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Sensors: the Enablers for Proactive Maintenance in the Real World

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Abstract

Nowadays, collecting complex information regarding a machine status is the enabler for advanced maintenanceactivities, and one of the main players in this process is thesensor. This paper describes modern maintenance strategies thatlead to Proactive Maintenance (PM), which is the most advancedone. The paper discusses the sensors that can be used to supportmaintenance, as pertaining to different categories, spanning fromcommon off-the-shelf sensors, to specialized sensors monitoringvery specific characteristics, and to virtual sensors. The paperproceeds then to detail three different real world examples ofproject pilots that make use of the described sensors, and drawsa comparison between them. In particular, each scenario has gotunique characteristics and prefers different families of sensors,but on the other hand provides similar characteristics on otheraspects. In fact, the paper concludes with a discussion regardinghow each scenario can benefit from PM and from advancedsensing.

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***Abstract*—Nowadays, collecting complex information regarding a machine status 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 Proactive Maintenance (PM), which is the most advanced one. The paper discusses the sensors that can be used to support maintenance, as pertaining to different categories, spanning from common off-the-shelf sensors, to specialized sensors monitoring very specific characteristics, and to virtual sensors. The paper proceeds then to detail three 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 got unique characteristics and prefers different families of sensors, but on the other hand provides similar characteristics on other aspects. In fact, the paper concludes with a discussion regarding how each scenario can benefit from PM and from advanced sensing.**

***Index Terms*—advanced maintenance, predictive maintenance, virtual sensors, use cases, pilots**

I. Introduction

The advances in industrial electronics are the leading forces for the fourth industrial revolution. In fact, while most factories have traditionally made heavy use of electronics and information technology to automate production (third industrial revolution), the novel paradigm aims at maximizing the benefits of information by the integration between multiple data sources, and by the ubiquitous access to the information itself [1].

A field that has gained momentum is the monitoring of industrial systems, since it is on the verge of profound changes. In the close future, maintenance of industrial systems will feature the revolution from traditional monitoring, based on the reaction to malfunctions, to advanced techniques that allow to greatly reduce response time – even to zero – by predicting faults. The most advanced maintenance paradigm is Proactive Maintenance (PM), which leverages information collected on the machines, and historical data, to infer the proper time to apply each maintenance action.

Building a PM service platform is the goal of the MANTIS Project [2], which is a European initiative that aims at enabling novel maintenance strategies of industrial machines pertaining to different industries. The project is focused on real world application of the developed techniques, and its pilots are centred on machines whose design was adapted for the inclusion of novel maintenance techniques. In this sense, the pilots are the testing grounds for the innovative functionalities of the PM service platform architecture, and for its future exploitation in the industrial world.

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

In Section II, this paper defines what PM is by building over other maintenance strategies, and describes how it is enabled by sensing activities. Section III delves into an analysis of sensors as pertaining to off-the-shelf, advanced, and virtual sensor categories; Section IV showcases the application of sensing techniques to maintenance in real pilots, and Section V discusses the differences and commonalities between the pilots and draws some conclusions on the topic at hand.

II. Supporting Concept: Maintenance

As stated in [3], maintenance is a strategic activity aimed to assure the operation reliability and/or a certain degree of continuity of equipment and/or processes while ensuring the safety of people that are part of it. 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 [4]. For that goal, several maintenance strategies have been defined, developed and adopted, namely: i) Corrective Maintenance (CM); Preventive Maintenance (PrM); Predictive Maintenance (PdM); and Proactive Maintenance (PM). These strategies are enabled by current technological progress and reflect the growing need for companies to be competitive [5].

CM also called Run-to-failure reactive maintenance can be described as a fire-fight approach, meaning that equipment is only replaced or repaired after it breaks. It has the advantage of minimizing manpower to keep things running. Disadvantages reside in unpredictable production capacity and high overall maintenance costs. PrM 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 stop for maintenance, but it improves equipment lifetime and it reduces malfunction probability [6].

Due to the periodic aspect of PrM, replacement of equipment may occur prematurely as well as failures can occur [7].

PdM, or condition-based maintenance, relies on physical measurements of the equipment condition (e.g.: temperature, vibration, noise, lubrication, corrosion [8]). In this sense, maintenance only happens in a need-based when a certain threshold is overcome. As a matter of fact: ”Predictive maintenance is a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation” [9]. Therefore, it did not emerge to replace corrective and preventive maintenance, but as an additional tool to improve them. Finally, PM includes different actions, from system design phase, workmanship, scheduling and maintenance procedures, to the usage of communication technologies, feedback information and optimization techniques [10]. PM benefits from the two previous maintenance strategies, since preventive and predictive methods are also applied. PM goes further by focusing on the root causes of the problems, and dealing with them before problems occur.

The successful implementation of PM strategies strictly depends on the availability of an efficient and effective monitoring infrastructure that can gather and analyze relevant machine operational data to identify possible breakdowns and their root causes. A PM service platform needs to include key technologies such as: Smart sensors, actuators and cyber-physical systems (CPS); Robust communication systems for harsh environments; Distributed machine learning for data validation and decision-making; Cloud-based processing, analytics and data availability; HMI to visualize information. In particular the foundation of such platform is the sensing capability, which is bestowed unto sensors and has the responsibility of nourishing the system with vital information from equipment and processes.

In this landscape, the State-of-the-Art features several research and innovation actions and projects founded by the European Community that are/were focused on the analysis of the data provided by sensors for the assessment of the equipment status such as: FP6-INNOTRACK, FP6-DYNAMITE [11], FP7-INTERAIL [12], FP7-PRIME [13], FP7- SELF-LEARNING [14], FP7-VORTEXSCAN [15], H2020-PROPHESY [16], H2020-PERFORM [17]. However, the works that have been realized within these actions mainly targeted: 1) the faults/anomalies detection from the data available from sensors; and 2) the diagnosis of the causes of these faults/anomalies. 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 PM in different domains of application.

III. Sensors for Machine Maintenance

Sensors used in advanced maintenance operations can be classified in a number of ways. Being focused on real world pilots, this paper categorizes the sensors as common mass-produced sensors (Subsection III-A), custom sensors that are created for specific maintenance applications (Subsection III-B), and virtual (software) sensors (Subsection III-C).

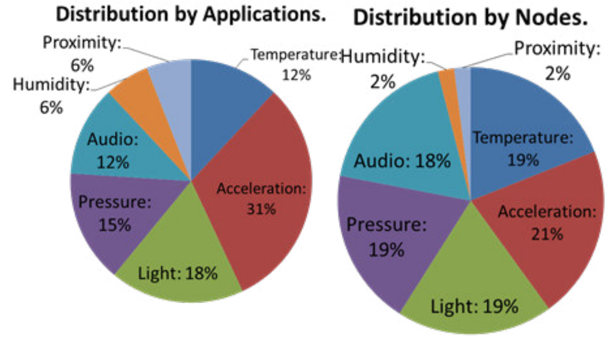

Fig. 1. Distribution of Sensor Types

A. *Off-the-shelf Sensors*

The work in [18] examined more than 300 devices in 12 different applications, and obtained a distribution of the sensor types by application usability and sensor nodes availability (see Figure 1). In particular, seven sensor types were identified as being the most common sensors: temperature, acceleration, light, force, audio, humidity and proximity. The analysis takes into account that most sensor nodes offer multiple physical data sources (e.g.: pressure, light and temperature).

Temperature effects can take place on materials (solids or fluids) and components. These effects can have a very significant impact on machines operation by causing increased wear, hydraulic systems degradation, materials expansion, etc. Temperature sensing allows for continuous analysis of temperature variation or its stability. For example, scanning bearing housing on motors can prevent major failures. Monitoring fluids' temperature is also useful, since some properties of fluids degrade when temperature increases.

Since mechanical systems are composed by moving parts that deteriorate over time and generate vibration, collecting acceleration data allows early detection of roller elements bearing faults, gear wear, etc.

Measuring pumps pressure can reveal physical changes in the pumps. Operating conditions, such as fluid type, temperature and speed, affect the pressure, and if pressure takes a value 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 lead to material damage [19]. Cavitation can be sensed by means of pressure, vibration or acoustic emission measurement.

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, it is possible to detect an unwanted object in a certain area, for example, a person near a cutting material machine and shutdown the machine safely.

Acoustic (audio) monitoring is strongly related to vibration sensors. While audio sensors ”listen” a component, vibration sensors register the motion of the component they are rigidly attached to. Acoustic sensors are commonly used to monitor bearing and gearboxes, in order to detect any working/movement variation.

Monitoring the percentage of humidity in a certain environment can be useful, since for example, high levels of humidity in an injection molding process line can add moisture to resins, potentially impeding that parts are molded properly. In gearboxes, the accumulation moisture can lead to gearbox corrosion, reduced efficiency and breakdown.

Proximity sensors can be used to measure parts displacement, improper presence of objects, or even vibration in rotational components. Another feature is the non-contact measurements, which makes use of sonar or infrared light emission to detect the presence of objects in a area.

B. 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 [20].

The early detection of cracks, allows the prevention of fracture failures. These cracks can be produced by an 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 like radiography, ultrasonic, penetrating liquid, magnetic particle inspection, etc.

Several sensing techniques can be applied to estimate or compute torque measures. Through components speed, it is possible to calculate torque and torque brake; an alternative method is using pressure sensors to correlate torque brake.

Other custom sensors 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. Oil condition monitoring allows detection of lubricant related engine wear and lubricant quality degradation, among other problems. Early problem detection leads to on-time, preventive adjustments that reduce machinery downtime.

C. Virtual Sensors

The virtual sensor is a technology used to retrieve more effective and accurate information from collected data [21]. 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 on not only on current sensor values but also on its time series.

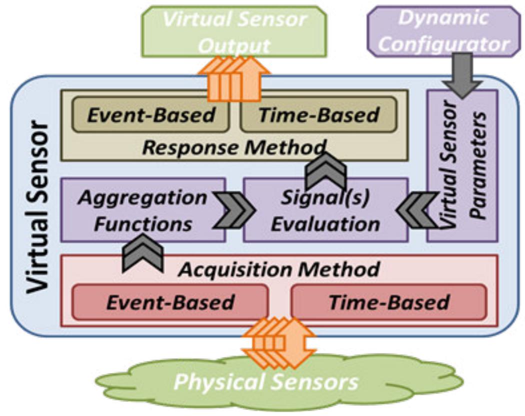

Fig. 2. View on the Virtual Sensor Architecture

The Virtual Sensor Architecture, whose view is represented in Figure 2, 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.

IV. Use cases

This section presents three pilots in which the usage of PM can provide added value to the monitoring process. All use cases feature real world factories and installation, and therefore provide a connection between the role that PM 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 (Subsection IV-A) exploits the composition of data from off-the-shelf sensors, the second one (Subsection IV-B) focuses on the use of custom sensors, and the third one (Subsection IV-C) features virtual sensors.

A. Monitoring of a Sheet Metal Bender

The Sheet Metal Bending Process pilot, whose architecture is represented in Figure 3, 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 4). The machine is

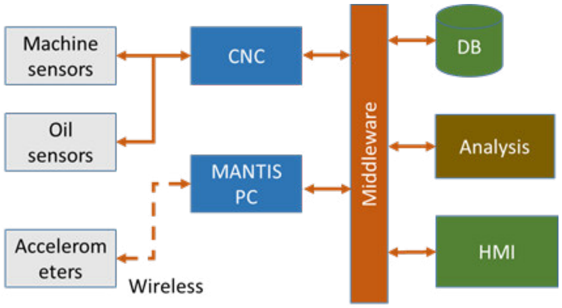

Fig. 3. Monitoring architecture for Sheet Metal Bender

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. This pilot aims at predicting machine failures before they occur, by means of machine learning techniques applied to collected data.

Data are collected from sensors that existed previous to the MANTIS project and that are already gathered by the Computerized 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 Subsection III-B) 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 contaminations 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 Celsius degrees, 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 analogic voltage signal with a range from $0V$ to $10V$ 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 4) pertaining to the off-the-shelf category (Subsection III-A) 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 bending motors, and the collected data can thus be used to perform PM 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 PM can predict failures.

The sensors are based on the Arduino 101 platform that provides a 3-axis accelerometer with a maximum amplitude range of $8g$, and are powered by two $9V$ batteries 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 *CurieBLE* library is used to send data from the Inertial Measurement Unit (IMU) of the sensor to the MANTIS-PC wirelessly via Bluetooth Low Energy (BLE).

Fig. 4. Frontal view of the machine with two IMU

The MANTIS-PC is a Raspberry Pi 3 Model B that acts as a 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 [22] protocol. The cloud hosts the components to store the data (Database, or DB), to analyze them (Analysis), and to interact with the user (Humam Machine Interface, or HMI).

B. Press Machine Maintenance

A stamping press is a metal working machine used to shape or cut metal by deforming it with a die. This pilot 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, each one with a force 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 PM activities in order to provide high availability but without extensive unnecessary maintenance operations.

PM activies in this pilot enabled by a cloud service platform, which makes use of data captured continuously, monitored, transmitted, stored and analyzed by intelligent sensors responding to the Custom Sensor category (see section III-B). In particular, two applications collect data from multiple data sources related to press structural health, cranks forces and wearing of gears and bushings.

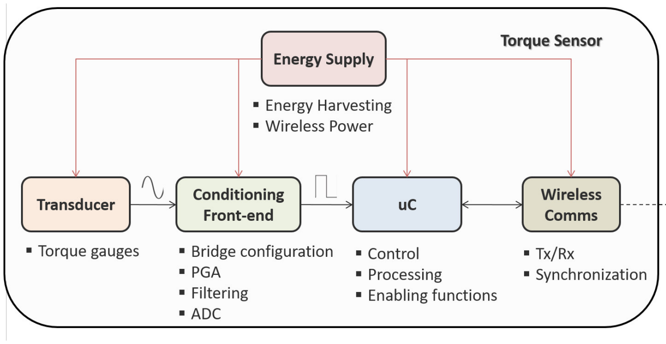

Fig. 5. Wireless torque sensor node block diagram

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.

The second application is represented in Figure 5, and it implies the sensorization of a gear shaft. A shaft-adapted wireless sensor node [23] comprises a transducer (torque oriented gauges), a signal conditioning circuit and a signal processing software, 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-zeroeing 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 ADC conversions in nodes [24]. 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 to protect it from vibrations and lubrication oiliness [25]. 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 battery. Thus, supplementary solutions such as wireless power or energy harvesting are under analysis.

C. Maintenance of Medical Devices

Modern medical devices have a large number of embedded sensors, and in this pilot PM 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 III-A), and data are distilled into more advanced information by means of virtual sensors (section III-C). 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 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.

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 6. 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 analyzed 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 PM 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

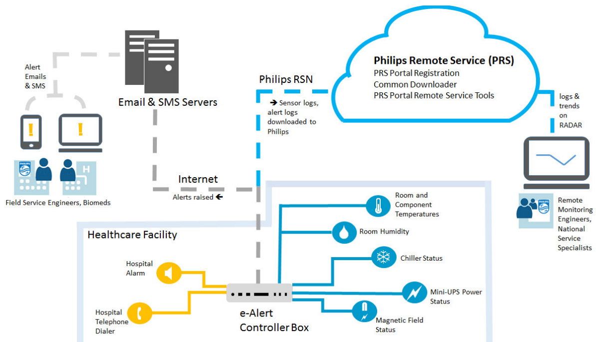

Fig. 6. Sensor box context diagram

not be possible, and thus it is of the outmost importance to remove device's downtime.

V. Discussion and Conclusions

In the paper the different maintenance strategies have been discussed, and a taxonomy of existing sensors has been presented. Three different real world pilots that showcase advanced maintenance operation have been presented.

The three pilots deal with maintenance of expensive devices, which are sold in limited volumes, and whose downtime is very expensive to the owner. In all discussed pilots, the devices were equipped from the beginning with a number of off-the-shelf sensors (see Subsection III-A), and the evolution towards PM involved adding custom sensors (see Subsection III-B) and off-the-shelf sensors driven by custom controllers. Some devices feature virtual sensors (see Subsection III-C) that embody local data processing capabilities, but in the context of PM, the bulk of data processing is done on the cloud. In fact, one of the most important challenges of PM involves adding communication capabilities to the device, usually by adding gateways based on cheap yet powerful platforms such as Raspberry Pis, to allow to store sensed data on the cloud for further processing, for example to compute behavioural patterns and perform comparison with other similar machines.

It appears that the commonalities found on the three pilots can be extended to most applications of PM in the real world. As future work, the implementation of the pilots will be finalized and the benefits obtained by means of different maintenance strategies will be measured, to provide a deeper understanding of the benefits of PM.

Acknowledgment

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