Predictive Maintenance for Infrastructure Asset Management

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***Abstract*—Optimal maintenance is one of the key concerns for asset-intensive industries in terms of reducing downtime and occurring costs. The advancement of data-driven technologies, affordable computing powers, and growing amounts of data introduced a paradigm with the name of predictive maintenance (PdM). PdM seeks to find out an optimal moment for the maintenance of an asset, where no early intervention leads to undue extra cost, and no late maintenance activity poses a safety risk. With the instrumentation of the cyber-physical system on assets, PdM transforms a typical structure into a smart structure that can send warnings in cases of near failure states. However, several practical challenges hamper the adoption of PdM solutions within industries. This article outlines a typical PdM modeling framework and its key components. Additionally, the adoption challenges, along with alternatives for implementation of the PdM solution are provided. This article concludes by offering several research directions that can accelerate the PdM adoption procedure.**

Think about all the times you had to endure train delay because of an expected switch failure, flight cancellation due to malfunction in air traffic control, traffic jams, or reduced speeds on the road due to unexpected, unannounced repair of roads/bridges. As a user, we expect the transport network to be efficient, reliable, and available perpetually. Nevertheless, well-maintained transport services and functional infrastructure are of vital importance to enable economic growth and access to jobs and services. With the expectations of availability and reliability comes the need for efficient and effective maintenance. The maintenance expenditure ranges from 50% to 70% with respect to the overall life cycle cost of a structure. These outlay of

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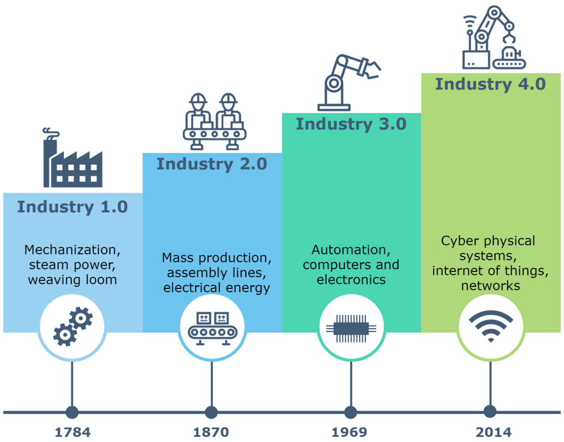

Figure 1. Industrial revolution 4.0:[1] The growing amount of data, affordable computing power, and cyber-physical systems, which enabled machine-to-machine communication, are key drivers behind the industry 4.0 revolution.

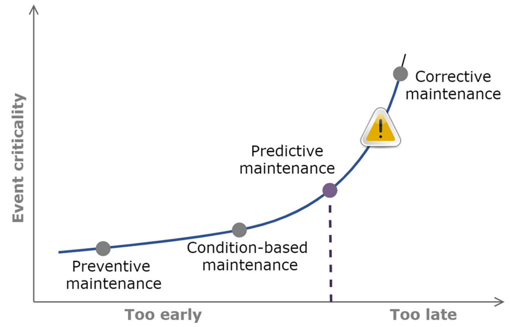

Figure 2. Overview of maintenance policies: Preventive, corrective, and condition-based are primary policies, in which the optimal time (before/after failure) to maintain an asset has been the main challenge. PdM promises to foresee the failure before it happens and provides a remaining useful lifetime of an asset.

maintenance are even higher in case of sudden break-down and scheduled activities. Predictive maintenance (PdM) seeks to prevent asset failures altogether and promise lower maintenance costs and higher reliability and availability. Typically, the PdM is defined in terms of industry 4.0, which is triggered by the sheer amount of data and economical computing power. Figure 1 provides a brief overview of the different stages of the industrial revolution.[1]

Industry 4.0 is based on cyber-physical systems that seek to connect physical devices with computing capabilities. Due to its connotation with the industrial revolution, industry 4.0 is mainly referred for the manufacturing domain. However, it is equally relevant for any asset-intensive sector, including infrastructure asset management.

In this article, we put forward a modeling framework to implement a PdM solution for infrastructure management. Next, the challenges in the adoption of PdM solutions are highlighted, and some alternatives are provided. Finally, the future research direction and conclusions are outlined.

MODELING FRAMEWORK OF PDM SOLUTION

Typically, the maintenance of infrastructure follows three types of policies, i.e., run-to-failure, planned maintenance, and condition-based maintenance (CBM). Since the scheduled maintenance leads to *the more, the better syndrome* of undue maintenance and the run-to-failure approach results in higher replacement costs; CBM has been one of the most preferred policies for the past few decades. Figure 2 provides an overview of typical maintenance policies along with PdM in the context of event criticality and time to maintain.[2]

The advancements of information and communication technologies have re-branded the CBM policy with the name of PdM. In its essence, PdM is similar to CBM, where the performance state of an asset drives the maintenance decisions. However, there are two critical differences between the PdM and CBM.

1. Instead of regular inspections, PdM proposes to perform *continuous monitoring* and reporting of remote assets by utilizing edge computing and sensing systems.
2. In contrast to developing structural-specific physical models, the (sensor) data is analyzed by machine learning techniques that notify about the current state and predict future conditions and maintenance needs.

By access to monitoring data using several sensors, digital technologies, and artificial intelligence techniques, the ambition of PdM is to develop self-diagnostic systems that alert the assets managers just-in-time in need of an intervention. An ideal modeling framework of PdM is

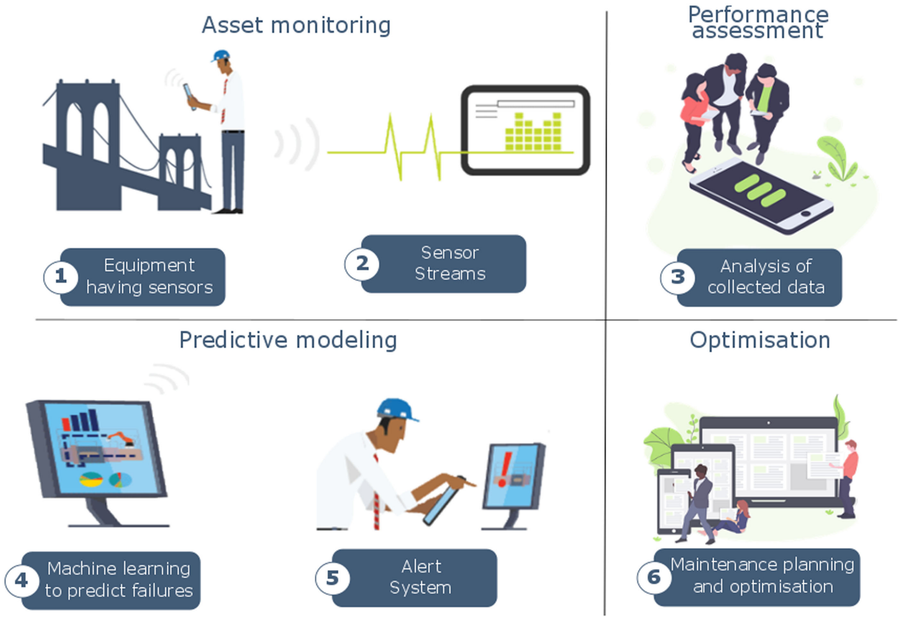

Figure 3. Ideal PdM framework: The framework covers the implementation of PdM solution in an end-to-end manner. The asset monitoring collects the data, which is further assessed to determine the performance level of assets. The future performance level and remaining useful lifetime are modeled using machine learning. Given the possible failure details of future, the optimal maintenance plans are developed.

depicted in Figure 3. In the following details, the key components of PdM in the context of infrastructure asset management are provided:

1. asset monitoring;
2. performance assessment;
3. predictive modeling; and
4. optimization.

All of these components come together to elevate a simple structure into a smart structure, which is capable of sending alerts in case of the deteriorating condition, expected failures, and intervention needs.

ASSET MONITORING

Condition assessment of structures relies heavily on visual inspections due to its affordability and nondestructiveness. Since visual inspections are susceptible to subjective judgments of inspectors, the different types of sensors are instrumented on the structure to record various parameters. The example of a few sensors and recorded parameter include temperature sensors, strain gauges, inclinometers to measure angle and slope, string pots to gauge linear position and velocity, and accelerometers. Depending on the geometry of assets, other monitoring instruments such as unmanned aerial vehicles, laser scanning, and measurement machines can be used.

PERFORMANCE ASSESSMENT

Several monitoring instruments can record diverse parameters from an asset/structure. However, acquisition of the quality data and converting it into useful information is a substantial challenge. Data collected from diverse procedures require different types of analysis, such as signal processing, time-series analysis for sensory data, and image processing from images and video data. Several preprocessing steps, including noise reduction, elimination of irrelevant features, imputing missing input have to be performed for robust performance assessment of an asset. Additionally, the ground-truth values (data labels) must also be established to comprehend the processed data and use it for predictive modeling. In addition to knowledge of domain experts, different models such as survival analysis, similarity models, mean-time to failure can be used for data labeling.

PREDICTIVE MODELING

In this step, the augmented data and preliminary analysis are used to develop data-driven prognostic and diagnostic models using machine learning algorithms. The possible use cases of predictive modeling for infrastructure asset management include:

i. Will the structure fail within the specified time interval? (Binary classification);
ii. Which maintenance actions are needed given the damage descriptions? (Multiclass classification);
iii. What is the remaining service life of an asset? (Regression);
iv. What is the leading cause of failure? (Interpretability).

The machine learning models can be developed to answer these specific questions using the historical data from sensor streams, asset register, maintenance records, and operational details. Given the type of problem as classification, regression or anomaly detection, different machine learning algorithms such as tree-based algorithms, linear regression, support vector machines, and neural networks can be employed to develop accurate predictive models. The developed models can then be bootstrapped into web APIs to integrate within core infrastructure for sending alerts to asset managers in case of possible detected damage or near-failure state of assets.

OPTIMIZATION

Optimization is the most important and often a missed step in the PdM framework. The key objective of PdM is to find the right balance between too early (planned) and too late (corrective) maintenance activities. In this step, optimal maintenance plans are developed that must not only consider the performance state of the structure but the budget limits, as well as impact on traffic and environment. Several decision-making techniques such as multicriteria decision analysis, evolutionary algorithms, dynamic programming, among others, can be utilized to prioritize assets, to develop cost-effective plans, and to combine maintenance activities of several assets for future interventions.

CHALLENGES OF PDM ADOPTION AND POSSIBLE ALTERNATIVES

Even with the promised benefits of PdM solutions, fewer asset-intensive industries have implemented it. Tiddens *et al*.[3] conducted an extensive case study from different asset domains and concluded that there is a gap between potential and realized benefits of PdM. According to another survey, from 103 operations and maintenance professional across Europe, North America and Asia pacific,[4] only 12% use machine learning for predictive analytics while 51% still employ traditional statistical modeling such as vibration monitoring, and thermal imaging, and use MS Excel as a main analysis tool. Similarly, a survey of 250 companies from the Netherlands, Germany, and Belgium shows that only 11% implemented PdM solution while 36% of them still mainly depend on visual inspection.[5] In this section, we outline the challenges that act as a barrier to the adoption of PdM solutions and provide alternatives to overcome them.

I. *Data collection and management*: Assets intensive industries have been collecting the data either by automated procedures or by specific business processes. Over time, the collected data is not only massive and dispersed across several IT systems, but it is also challenging to acquire, manage, and process by traditional software and tools within a tolerable time. The PdM aggravates this challenge even further by proposing to perform continuous monitoring of the structure, which results in even more data collection. There is a need to make linked data and web semantic technologies accessible in order to manage the large amount of data transparently.
II. *Technology*: The PdM introduces several new technologies, which could be one of the main challenges in its adoption. The advertised benefit of artificial intelligence and machine learning either brings unrealistic expectations or skepticism from domain experts. Due to the black-box nature of the predictive models, it is often impossible to communicate and comprehend the reasoning behind the model results. Additionally,

the use of advanced technology also brings complexity and compatibility issues with the legacy computerized system.

III. *Data security*: Asset intensive industries employ several third-party companies for the management and maintenance of the assets. However, due to several sources of data collection as a part of PdM, the challenges of data security may rise. In particular, the dilemma of who owns the data, how to use the data, and what are the rights of the contractor on the acquired data. According to Bauerand Horváth,[6] data confidentiality, integrity, and availability are some of the main decision factors in adopting PdM. The data security concerns can be dealt via privacy-preserving machine learning, which includes multiparty computation and homomorphic encryption for privacy preservation and differential privacy for data disclosure.

IV. *Economic feasibility*: From the business perspective, there are several reasons that pose economic feasibility as PdM adoption challenges, such as: 1) there is a possible lack of understanding about how PdM can help in the decision-making process and how it can help in developing cost-effective plans; 2) there are no straightforward metrics to estimate the return on investment of PdM projects; and 3) PdM requires substantial investment in technology and possible changes in legacy processes and systems. This also requires investment in training and development programs for the employees.

V. *Organizational factors*: The lack of vision on digitization and its prospective benefits to the organization from top management is one of the central challenges. Additionally, the level of satisfaction with the current systems is also one of the main (limiting) drivers. If an agency is satisfied with its current system and does not see a performance gap, it is less likely to invest in PdM solutions. As PdM demands expertise from various business domains such as maintenance and management, edge (sensor) computing, data analytics, the organizational structure as (de)centralized plays a significant role in the adoption of advanced technologies.

Since the implementation of an end-to-end PdM solution requires a substantial investment and change in existing processes, different alternatives may be adopted to still harvest the benefits of PdM. Instead of instrumenting a continuous condition monitoring system, it is possible to use data collected from traditional business processes and develop prognostic and diagnostic predictive models using machine learning, as reported in the paper by Bukhsh *et al.*[7] This will also require minimal changes in existing business practices as predictive models would have used the data from in-use business processes. In order to gradually develop the trust of domain experts on predictive modeling, it is paramount to focus on interpretability and posthoc analysis of models developed using machine learning. The interpretability of models will outline the rationale behind discovered patterns, whereas posthoc analysis will ensure that the models provide the answers to the defined questions. Besides, with the structured dataset, techniques like decision-tree and random forest can be used for modeling as they are good in predictive performance and yet provide explainable results.

CONCLUSION AND FUTURE DIRECTIONS

The PdM has gained substantial attention from academics as well as the manufacturing and transportation industries. The estimated increase in the global PdM market from $2.08 billion in 2018 to $23 billion by 2026, by Allied Market Research, warrants its utility for the maintenance domain. However, the adoption and implementation of PdM for asset management will not be feasible without the focus on long-term digitalization strategies from the top management. This demands substantial changes in legacy systems and current decision-making practices along with the need for skilled staff. Meanwhile, the research towards low-cost data solutions and interpretable machine learning technologies will make the PdM desirable and accessible. The notable example of low-cost data collection solutions includes the use of accelerometer data from smartphones to detect potholes on pavements[8] and the use of dashboard camera images through crowdsourcing for condition assessment of roads.[9] With the help of low-cost solutions, the autonomous data collection and analysis pipelines can be established, which can be used as an input for performance assessment and predictive modeling of assets. Finally, the interpretability of the machine learning models is of critical importance for PdM success. The interpretability is not limited to the models' results alone; instead, it must also cover the posthoc analysis, descriptive and prescriptive analysis, and models relevancy to the problem domain.

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