Evolving From Predictive to Liquid Maintenance in Postmodern Industry

Manuel Lozano Rodriguez
https://orcid.org/0000-0002-4182-8010
American University of Sovereign Nations, Spain

Carlos E. Torres
Power-MI, USA

INTRODUCTION

Liquid Maintenance is the Predictive Maintenance (PdM) evolution to thrive in the incoming industrial era. Industry, and subsequently, maintenance and, namely, PdM are unready to face the near-future incoming challenges since they are anchored in an obsolete paradigm alien to the incoming cyber-physical reality and unfit for unbelievable data density. In addition to this, PdM is wormed by philosophical hiddenness around Time and taxonomies abuse; it is not the sound subdiscipline it appears to be. So PdM professionals are doomed to dialogue and get along with AIs if we want to break our human predictiveness ceiling glass and keep PdM improving. In this paper, the authors will explain not only the turn of the tide but how to flow towards a non-essentialist PdM paradigm.

Maintenance happens in a non-deterministic polynomial-time hard (Abedi et al., 2017). In practice, it points out that early and tardy maintenance works are the norm rather than the exception. More even, industry keeps stuck to the Adam Smith paradigm of labour division extended to maintenance and the way it's understood. Furthermore, the taxonomy as used in industry so many times is too close to Aristotelian verbiage and essentialism which makes it a somewhat immature field of study. And, to cap it all, meagre effort has been put in determining the way from scientific research to taxonomies, which is a long time encysted issue (Fales, 1979). Standardising the whole of maintenance activities is not quite different from setting a quality standard and shares a weak point with it. Great ideas as Total Quality Management not resulted so great when implemented: rigid and strong quality standards give room for a group feeling judged by the standards of others, so, rather than spreading quality it raised dissent and distrust (Brown & Duguid, 2017, p. 135).

Traditionally, what made a factory to be a factory was to be a firm's place where machines produce things -hopefully, in more efficient ways everyday. However, old-fashioned firms are disappearing and the whole industry is diving into a reality where the machines, the goods and foremost the places are belittled by the importance of their digital dimension, sustainable chains of value and the flexibility that smart-tech brings to business opportunities. By the same token, the importance of AI in PdM becomes paramount. Even if it's needed to demystify the breakthrough technologies that will revolutionise everything, the machine learning use in PdM, as in 2022, has grown exponentially (Redmon, 2021; Carvalho et al., 2019). It seems not to be a critical juncture but a structural shift. According to the McKinsey Global Institute, more than 60% of all manufacturing activities in the late 2010s could have been automated with the automation technology then (McKinsey Global Institute, 2016; 2017a). So, it's not surprising

DOI: 10.4018/978-1-7998-9220-5.ch130

that the value of 4IR techs is expected to share $3.7 trillions in value and become the next economic growth engine (McKinsey Global Institute, 2017b; Leurent & De Boer, 2018).

Physical, digital, and even biological entities are getting blurrier while Time remains indefinite: in such scenarios PdM can't help melting with the 4IR and become a Liquid Maintenance.

BACKGROUND

The Present of Maintenance

Getting the best value for money in maintenance actions is very important for all industries and manufacturers (Wongmongkolrit & Rassameethes, 2011). So much so that the people in charge of maintenance are continuously justifying the costs associated with their activities to prevent getting defunded after the plans for asset management (Martinez-Monseco, 2020). The goals of every plant manager are to maximise "overall equipment effectiveness (OEE) and improve asset reliability and maintainability to ensure timely product delivery and profitability" (Lee, Lapira & Siegel, 2011).

Consequently, the maintenance programme objectives, framed in maintenance philosophy are:

- Maintaining functionality and safety
- Optimising availability and future items design
- Track criticality
- Attain a minimum total life cycle cost (LCC), including maintenance costs and costs of residual failures (Carretero, et al., 2000)

Fulfilling these objectives, in spite of economic constraints, takes moving beyond traditional data collection to information creation: this is the biggest shift in the industrial landscape today (Lee, Lapira & Siegel, 2011). Monitoring dynamic systems for PdM in real-time is a hell of a process involving in turn several techniques applied in successive preprocessing steps such as: data cleaning, missing values treatment, outlier detection, feature selection, or imbalance compensation (Cernuda, 2019). Anyhow, cutting-edge fields such as software engineering are shifting towards raw-data-centrism and widening to include new types of them (Felderer, Russo & Auer, 2019). It can be seen, for example, in the case of sensors in industrial plants using video and audio formats. To prevent fall behind, PdM should move with our data-intensive times and think more like explorers than engineers. In fact, real-time assessment of behaviours during cyber-physical production in a data-intensive environment is an uncharted land for PdM. Thankfully we don't lack pioneers. Nested in the core of industry, PdM shouldn't miss a thing when it comes to learn of the frugal heuristics school that entrepreneurship is and copy its sense-making and fuzziness in situations of data scarcity (Ghezzi, 2020).

Literature review on PdM and AI in the 4IR dawn stresses the importance of decision making algorithms triggered by failure predictions in a smart-manufacturing stage while detaching, however, its lifelong engineer-centrism in favour of multidisciplinarity (Bousdekis, Lepenioti, Apostolou & Mentzas, 2019; Zonta et al., 2020). Namely, PdM is benefiting from artificial neural networks (ANN) which can learn from process data of fault simulation (Krenek, Kuca, Blazek, Krejcar & Jun, 2016). It has been very useful, for example, when estimating criticality at power plants in order to schedule maintenance works before an expected breakdown data (Özcan, Danışan, Yumuşak and Eren, 2020). Specifically, the literature review of machine learning methods applied to predictive maintenance highlights even more

Development of a Charge Estimator for Piezoelectric Actuators: A Radial Basis Function Approach

Morteza Mohammadzaheri, Mohammadreza Emadi, Mojtaba Ghodsi, Issam M. Bahadur, Musaab Zarogand Ashraf Saleem (2020). *International Journal of Artificial Intelligence and Machine Learning (pp. 31-44).*

www.irma-international.org/article/development-of-a-charge-estimator-for-piezoelectric-actuators/249251