

BENEFITS AND CHALLENGES OF USING DIGITAL TWIN FOR PREDICTIVE MAINTENANCE FOR A SUSTAINABLE SUPPLY CHAIN

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INTRODUCTION

In the face of the growing complexities of supply chains, the digitization of equipment, processes, and products is gaining more relevance. Artificial Intelligence (AI), Internet of Things (IoT), Industrial Internet of Things (IIoT), and machine learning have become the center of attention for all manufacturing industries now. Maintenance is a significant component in the manufacturing industry and has a direct impact on supply chain sustainability. Identifying the right time to conduct machine maintenance is a significant challenge for many industries. This is where Predictive Maintenance (PdM) comes into play. PdM can have a positive and lasting impact on the environment and supply chain sustainability. However, the traditional predictive maintenance methods have not been able to meet the development needs of the companies. Digital Twin, a virtual model powered by AI (Artificial Intelligence), and an abundance of data has shown considerable potential in aiding process-based strategy for predictive maintenance in manufacturing.

RESEARCH QUESTION



Q: What are the benefits and challenges of using Digital Twin for Predictive Maintenance?

This study aimed to:

- build an understanding of the potential of digital twin in improving predictive maintenance by discussing key technologies and model-based simulations required to build a reliable digital twin model
- highlight the gaps and operational challenges in the adoption and implementation of the digital twin model
- present the potential benefits to supply chain and environmental sustainability with the successful deployment of digital twin in the manufacturing industry

METHODOLOGY

This exploratory research included a scoping literature review with a qualitative analysis done on:

- Peer-reviewed academic articles
- Textile industry published articles
- Consulting industry reports (McKinsey & Co. and BCG)

The method used for analyzing the qualitative data was Thematic analysis. The literature was coded on NVivo. A tentative list of codes was created and modified during the analysis. The final list of codes were then grouped into different clusters to derive the main themes for the paper.

FINDINGS

OPERATIONAL CHALLENGES

PdM integration into a common DT framework still remains a daunting challenge as it requires extensive research and development issues to be resolved. The main challenges for a successful implementation of DT-PdM technology fall into three broad categories as described below.

- Data-based:** For data-based fault diagnosis, the volume of data is not enough to train a reliable model. It performs well for known anomalies or risks in physics-based modelling, but it is unable to identify unexpected anomalies.
- Process-based:** Many industrial environments are complex realities or socio-technical systems and because of their volatility and unpredictability, it is difficult for the current AI algorithms to simulate and predict the correct workplace models.
- Resource-based:** The affordability of DT implementations means that their accessibility is contingent upon the availability of resources, which is frequently inadequate or poor in developing countries that are the dominant markets for the manufacturing industries.

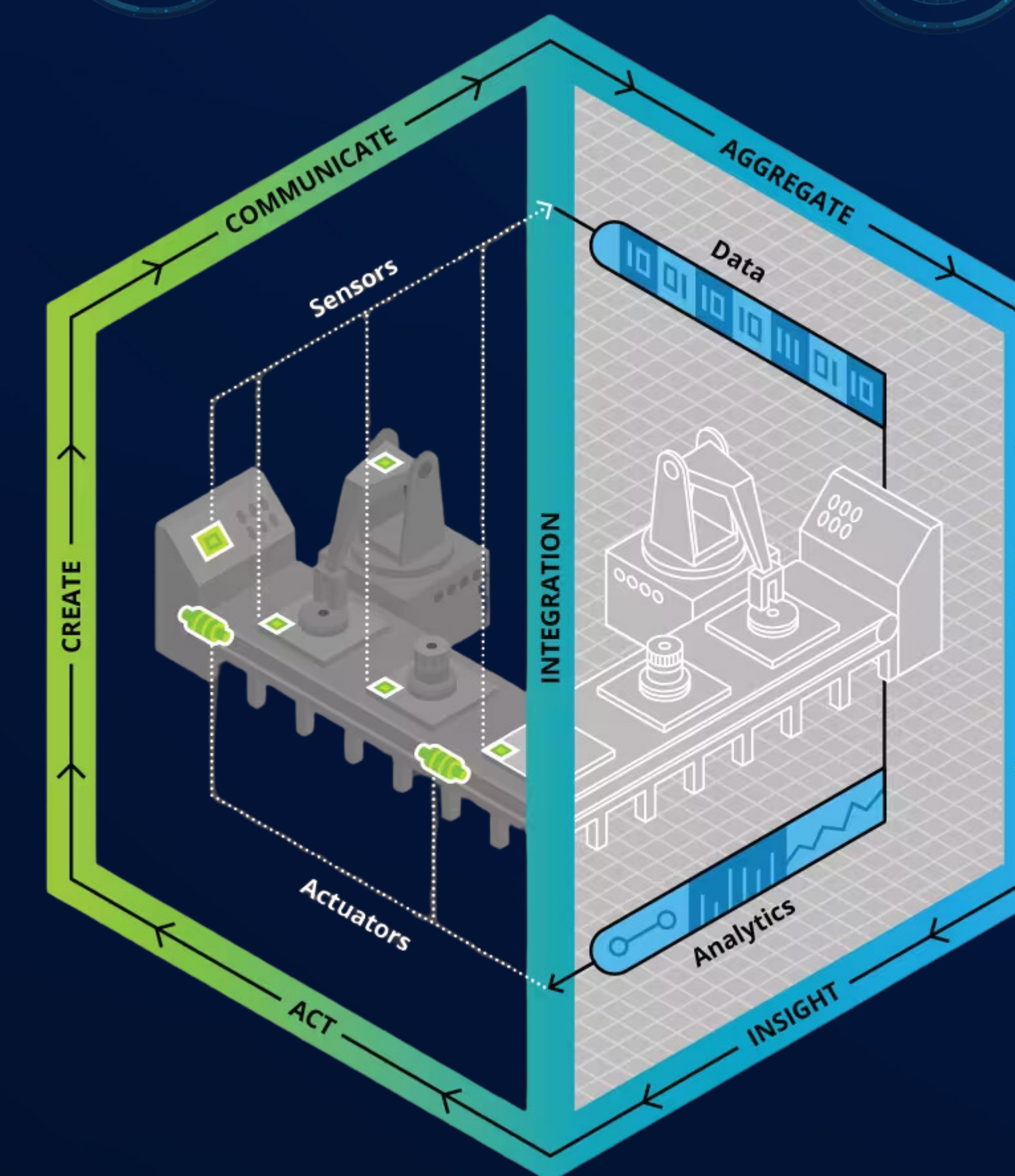
BENEFITS

While there are significant challenges in the path of successful DT-PdM deployment, there are several benefits to business and supply chain if it is adopted.

- Better Decision-Making:** The increasing disturbances and complexities in manufacturing phase call for intelligent and dynamic production planning. The use of digital twins enables globally optimized production planning in response to real-time status changes.
- Efficiency & Profitability:** By emulating the execution of a particular plan, emphasising risks and opportunities, and incorporating the insights back into the planning process, the digital twin helps to optimise sales and operations planning, also known as S&OP.
- Supply Chain Resilience:** Based on the ability of digital twin to store and simulate detailed data on the content and life-cycle of the products, it can trace any issues back to the supplier facilities and recommend appropriate corrective action and waste reduction.
- Environmental Sustainability:** In the manufacturing sector, where water consumption is extremely high, digital twins can play a critical role in ensuring the best possible water conservation strategies.



DIGITAL TWIN MODEL



Source: (Parrott & Warshaw, 2017), Deloitte University Press

DISCUSSION

1. The difficulties of employing digital twin models for maintenance have been extensively studied. Nonetheless, a single platform built on common techniques for producing DT models is not available. Therefore, a general framework with high-fidelity models needs to be defined and more research is required for that.
2. IoT is not exactly IIoT (Industrial IoT). In the real-time dynamic manufacturing environment, it can be difficult to navigate in a complex advanced manufacturing environment, which contains thousands of different types of sensors and a large number of digital devices that require huge costs of implementation. The industrial ecosystem requires solutions and models that are reliable and resilient while adhering to the industry regulations and standards. The current models on the market do not perfectly meet all the needs.

CONCLUSION

According to McKinsey Operations Practice Report, the growing interest in digital twins, combined with the advancing technologies, is prompting investments of more than \$48 billion by 2026. Digital Twin for Predictive Maintenance is a promising solution for supply chain and environmental sustainability.

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