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Industrial Robots and Collaborative Robots: A Comparative Study

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***Abstract*—In the era of Industry 4.0 and advancements in artificial intelligence tools, the industry is increasingly moving towards automation and reducing human intervention in production processes. In this context, industrial robots play a crucial role in modern industry, not only enhancing production and improving product quality but also addressing production uncertainties and, most importantly, reducing maintenance and production costs. To this end, the present paper proposes a comparative study of industrial robots and collaborative robots, based on a review of the literature published over the past five years. This analysis revealed that both types of robots share similarities in the nature of the faults encountered. However, the type of applications and their working environments require distinct strategies: early predictive maintenance is necessary for collaborative robots, while preventive maintenance is more suitable for industrial robots. These approaches rely on classification methods such as k-Nearest Neighbors algorithms, Convolutional Neural Networks, Random Forests, Support Vector Machines, and other neural networks for fault detection and effective trajectory control. The findings of this study will provide valuable information and serve as a significant resource for future researchers addressing challenges related to the use of these robots.**

Keywords— Artificial intelligence, Cobot, Industrial Robots, Maintenance, Optimization, Production.

I. INTRODUCTION

Technological development and the integration of digital technologies have had a significant positive impact on the world. Thus, Industry 4.0 has transformed not only education systems [1]. And medical practices, but also the industrial sector, especially in the optimization of production and maintenance [2]. The current trend is to establish an automated industrial process that is resilient to disruptions and facilitates maintenance interventions.

In this context, the use of robots in industry is growing rapidly. According to the latest statistics published by the International Federation of Robotics (IFR) in Frankfurt on September 24, 2024, the World Robotics report lists 4,281,585 robots in operation in factories around the world, an increase of 10%. Annual installations exceeded half a million units for the third year in a row. By region, 70% of the new robots deployed in 2023 were installed in Asia, 17% in Europe and 10% in the Americas [3].

The report also compares the evolution of the number of traditional and collaborative industrial robots installed each year between 2017 and 2022, the report shows a • Dominance of traditional industrial robots of 498000 units in 2022 and 55000 units for collaborative robots [4].

These statistics illustrate the increase in the use of robots, especially with the introduction of artificial intelligence (AI) technologies. However, investing in one type of robot over another should be thoroughly benchmarked. This analysis should examine their operational readiness, maintainability and ease of integration with digital systems.

The objective of this paper is to carry out a comparative study between traditional industrial robots and collaborative robots in the context of industry.

To achieve these objectives, the following sections of the report are organized as follows: Section 2: Research Methodology, Section 3 Results and Discussion, and Section 4 Conclusion and Perspectives.

II. RESEARCH METHODOLOGY AND CLASSIFICATION OF PUBLICATIONS

The objective of our study is to carry out a comparative analysis between industrial robots and collaborative robots. Thus, we have adopted the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), an approach that allows the selection of publications according to the desired criteria, the main steps are:

- Identification of research questions: in order to identify clearly the issues to be explored;
- Implementation of the research protocol: aims to Define the criteria, databases and methodologies for selecting publications;
- Extraction and analysis of results: analyses and synthesizes the information collected to meet the objectives set.

These steps are detailed as follows:

A. *Research questions:*

To guide and circumscribe our scope of study, we formulated the following questions:

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• QR1: What types of robots exist in the industry, and what are their main applications?

• QR2: What is the nature of the most frequent breakdowns for industrial and collaborative robots?

• QR3: What types of maintenance are best suited for industrial and collaborative robots?

• QR4: What artificial intelligence (AI) techniques are used in the maintenance of industrial and collaborative robots?

• QR5: What are the trajectory control methods used for industrial and collaborative robots?

B. *Selection process*

Database Selection: Our study is based on a rigorous selection of scientific articles published in the Scopus and IEEE databases over the last ten years.

Inclusion and Exclusion Criteria: The study includes scientific articles published between 2014 and 2024 that focus on industrial robots or robots operating in collaborative environments. Publications prior to 2014, as well as those with insufficient or unverifiable content quality, are excluded. Detailed criteria are provided in Table I.

Selection Process: The selection process begins with an initial search in the Scopus and IEEE databases using the keywords ROBOT AND COLLABORATIVE OR INDUSTRIAL AND ROBOT. This is followed by an initial screening of titles and abstracts to assess thematic relevance and adherence to the inclusion and exclusion criteria. The selected articles are then subjected to a full-text review before being validated and synthesized. The selection process is illustrated in Fig.1.

III. RESULTS AND DISCUSSION

This application of the method led us to extract 55 articles addressing the topic of industrial and collaborative robots. To conduct our study effectively, we have established the following comparison criteria, which will be presented in the subsequent sections. These criteria are as follows for both types of industrial and collaborative robots:

- Type of robots
- Nature of Robot Failures
- Type of Maintenance:
- Techniques and Algorithms Associated with Maintenance collaborative robots.
- Trajectory Control Methods

A. *The Type of robots*

This section is primarily dedicated to identifying the types of robots used in the industry as the first criterion for comparing robots. The analysis of the selected publications allowed us to classify these robots into two main categories: industrial robots and collaborative robots (Cobots).

1) *Industrial robots*

Industrial robots are programmable machines designed to perform repetitive tasks in automated environments. These robots typically consist of a manipulator arm and a control system. Within this category, several types of industrial robots can be identified, as follows:

TABLE I. INCLUSION AND EXCLUSION CRETERIA

Inclusion		Exclusion	
Criteria	**Explication**	**Criteria**	**Explication**
Publication Perio	2014 - 2024	Publication period	Articles published before 2014
Type of publication	Articles	No scientific Publications	Publications which are not scientific in nature or validated
Contexts Study	Industrial Application of industrial robots and collaborative robots in their environment	Lack of methodological quality	Publications fail to confirm data standard
Thematic Relevance	Articles addressing or providing comparative analysis of industrial and collaborative robots in industrial settings	Absence of industrial applicability	Publication addresses robots not related to real words industrial applications

Fig. 1. Research selection process

- **SCARA Robots** (Selective Compliance Assembly Robot Arm): Invented in 1979 by Professor Hiroshi Makino, these robots are designed to perform tasks requiring speed, precision and repeatability, often in automated environments such as printed circuit assembly and handling of small parts [5]. The robot is rigid along the vertical axis (Z-axis) but flexible along the horizontal axes (X and Y). It generally has 3 to 4 degrees of freedom, allowing for quick and precise movements.
- **Delta Robots** are a type of parallel robot consisting of three (or sometimes more) articulated arms connected to a mobile platform. They have 3 to 4 degrees of freedom, enabling movements along the X, Y, and Z axes (and sometimes rotation around the Z-axis). Delta robots are designed to perform tasks that require high speed, precision, and repeatability, often in automated industrial environments[6],[7],[8].
- **Cartesian Robots** are robots whose movement is defined by a Cartesian coordinate system (X, Y, Z axes). They have 3 degrees of freedom (X, Y, Z axes) and are designed for applications such as assembly, pick-and-place tasks, and CNC operations, where linear motion and precision are essential [9], [10].
- **Cylindrical Robots** are robots whose mechanical configuration is based on a cylindrical coordinate system. They have three main axes: the vertical axis (Z), the radial axis (R), and the rotational axis (θ). They are designed for applications such as assembly, material handling, and machine tending, where cylindrical motion is advantageous[11], [12].
- **Articulated Robots** are equipped with multiple axes of movement, typically ranging from 4 to 7 axes, allowing them to move their end-effector (tool or gripper) in various directions. They are designed for applications such as welding, painting, assembly, material handling, and packaging, where versatility and flexibility are crucial [13], [14].
- **Polar Robots** are manipulator robots characterized by the exclusive use of articulations. The movement is typically described by two parameters: the radius (r) and the angle (θ). They are used for applications requiring rotational motion and are often found in tasks such as welding, material handling, and machining [15].
- **Hybrid Robots** combine different types of mechanical structures, power sources, and modes of locomotion in a synergistic way to maximize the advantages of each. They are designed to perform tasks such as lifting or assembling objects, as well as cognitive tasks like autonomous navigation or object recognition [16].
- **Mobile Robots** are robots capable of moving autonomously or remotely within their environment. They use various mechanisms for movement, such as wheels, tracks, legs, or flying systems (drones). They may integrate cameras and sensors for tasks like navigation, object detection, and surveillance. They are designed for applications such as exploration, inspection, logistics, and surveillance in environments that require mobility and adaptability [17], [18]. The other applications are provided by the Table II

TABLE II. INDUSTRIAL ROBOTS

Industrial Robot		
Type	**Applications**	**References**
Scara	Printed Circuit Board (PCB) Assembly, Component Insertion, Testing	[19]
	Handling Small Parts, Packaging, Sample Handling	[20]
Delta	Packaging, sorting, palletizing.	[6]
	Assembly, dosing, filling	[7]
	Pick and place	[8]
Cartesian	Handling for moving loads from one point to another	[9]
	Assembly: Placing parts or objects in specific areas.	[10]
	Laser, plasma or water jet cutting operations	[21]
Cylindrical robot	Three-dimensional welding: Using a welding torch for precise deposits in rotating structures	[11]
	Material Handling: Training in tasks such as lifting and sorting lightweight objects.	[12]
Articulated	Pick-and-place tasks in outdoor environments particularly for brick handling in fields.	[13]
	Pipeline Maintenance and Inspection: This robot is used for pipeline maintenance and inspection, especially in industrial environments, where pipelines of different diameters require regular monitoring to avoid failures.	[14]
	High-precision handling: This application concerns handling processes in high-tech industries, requiring high precision for tasks such as processing and handling delicate components, such as silicon wafers in this case.	[22]
Polar	Uses a combination of wind and electric power to solve challenges of power delivery and autonomous control in polar environments.	[15]
Hybride	Hybrid wheeled-legged robot: A robot capable of using both wheels and legs to move, allowing it to adapt to different types of terrain.	[16]
	Transport of goods in automated industrial environments.	[17]
	Inspection and exploration in restricted and difficult-to-access environments	[18]
	Perform essential tasks for the construction and maintenance of fusion reactors, particularly in low visibility working conditions and with space restrictions	[23]

2) Collaborative robots

Collaborative robots (or Cobots) are robots that work in direct interaction with humans in a shared work environment, while adhering to safety regulations. They are capable of performing tasks collaboratively with humans in close proximity to workers. They are used for applications such as polishing. [24]. Performing shared tasks such as navigation, motion planning, and contextual decision-making. [25] Assembly of complex components and welding processes that require precision and active collaboration. [26]. And in medical field to assist in surgery and reduce dependence on nursing staff. [27] . The classification of these robots is illustrated in Fig. 2.

These Cobots can be classified into two categories direct collaboration and indirect collaboration as shown in Table III:

- Direct collaboration involves immediate and real-time interaction between a robot and a human in a shared workspace, without any physical separation. In this collaboration we distinguished four level of collaboration as illustrated in Fig. 3:
- Coexistence: where the robot and the robot share the same workspace but their tasks are disconnected and no babbling in time
- Sequential collaboration: where the human and the robot can work on the same task but their actions are done one after the other
- Cooperation collaboration: the human and the robot work simultaneously and their movements are coordinated
- Reactive collaboration: The highest level of collaboration where the robot reacts in real time to human movement
- Indirect collaboration involves an interaction where the human and the robot do not necessarily share the same space or act asynchronously.

TABLE III. COLLABORATIVE ROBOTS

Collaborative robot		
	Applications	**References**
Direct collaboration	Robot-assisted collaborative polishing,	[24]
	Manufacturing, disassembly for remanufacturing and end-of-life component management	[28]
	Manufacturing Industry Increasing Productivity and Quality in Welding and Assembly Operations	[26]
	Agrifood: Improving productivity and job quality in meat processing facilities.	[29]
Indirect collaboration	Food Industry: Objectively Assessing the Quality of Rehydration of Infant Formula	[30]
	Medicine: Performing complex operations inaccessible to humans	[27]
	Manufacturing: Navigate and interact in shared spaces with human operators.	[25]

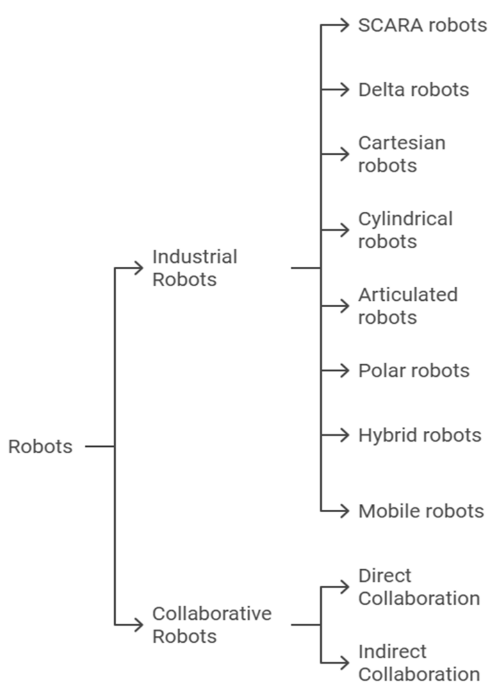

Fig. 2. Types of robots in industry

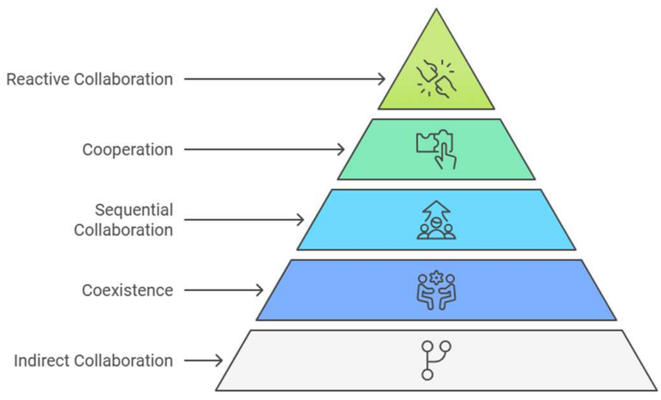

Fig. 3. Level of Collaboration

B. The nature of robot failures and maintennace

The second criterion analyzed in this study is the nature of failures associated with robots. In this regard, the study reveals that industrial robots and Cobots are likely to suffer from the same four main categories of failures: mechanical, electrical, software-related and interaction with their work environment. Thus, the differences between these failures for industrial robots and collaborative robots can be summarized as follows:

- Mechanical Failures: For industrial robots, these are, in most cases, classic failures related to wear on gears and bearings, as well as misalignment of axes due to intensive work cycles and heavy loads [31], [32], [33]. However, for collaborative robots, mechanical failures are less frequent thanks to gentler work cycles and generally lighter loads [34], [35].
- Electrical Failures: For industrial robots, these failures may be related to power surges, short circuits, or wear on electronic components [36], [37], [38]. Collaborative robots also experience similar failures but with a lesser impact due to the simpler design of their electronic systems.
- Software Failures: For industrial robots, these failures are generally linked to programming errors, software bugs, or incompatibilities with other systems [42], [43],[44]. For collaborative robots, the failures can be similar, but their simpler programming reduces software complexities [45],[46].
- Failures Related to Environmental Interaction: For industrial robots, these failures are limited to accidental collisions [33]. In contrast, for collaborative robots, such failures include specific functional issues related to their interaction with humans and the surrounding environment [39] [34].

Table IV shows the main types of breakdowns recorded by Robots

TABLE IV. NATURE OF FAILLURES

Nature of failure	Industrial robots		Collaborative robots	
	Description	**Reference**	**Description**	**Reference**
Mechanical	Wear and tear, overload often caused by intensive work cycles and heavy loads.	[40] [32]	Less wear and tear on the seals	[41] [35]
Electrical	Overvoltage, short circuits or wear and tear of electronic components.	[36] [37] [38]	Overvoltage, short circuits, sensor failures	[42]
Software	Programming errors, software bugs, or incompatibilities with other systems.	[43] [44] [45]	Simpler programming of Cobots reduces software complexities.	[46] [47]
interaction with the environment	Collisions and shocks due to the absence of safety barriers.	[33]	Fewer collisions thanks to human-robot collaboration.	[34] [39]

Thus, this comparison reveals that Industrial robots, due to the nature of their breakdowns, require stricter maintenance due to their demanding environments and intensive work cycles. As a result, their maintenance is increasingly oriented towards preventive strategies to ensure the continuity of production and regular monitoring of critical components.

On the other hand, Cobots require specific approaches that can combine different types of maintenance, preventive and conditional, to ensure the fluidity and safety of tasks in collaborative environments.

C. *Suitable type of maintenance*

This part is dedicated to the study of the third comparison criterion, which is the type of maintenance to be adapted for each type of robot. The Tables V and VI illustrate the failures and the type of maintenance associated with industrial robots and Cobots according to the literature. The comparison of these Tables is as follows:

- Predictive maintenance emerges as the most commonly used type of maintenance for both robot types. This maintenance encompasses various methods based on monitoring, diagnosis, and data analysis [35], [36], [39], [42], [44], [46].
- Conditional maintenance is primarily used for Cobots and is characterized by the integration of the equipment's actual state, often in collaboration with human feedback[34]. [47].
- Preventive maintenance is generally applied to industrial robots due to the nature of their working environment. Its primary goal is to prevent failures before they occur [32], [33]; [43].

TABLE V. MAINTENNAE AND ATURE OF FAILLURE OF COBOTS

COBOT		
Maintenance	**Nature of failure**	**Reference**
Predictive	Functional failures leading to abnormal trajectories, movement errors, loss of precision	[39]
	Mechanical failures (joint wear, overload)	[35]
	Mechanical breakdowns,	[42]
	Induced functional failures	[46]
Conditional	Collision risks, malfunctions	[34]
	Induced functional failures	[47]

TABLE VI. MAINTENNAE AND ATURE OF FAILLURE OF INDUSTRIAL ROBOTS

Industrial robots		
Maintenance	**Nature of Failure**	**Reference**
Predictive	Miscellaneous failures (mechanical, electrical, etc.)	[36]
	Mechanical, electrical, software failures	[31]
	Mechanical, electrical failures, related to component degradation	[44]
	Mechanical, electrical failures, related to software	[38]
	Mechanical failures (gear wear)	[45]
	Hardware failures, software errors, collisions	[32]
Preventive	Hardware failures, software errors, collisions	[43]
	Mechanical, electrical, electronic failures (Failure of critical components or component groups)	[33]

Thus, the study highlights that while industrial robots and Cobots share similarities in the types of failures they encounter, differences in design, usage, and working environments lead to varying levels of severity and criticality of these failures. Therefore, it is essential to focus on maintenance techniques that are tailored to the specific type of robot and its intended applications

D. Maintenance techniques

This section focuses on the techniques used for robot maintenance in the industry. These techniques are classified according to the nature of the task to be performed into three types, as follows:

- Failure Prediction: This category includes techniques used to anticipate robot malfunctions and breakdowns.
- Diagnosis: This group of techniques analyzes and examines the causes behind the occurrence of degradations.
- Maintenance Planning: This category encompasses techniques aimed at optimizing the timing and manner in which maintenance operations are carried out.

TABLE VII. COBOT MAINTENANCE TECHNIQUES

COBOT			
References	**Technique**	**Data type**	**Task type**
[34]	Real-time monitoring, behavior analysis, anomaly detection	Temporal	Diagnostic
[41]	Classification algorithms, regression,	Temporal Images	
[46]	Long Short-Term Memory networks, k-nearest neighbors	Temporal	Failure prediction
[47]	Classification algorithms, regression for failure prediction	Temporal	
[47]	Human-in-the-Loop, Machine Learning	Temporal, textual, images,	
[48]	Data-driven modeling	Temporal, textual, images,	
[49]	Mixed Perception	Images	Maintenance planning
[50]	Markov Decision Process (MDP), Proximal Policy Optimization	Temporal	

The Tables VII and VIII present the techniques employed to ensure effective maintenance of Cobots and industrial robots. The findings highlight that the most commonly used approaches are primarily based on machine learning and data analysis to anticipate issues. These results are as follows:

For Cobots, the observations show that:

- •Most techniques applied to Cobots focus primarily on early anomaly detection to ensure safety in collaborative work environments.
- Leveraging diverse data types (temporal, images, and textual) enables a comprehensive analysis of the robot's condition.
- The complementarity offered by combining deep learning, classification, and regression techniques proves particularly effective for optimizing maintenance intervention.

TABLE VIII. INDUSTRIAL ROBOT MAINTENANCE TECHNIQUES

Industrial Robot			
References	**Technique**	**Type of data**	**Task type**
[50]	DQN, PPO,	Temporal	Maintenance planning
[33]	Optimization methods, reliability analysis	Temporal	
[37]	Long-term memory networks, k-nearest neighbors	Temporal	Failure prediction
[51]	Gaussian mixture models	Digital data,	
[43]	Long short-term memory (LSTM) network, k-nearest neighbors (KNN), knowledge graphs (KGS)	Temporal	
[37]	One-class novelty detection (using SVR and ELM)	Temporal.	
[31]	Physical modeling enriched with degradation curves, digital twin	Temporal	
[44]	Physics-based models; Digital Twin	Temporal	
[43]	Speech recognition, natural language processing (NLP)	Textual (NLP), temporal (speech recognition).	Diagnostic
[37]	ML algorithms	Images, textual	
[52]	Novelty detection models	Temporal	
[31]	Neural networks, Deep learning	Images, textual, temporal	
[53]	Random forests, k-NN	Numerical or categorical data)	
[54]	Speech recognition and image processing	Temporal	
[55]	Wireless Sensor Network (WSN)	Temporal	

Regarding industrial robots:

- Physical and mathematical models provide a deep understanding of degradation mechanisms while accelerating failure prediction.
- Classification algorithms such as k-Nearest Neighbors (k-NN), Convolutional Neural Networks (CNNs), Random Forests, Support Vector Machines (SVMs), and neural networks (Machine Learning and Deep Learning) are widely used to identify different types of failures.
- The Tables VII and VIII highlight the vast amount of digital data managed by industrial robots, meticulously analyzed to detect anomalies.

Moreover, it is also observed that:

- Machine learning techniques, such as neural networks, Support Vector Machines, and Random Forests, are ubiquitous for both types of robots.
- Extracting information about the robot's condition relies primarily on utilizing various data types (temporal, images, and textual), which significantly improves predictions.

Thus, according to the above-mentioned results, the presented maintenance techniques highlight the crucial importance of ensuring the reliability and availability of industrial and collaborative robots. By taking advantage of advances in artificial intelligence and data analysis, the techniques used in robot maintenance can become increasingly personalized, allowing optimal adaptation to the unique characteristics of each robot and its operational environment.

E. Trajectory Tracking Methods

This section focuses on analyzing another comparison criterion: the control and trajectory tracking methods used by robots. These methods are categorized into three groups: methods for robot manipulation, methods for navigation, and methods for trajectory tracking. The analysis of the published articles highlights the following points: The methods outlined in Table IX are applicable to all robots, whether Cobots or industrial robots. Maintenance remains a determining factor in assessing their impact in terms of maintenance.

TABLE IX. TRAJECTORY TRACKING TECHNIQUES

Manipulation	
Methods	**References**
Non-smooth control based on non-smooth observer	[59]
Self-organizing fuzzy neural network-based control	[60]
Control Nonlinear control Servo-constraint-based control,	[56]
Servo-constraint-based control, linear-quadratic state feedback control, input-output linearization	[61]
Neural network-based control	[57]
LAMDA9-based control	[62]
Cascade control 35	[63]
Navigation	
Integral sliding mode control (VISMPDC) combined with an unspecified control method	[64]
Dynamic control	[65]
Hybrid control (predictive and nonlinear)	[66]
Acceleration-level control	[67]
Adaptive nonlinear control	[68]
Reinforcement learning	[58]
Hybrid control (feed-forward negative feedback and PID)	[69]
Model predictive control (MPC) with event triggering	[70]
Path tracking	
State feedback sliding mode control	[71] [72] [73] [74]
MINCO-based path planning, tracking trajectory based on model predictive control (MPC)	[75]
FOPID (fractional) control	[76]
Automatic parameter optimization	[77]

• For industrial robots: methods based on robust controls, in particular; nonlinear controls [56]. Sliding mode control [48]. Are used to ensure high precision in well-structured environments. In addition, predictive algorithms such as Model Predictive Control (MPC) [67].Trajectory planning are used to minimize mechanical errors and optimize the production cycle, while neural networks [57].Aare used for trajectory optimization.
• Concerning Cobots, the analysis shows that the use of adaptive algorithms, in particular fuzzy control [49].And reinforcement learning [58]. Are used to facilitate the robot's interaction with humans and to cope with disturbances. On the other hand, hybrid methods that combine several controls such as learning or fuzzy logic, [61]. As well as smooth trajectory planning such as Minimum Control (MINCO) are generally adapted to the collaborative environment to guarantee and preserve work safety.

Thus, it can be concluded that the methods employed enhance precision, productivity, and fault prediction for industrial robots. In contrast, for Cobots, the applied methods focus on improving human-machine interaction. Furthermore, AI tools such as neural networks and hybrid algorithms support proactive maintenance for both types of robots.

IV. CONCLUSION AND IMPLICATIONS

This study compares industrial and collaborative robots based on their typology, failures, maintenance methods, and trajectory control. Industrial robots are preferred for their robustness, while collaborative robots are gaining popularity due to their flexibility and human interaction capabilities.

Both types have similar failures (mechanical, electronic, software and environmental). Predictive maintenance is the most common approach, with condition-based maintenance more appropriate for collaborative robots and preventive maintenance more appropriate for industrial robots.

Machine learning techniques improve robot health monitoring. Industrial robots rely on robust control and predictive algorithms to optimize production, while collaborative robots use adaptive algorithms for better human interaction.

The study has some limitations, such as excluding emerging robots and lacking in-depth analysis of safety standards and hybrid maintenance approaches.

REFERENCES

[1] F. Abnoulgid, S. Aouhassi, K. Mansouri, et F. Akef, « Bibliometric Analysis of Publications: University 4.0 and Higher Education Quality (HEQ) », in *2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, mai 2024, p. 1-10. doi: 10.1109/IRASET60544.2024.10548276.

[2] M. L. Soudani, S. Nissabouri, et M. E. H. Ech-Chhibat, « Maintenance and Production Optimization using artificial intelligence (AI) Tools: A Bibliometric Analysis and Review », présenté à 2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology, IRASET 2024, 2024. doi: 10.1109/IRASET60544.2024.10549204.

[3] I. I. F. of Robotics, « Record of 4 Million Robots in Factories Worldwide », IFR International Federation of Robotics. Accessed on: December 2, 2024. [Online]. Available at: https://ifr.org/ifr-press-releases/news/record-of-4-million-robots-working-in-factories-worldwide

[4] I. I. F. of Robotics, « International Federation of Robotics », IFR International Federation of Robotics. Accessed on: December 2, 2024. [Online]. Available at: https://ifr.org/industrial-robots

[5] W. S. Barbosa *et al.*, « Industry 4.0: examples of the use of the robotic arm for digital manufacturing processes », *Int J Interact Des Manuf*, vol. 14, nº 4, p. 1569-1575, déc. 2020, doi: 10.1007/s12008-020-00714-4.

[6] C. LIU, G.-H. CAO, Y.-Y. QU, et Y.-M. CHENG, « An improved PSO algorithm for time-optimal trajectory planning of Delta robot in intelligent packaging », *Int J Adv Manuf Technol*, vol. 107, nº 3, p. 1091-1099, mars 2020, doi: 10.1007/s00170-019-04421-7.

[7] J. de D. Flores-Mendez, H. Schiøler, S. Bai, et O. Madsen, « Force estimation and control of Delta Robot for assembly », in *2021 IEEE Conference on Control Technology and Applications (CCTA)*, août 2021, p. 640-647. doi: 10.1109/CCTA48906.2021.9658767.

[8] A. Elassal, M. Abdelaal, M. Osama, et H. Elhnidy, « Low-cost parallel delta robot for a pick-and-place application with the support of the vision system », *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 8, p. 100518, juin 2024, doi: 10.1016/j.prime.2024.100518.

[9] M. Anbarasi, V. Dharnish Kumar, et M. Ilavazhagan, « Warehouse Handling utilizing Cartesian Robots », *Warehouse Handling utilizing Cartesian Robots*, vol. 6, nº 5, 2019, Consulté le: 4 décembre 2024. [En ligne]. Disponible sur: https://www.kalaharijournals.com/resources/IJME_Vol7.1_474.pdf

[10] J. L. DeVries, « Assembly in action: Engineers mesh cartesian robot with roller pinion system », *Assembly*, vol. 60, nº 12, p. 20-27, 2017.

[11] X. Lai, Y. Xu, et J. Zhou, « Research and forming effect analysis on slicing algorithm of cylindrical coordinate robot welding », *Hanjie Xuebao/Transactions of the China Welding Institution*, vol. 39, nº 7, p. 81-87, 2018, doi: 10.12073/j.hjxb.2018390180.

[12] J. V. Joromat *et al.*, « PLC-Based Electro-Pneumatic Cylindrical Robot with Color Object Detection and Vacuum End Effector for Material Handling Trainer », présenté à 2023 IEEE 15th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM 2023, 2023. doi: 10.1109/HNICEM60674.2023.10589075.

[13] T. Anzai, M. Zhao, T. Nishio, F. Shi, K. Okada, et M. Inaba, « Fully Autonomous Brick Pick and Place in Fields by Articulated Aerial Robot: Results in Various Outdoor Environments », *IEEE Robotics and Automation Magazine*, vol. 31, nº 2, p. 39-53, 2024, doi: 10.1109/MRA.2023.3276265.

[14] F. Meng, S. Wang, K. Xu, et Y. Zheng, « ANALYSIS AND RESEARCH ON OBSTACLE-CROSSING CHARACTERISTICS OF ARTICULATED VARIABLE-DIAMETER PIPE CLIMBING ROBOTS », *International Journal of Mechatronics and Applied Mechanics*, vol. 2024, nº 17, p. 23-31, 2024, doi: 10.17683/ijomam/issue17.3.

[15] L. Guo, G. Liu, Y. Luo, P. Jiang, et J. Zhao, « A wind-electric hybrid polar roaming robot: Design, modeling, and experiments », *Journal of Field Robotics*, vol. 41, nº 1, p. 131-143, 2024, doi: 10.1002/rob.22249.

[16] C. Grand, F. Ben Amar, F. Plumet, et P. Bidaud, « Evaluation of the locomotion modes for an hybrid wheel-legged robot evolving in outdoor environment », *Mecanique et Industries*, vol. 6, nº 3, p. 353-364, 2005, doi: 10.1051/meca:2005041.

[17] H. Jo, S. Seo, J. Kim, et F. Bien, « A coreless track-type seamless wireless charging system using co-planar wires enabling quasi-free planar movements for mobile logistics robots », *Applied Energy*, vol. 375, 2024, doi: 10.1016/j.apenergy.2024.123943.

[18] S. E. Nodehi, L. Bruzzone, et P. Fanghella, « Porcospino, spined single-track mobile robot for inspection of narrow spaces », *Robotica*, vol. 41, nº 11, p. 3446-3462, 2023, doi: 10.1017/S0263574723001108.

[19] A. BURISCH, seven SOETEBIER, et J. WREGE, « DESIGN OF A PARALLEL HYBRID MICRO-SCARA ROBOT FOR HIGH PRECISION ASSEMBLY », *Mechatronics and Robotics*, vol. 4, p. 1370-1380, 2004.

[20] M. HAJDUK, J. SEMJON, et J. VARGA, « Utilization of SCARA Robots in the Assembly of Electrical Contacts », *International Journal of Mechanical Engineering and Robotics Research*, vol. 4, p. 360-365, 2017.

[21] U. SIMSIR, et L. CDR, « CUTTING METHODS AND CARTESIAN ROBOTS », *ournal of Naval Science and Engineering*, vol. 5, nº 2, p. 35-42., 2009.

[22] P. Gümbel et K. Dröder (2), « Precision optimized process design for highly repeatable handling with articulated industrial robots », *CIRP Annals*, vol. 73, nº 1, p. 25-28, 2024, doi: 10.1016/j.cirp.2024.03.008.

[23] C. Li, H. Wu, H. Eskelinen, H. Handroos, et M. Li, « Design and implementation of a mobile parallel robot for assembling and machining the fusion reactor vacuum vessel », *Fusion Engineering and Design*, vol. 161, 2020, doi: 10.1016/j.fusengdes.2020.111966.

[24] H. Zhou, X. Zhang, et J. Liu, « A corrective shared control architecture for human–robot collaborative polishing tasks », *Robotics and Computer-Integrated Manufacturing*, vol. 92, 2025, doi: 10.1016/j.rcim.2024.102876.

[25] C. Zheng *et al.*, « Semantic map construction approach for human-robot collaborative manufacturing », *Robotics and Computer-Integrated Manufacturing*, vol. 91, 2025, doi: 10.1016/j.rcim.2024.102845.

[26] Y. Cao, Q. Zhou, W. Yuan, Q. Ye, D. Popa, et Y. Zhang, « Human-robot collaborative assembly and welding: A review and analysis of the state of the art », *Journal of Manufacturing Processes*, vol. 131, p. 1388-1403, 2024, doi: 10.1016/j.jmapro.2024.09.044.

[27] D. Rekha et H. K. Kaliyappan, « Collaborative robot acting as scrub nurse for cataract surgery (CRASCS) », *Journal of Robotic Surgery*, vol. 18, nº 1, 2024, doi: 10.1007/s11701-024-02089-0.

[28] L. Zhu, Y. Chen, et J. Mumtaz, « Multi-objective human-robot collaborative disassembly line balancing considering components remanufacture demand and hazard characteristics », *Computers and Industrial Engineering*, vol. 197, 2024, doi: 10.1016/j.cie.2024.110621.

[29] R. Wright, S. Parekh, R. White, et D. P. Losey, « Safely and autonomously cutting meat with a collaborative robot arm », *Scientific Reports*, vol. 14, nº 1, 2024, doi: 10.1038/s41598-023-50569-4.

[30] B. Mozafari, N. O'Shea, M. Fenelon, R. Li, D. F. M. Daly, et R. Villing, « An automated platform for measuring infant formula powder rehydration quality using a collaborative robot integrated with computer vision », *Journal of Food Engineering*, vol. 383, 2024, doi: 10.1016/j.jfoodeng.2024.112229.

[31] P. Aivaliotis, Z. Arkouli, K. Georgoulias, et S. Makris, « Degradation curves integration in physics-based models: Towards the predictive maintenance of industrial robots », *Robotics and Computer-Integrated Manufacturing*, vol. 71, 2021, doi: 10.1016/j.rcim.2021.102177.

[32] Y. Yang *et al.*, « An Industrial Case Study on the Monitoring and Maintenance Service System for a Robot-Driven Polishing Service System under Industry 4.0 Contexts », *Systems*, vol. 11, nº 7, 2023, doi: 10.3390/systems11070376.

[33] H. Dui, H. Xu, L. Zhang, et J. Wang, « Cost-based preventive maintenance of industrial robot system », *Reliability Engineering and System Safety*, vol. 240, 2023, doi: 10.1016/j.ress.2023.109595.

[34] K. Aliev et D. Antonelli, « Proposal of a monitoring system for collaborative robots to predict outages and to assess reliability factors exploiting machine learning », *Applied Sciences (Switzerland)*, vol. 11, nº 4, p. 1-20, 2021, doi: 10.3390/app11041621.

[35] A. S. M. Sahan, S. Kathiravan, M. Lokesh, et R. Raffik, « Role of Cobots over Industrial Robots in Industry 5.0: A Review », présenté à 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation, ICAECA 2023, 2023. doi: 10.1109/ICAECA56562.2023.10201199.

[36] S. Weerasinghe et T. Silva, « Ontology Based Machine Learning Approach for Predictive Maintenance of Industrial Robots », présenté à 7th SLAAI - International Conference on Artificial Intelligence, SLAAI-ICAI 2023, 2023. doi: 10.1109/SLAAI-ICAI59257.2023.10365031.

[37] U. Izagirre, I. Andonegui, I. Landa-Torres, et U. Zurutuza, « A practical and synchronized data acquisition network architecture for industrial robot predictive maintenance in manufacturing assembly lines », *Robotics and Computer-Integrated Manufacturing*, vol. 74, 2022, doi: 10.1016/j.rcim.2021.102287.

[38] N.-G. Kim et D. Seo, « A Study on Predictive Maintenance System for Industrial Robot RV Reducers Based on AI and ROM », *Lecture Notes in Electrical Engineering*, vol. 1217 LNEE, p. 317-322, 2024, doi: 10.1007/978-981-97-4182-3_41.

[39] E. Wescoat, M. Krugh, et L. Mears, « Random forest regression for predicting an anomalous condition on a UR10 cobot end-effector from purposeful failure data », présenté à Procedia Manufacturing, 2021, p. 644-655. doi: 10.1016/j.promfg.2021.06.064.

[40] Z. Ren, Z. Yu, W. Zhang, et Q. Lei, « Streamlining Industrial Robot Maintenance: An Intelligent Voice Query Approach for Enhanced Efficiency », *IEEE Access*, vol. 12, p. 121864-121881, 2024, doi: 10.1109/ACCESS.2024.3452269.

[41] A. Polenghi, L. Cattaneo, et M. Macchi, « A framework for fault detection and diagnostics of articulated collaborative robots based on hybrid series modelling of Artificial Intelligence algorithms », *Journal of Intelligent Manufacturing*, vol. 35, nº 5, p. 1929-1947, 2024, doi: 10.1007/s10845-023-02076-6.

[42] B. I. Ismail, M. F. Khalid, R. Kandan, H. Ahmad, M. N. Mohd Mydin, et O. Hong Hoe, « Cobot Fleet Management System Using Cloud and Edge Computing », présenté à 7th IEEE International Conference on Engineering Technologies and Applied Sciences, ICETAS 2020, 2020. doi: 10.1109/ICETAS51660.2020.9484266.

[43] X. Wang, M. Liu, C. Liu, L. Ling, et X. Zhang, « Data-driven and Knowledge-based predictive maintenance method for industrial robots for the production stability of intelligent manufacturing », *Expert Systems with Applications*, vol. 234, 2023, doi: 10.1016/j.eswa.2023.121136.

[44] C. Nentwich et G. Reinhart, « Towards Data Acquisition for Predictive Maintenance of Industrial Robots », présenté à Procedia CIRP, 2021, p. 62-67. doi: 10.1016/j.procir.2021.11.011.

[45] Y. Yang, M. Yang, et P. Jiang, « The Design of an Integrated Monitoring and Maintenance Framework for Newly Developed Equipment: Using Industrial Robot as Example », présenté à IFAC-PapersOnLine, 2022, p. 42-47. doi: 10.1016/j.ifacol.2022.04.167.

[46] H. Ahmad, M. F. Khalid, R. Kandan, M. N. M. Mydin, B. I. Ismail, et O. H. Hoe, « A Unified Dashboard for Collaborative Robot Management System », présenté à 2020 IEEE Student Conference on Research and Development, SCOReD 2020, 2020, p. 5-9. doi: 10.1109/SCOReD50371.2020.9251036.

[47] A. Polenghi et M. Macchi, « Proposal of a human-in-The-loop-based framework for advancing maintenance applications for collaborative robots », présenté à IFAC-PapersOnLine, 2024, p. 742-747. doi: 10.1016/j.ifacol.2024.09.214.

[48] E. S. Kolvig-Raun, M. B. Kjaergaard, et R. Brorsen, « Joint Stress Estimation and Remaining Useful Life Prediction for Collaborative Robots to Support Predictive Maintenance », *IEEE Robotics and Automation Letters*, vol. 9, nº 4, p. 3554-3561, 2024, doi: 10.1109/LRA.2024.3368296.

[49] C. Liu, Z. Zhang, D. Tang, Q. Nie, L. Zhang, et J. Song, « A mixed perception-based human-robot collaborative maintenance approach driven by augmented reality and online deep reinforcement learning », *Robotics and Computer-Integrated Manufacturing*, vol. 83, 2023, doi: 10.1016/j.rcim.2023.102568.

[50] B. Hu, Z. Chen, M. Zhen, Z. Chen, et E. Pan, « System-Level Predictive Maintenance Optimization for No-Wait Production Machine–Robot Collaborative Environment under Economic Dependency and Hybrid Fault Mode », *Processes*, vol. 12, nº 8, Art. nº 8, août 2024, doi: 10.3390/pr12081690.

[51] F. Cheng, A. Raghavan, D. Jung, Y. Sasaki, et Y. Tajika, « High-Accuracy Unsupervised Fault Detection of Industrial Robots Using Current Signal Analysis », *2019 IEEE International Conference on Prognostics and Health Management (ICPHM)*, p. 1-8, juin 2019, doi: 10.1109/ICPHM.2019.8819374.

[52] D. Seo, M. Kim, et N. Kim, « Failure Diagnosis and Maintenance of Industrial Robot Based on Deep Learning and Augmented Reality », *Lecture Notes in Electrical Engineering*, vol. 1217 LNEE, p. 323-328, 2024, doi: 10.1007/978-981-97-4182-3_42.

[53] R. Pinto et T. Cerquitelli, « Robot fault detection and remaining life estimation for predictive maintenance », *Procedia Computer Science*, vol. 151, p. 709-716, janv. 2019, doi: 10.1016/j.procs.2019.04.094.

[54] J.-X. Chen, G.-S. Huang, et M.-H. Yen, « A Study on the Application of Industrial Robot Based on the Integration of Speech Recognition and Image Processing », in *2021 International Conference on System Science and Engineering (ICSSE)*, août 2021, p. 403-407. doi: 10.1109/ICSSE52999.2021.9538409.

[55] J. A. Fadhil, A. F. Hussein, L. A. Z. Qudr, et A. H. Sabry, « Wireless monitoring of power consumption for industrial robot during a pick and place task for predictive maintenance », *Journal of Theoretical and Applied Information Technology*, vol. 99, nº 12, p. 2964-2971, 2021.

[56] Z. Song, T. Ma, K. Qi, E. Spyrakos-Papastavridis, S. Zhang, et R. Kang, « A Trajectory Tracking Control Based on a Terminal Sliding Mode for a Compliant Robot with Nonlinear Stiffness Joints », *Micromachines*, vol. 13, nº 3, 2022, doi: 10.3390/mi13030409.

[57] D. Trujillo, L. A. Morales, D. Chávez, et D. F. Pozo, « Trajectory Tracking Control of a Mobile Robot using Neural Networks », *Emerging Science Journal*, vol. 7, nº 6, p. 1843-1862, 2023, doi: 10.28991/ESJ-2023-07-06-01.

[58] T. Ashida et H. Ichihara, « Policy iteration-based integral reinforcement learning for online adaptive trajectory tracking of mobile robot », *SICE Journal of Control, Measurement, and System Integration*, vol. 14, nº 1, p. 233-241, 2021, doi: 10.1080/18824889.2021.1972266.

[59] L. Han, J. Mao, C. Zhang, R. W. Kay, R. C. Richardson, et C. Zhou, « A Systematic Trajectory Tracking Framework for Robot Manipulators: An Observer-Based Nonsmooth Control Approach », *IEEE Transactions on Industrial Electronics*, vol. 71, nº 9, p. 11104-11114, 2024, doi: 10.1109/TIE.2023.3331098.

[60] T. Zhao, P. Qin, et Y. Zhong, « Trajectory Tracking Control Method for Omnidirectional Mobile Robot Based on Self-Organizing Fuzzy Neural Network and Preview Strategy », *Entropy*, vol. 25, nº 2, 2023, doi: 10.3390/e25020248.

[61] M. Morlock, M. Burkhardt, R. Seifried, et P. Eberhard, « End-effector trajectory tracking of flexible link parallel robots using servo constraints », *Multibody System Dynamics*, vol. 56, nº 1, p. 1-28, 2022, doi: 10.1007/s11044-022-09836-x.

[62] L. Morales, M. Herrera, O. Camacho, P. Leica, et J. Aguilar, « LAMDA Control Approaches Applied to Trajectory Tracking for Mobile Robots », *IEEE Access*, vol. 9, p. 37179-37195, 2021, doi: 10.1109/ACCESS.2021.3062202.

[63] H. Yang, S. Wang, Z. Zuo, et P. Li, « Trajectory tracking for a wheeled mobile robot with an omnidirectional wheel on uneven ground », *IET Control Theory and Applications*, vol. 14, nº 7, p. 921-929, 2020, doi: 10.1049/iet-cta.2019.1074.

[64] S. Lu et J. Zhao, « Research on Tracking Control of Circular Trajectory of Robot Based on the Variable Integral Sliding Mode PD Control Algorithm », *IEEE Access*, vol. 8, p. 204194-204202, 2020, doi: 10.1109/ACCESS.2020.3027772.

[65] X. Gao, L. Yan, et C. Gerada, « Modeling and analysis in trajectory tracking control for wheeled mobile robots with wheel skidding and slipping: Disturbance rejection perspective », *Actuators*, vol. 10, nº 9, 2021, doi: 10.3390/act10090222.

[66] F. Kordi, S. Mobayen, H. Rezaalikhani, et J. Nikoukar, « Hybrid trajectory tracking control of wheeled mobile robots using predictive kinematic control and dynamic robust control », *Asian Journal of Control*, 2024, doi: 10.1002/asjc.3503.

[67] N. Cang *et al.*, « Kinematic Modeling and Trajectory Tracking of Two-Wheeled Mobile Robot Manipulators at the Acceleration Level », *IEEE Access*, vol. 12, p. 159138-159151, 2024, doi: 10.1109/ACCESS.2024.3487616.

[68] D. Zhu, Y. He, et F. Li, « Trajectory Tracking of Delta Parallel Robot via Adaptive Backstepping Fractional-Order Non-Singular Sliding Mode Control », *Mathematics*, vol. 12, nº 14, 2024, doi: 10.3390/math12142236.

[69] D. Chen et J. Wu, « Hydrodynamic response on trajectory tracking of a tethered underwater robot system under hybrid control algorithms of umbilical cable and propellers », *Discover Applied Sciences*, vol. 6, nº 9, 2024, doi: 10.1007/s42452-024-06145-0.

[70] N. He, L. Qi, R. Li, et Y. Liu, « Design of a Model Predictive Trajectory Tracking Controller for Mobile Robot Based on the Event-Triggering Mechanism », *Mathematical Problems in Engineering*, vol. 2021, 2021, doi: 10.1155/2021/5573467.

[71] J. Xue, J. Chen, A. Stancu, X. Wang, et J. Li, « Spatial Trajectory Tracking of Wall-Climbing Robot on Cylindrical Tank Surface Using Backstepping Sliding-Mode Control », *Micromachines*, vol. 14, nº 3, 2023, doi: 10.3390/mi14030548.

[72] S. Pekris, R. D. Williams, T. Atkins, I. Georgilas, et N. Bailey, « Model-based trajectory tracking of a compliant continuum robot », *Frontiers in Robotics and AI*, vol. 11, 2024, doi: 10.3389/frobt.2024.1358857.

[73] V.-T. Tran, B.-S. Nguyen, T. Vu, et N.-T. Bui, « Trajectory Tracking Control of Pneumatic Cylinder-Actuated Lower Limb Robot for a Gait Training System », *Engineering, Technology and Applied Science Research*, vol. 14, nº 4, p. 15367-15372, 2024, doi: 10.48084/etasr.7733.

[74] T. Ma, Z. Song, Z. Xiang, et J. S. Dai, « Trajectory tracking control for flexible-joint robot based on extended Kalman filter and PD control », *Frontiers in Neurorobotics*, vol. 13, 2019, doi: 10.3389/fnbot.2019.00025.

[75] M. Li, K. Hu, W. He, E. Hu, C. Tang, et G. Zhou, « Research on Trajectory Planning and Tracking Methods for Coal Mine Mobile

Robots », *Applied Sciences (Switzerland)*, vol. 13, nº 17, 2023, doi: 10.3390/app13179789.

[76] A. Belkhiri, A. Amouri, et A. Cherfia, « Design of Fractional-Order PID Controller for Trajectory Tracking Control of Continuum Robots », *FME Transactions*, vol. 51, nº 2, p. 243-252, 2023, doi: 10.5937/fme2302243B.

[77] L. Roveda, M. Forgione, et D. Piga, « Robot control parameters auto-tuning in trajectory tracking applications », *Control Engineering Practice*, vol. 101, 2020, doi: 10.1016/j.conengprac.2020.104488.