Challenges to IoT-enabled Predictive Maintenance for Industry 4.0

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***Abstract*—The Industry 4.0 paradigm is boosting the relevance of Predictive Maintenance (PdM) for manufacturing and production industries. PdM strongly relies on Internet of Things (IoT), which digitalizes the physical actions allowing human-to-human, human-to-machine and machine-to-machine connections for intelligent perception. Several issues still need to be addressed for reaching the maturity stage for widespread application of PdM. To do this, IoT needs to be empowered with data science capabilities, to reach the ultimate objective of digitalization, which is supporting decision making to optimally act on the physical systems. In this paper, we present a comprehensive outlook of the current PdM issues, with the final aim of providing a deeper understanding of the limitations and strengths, challenges and opportunities of this dynamic maintenance paradigm. This is done through extensive research and analysis of the scientific and technical literature. On this basis, the work outlines some main research issues to be addressed for the successful development and deployment of IoT-enabled PdM in industry.**

***Index Terms*—Predictive Maintenance, IoT, Industry 4.0.**

I. Introduction

Industry 4.0, the fourth industrial revolution ([1], [2], [3]), aims at creating smart factories, equipped with disruptive technologies such as advanced robotics, 3-D printing, high computing power and connectivity, etc., which are integrated with analytical and cognitive technologies that enable machine-to-machine (M2M) and machine-to-human (M2H) communication. The smart factory provides the opportunity of offering new services and products to customers, with efficiency, standards of quality and reliability higher than before. These allow expanding the value chain by generating new business models that create value for customers and revenue for manufacturing companies ([4], [5]).

One of the opportunities (among others) most spoken of in Industry 4.0 is Predictive Maintenance (PdM), which makes use of condition monitoring data to detect anomalies (i.e., recognize deviations from normal operating conditions) in production processes, manufacturing equipment and products, diagnose (i.e., characterize the occurring abnormal state) and prognose (i.e., predict the future evolution of the abnormal state up to failure). The set of detection, diagnostic and prognostic tasks is often referred to as Prognostics and Health Management (PHM, [8], [9], [10], [11], [12]). The capability of performing these tasks with sufficient accuracy provides the opportunity of setting efficient, just-in-time and just-right maintenance strategies: in other words, providing the right part to the right place at the right time. This opportunity is big, because doing this would maximize production profits and minimize all costs and losses, including asset ones ([13]).

Boosted by the intuitive and appealing potential of PdM, the industry is making significant investments for equipping itself with the elements necessary for deploying PdM. For example, the investments by the Italian industry in research & development & innovation for Industry 4.0 increased by 15% in 2017, a significant part of which allocated to PdM [17], and similar investments are reported in other countries (e.g., [18]). This situation has sparked the birth of a large number of PdM specialized companies, commercial softwares, dedicated journals and conferences, etc.

The Internet of Things (IoT) is a main pillar of PdM ([6], [7]), as it allows translating physical actions from machines into digital signals used for PdM. Namely, IoT continuously streams data from sensors such as temperature, vibration, etc. and from other sources, such as a machine Programmable Logic Controller (PLC), Manufacturing Execution system (MES) terminals, Computerized Maintenance Management systems (CMMSs, [14], [15], [16]), or even an Enterprise Resource Planning (ERP) system. These pieces of information provide the basis for setting PdM approaches.

Up to now, the focus of the effort made has been mainly on the development of hardware (i.e., IoT, smart meters, etc. [6], [7], [19], [20]) and software (e.g., PHM tools, platforms for IoT interconnection and clouding, etc. [21], [22], [23]), for tracking the health state of monitored components. On the other hand, the industrial-scale deployment of PdM involves many other aspects and impacts various sectors of the workplace involved in maintenance (i.e., workers can use smart systems, maintenance engineers can analyze big data for the maintenance process), logistics (spare parts and warehouse management can be driven by the PHM results), Occupational Health, Safety & Environment (OHSE, smart system information can be used for updated monitoring of risks), design (the use of smart components may lead to different reliability allocation solutions), top management (new business opportunities can arise in services), etc. [6]. To bridge the gap, IoT needs to be integrated with data science and modeling capabilities, to reach the ultimate objective of digitalization, which is supporting decision making to optimally act on the physical systems.

In this paper, we present a comprehensive outlook of the

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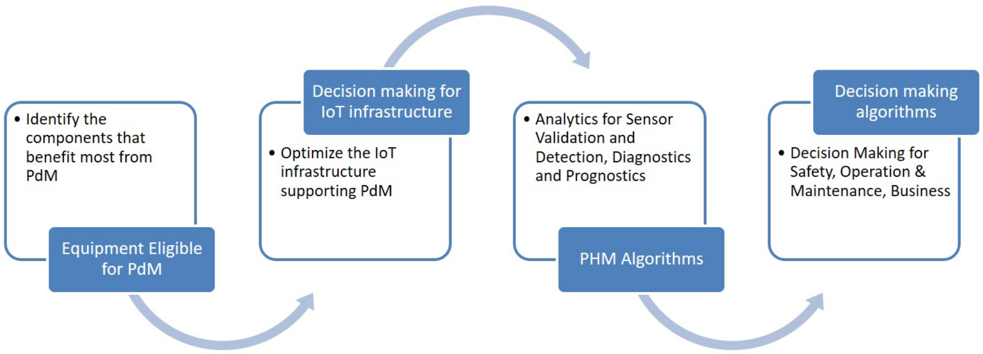


Fig. 1. PdM development activities

current PdM issues, with the final aim of providing a deeper understanding of the limitations and strengths, challenges and opportunities of this dynamic maintenance paradigm. This is done through extensive research and analysis of the scientific and technical literature. On this basis, the work outlines some main research issues to be addressed for the successful development and deployment of IoT-enabled PdM in industry.
The remainder of the paper is presented according to the PdM development activities represented in Figure 1. The selection of the components which would benefit most from PdM is a fundamental issue to address for the effective application of PdM. This is overviewed in Section II. Once the components eligible for PdM have been identified, the next step is to properly design the IoT infrastructure in support to PdM. The issues related to this topic are presented in Section III. Section IV focuses on the issues related to the development of the algorithms and methods for PdM, which are generally addressed once the monitoring data from IoT are available. The last step concerns the exploitation of IoT-enabled monitoring, to really ensure that PdM brings an added value. The decision making issues to achieve this objective are presented in Section V. Finally, conclusions of the work are given in Section VI.

II. Which components for predictive maintenance

Maintenance approaches are generally divided into two main groups: corrective maintenance (CM) and preventive maintenance. Under CM, the components are operated until failure; then, repair or renovation actions are performed. Preventive maintenance, instead, encompasses all actions performed in an attempt to retain an item in specified conditions, by providing systematic inspection, detection and prevention of incipient failures (e.g., [8], [24], [25]). Accordingly, preventive approaches can be further divided into three sub-groups ([8], [26]): Scheduled Maintenance (SM), if the actions are performed based on a pre-fixed basis, Condition-Based Maintenance (CBM), which uses condition monitoring to identify problems at an early stage and perform maintenance when the degradation level reaches a threshold, and PdM, which can be regarded as an advancement of CBM: the degradation of the component is predicted in the future and its Remaining Useful Life (RUL) is estimated.
A tempting misconception within the Industry 4.0 paradigm is that PdM is always the best maintenance policy. This is not so. Rather, the opportunity for maintenance in Industry 4.0 lies in the possibility of defining the optimal maintenance for every component, taking into account its specificity within the system, e.g., applicable safety and environmental legislation, quality standard, importance for business, physical and functional characteristics, etc.
Reliability Centered Maintenance (RCM, [27], [28], [29]) was proposed in the 1970's (i.e., at the beginning of the third industrial revolution determined by automation) to address the issue of selecting the best maintenance strategy for every component in a system. Nowadays, RCM is standardized for the different industrial sectors (e.g., [25], [30]) and is supported by the availability of advanced CMMS, with many success cases reported (e.g., [27], [31], [32]).
The main idea of RCM is to concentrate the maintenance efforts on the components of the asset most critical for safety and business, and apply to them the most effective maintenance approach, as resulting from the analysis of their reliability characteristics. To do this, RCM relies on a decision flowchart, whose first question is about the possibility of monitoring the condition of the component, i.e., a physical variable indicative of the component degradation state, and defining a threshold value for it, at which to do maintenance on the component to avoid its failure with major consequences ([25], [30]). In case of affirmative answer, CBM can be considered technically feasible; otherwise, the decision flowchart proceeds with other questions about the reliability characteristics of the component to check the applicability of scheduled maintenance; if also this is not applicable, the component is inevitably run to failure and taken care of by corrective maintenance.
The rationale underlying RCM is applicable to Industry 4.0, but with some major limitations:

- The first RCM question on the possibility of condition monitoring for the applicability of CBM can be misleading in the practice of Industry 4.0: whilst it goes without saying that CBM is doable in case of affirmative answer to the question, a negative answer does not necessarily imply that CBM must be abandoned. In fact, PHM approaches have been developed (e.g., Principal Component Analysis (PCA), Auto-Associative Kernel regression (AAKR), Self Organizing Maps (SOM), etc. [33], [34], [35], [36], [37]) for detecting early failures in a component based on multiple signals not directly measuring

the condition of that component. Indeed, PHM methods of feature extraction and selection (e.g., wavelet tranform [38], [39], [40]) can find combinations of features from the available signals that although not directly measuring the component degradation state, can infer it, and CBM can be developed on this basis.
- PdM does not enter the decision flowchart for maintenance selection. A positive answer to the first RCM question on CBM does not necessarily mean that also PdM is feasible, as the condition monitoring for CBM may not provide the information needed for PdM (e.g., [41]).
- Cost-effectiveness of the maintenance strategy must be considered, as CBM and PdM require investment costs in software, instrumentation, knowledge, etc. which must be justified by the benefits they can yield.

From these considerations, it emerges that RCM needs to be extended for its application to the Industry 4.0 context: clear and solid ways are needed to guide the decision makers in the identification of those components for which PdM would be the right maintenance choice.

A. *Economics of PdM*

Development of IoT-enabled PdM for Industry 4.0 makes sense if it is proved to be more profitable than the other maintenance approaches. Maintenance cost models must, then, be developed to evaluate the economic benefits of PdM. However, only few attempts have been made in this sense ([42]), in spite of relevance that this issue for the decision ìs in investing in IoT for PdM.

A few works (e.g., [43], [44], [45], [46], [47], [48], [49]) have attempted to evaluate the cost-benefit of PdM through the commonly used financial metrics such as Return on Investment (RoI), Net Cash Flow, Cumulative Cash Flow, Payback, Net Present Value, and Internal Rate of Return. These works, however, rely on simulation instead of developing general analytical approaches ([42]).

Another cost-benefit metric proposed is the Technical Value (TV, [50]), which accounts for the performance in detection, diagnostics and prognostics of critical failure modes and the costs associated with false alarms. However, TV contains cost terms that are difficult to estimate (e.g., the savings realized by isolating a fault in advance) and it makes use of constant performance metrics, i.e., independent on time (e.g., the probability of a failure mode). Finally, TV does not give due account to erroneous detection, diagnosis and prognosis.

Partially Observable Markov Decision Processes (POMDP, [51], [52], [53]), have been used to estimate the Value of Information (VoI, [54]) of data measured by sensors installed on civil infrastructures, accounting for the uncertainty in the condition monitoring. Roughly speaking, VoI is the maximum cost a decision-maker is willing to pay for getting the information, which is worth acquiring only if its value is above its cost ([54]). Although this framework seems very promising, there are two main issues preventing its application to Industry 4.0. Namely, the VoI definition relates to the expected savings that can be yielded by reducing the uncertainty in the estimations of the degradation state thanks to the measurement collected by sensors or even inspections, i.e., VoI is used for selecting explorative and inspection actions ([51], [52], [53]). Then, it is a relative value, which does not allow for a fair comparison of PdM with the other approaches not based on sensor monitoring. The second issue limiting the VoI approach application is that the algorithms adopted are very time consuming and applicable to scaled-down case studies, only, in which the number of state-action pairs is not large.

A model for evaluating the system-level value of PdM has been proposed in [55], within a real options framework. PdM is seen as a tool for the Decision Maker (DM) to invest options of performing maintenance actions in the future and a cost–benefit–risk model is developed. Some issues remain for its application to industrial practice, including the need of estimating the difference in the costs of performing CM instead of a RUL-driven maintenance. Moreover, although [55] considers time-dependent RUL predictions, these are not linked to the performance of the predictive algorithms (e.g., accuracy, precision, etc.), and a Brownian motion process is used to describe the evolution of the economic indicators related to RUL predictions entering the options model. In addition, the model considers CM as the only possible alternative to PdM, and not other preventive maintenance approaches: however, there can be cases in which the economic performances of CM and SM are superior to those of CBM and PdM ([8]). Refined analytical methods are developed in [42], for the cost-benefit analysis of canary-based PHM; in [56], [57], to maximize the component resilience, which is defined as a combination of reliability and restoration, the latter being a function of the PHM characteristics; in [58], where a life-cycle maintenance cost analysis framework is developed, which considers time-dependent false and missed alarms for fault diagnosis; in [59] and [60], where time-variant metrics of the literature ([61]) are linked to component reliability and availability, respectively, to derive the economic performance of PHM capabilities of different quality levels. These analytical approaches, however, do not fully capture the dynamics of the CBM context, where a decision must be taken every time the PHM algorithms are run.

The enhancement of the economics models is a mandatory condition for the industry to unleash investments in IoT for PdM. The reviewed literature is schematized in Table II-A.

B. *PdM for production and product*

To answer the topical question ”is PdM convenient for this equipment?”, we need to distinguish the case where PdM is considered for a product from that in which it is applied to the equipment of a production process.

In the former case, the economic justification can be relatively simple: several companies of different industrial sectors (i.e., manufacturing [62], aviation [13], [63], [64], mining [65], energy [22], [66], etc.) look into PdM simply because it gives commercial competitiveness. Furthermore, new sources

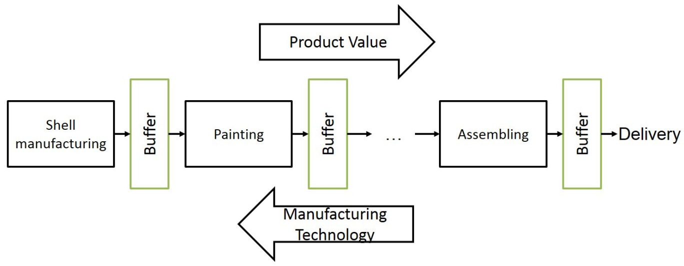


Fig. 2. scheme of a production process in the automotive industry

	RoI	TV	Cost	VoI	Resilience
Time independent PHM metrics	[43], [44] [45], [46], [47] [48], [49]	[50]	[42]	[51], [52], [53]	[56], [57]
Time dependent PHM metrics			[58] [59] [60]		

TABLE I
ECONOMICS OF PDM: SYNOPTIC

of income can generate thanks to new opportunities of added values in service, by taking over portions of the clients' business risks and other (financial) burdens: the possibility of new business may be a sound justification per se for investing in PdM.

In case of manufacturing processes, the value of PdM and, thus of the IoT infrastucture, is more difficult to assess. To show this, we consider the example of a manufacturing process in the automotive industry but draw some general considerations. Figure 2 shows the scheme of a manufacturing process made of different steps, possibly spaced by buffers. Generally speaking, the more stringent the application of the just-in-time paradigm, the smaller the buffers; the later the process step, the larger the value of the half-processed units and, thus, the smaller the buffers. From the PdM perspective, the earlier production phases (i.e., shell manufacturing through welding, milling, etc.) are the most promising ones, as these are performed in the capital-intensive parts of the plant, with robots, transportation means, welding systems, etc. On the contrary, in the latest step (i.e., assembly), where the production flow is more time-sensitive, there are mainly screwdrivers, traveling cranes, etc., in relatively large redundancy and with the largest manning level.

In this scheme, the value of PdM heavily depends on the buffers, whose level Bf to withstand a downtime of D hours of the upstream production step can be estimated as:

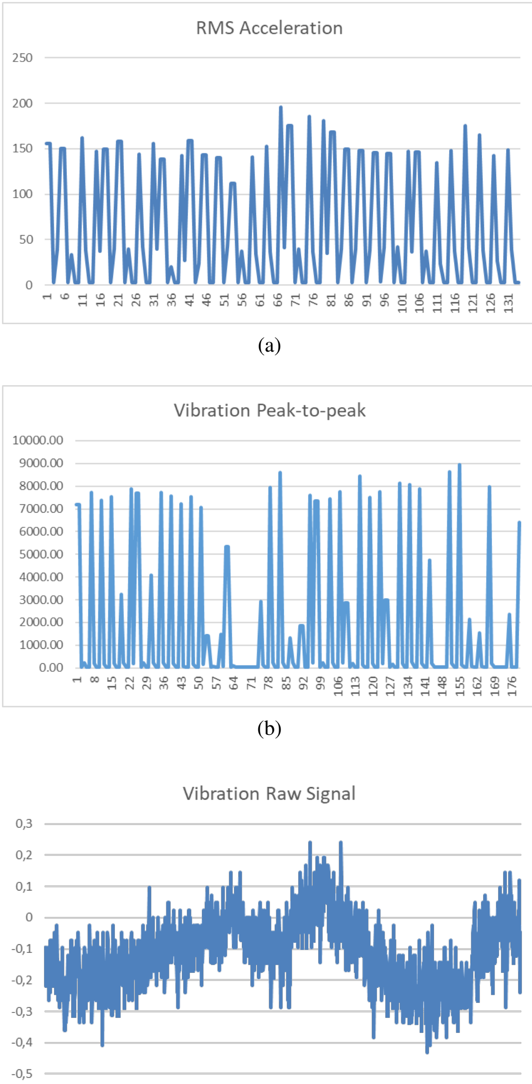
$$Bf = \frac{1}{takT} \times D \quad (1)$$

where $takT$ is the takt time in hours (i.e., the average time between the start of production of one unit and the start of production of the next unit). To consider reasonable values, we can conservatively assume an extremely long downtime $D = 10$ h and $takT = 6$ min $= 0.1$ h; then, we get $Bf = 100$. If C_p is the cost of the product at the end of the production step, the mobilized capital reads $Mc = C_p \times Bf$. For example, if $C_p = 3000$ €, then $Mc = 300'000$ €. Assuming a capital cost of $10\%/$year, it turns out that $30'000$ € per year is the cost that PdM has to payoff to avoid business interruptions. This value is much smaller than any massive investment in IoT for PdM. Then, this is doable only if we are able to both estimate the other indirect costs of failure, such as costs for re-filling the buffer, costs of warehouse, costs related to conservative settings of scheduled maintenance intervals that result in over-maintenance expenses, etc., and prove that these costs are large enough to justify significant investments in PdM. This emphasizes the need for sound cost models encoding PdM for IoT investment justification.

III. IoT INFRASTRUCTURE AND DATA MANAGEMENT FOR PDM

A major misbelief in Industry 4.0 concerns the assumption that larger amounts of acquired data and, thus, more widespread and performing IoT networks, always result in better performance of PdM. This is not so, as acquiring, storing, maintaining and analyzing data entail a cost that increases with the amount of data. As pointed out in [11], the final objective of digitalization should be that of acquiring smart data, rather than big data. To show this, we briefly report about an experience concerning the data acquisition from bearings installed in a manufacturing plant, to outline general considerations. In that plant, the raw bearing vibration data are acquired at a frequency of 1.6 kHz. Due to data storage limitations, these raw data are not stored into the servers. Rather, only two features are extracted from the raw signal, i.e., Root Mean Square (RMS) acceleration and peak-to-peak vibration, which are then averaged on a period of 0.5 seconds and recorded in the data storage system.

These two features have proved to be effective in identifying abrupt failures. Nonetheless, their informational content is not useful for developing a PdM approach. To wit, Figures 3b and 3c refer to a bearing case study and show the available bearing acceleration RMS and peak-to-peak values, respectively, over a time window of almost 130 samples (i.e., almost 65 seconds), whereas Figure 3a shows the raw signal data relevant to the first part of almost 5 seconds of the same time window. From their comparison, it is clear that the averaging leads to hiding the information contained in the raw signal, as signals averaged on relatively long time windows encode different working conditions with variable loads and speeds, which



(c)

Fig. 3. (a) Bearing acceleration raw data. (b) Bearing acceleration RMS. (c) Bearing acceleration peak-to-peak.

the vibration signals are sensitive to. The analysis of these signals for prediction can lead to misunderstanding in their interpretation.

Given that RMS and peak-to-peak values cannot be used for prediction, it is clear that storing them for long time windows (the bearing life duration is 3-4 years in the application considered) is not cost-effective, as we do not need to rely on values relevant to old conditions to capture abrupt changes ([67], [68], [69]).

Based on these considerations, the final strategy proposed can be to i) collect vibration RMS and peak-to-peak features; ii) store them for relatively short time windows (i.e., a few months); iii) complement this information with features useful for prediction, extracted from the raw data (i.e., wavelet transforms in the specific case), acquired every couple of weeks in a tailored, baseline reference setting of working conditions.

Although the proposed strategy has been, indeed, effective in the application considered and seems to be of engineering good sense, nontheless a general framework for optimizing the management of the IoT infrastructure supporting PdM is needed. This is still lacking, to the authors best knowledge. Then, we give insights to formalize the issue, while leaving its solution as a urgent challenge for researchers.

Consider a simplified model of a data acquisition chain from a piece of equipment monitored by S sensors, $s = 1, ..., S$, which can be positioned in locations $l \in \mathcal{L} = \{1, ..., L\}$ (Figure 4). We introduce matrix $\mathbf{P}$, whose (s, l) entry is set to 0 when sensor s is not positioned in location l, and to 1, otherwise. Each sensor acquires data at a bit rate $f_s \cdot b$ Gbit/h, where f_s is the sampling frequency in h^{-1} and b the bit resolution in Gbit. We consider vector $\mathbf{f} = [f_1, ..., f_S]$. Sensor data are transmitted to a local computing unit at a maximum rate R_1 Gbit/h (second block in Figure 4). The local computing unit extracts sets of features $\mathbf{\Phi_s} = [\Phi_s^1, ..., \Phi_s^{\phi_s}]$, which are appended to vector $\mathbf{\Phi} = [\mathbf{\Phi_1}, ..., \mathbf{\Phi_S}]$ (third block in Figure 4). The features are extracted on a time window of Δt hours and every feature extraction requires time dt_j^s, $s = 1, ..., S$, $j = 1, ..., \phi_s$. The extracted features are sent to a server of memory capacity M Gbit, without data compression (last two blocks in Figure 4). The transferring rate for this second transmission line is R_2 Gbit/h.

Finally, the measurements are performed every $\tau > \Delta t$ hours, over a conservatively (i.e., longer) estimated component lifetime of T hours.

Notice that for the sake of simplicity, the units of measurement have been kept coherent and proper coefficients are required to use the units normally adopted in practice. For example, the sampling frequency is usually measured in KHz: then, we need to multiply this value by $3'600'000$ to get the corresponding frequency value in h^{-1}; similarly, features are calculated on time windows of a few seconds, whereby Δt expressed in seconds must be divided by 3600 to get the corresponding value in hours.

The optimization of the sensors allocation can be considered within the PDA framework ([70]), which seeks the optimal portfolios of sensor allocation solution $\mathbf{X} = [\mathbf{P}, \mathbf{f}, \mathbf{\Phi}, \tau]$ such that

$$\max_{\mathbf{X}} VoI(\mathbf{X}) \tag{2}$$

$$\sum_{l=1}^{L} \mathbf{P}(s,l) \leq 1 \qquad s \in \{1,...,S\} \tag{3}$$

$$\sum_{s=1}^{S} \mathbf{P}(s,l) \leq 1 \qquad l \in \{1,...,L\} \tag{4}$$

$$f_s \leq \left(\sum_{l=1}^{L} \mathbf{P}(s,l) \right) \cdot f_{max} \qquad s \in \{1,...,S\} \tag{5}$$

$$\phi_s \leq \sum_{l=1}^{L} \mathbf{P}(s,l) \qquad s \in \{1,...,S\} \tag{6}$$

$$b \cdot \sum_{s=1}^{S} f_s \leq R_1 \tag{7}$$

$$max(\sum_{s=1}^{S} \sum_{j=1}^{\phi_s} dt_j^s, \Delta t_{deg}) \leq \Delta t \tag{8}$$

$$\frac{1}{\tau} \sum_{s=1}^{S} |\mathbf{\Phi_s}| \cdot b \leq R_2 \tag{9}$$

$$\frac{T}{\tau} \cdot \sum_{s=1}^{S} |\Phi_s| \cdot b \leq M \tag{10}$$

$$\sum_{s=1}^{S} c_s \cdot \sum_{l=1}^{L} \mathbf{P}(s,l) + \\ + c_r(R_1) + c_c(\Delta t, \mathbf{\Phi}) + c_r(R_2) + c_m(M) \leq B \tag{11}$$

where c_s is the cost of a sensor, c_r, c_c and c_m are functions that link the cost to the required transmission rate, computational capability and memory capacity, respectively, whereas B is the available budget, which must not be exceeded (Eq. III). In words, the VoI function maps the variables in solution $\mathbf{X}$ onto the maximum investment in PdM that a DM is willing to pay (Eq. 2).

Eqs. 3 and 4 state that, respectively, every sensor can be installed in a single location, at most, and every location can accommodate a single sensor, at most. The position and the number of sensors are fundamental drivers for PdM to be profitable: the larger the number of sensors, the larger the information available and, thus, the chances of identifying and extracting information relevant for the development of effective PdM, also by exploiting correlations among the signals [71]. Obviously, the larger the number of sensors, the larger the investment costs.

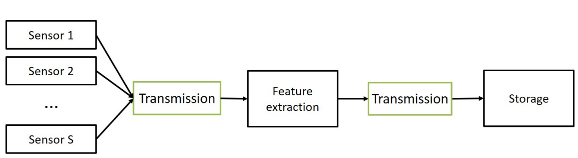


Fig. 4. Data acquisition and storage chain

With respect to the sensor positioning, the relationship with VoI has been investigated in [72], building on a relatively wide literature (e.g., see [73] for an overview). The model in [72] should be extended to include costs and benefits related to overall system resilience [56], flexibility [74], risk, etc. and the other decision variables of $\mathbf{X}$. In fact, the acquisition frequency is also a fundamental parameter for the PHM algorithm to give information valuable for PdM: the frequency should be large enough to catch the information relevant for PdM, as emerged from the bearing application mentioned above; on the contrary, if it is too large, there can be an overload on both the transmission link and the local computing unit, with consequent increments of costs c_r and c_c. In this respect, Eq. 5 states that rate f_s is lager than 0 only when sensor s is installed, and it is always smaller than f_{max}, whereas Eq. 6 indicates that features can be extracted from sensor s only if this has been installed. Moreover, Eq. 7 sets a constraint on the capacity of the data transmission link, which must be large enough to allow continuous data transmission. The larger the value of R_1, the larger the cost: c_r should be thought of as the result of an embedded optimization problem, which finds the technological solution that guarantees the fulfillment of the constraint in Eq. 7 at the smallest cost. Yet, the larger the rate R_1, the larger the time required to process the data by the computing unit that extracts the features, the larger the computational costs: $c_c(\Delta t, \mathbf{\Phi})$ is the minimum cost of the technological solution that guarantees that features $\mathbf{\Phi}$ are calculated before a new dataset is acquired. Given $\mathbf{\Phi}$, the smaller the value of Δt, the larger the computational capability required.

The main requirement for the duration of data collections, Δt, is that it be large enough to capture all the characteristics of the component behavior (Eq. 8). We refer to this minimum duration as Δt_{deg}, whose value depends on the specific application. For example, in the bearing case study, Δt_{deg} must be large enough that the vibrational signal encodes all the vibration conditions. If the acquisition time interval is too short, then the collected signal is not able to represent the bearing functional behavior, whereas if it is too large there can be limitations to the storage of the collected data on the local computing unit. Therefore, also in this case, it is necessary to identify a compromise between the richness of information and the storage burden. Moreover, as expressed in Eq. 8, the value of Δt must be larger than the computational time required to calculate the features.

Finally, the time interval τ between two successive data collections is also an important decision variable, which should be tuned to the specific characteristics of the degradation process to ensure that the maximum rate R_2 is not exceeded (Eq. 9). In the bearing application, the degradation process is slow ($T > 4$ years), whereby a compromise solution must be found between the granularity of the information over time, the required data transmission rate and the storage capacity, which must be large enough to store data over the whole life of the component T (Eq. 10).

To make the final investment decision, the optimal solutions corresponding to different budget levels are, then, found and compared (e.g., [75], [76]).

This optimization issue is further challenged by another trend within the Industry 4.0: edge computing ([23], [77]). Namely, data computation can be done at the "edge", meaning that pre-processing can be performed on the machines where data are gathered from to directly inform machine operators and maintenance technicians. As data is beginning to approach the zettabytes (i.e., 10^{21} bytes), edge computing can be exploited to reduce the overall burden on a computer network by properly distributing the processing effort to a network outer nodes, which alleviates the core network traffic and improves application performances ([77]).

A. Dependability of IoT

An additional relevant topic deserving further investigation is the interdependence of PdM and the dependability of IoT, which is defined in [78] as 'the ability to deliver services that can justifiably be trusted'.

Intuitively, IoT communications for PdM have to satisfy stringent requirements in terms of timeliness and correctness, as the information they exchange is critical for ensuring an effective and safe behavior of the monitored components. Hence, the communication network must be engineered to meet stringent delay deadlines, be robust to packet losses and, finally, be safe and resilient to damages [79].

To this aim, different technologies are currently being developed, especially within the 5G paradigm, which are critically reviewed in [79], [80], [81], [82], [83], to cite a few.

In spite of these advancements, however, a fundamental research work is still required to include in PdM modeling and analysis the trust to the IoT. In fact, in industrial practice the dependability of communication is often characterized through parameters such as packet delivery ratio, outage probability, Signal to Interference and Noise Ratio (SINR), Bit Error Rate (BER) [84]. Although these metrics are intuitively related to the conventional understanding of dependable communication, nonetheless they are not sufficient to fully characterize the capability of IoT for supporting PdM. This is due to the fact that IoT are extremely complex and distributed Cyber-Physical systems of systems (CPSoS), with a multitude of interconnections, also with the human environment, under strict legal and regulatory constraints ([85], [86]). This means that to fully capture the trustworthiness of IoT for PdM applications, we must integrate in PdM modeling several concepts such as cyber-security, reliability, resilience, etc. ([85]). To the authors' best knowledge, this is an almost unexplored field ([88]), especially for the 5G connectivity technology, which promises to be at once truly ubiquitous, reliable, scalable and cost-efficient.

IV. PHM Algorithms for PdM

A. PHM algorithms taxonomy

A wide range of methods have been developed for detection, diagnostics and prognostics, as extensively discussed in the literature ([9], [10], [89], [90], [91], [92], [93], [94]), and with many successful applications reported (e.g., see [6] for an overview).

In general, PHM methods can be divided into two main classes, although hybrid methods exist too ([95]):

- Data-driven methods, which use monitored operational data related to the component health conditions. These are collected in experiments and/or on-field, and can be exploited when the understanding of component operation is not straightforward or when the component is so complex that developing an accurate physical model is prohibitively expensive ([89]). IoT-enabled PdM relies on this class of algorithms, for which a taxonomy is proposed in Table II. Given the huge number of works in the field, the reference list is certainly partial, although it includes literature reviews on specific classes of algorithms. Notice that in some cases the boundaries between the algorithms classes become weak.
- Model-Based methods, in which physical models of the component are used for the estimation of its healthy conditions and the prediction of its degradation. The benefit of resorting to these models lies in that they can be applied to components for which data from abnormal operating conditions are lacking (e.g., safety-critical systems, capital parts, equipment conservatively maintained, etc.). In these cases, data-driven models can neither diagnose the anomalous behavior of the component nor predict its failure trajectory. On the contrary, physics-based or physics-of-failure models (e.g., [6]) can be developed for simulating the degradation mechanisms affecting the component (e.g., [64], [114], [115], [108]) and used for RUL prediction. In the Industry 4.0 era, these models are at the basis of the development of Digital Twins. However, the development of physics-based models is not always practicable because it is very costly and, also, these models often do not fully take into account the effects of the external conditions and rely on parameters that are difficult to estimate ([116]) .
  Notice that these models are not relevant for IoT-enabled PdM, which rely on data provided by IoT.

B. Challenges

A virtuous loop of research and industry is sustaining this, whereby research solutions continue to provide opportunities of improvement to industry, while industry provides new challenges to research. Despite the availability of PHM algorithms, the companies that want to benefit from Industry 4.0 still need to trade off the opportunities of PdM against the capital expenditures required to purchase the necessary instrumentation, software and specialized knowledge. This downside is perceived large at the beginning of the development of PdM, when real data of normal and abnormal equipment behaviors are lacking or scarce, and in case of new systems, when there is no experience on their operation. This situation can lead the companies to distrust the investment in PdM solutions.

For a systematic and rationale decision making on PdM investment, the actual challenge is to embedd the cost models presented in Sections II and V in adaptive and robust frameworks for guiding PdM development: these should allow updating and adjusting the PHM algorithms for PdM on the basis of the Knowledge, Information and Data (KID, [11]) that incrementally become available as the development goes on from the design to its operation, which tends to continuously evolve, due to deterioration of components and sensors, main-

TABLE II
PHM ALGORITHMS OUTLOOK

Algorithm	Brief Description	Pros	Cons
Markov Models (MM) including: • Hidden Markov Models (HMM); • Semi-Markov Models (SMM); • Hidden SMM; ([96], [97], [98], [99]).	A Markov model is a sequence of infinitely many states representing the component degradation from new to failed. Transition probabilities among the states depend on the current state and not on the path followed to reach it. Differently from MM, the SMM transitions depends also on the sojourn time in the current state. HMM assumes the degradation to be not directly observable.	• Appropriate when degradation can be described by discrete states; • Simple in the analytical definition and easy to be understood even by non-expert analysts; • Can rely on a sound literature.	• Can be computationally expensive and can require a large number of simulations; • Require the definition of the degradation states and the estimate of the transition state probabilities.
Artificial Neural Networks (ANN), including: • Convolutional NN; • Extreme Learning Machines (ELM); • Radial Basis Networks (RBN; • Recurrent Neural Networks (RNN); • Echo State Networks (ESN); • Auto-Encoders; • Self Organizing Maps (SOM); • Long Short Term memory (LSTM); ([64], [100], [101], [102], [103] [104], [105], [106], [107], [108])	ANN consist of processing elements called neurons, which interact with each other through numerically weighted connections among the input, hidden and output layers. Training data are used to build a regression model by adjusting the connection weights between neurons to reduce the errors between the network and the target outputs [107]. The trained ANN process new data and give an estimate of the expected output [95]. RNN and its advanced versions (ESN, LSTM, etc.) are ANN, whose neurons contain feedback connections from the hidden or output layers to the preceding layers. These connections add to the ANN the ability of processing temporal dependencies between the inputs and the outputs and, thus, dynamic information. Auto-Eorders are ANN used to learn efficient data codings in an unsupervised manner.	• Provide good functional mappings between input and output data points in many practical PHM instances ([100]).	• ANN require large amount of training data that have to be representative of true data range and variability [95]; • Performance depends also on the capability of the user to identify the optimum setting (i.e., number of neurons, layers, activation functions, etc.); • The operating and training processes are "black boxes", as the understanding of the built models, except from qualitative, is hard to catch ([92]); • ANN can have a slow convergence during the training process [89].
Statistical techniques, including: • Principal Components Analysis; • Regression Models (Linear, Logistic, etc.); • ... ([33], [34], [93], [109], [110]).	Rely on both the Bayesian and frequentist frameworks, thus giving a probabilistic interpreation to the results.	• Rigorous theoretical background; • Uncertainty on parameters estimation.	• Lots of data required for frequentist approaches; • Bayesian approaches can be computationally expensive.
Instance-Based methods, including: • Fuzzy Similarity; • K-Nearest Neighbors; • Kernel Machines (e.g., Support Vector Machines, Relevance Vector Machines, Gaussian Fields, Auto Associative Kernel Regression); ([33], [38], [111], [112], [113]).	Rely on stored data as training set; when predicting a value of a new instance, they compute its distances from or similarities to the available training instances.	• Efficient with both small and large datasets; • Can provide real-time analysis and guarantee a good generalization performance; • Can handle non-linear and complex system modelling; • Models are built directly from the training instances themselves.	• Parameters tuning strongly affects the performance; • Heavy memory usage for storing all training instances; • Risk of overfitting.

tenance activities, upgrading plan involving the use of new components and system architectures, and the modifications of the operational and environmental conditions. These modifications of the system behavior, which are typically referred to as concept drifts or operation in an Evolving Environment (EE, [69]), challenge the PHM algorithms development.

PHM in EE has been recently addressed by transfer learning [117] and incremental learning approaches [118]. The former refer to predicting the labels of samples drawn from a target domain (e.g., system of a fleet working in a new environment), given labeled samples drawn from a source domain (e.g., data from a system of the same fleet, with longer experience) and unlabeled samples drawn from the target domain itself (i.e., data from the new system). Algorithms for this domain adaptation are carefully revised in [117], where relavant challenges are also outlined. These mainly refer to computational

and analysis burdens, and to reduce the analyst knowledge about the specific application of interest that is often required to select an appropriate transformation among many possible alternatives.
Incremental learning approaches can be divided into passive and active approaches. The former adapt the empirical model every time new batches of data become available. This is time consuming and not always doable, as it requires the availablity of labeled time series and empirical model retraining. On the contrary, active approaches allow adjusting the models only when the occurrence of a concept drift is detected. They are typically classified into the following categories [119]:

- Sequential analysis-based approaches, which analyze the newly acquired signals one by one, until the probability of observing the subsequence under a new distribution is significantly larger than that under the original distribution [120].
- Data distribution-based drift detection approaches, which consider distributions of raw data from two different time-windows: a fixed window containing information of the past time series behavior and a sliding window containing the most recent acquired data [121].
- Learner output-based drift detection approaches, which are based on the development of a learner (classifier) and the tracking of its error rate fluctuations [122].

A drawback of the application of active approaches in PHM is that the activities of concept drift detection, data labeling, and empirical model updating are sequentially and independently performed. This requires the use of different algorithms which exploit the same information, contained in the time series data stream, for different purposes and at different times.
To conclude, the adaptivity characteristic of the methodologies and algorithms give the possibility of tracking the development of the PHM system and the improvement of its performance. However, this requires computational and analysis burdens. The challenging issue is on how to simplify and, thus, make faster and cheaper the development of PHM solutions.

V. Decision making with PdM

Once the PHM algorithms have been developed and their performance validated, the information about the RUL of the equipment is exploited for PdM under different perspectives. We consider the following three: safety, business, and Operation and Maintenance (O&M).

A. *Decision making for safety*

Intuitively, prediction capabilities can strongly impact on safety, as they allow monitoring the risk of failure of the components giving, thus, the opportunity of preventing failures by PdM.
Although many experiences are reported in the literature about the possible applications of PdM to safety critical contexts (e.g., nuclear [127], [128], [129], aerosapce [130], [131]), a structured modeling approach that quantifies the benefit of PdM for safety is still lacking, as witnessed by the fact that safety standards still consider that many enhancement steps are necessary to make the PdM technology mature enough to be implemented in safety critical systems ([131], [132]).
To develop this modeling framework, on the one hand one can build on the model in [59], in which the relationship between the PHM algorithms sustaining PdM and the probability of failure has been formally developed. This allows defining the values of the thresholds for a set of performance metrics that guarantee a desired level of safety, with adequate margins related to the uncertainties.
On the other hand, PHM can be embedded in dynamic Probabilistic Risk Assessment (PRA) models (e.g., [133]), to integrate the dynamic predictions, and their uncertainties, with the actions performed by operators and automatic control systems. A first attempt is proposed in [134], which, however, does not consider the dynamic character of predictions.
The capability of modeling the impact of predictions on safety also allows to balance reliability allocation schemes by installation of PdM capabilities and by redundancy. This topic has been partially addressed in [56], [57], [135], but there is still research work to do for investigating the impact of PdM on the optimal reliability allocation for safety.
Finally, the impacts of IoT on safety critical aplications is still an unexplored research area, to the authors best knowledge.

B. *Decision making for business*

A significant part of the value of PdM comes from indirect consequences of the prediction capabilities. For example, the benefit of PdM for wind farms may come not solely from the obtained increase in availability, but also from the improvement in the logistics for maintenance operations enabled by the knowledge of the component RULs (e.g., [136], [137]).
In a manufacturing plant, economic benefit from PdM may come from the warehouse management, which can rely on the RUL knowledge to set a just-in-time logistic support that reduces the stored spares.
In the car market, the business of PdM relates to the marketing opportunities of selling a car with this appealing technology, which provides the driver with the current health state of the car and the remaining time up to failure (e.g., brake pads consumed). Cross-selling opportunities come from the workshop services: the after-sales department can propose a service which directly makes an appointment at the preferred workshop, which is prepared for receiving the car, for a very fast intervention with discounted spares. This also enhances the customer loyalty. Additional benefits come from the control of the dealers' operations, which gives the possibility of both improving the replenishment plans of the spare depots serving the dealers, and allocating the after-sales budgets to the dealers based on their actual selling performances. Finally, the prediction capabilities allow proposing a business model of selling the run kilometers instead of the car. A similar example is that of the turbine engines for aircrafts [138], in which the manufacturer sells the fired hours instead of selling the turbines, in a win-win setting.

C. *Decision making for O&M*

To fully exploit the prediction capabilities, the PdM analytics must enter the asset-level management decision making, which must consider the impact of maintenance on logistics, safety, costs, etc. An holistic management of the asset with respect to maintenance is also referred to as Prescriptive Maintenance [139]. This entails the integration of various asset management and maintenance systems to prescribe optimal solutions to manage maintenance at the asset level. For example, whilst predictive maintenance might recommend that the bearings of the application mentioned in Section III be overhauled, a prescriptive view may also inform the DM that if the equipment loading conditions are slowed down, the time to failure can increase up to the already scheduled maintenance window, also verifying whether the planned production requirements can still be met. To do this, prescriptive systems must be 'cognitive', which means relying on advanced technology at the intersection of big data, machine learning, and artificial intelligence analytics ([139]).

Some developments are proposed in [140], [141], [142], [143], but on specific, scaled-down applications, not transferable to industrial practice. This confirms the need for further research and development on this.

VI. Conclusions

In the Industry 4.0 era, the available smart and connected devices give companies the opportunity of redefining their businesses by rethinking nearly everything they do. In particular, the new technologies, including IoT, enable the development of PdM, which is transforming the way of thinking maintenance: from cost to business opportunity.

IoT-enabled PdM is attracting considerable investment from industries and increasing attention by research, as witnessed, for example, by the many initiatives and confrontation forums established by academy and industry for discussion and experience-sharing of PdM solutions, in various industrial fields.

The development for PdM has thus far mainly concerned hardware and software for remote tracking the health state of monitored equipment. Indeed, we have shown that the PdM value chain is much longer, including many activities upstream and downstream the collection of data and the execution of the maintenance labour. For the full develoment of PdM and its deployment in practice, it is important to build integrated cost-benefit models that include the impact of the PdM on the entire asset management.

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