1. Introduction

* Highlights the importance of predictive maintenance (PdM) in reducing costs and increasing efficiency in the Industry 4.0 era.
* Identifies key challenges in implementing PdM: noisy or erroneous sensor data, need for timely processing of high data volumes, and lack of generalized solutions.
* Focuses on three main perspectives to address these challenges: anomaly detection, prognostics, and architectural perspectives.

1. Review approach

* Searched Scopus and Web of Science databases for papers published in the last six years.
* For anomaly detection, papers without sensor data or industrial use cases were excluded, and categorized based on centralized or distributed architectures.
* For prognostics, the focus was on data-driven approaches, with brief definitions of physics-based and knowledge-based approaches for context.
* For architectural perspectives, papers were chosen based on novelty in interaction between cloud, fog, and edge layers and potential to address the 5 V's of Big Data in industry.

1. Anomaly detection

* Categorizes anomalies as point, behavioral, or contextual, and detection techniques as statistical or machine learning (ML) based.
* Notes the importance of distinguishing between anomalies caused by machinery events (informative) and sensor issues (noise).
* Reviews centralized and distributed approaches, summarizing techniques, datasets, and results (Tables 1 and 2).

3.1 Centralized approaches

* Techniques include spatial and temporal correlation, clustering, and majority voting.
* Datasets are often real-world with synthetic anomalies introduced.

3.2 Distributed approaches

* Exploit edge devices and fog layers for multi-stage detection and reduced latency.
* Techniques include fuzzy theory, unsupervised clustering (e.g., DBSCAN), and micro-clustering.

3.3 Current challenges, trends, and future directions

* Highlights the need to distinguish between informative events and sensor noise, and the lack of labeled real-world datasets.
* Suggests integrating anomaly detection with prognostics to improve model accuracy and generalization.

1. Prognostics methods

* Categorizes approaches as knowledge-based, physics-based, and data-driven (statistical and ML).
* Focuses on data-driven methods, with summaries of techniques, case studies, and contributions (Table 3).

4.1 Knowledge-based approaches

* Rely on expert knowledge and include rule-based, fuzzy logic, and case-based reasoning methods.
* Mainly used for diagnostics rather than prognostics.

4.2 Physics-based models

* Exploit mathematical models of physical processes affecting asset health, but require deep domain knowledge.

4.3 Data-driven approaches

* Leverage sensor data to build behavioral or degradation models and estimate remaining useful life (RUL).
* Statistical methods include hidden Markov models, Wiener process models, and proportional hazards models.
* ML methods include artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), and XGBoost.

4.4 Current challenges and future directions

* Notes the lack of generalization, with most methods being specific to a part or equipment type.
* Suggests integrating anomaly detection events as input features and considering interactions between components' degradation.

1. Architectural perspective

* Reviews the evolution from centralized cloud-based architectures to decentralized edge-fog-cloud solutions.
* Summarizes recent contributions exploiting edge, fog, and cloud layers for PdM (Table 4).

5.1 Main recent contributions

* Architectures leverage edge devices for data collection, pre-processing, and analytics, fog nodes for aggregation and routing, and cloud for storage and complex analysis.
* Technologies like Docker containers and AI accelerators enable flexible, scalable, and performant solutions.

5.2 Challenges and future directions

* Highlights the need for full exploitation of edge-cloud interactions and integration with enterprise systems like manufacturing execution systems (MES).
* Suggests adopting technologies like Docker and more powerful edge devices to distribute services flexibly.

1. Conclusion

* Reiterates the importance of anomaly detection, prognostics, and architectural perspectives in developing generalized, effective PdM systems.
* Emphasizes the potential of integrating anomaly detection with prognostics to improve model accuracy and generalization.
* Stresses the need for efficient, flexible architectures leveraging edge, fog, and cloud resources to meet the demands of Industry 4.0.

Definitions:

1. Predictive Maintenance (PdM):
   1. A proactive maintenance strategy that uses sensor data and analytics to predict equipment failures and schedule maintenance accordingly, aiming to reduce costs and increase efficiency.
2. Data-driven Approaches:
   1. Prognostics methods that leverage historical sensor data to build statistical or machine learning models of an asset's behavior or degradation patterns.
3. Edge Computing:
   1. A distributed computing paradigm that brings computation and data storage closer to the sources of data (e.g., sensors and devices), reducing latency and bandwidth requirements.
4. Fog Computing:
   1. An architecture that extends cloud computing to the edge of the network, providing a decentralized platform for data processing, storage, and analysis between the cloud and end devices.