Predictive Maintenance in Industrial Robotics Using Big Data: Techniques, Challenges, and Opportunities

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Abstract — **In industrial robotics, predictive maintenance is important to improve efficiency and reduce costs, addressing early detection and diagnosis of failures. The use of Big Data allows us to identify patterns and trends that at first glance are complex. This review examines research on the application of big data in predictive maintenance of industrial robots, which use advanced techniques such as cloud-based architectures, filtering algorithms, and machine learning. The review methodology included an analysis of the big data techniques used, the challenges identified, and the opportunities presented. The results show significant improvements in the accuracy of predictions and fault diagnoses. Key anomaly drivers were identified that improved production performance and enabled accurate fault identification and reduced downtime in industrial robots. Despite the benefits, challenges remain in data security and communications latency, underscoring the need to develop innovative algorithms and techniques to balance computing load and minimize delays. The continuous evolution of these techniques promises to improve the failure management capacity in industrial robotics, thus optimizing the operability and efficiency of robotic systems.**

Keywords— Predictive maintenance, industrial robotics, big data, fault prediction

I. Introduction

In the era of Industry 4.0, the integration of advanced technologies has revolutionized traditional industrial processes, transforming them into more intelligent and connected systems [1]. This industrial paradigm, characterized by the interconnection and digitalization of factories , has significantly opened doors to innovations in various fields, including predictive maintenance in industrial robotic systems [2], [3].

Predictive maintenance has become one of the most promising applications of big data in industrial robotics. This approach not only anticipates potential failures before they occur but also optimizes maintenance schedules, reduces costs, and enhances the operational efficiency of robotic systems. The analysis of large volumes of data generated by sensors and robotic control systems enables the identification of patterns and trends that facilitate the prediction of failures and the planning of preventive maintenance.

Ariyaluran Habeeb et al. [4] illustrate how data management and processing can uncover anomalous behavior and predict imminent failures, transforming maintenance from a necessary evil into a strategic factor that positively impacts the productivity and efficiency of industrial processes. Advanced techniques such as machine learning, data mining and artificial intelligence are essential [5]. This approach not only improves the accuracy of fault classification, but also significantly accelerates the processes, demonstrating the potential of big data in practical applications.

The implementation of predictive maintenance techniques in industrial robotics offers multiple benefits, including reduced downtime, optimized maintenance costs, and extended equipment lifespan. In addition, it enables more efficient resource management and an improvement in the quality of the final product. Stefanini et al. [6] illustrate how the adoption of these technologies has enabled Italian companies to improve the quality and safety of their processes, reducing operating costs and increasing sustainability.

However, the benefits are not without challenges. The implementation of predictive maintenance systems faces significant challenges, such as high initial investments, lack of qualified labor, and difficulties in integrating new technologies with existing infrastructures. Moreover, the accuracy and reliability of predictive models depend on the quality and quantity of the available data, as well as the ability of the algorithms to process and analyze this data effectively.

Recent studies, by Zonta et al. [7] and Borgi et al. [8] have demonstrated the effectiveness of predictive maintenance in various industrial contexts, highlighting significant improvements in the efficiency of management systems and failure detection in real production environments. The use of big data for predictive maintenance in industrial robotics represents an important advance in Industry 4.0, providing a solid foundation for enhancing efficiency and productivity. Through the implementation of advanced data analysis techniques, companies can anticipate and prevent failures, optimizing their operations and reducing costs. However, addressing the challenges associated with integrating these technologies to maximizing their benefits. This literature review offers an overview of how these technologies are transforming industrial robotics and provides valuable guidance for future research and practical implementations in this field.

This article is structured into four sections, with the introduction in Section I, the methodology outlined in Section II, and the results and discussion presented in Section III. The conclusions are described in Section IV.

II. METHODOLOGY

A. Design of the research

This review addresses the following research question: How can big data analytics predict and prevent failures in industrial robotic systems? To explore this, the review utilized databases including Web of Science (WoS), APA PsycNet, IEEE Xplore, SpringerLink and Scopus for their extensive coverage and rigorous indexing of high-quality scientific articles. The review adhered to a systematic approach as outlined by the PRISMA method guidelines (Preferred Reporting Items for Systematic Reviews and Meta- Analyses) [9].

For each database, specific search queries were crafted using key terms pertinent to the research question, such as “big data”, “predictive maintenance”, “fault prediction”, “robot”, and “robotics”.

B. Inclusion criteria

The inclusion criteria were as follows: (i) Peer-reviewed scientific journal articles; (ii) Studies focusing on the application of big data in the predictive maintenance of industrial robotics; (iii) Articles in English; (iv) Articles published between 2010 and 2024; (v) Studies providing empirical data or relevant case studies.

C. Exclusion criteria

Exclusion criteria included: (i) Review articles, surveys, and systematic reviews; (ii) Studies lacking specific data on the use of big data in predictive robot maintenance.

D. Data extraction

Data extraction was conducted systematically and rigorously to address the research question. Each article was evaluated against the inclusion criteria. Two researchers (F.A.-C. and J.B.) extracted pertinent information, with any discrepancies discussed in meetings with I.A.-C. and D.Y. to reach a consensus. This collaborative approach ensured the reliability and validity of the data extracted.

III. RESULTS AND DISCUSSION

The synthesis of findings from selected studies offers a complete view of the use of big data in predictive maintenance for industrial robotics. The analysis unveiled a rich landscape of advanced techniques, significant challenges, and promising opportunities, providing a robust framework for future studies and practical implementations in the field. The PRISMA flowchart of this review is depicted in Figure 1, while Table 1 outlines the effectiveness of various big data techniques in enhancing prediction accuracy and fault diagnoses.

A. Advances in techniques

The use of advanced big data techniques in predictive maintenance of industrial robotics has proven to be essential to improve efficiency and precision in fault detection and diagnosis. Zhang [10] implemented a cloud-based CPS architecture with Interacting filtering algorithms. Multiple Model (IMM) and Kalman filters for analyzing historical and real-time data stored in HBase. This approach not only improved predictions for low-entropy data but also enabled real-time monitoring, significantly reducing the root mean square error (RMSE) compared to traditional methods. The integration of these advanced algorithms facilitates early failure detection, providing a quick and effective response in predictive maintenance management.

Similarly, Xian [11] developed a parallel machine learning algorithm with Apache Spark , using Empirical Mode Decomposition (EMD) to extract features from vibration signals and parallel Support Vector Machines (SVM) for fault classification in mobile robot bearings. This system achieved superior classification accuracy and speed, with an average F1 score of 97.9%. Spark 's parallel processing capability made it possible to handle large volumes of data in real time, improving the efficiency and accuracy of the predictive maintenance system.

Moreover, Lin [12] designed a CPS-based automated management platform for predictive maintenance, employing big data analytics and cloud computing with Apache Hadoop and Spark. This platform made it possible to identify key anomaly drivers and improve production performance through anomaly detection and prevention. The use of these technologies in the cloud facilitates the processing and analysis of large data sets, providing a detailed view of the status of robotic systems.

Yoo et. al [13] developed a predictive maintenance system for wafer transfer robots using acceleration sensors , K -means algorithms and neural network models. The research demonstrated a 97 % accuracy in predicting failures, highlighting the effectiveness of integrating machine learning algorithms and big data analysis in predictive maintenance.

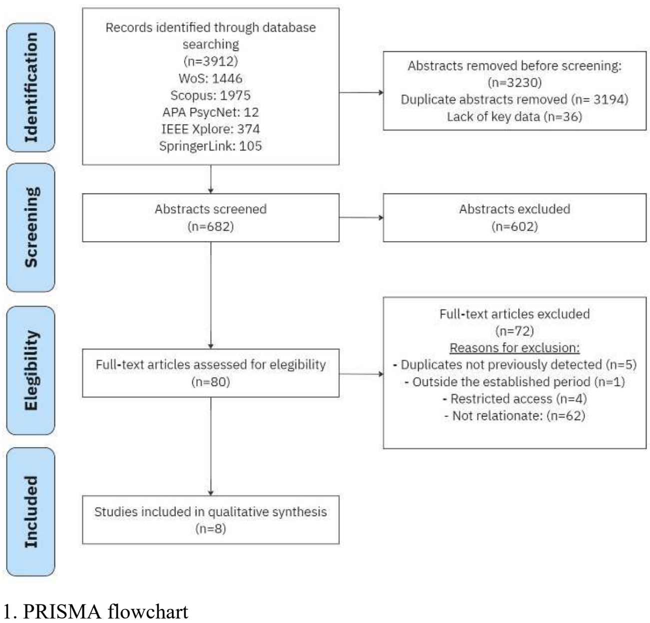

Fig. 1. PRISMA flowchart

B. Challenges in implementation

The implementation of big data in industrial robotics faces several significant challenges. Data security and privacy are critical concerns, especially with the integration of cloud technologies. Wan et al. [14] pointed out the need to establish management rules and legal provisions to mitigate security risks, such as data privacy and protection against cyberattacks. The vulnerability of systems to cyber-attacks can compromise the integrity and confidentiality of data, requiring robust security measures and strict data management policies.

Additionally, latency in communications between robots and the cloud platform can impact real-time performance. Panicucci et al. [15] highlighted the importance of developing innovative algorithms and techniques to balance the computing load and minimize delays, thus ensuring efficient and accurate performance. Latency can introduce delays in fault detection and response, negatively affecting the effectiveness of predictive maintenance.

Data compatibility and standardization also represent significant challenges. The diversity of data formats generated by different devices and sensors requires robust and flexible interfaces in cloud platforms [13]. Mitrea and Tamas [16] addressed this issue by implementing feature selection techniques and prediction models that improve speed and robustness in production, achieving a prediction accuracy greater than 96%. The standardization of data formats and interoperability between different systems are essential to maximize the efficiency and precision of big data analysis in industrial robotics.

C. Opportunities to improve performance and efficiency

Despite the challenges, the opportunities offered by big data in predictive maintenance of industrial robotics are vast. The possibility of improving the performance and energy efficiency of robotic systems is one of the greatest advantages. Wan et al. [14] highlighted how the use of big data and cloud computing can reduce costs and increase processing capacity, allowing robots to handle more complex tasks and collaborate more effectively.

The integration of predictive analytics and 3D visualization techniques into microservices architectures, such as the one implemented by Panicucci et al. [15], offers the ability to identify failures more accurately and reduce downtime, increasing the accuracy in predicting the remaining useful life (RUL) of industrial robots. Similarly, Yoo et al. [13] demonstrated that the implementation of maintenance systems predictive in diverse environments industrial, improve reliability and efficiency robot operations.

The application of big data and machine learning techniques in predictive maintenance not only optimizes robot performance but also minimizes downtime and maintenance costs, providing significant added value to the manufacturing industry.

D. Implications for practice

Big data techniques and cloud-based CPS systems have significant implications for practice in the robotics industry. Improved accuracy and speed of fault detection can reduce downtime and maintenance costs, increasing operational efficiency. The ability to analyze data in real time allows for faster and more effective response to emerging problems, improving the reliability of robotic systems [17].

Furthermore, personalization of treatments in robotic rehabilitation applications can significantly improve outcomes for patients, increasing the effectiveness of therapies and patient satisfaction [18]. The integration of advanced visualization and predictive analytics facilitates more proactive and efficient maintenance management, allowing technicians and engineers to make informed decisions based on accurate and up-to-date data.

E. Implications for research

To advance the field of predictive maintenance in industrial robotics, future research should focus on several key aspects. First, there is a need to develop innovative algorithms and techniques that address latency and security challenges in data communication, as indicated by [19]. Creating data standards and interoperability between different systems and platforms are essential to improve the efficiency and accuracy of big data analysis.

Additionally, research should explore new applications of big data in personalizing treatments and optimizing the performance of robotic systems. The integration of emerging technologies, such as artificial intelligence and quantum computing, can offer new opportunities to improve data analysis and management in predictive maintenance. Finally, collaboration between academia, industry and government should be encouraged to develop policies and regulations that support the safe and effective implementation of big data in industrial robotics.

IV. Conclusions

Predictive maintenance based on big data represents a significant innovation in industrial robotics, offering marked improvements in operational efficiency and cost reduction. The studies reviewed demonstrate that the implementation of advanced techniques, such as cloud-based CPS architectures and machine learning algorithms, allows for more accurate and faster fault detection and diagnosis. Improvements in prediction accuracy and real-time monitoring capabilities are especially notable, with examples of reduced root mean square error and high accuracy in fault classification. However, progress in this area is not without challenges. Data security and communications latency remain critical issues that require innovative solutions. Compatibility and standardization of data formats also present significant obstacles.

Despite these challenges, the opportunities that big data offers in predictive maintenance are vast. The possibility of improving the performance and energy efficiency of robotic systems, as well as customizing treatments in specific applications, highlights the transformative potential of these technologies. However, it is important to recognize current limitations, such as the need for robust data infrastructure and the high cost of initial implementation. Furthermore, the integration of these technologies requires specialized skills and may face organizational resistance.

Future work should focus on developing solutions to improve data security and reduce communication latency, as well as creating standards for data format compatibility. The continuous evolution and refinement of these techniques are essential to maximize their impact and ensure their effective integration into industrial robotics. Ultimately, the adoption of big data in predictive maintenance promises to revolutionize failure management and improve the sustainability and productivity of the robotics industry.

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TABLE I. ANALYSIS OF THE STUDIES INCLUDED IN THE REVIEW

Reference	Purpose of the study	Methodology	Big data techniques	Main findings
N. Zhang [10]	Examine the feasibility of using a cloud-based platform for big data-driven CPS modeling in industrial robots.	Design of cloud-based CPS architecture, IMM and Kalman filtering algorithms.	IMM filtering algorithm, real-time and historical data analysis, HBase for distributed storage.	Better predictions of low-entropy data, real-time monitoring, reduced root mean square error compared to traditional methods.
G. Xian [11]	Improve the efficiency of fault classification in mobile robot bearings using a parallel ML algorithm.	Designed a parallel ML algorithm with Spark, used EMD to extract features from vibration signals.	Spark, Parallel SVM, EMD, Mesos, Scala	Better precision and classification time than existing methods, precision, recall and F1 score average of 97.3%, 97.8%, and 97.9% respectively with 17 slave nodes.
Lin and Yang [12]	Evaluate and design an automated management platform based on CPS for predictive maintenance and management of abnormalities in industrial processes.	Manufacturing execution system (MES), big data analytics, cloud computing.	Big Data analysis, cloud computing with Apache Hadoop and Spark.	Identification of key anomaly drivers, improving production performance through anomaly detection and prevention.
Yoo et al. [13]	Develop a predictive maintenance system for wafer transfer robots using acceleration sensors, K-means algorithms and neural network models.	Data collection with acceleration sensors fixed on the robots. Implementation of a K-means algorithm to cluster acceleration data. Development of a neural network model to predict failures based on clustered data.	K-means algorithm for data clustering. Neural network model for fault prediction. Acceleration sensor data analysis.	Accuracy of 97% in predicting failures, demonstrating the effectiveness of the big data-based approach for predictive maintenance of robots.
Panicucci et. at [15]	Design and implement a cloud architecture for predictive maintenance and abnormality management in industrial systems using CPS.	Apache Spark, Docker, HDFS, MLLib, Gaussian kernel density estimation	Microservices architecture, edge and cloud integration, predictive analytics techniques, 3D visualization	Accurate identification of failures in industrial robots, reduction of downtime, increase in the accuracy of remaining useful life (RUL) prediction.
Mitrea and Tamas [16]	Analyze and improve the performance of the Baxter robot using data mining methods.	CFS, Consistency Subset Eval, Gain Ratio Attribute Eval, Bayesian Belief Networks, SVM, MLP, AdaBoost, DBN, SAE	Root Cause Analysis (RCA), feature selection, prediction models, supervised classification, regression	Improved speed and robustness of the Baxter robot in production, prediction accuracy greater than 96%.
Blanco et. at [20]	Explore the use of industrial robotic manipulators in a smart factory. Propose an online communication algorithm with smart manufacturing capabilities to resolve interactions in real time.	Smart factory case study. Implementation and evaluation of an online communication algorithm. Use of simulations and experiments with a real robot.	Machine Learning, Predictive Analysis, real-time processing, distributed storage.	Improving efficiency in smart manufacturing. Real-time control of robot parameters. Compliance with Industry 4.0 standards.
Zhao et. at [21]	Solve the problem of autonomous movement of intelligent harvesting robot through big data analysis.	Data collection with laser measurement sensors, CCD camera and electronic compass. Image analysis and signal processing. Implementation of fuzzy control methods.	Analysis of sensor data to determine the position and heading of the robot. Route planning based on big data analysis.	The system has a high capacity to perceive the orchard environment. Path planning based on big data analysis is effective in avoiding obstacles and guiding the robot autonomously.