been reached, the AE Sensors, which are installed on board, are deployed and so the signal acquisition begins. The acquisition is done through a Red Pitaya which makes the analogical-digital conversion. The data are transferred in real time to the ground control box where there are two possible options: (a) real-time signal processing can be executed to visualize and assess in situ the status of the wind turbine. (b) The data can be uploaded into the cloud for post processing.

4.5. Discussion

The four pilots deal with the maintenance of expensive devices, which are sold in limited volumes, and whose downtime is very expensive to the owner.

The pilots were selected to corroborate the sensor categories defined in Section 3. In fact, even though all the pilots pertain to the application area of CBM, they have different characteristics, leading to the employment of different categories of sensors.

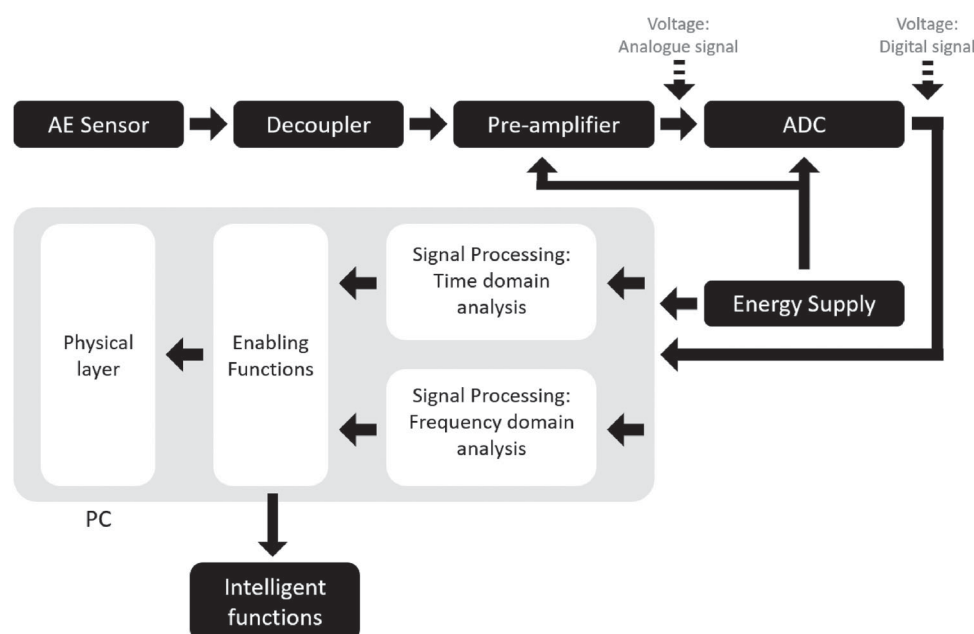


Figure 15. Wind turbine monitoring process.

The first pilot (Section 4.1) involves the monitoring of machines that are sold to factories far away from the machine manufacturer, and the goal is to predict when a failure will occur to send spare parts proactive and reduce downtime. The pilot exploits the composition of data from off-the-shelf sensors, the rationale being that the sensorization must abide to a trade-off between the cost of a failure and the sensorization itself.

The second pilot (Section 4.2) focuses on the use of custom sensors, which are much more expensive than off-the-shelf sensors since they do not benefit from economy of scale. Anyway, the machines monitored in the second pilot are much larger and more expensive than in the first one and thus allow for using much more expensive sensorization.

The third pilot (Section 4.3) considers cheaper machines that are sold in higher volume. In this case, the CBM strategy involves to leverage the data collected by all the machines to look for a baseline, and for outliers that are hints of incoming failures. This pilot thus features virtual sensors, since the most important work is done on the cloud by software sensors that use the large volume of data collected from multiple machines.

The fourth pilot (Section 4.4) uses a set of off-the-shelf sensors installed dynamically onto machines that are deployed outdoor. The environmental hazards that can hurt the machines can take their toll on the sensors too, having an impact on sensor aging, and the implemented solution was to renew the sensors periodically. The sensors themselves are off-the-shelf since, even though the monitored machines are extraordinarily expensive, the sensors are supposed to have a limited lifetime and thus have to be reasonably cheap.

5. Conclusion

This paper describes different CBM strategies. CBM's dependency on sensor data was in fact the motivation for this research. The classification of sensor requirements, capabilities and aging effects is done using four different real-life pilots. In these pilots, the devices are equipped with a combination of off-the-shelf sensors (see Section 3.1) and custom sensors (see Section 3.2). Some sensors are based on physical sensing units to collect data from the environment (e.g. shop floor, machines) and are prone to aging (Section 3.3). Other sensors are based on virtual sensors (see Section 3.4) that embody local data processing capabilities.

In the context of CBM, the bulk of data processing is done on the cloud, for example to compute behavioural patterns and perform comparison with other similar machines. One of the most important prerequisites for CBM is to equip devices with communication capabilities, usually by adding gateways based on cheap yet powerful platforms such as Raspberry Pi, to transfer data from the device to the cloud. The importance of sensors in devices is clear for the monitoring industry,

but our research shows the importance of cost-effective physical and virtual sensors. Such sensors enable industries to increase the scale of sensors and harvest the potential savings of CBM strategies.

Anyway, many industries still struggle when confronted with the trade-off between the investment required for sensorization and the magnitude of the savings brought in by CBM. As a future work, we plan to study the economics of increased sensorization.

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