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AI-Enhanced Mobile and Collaborative Robotics for Autonomous Inspection and Predictive Maintenance in Smart Manufacturing

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Abstract: The implementation of new Industry 4.0 technologies in robotics (mobile and collaborative robotics) with artificial intelligence (AI) is reshaping maintenance planning in advanced manufacturing. This paper analyzes the application of robotic systems combining collaborative robots (cobots) and autonomous mobile robots (AMRs) as support for predictive maintenance. Predictive maintenance is based on continuous real-time visual monitoring with the goal of managing faults. A mixed-methods approach was used, combining quantitative metrics such as downtime reduction, mean time to repair, and return on investment with qualitative staff assessments. The results of implementing robotic systems to support predictive maintenance indicate a significant reduction in production downtime, increased operational efficiency, and faster resolution of faults in the manufacturing process. In addition to technical efficiency, the study analyzes the economic feasibility, stability, and challenges of implementing AI vision systems within Industry 4.0. Compared to previously published studies in this field, this work is distinguished by the implementation of a cobot and an AMR in a unified system for visual inspection and control, with real-time data used for predictive maintenance. The system is connected to Computerized Maintenance Management Systems software for maintenance planning and monitoring and Enterprise Resource Planning software for real-time business activity planning. The results demonstrate that the integration of advanced robotics, computer vision, and machine learning algorithms enables the transformation of the traditional reactive approach into a proactive asset management model, thereby ensuring a long-term sustainable increase in reliability, safety, and competitiveness of the manufacturing processes.

Keywords: monitoring, predictive maintenance, mobile robots, AI, Industry 4.0

1. Introduction

In modern industrial environments, the demands for maintenance have shifted toward unprecedented levels of precision, operational safety, and efficiency. Conventional maintenance approaches increasingly struggle to meet these requirements, especially given the costly consequences of unplanned production line interruptions, which can lower productivity and weaken an organization's competitive position. Historically, two main maintenance models have been dominant: reactive maintenance—performed only after a breakdown—and preventive maintenance—conducted at fixed intervals regardless of equipment condition. While the first leads to unpredictable operational stoppages, the second often causes unnecessary interventions and resource expenditures when the equipment is still functioning optimally [1, 2]. The growing complexity of production systems, coupled with stricter requirements for continuous operation, has accelerated the adoption of predictive maintenance (PdM) and autonomous inspection systems. Enabled by Industry 4.0 innovations, PdM integrates real-time sensor data with advanced analytics to anticipate potential failures before they occur [3, 4]. This approach leverages technologies such as industrial Internet of Things (IoT) networks, sensor arrays, and artificial intelligence (AI) algorithms, offering benefits that include reduced downtime, improved spare parts management, extended asset lifespan, and enhanced occupational safety. Compared with preventive and reactive strategies, PdM provides a more targeted and cost-efficient solution, aligning maintenance efforts directly with the actual condition of machinery. Autonomous mobile robots (AMRs) and collaborative robots (cobots) have emerged as enabling technologies for implementing PdM in real-world industrial environments. AMRs equipped with advanced vision systems and localization technologies are capable of navigating complex layouts and performing inspections of critical infrastructure points without human intervention [5]. Their integration with AI and computer vision enables fully automated monitoring, predictive decision-making, and reduced exposure of personnel to hazardous conditions. Cobots, in contrast, are designed for safe interaction with human workers in shared workspaces without physical barriers. They excel in tasks that require fine diagnostics, rapid part replacement, and real-time data processing, thereby enhancing the flexibility and responsiveness of maintenance workflows. Hybrid systems, which combine mobile robotic platforms with collaborative arms, further expand operational possibilities. For example, mobile cobots such as the KUKA KMR iiwa can achieve sub-7 mm accuracy through

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feature mapping, making them suitable for high-precision industrial inspections [6–8]. Other configurations, like the Jackal platform combined with the Kinova Gen3 manipulator, are deployed in environments where autonomy and stability need to be carefully balanced. Moreover, the application of Prognostics and Health Management frameworks, supported by deep learning models, facilitates accurate fault forecasting and timely intervention, leading to cost optimization and minimal production disruptions. The literature highlights that performance evaluation of such systems typically focuses on coverage of inspection points, adaptability to changing operating conditions, and interoperability with other digital tools [9]. Successful implementation requires a systemic approach encompassing infrastructure readiness, robust data analytics, and stringent safety protocols [10]. Unlike prior studies that typically address either mobile robots or cobots in isolation, the novelty of this research lies in the integration of a MiR200 AMR and a UR10e cobot into a unified system for visual inspection and PdM. A distinctive contribution of this study is that the robotic setup is fully connected to Computerized Maintenance Management Systems (CMMS) and Enterprise Resource Planning (ERP) platforms in real time, enabling direct translation of inspection data into maintenance and operational decisions. To our knowledge, such a comprehensive integration has not been documented in the existing literature, which highlights the innovative character of the present research. This paper aims to analyze the potential and limitations of AMRs and cobots for industrial inspection and maintenance in real time. Particular attention is given to their role in reducing downtime through autonomous visual inspection, enhancing operational efficiency, and improving system reliability. Additionally, the study examines the comparative advantages of these systems over conventional maintenance methods, along with technical and organizational challenges associated with their integration into operational workflows.

2. Theoretical Framework and Literature Review

In this chapter, the theoretical basis for the application of AMRs and cobots in inspection, monitoring, and maintenance tasks of manufacturing processes in real time is established. The core Industry 4.0 technologies, the operational role of service robots in visual inspection enhanced by AI and machine learning (ML), and error management techniques are examined, while empirical evidence providing insights into downtime reduction and maintenance costs is simultaneously analyzed. Robotic systems are evolving from task executors to proactive data collectors and analyzers with the aim of continuously optimizing manufacturing processes. By integrating sensor networks, advanced analytics, and digital twin technologies, adaptive systems are obtained that are capable of making decisions reflecting the current state of equipment in the production process and its environment.

2.1. Predictive maintenance and core technologies

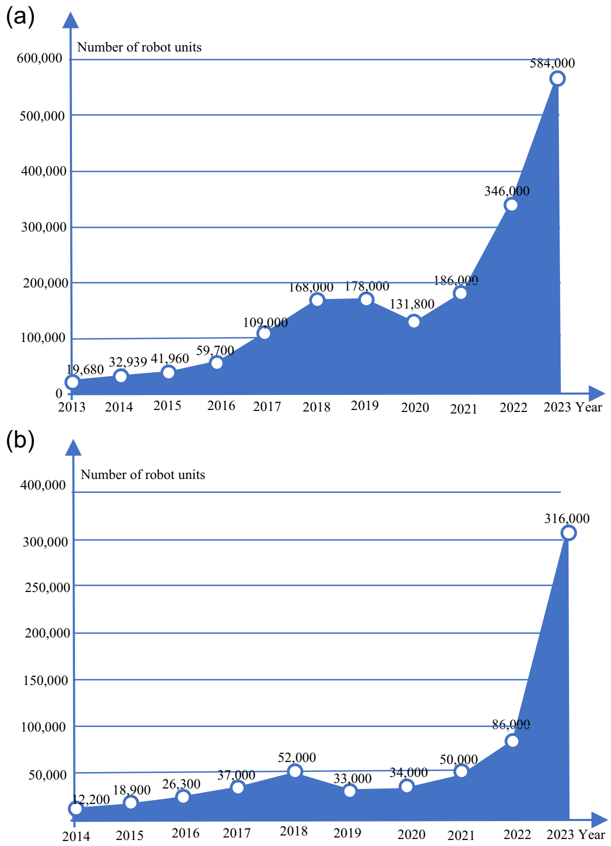
PdM is a maintenance approach that relies on continuous data monitoring, using robotic systems equipped with advanced sensor technology and AI, which are capable of predicting when equipment failure might occur in the production process, thereby preventing unexpected breakdowns and ensuring optimal use of equipment in manufacturing operations. Previous studies have identified several different architectural models for PdM, such as the Open System Architecture for Condition-Based Maintenance (OSA-CBM) model, PdM 4.0, and cloud computing–based platforms, which represent a core technology of Industry 4.0. The methodology itself ranges from classical ML algorithms to deep neural networks designed for fault detection and remaining useful life prediction [11]. Notable successful industrial implementations have been reported in the literature, where companies such as Aquanta and Gecko Robotics have used integrated robotic systems for monitoring, control, and supervision of production systems, applying predictive analytics to detect failures and thus significantly reduce downtime and optimize maintenance. PdM is enabled by technologies that include temperature, ultrasonic, vibration, light detection and ranging (LiDAR), and pressure sensors, AI systems, and big data processing; these integrated technologies facilitate real-time decision-making. The mentioned technologies operate within a comprehensive cyber-physical infrastructure that connects devices with IoT networks, big data frameworks, and cloud computing resources. Enhanced by additive manufacturing, augmented reality, and virtual reality technologies, they represent the fundamental technologies of Industry 4.0, enabling remote monitoring and control of production processes [12]. This approach transforms reactive maintenance into interactive maintenance, thereby extending the lifespan of equipment and providing a competitive advantage in the global market.

2.2. Service robots in industrial settings

Service robots are defined as autonomous or semi-autonomous systems designed to perform useful tasks that support human operators or equipment in professional and industrial environments [13]. The primary categories in industrial use include AMRs, cobots, and specialized inspection robots. Their deployment has substantially improved safety, reliability, and operational efficiency, with port logistics being a notable application area. To better understand global adoption patterns, an analysis of professional service robot implementations over the past 13 years, based on statistical data published by the International Federation of Robotics, the United Nations Economic Commission for Europe, and the Organisation for Economic Co-operation and Development. The findings, illustrated in Figure 1(a), show a consistent upward trend, underscoring the increasing strategic importance of robotics in contemporary industrial systems [14–16].

By analyzing Figure 1(a), we conclude that in the period from 2013 to 2023, there has been significant use of service robots for professional purposes, with a notable increase from 2016. The most significant application of service robots has occurred in recent years: in 2022, 346,000 robot units were deployed, and by 2023, the deployment increased to 580,000 robot units. The result of such an application of service robots for professional use is the implementation of core Industry 4.0 technologies, and robotic technology is one of the fundamental technologies without which the implementation of Industry 4.0 in manufacturing processes cannot be imagined. The increase in the implementation of robotic technology in manufacturing processes is driven by technological innovations, the increased automation of manufacturing processes themselves, and the reduction in the cost of robotic systems. In Figure 1(b), the trend of service robot use in logistics in the period from 2014 to 2023 is shown. The use of service robots in logistics showed a continuous upward trend from 2014 to 2018. In the period from 2018 to 2020, the trend slightly declined, which can be associated with the impact of the COVID-19 pandemic. The trend of significant growth in the use of service robots in logistics began in 2021, so that in 2022, around 86,000 robot units were deployed, and by the following year, 2023, the highest growth was recorded, with 316,000 robot units deployed. In recent years, in all highly developed countries, there has been the implementation of Industry 4.0 and significant automation of all processes. The growth trend in the use of service robots is

Figure 1
Deployment of service robots for (a) professional applications and (b) logistics worldwide, 2013–2023



associated with increased trade, higher demand for rapid package processing, and the implementation of advanced technologies in mobile robotics. Service robots for professional use are applied in all segments of industrial sectors to perform tasks hazardous to human health, including monitoring and control of manufacturing processes for the early detection of potential failures.

Figure 2 shows different designs of AMRs equipped with advanced sensor systems for comprehensive inspection, monitoring, and condition analysis of manufacturing processes [17, 18].

2.2.1. Collaborative robots (cobots): Technological foundations and industrial applications

Cobots are second-generation industrial robots and differ from standard first-generation industrial robots because they are more advanced, safe to work alongside humans, easy to program, and adaptable for performing various tasks [19]. The advantages of cobots stem from their role in supporting rather than replacing human labor in collaborative workplaces. Collaboration with cobots requires multiple levels of human safety strategies, so many implementations still lack adequate safety protocols and compliance with standards.

The development of cobots is the result of progress in several technological fields such as:

Advanced sensor technologies: Cobots are equipped with 3D cameras, LiDAR systems, and force and torque sensors, enabling them to detect human presence and immediately stop operation to prevent accidents.

Artificial intelligence and machine learning: By using AI, cobots learn from environmental feedback, recognize behavioral patterns, and adjust their operations, thereby reducing the number of tasks and the need for frequent reprogramming.

Safety engineering: Cobots are designed in accordance with international standards such as ISO/TS 15066, which ensures strict limits on force, speed, and reaction time without interfering with human response.

Simple programming: Unlike first-generation industrial robots, cobots can be trained through intuitive methods such as demonstrations performed by operators, allowing the robot to learn through tasks.

These advantages are particularly beneficial for small and medium-sized enterprises (SMEs):

Efficient flexibility: For various production processes, cobots can be easily moved and reprogrammed and can be simply adapted for mass production.

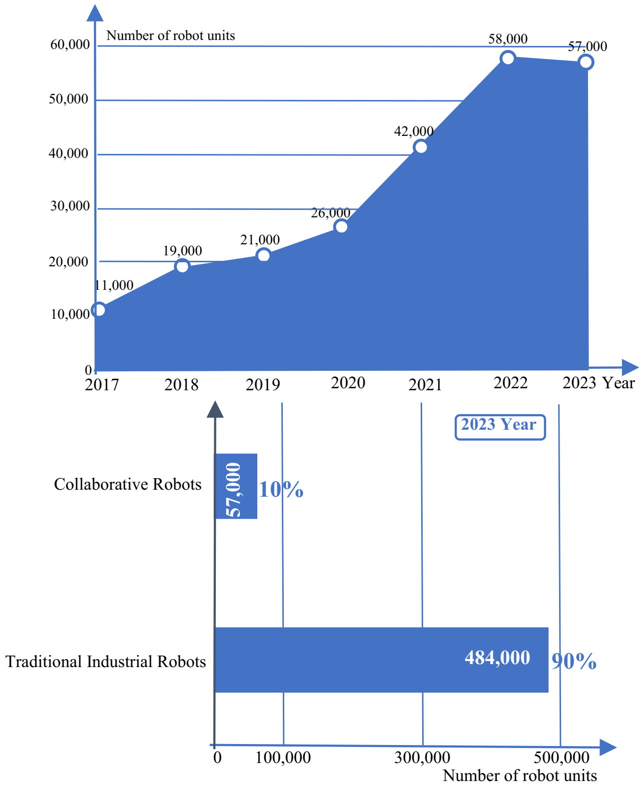
Cost-effectiveness: They are less expensive than first-generation industrial robots, have lower maintenance costs, improve workplace safety, and actively contribute to reducing workplace injuries.

Increased productivity: The joint action of human knowledge and robot precision leads to increased productivity and reduced production errors.

Currently, the implementation of cobots takes place in all sectors such as packaging, assembly, welding, laboratories, quality control, food and pharmaceutical production, etc. Robot manufacturers such as FANUC, ABB, Universal Robots, Techman Robot, and KUKA are driving innovations in this field, expanding the range of their applications. It is particularly important to highlight the company Universal Robots, which in 2008 launched the UR5 cobot—one of the earliest commercially available robots that is safe to work alongside humans. They have developed models such as UR3, UR5e, UR10e, and UR20, which are used in industrial facilities around the world. The trend of cobot applications worldwide is shown in Figure 3 [14–16].

Figure 2
Structural variations of service robots utilized in predictive maintenance applications

Figure 3
Implementation trends of collaborative robots (2017–2025) and 2023 deployment compared to traditional industrial robots



The growth trend of cobot applications on an annual basis is illustrated in Figure 3 for the period from 2017 to 2023, showing a clear increase from 11,000 to 58,000 robot units. The trend of cobot implementation is positive but still insufficient, as in 2023, it accounted for only 10% compared to traditional industrial robots (Figure 3). The growth trend in cobot applications is associated with the implementation of Industry 4.0 and its core technologies, such as AI, cloud computing, the IoT, and digital twins, which enable improved operational flexibility and integration of cobots within smart manufacturing processes.

Cobots are not used as a replacement for human labor but work together with humans to increase productivity, safety, and flexibility of manufacturing processes [20]. They are well-suited for use in SMEs and can be integrated into existing production processes with minimal disruptions. A notable area of cobot application is in PdM, where they operate together with a mobile platform equipped with all the mentioned sensors, as shown in Figure 4. Their use in PdM optimizes operational efficiency and reduces downtime [21–23].

Cobots represent a support in the transition to manufacturing processes that are not only highly automated but also adaptable and intelligent [24]. They are increasingly used for advanced tasks in inspection and maintenance. A significant example is the company Air-Cobot, which enables autonomous visual inspection of aircraft in close coordination with human operators. By implementing these advanced technologies, cobots today can operate in unpredictable and dynamic environments, providing high value in industries where safety and precision are paramount. The implementation of cobots promotes deeper integration of Industry 4.0 technologies, thereby giving SMEs access to advanced technologies that were previously economically unattainable for them [25].

2.3. AI/ML-enhanced visual inspection

Modern robotic inspection platforms leverage an array of sensing technologies—ranging from 2D/3D cameras to LiDAR, stereoscopic setups, and time-of-flight sensors—supplemented by robust software frameworks like OpenCV, PyTorch, and TensorFlow. This synergy ensures high repeatability and precision in identifying defects and irregularities. Deep learning techniques, for example, have been applied in the automotive sector to detect scratches, select components, and locate anomalies via object detection, segmentation, and anomaly detection models [26]. In industrial scenarios, the shortcomings of 2D vision systems—such as sensitivity to lighting variations and airborne particles—are often addressed through the deployment of 3D sensors and advanced real-time algorithms. Coupling these systems with AI-driven modules allows on-the-fly adjustment of inspection parameters based on changing environmental conditions, thereby reducing false positives and missed detections. When integrated with digital twin technology, these platforms enable virtual testing and process optimization before physical rollout, transforming inspection from a reactive quality control step into a proactive element of predictive and preventive maintenance.

2.4. Integrated real-time fault management

Managing equipment faults in real time involves linking robotic systems to platforms like CMMS and ERP solutions to align technical, logistical, and administrative workflows. Within inspection-based operations, intuitive human–machine interfaces give operators visibility into system status, the ability to trigger inspections, and access to live analytical feedback [26]. This level of integration reduces fault response time by enabling the

Figure 4
Design variations of collaborative robots on mobile platforms for predictive maintenance applications

automatic generation of repair orders based on sensor data. More sophisticated implementations—such as hydro-inspection systems—combine automated anomaly detection with operator guidance and multi-system connectivity. In an Industry 4.0 framework, these capabilities are enhanced through IoT networks, cloud-based analytics, and digital twins, allowing for proactive intervention planning and resource optimization. The outcome is greater system reliability, minimized downtime, and improved operational sustainability.

2.5. Evidence from practice: efficiency gains and cost reductions

Field data consistently demonstrate that autonomous robotics and AI-supported PdM can produce significant operational savings while extending asset lifespans. For example, predictive platforms have helped companies such as Coca-Cola and Siemens Energy lower maintenance expenses by as much as 23% annually through early problem detection and improved scheduling.

On automated lines, the deployment of cobots such as the UR10e in welding and assembly has halved production cycle times and boosted overall throughput—critical advantages for SMEs constrained by limited human resources [27]. Similar trends appear in mining, where autonomous inspection units have replaced manual checks, leading to both improved safety and reduced downtime. In one food processing facility, integrating mobile robots into a CMMS environment cut emergency interventions by 35% and saved approximately USD 180,000 annually. Positions shown in Figure 5 clearly demonstrate that the benefits of robotic system implementation extend beyond direct maintenance cost reductions, encompassing significant decreases in unplanned downtime, which in turn enhances overall production capacity. Furthermore, improvements in workplace safety and the reduced exposure of workers to hazardous tasks constitute an additional—albeit less quantifiable—advantage [28, 29]. Empirical evidence indicates that the integration of mobile and collaborative robots with advanced analytics platforms fosters sustainable operational advantages and strengthens the competitive positioning of enterprises within the Industry 4.0 framework.

3. Research Methodology

3.1. Methodological framework

In this paper, we adopt an integrated methodological concept by combining qualitative and quantitative approaches to obtain a comprehensive assessment of the role of cobots and AMRs in the autonomous process of control, monitoring, and maintenance within the production process. The analytical model in Figure 6 illustrates the selection of a case study, how the roles of an AMR or a cobot can be defined, and how their performance can be evaluated based on predefined key performance indicators (KPI).

In this paper, the numerical analysis is focused first on collecting and then processing measurable efficiency indicators, taking the mean time to repair (MTTR), then the mean time between failures (MTBF), total number of stoppages, and total downtime. The analytical part of the research is through a case study. It enabled us to gain an in-depth understanding of the adoption of Industry 4.0 technologies within the production process in any environment. The experimental research was conducted according to a predefined test scenario in which an AMR and a cobot perform their tasks, which include control, monitoring, inspection, and PdM. A comparative analysis with data from before the implementation of robotic systems gives us a clear picture for assessing changes in operational efficiency. Such a mixed-methods approach is recognized in industrial and mobile robotics research to achieve a balance between empirical results and contextual insights [30, 31].

Figure 5
Impact of robotic systems implementation on downtime reduction and annual cost savings

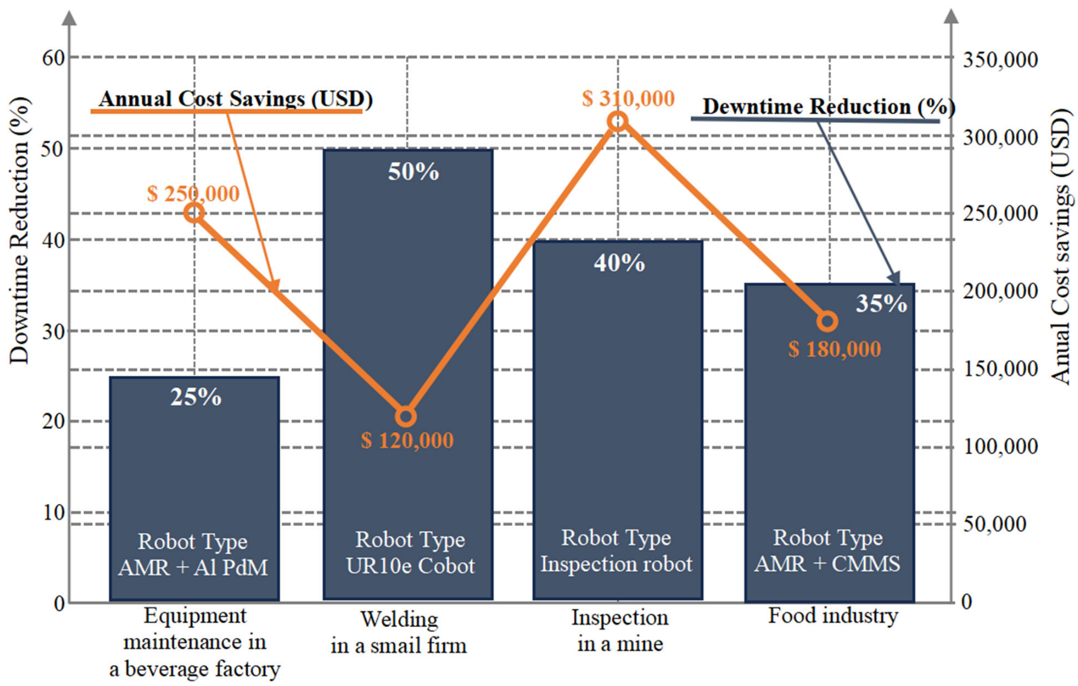
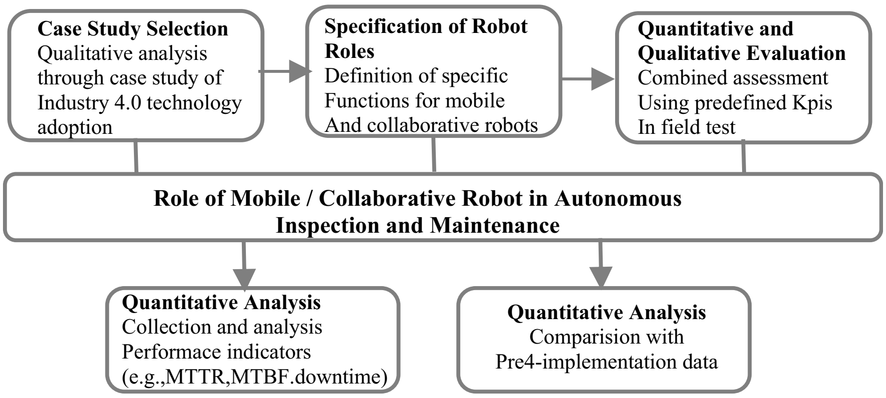


Figure 6
Methodological framework of the study



3.2. Selection of industrial setting and case study design

The research is based on a case study conducted in the automotive industry, a sector identified for its advanced integration of Industry 4.0 technologies [32]. The selected production line comprises multiple stages, including subassembly, visual inspection, and final quality testing, with a strong emphasis on meeting stringent safety and reliability requirements.

The decision to focus on the automotive sector was guided by several factors:

Advanced automation infrastructure – established readiness for robotic and digital system integration.
High financial impact of downtime – unplanned stoppages can incur losses exceeding several tens of thousands of euros per hour.
Complex inspection requirements – necessitating the integration of visual and sensor-based inspection technologies relevant to this research.

The production environment integrates cobots at various workstations with AMRs responsible for intralogistics tasks, such as component transport and preliminary inspection. This hybrid configuration offers an optimal platform for assessing the combined performance of mobile and collaborative robotic systems in real industrial conditions. The case study was conducted in a European automotive manufacturing facility characterized by a high degree of automation and digitalization. Data were obtained through a combination of direct and indirect sources. Primary data included automated records from the CMMS platform, financial and operational data from the ERP system, and IoT-enabled sensor streams generated by the robotic units. Secondary data included internal company reports on production efficiency and maintenance costs, which were accessed under confidentiality agreements. The experimental setup employed two robotic units: one MiR200 AMR and one UR10e cobot. Together, these robots covered the inspection and maintenance of a critical production line segment that historically exhibited frequent unplanned downtimes. This hybrid configuration enabled the collection of quantitative performance indicators and qualitative feedback from operators, ensuring a comprehensive evaluation of the system's effectiveness.

3.3. Functional role of mobile and collaborative robots in the system

The system under analysis employed a MiR200 AMR and a UR10e cobot. The AMR is equipped with multiple sensing modalities:

LiDAR for autonomous navigation and obstacle avoidance,
RGB-D camera for visual inspection,
Ultrasonic sensors for detecting objects in close proximity.

The UR10e cobot is integrated with both 2D and 3D industrial imaging systems and operates in combination with anomaly detection algorithms based on convolutional neural networks (CNNs) implemented in the PyTorch framework. In this study, a ResNet-50 CNN architecture was employed, trained on a dataset comprising 12,000 annotated images of real-world components. The MiR200 AMR is equipped with a SICK LiDAR LMS111 sensor (0.25° angular resolution, 20 m range) and an Intel RealSense D435 RGB-D camera (1280 × 720 pixels). The UR10e cobot is integrated with a Basler ace2 Pro 3D camera (3.2 MP, 60 fps). Interfacing with CMMS and ERP platforms is achieved via the MQTT protocol for IoT integration, alongside the OPC UA standard to ensure industrial interoperability. The deep learning models were trained using a dataset of actual production line components to detect micro-cracks, surface scratches, and deformations that are not discernible to the human eye.

The integration of an AMR and a cobot, both equipped with advanced sensor arrays, enables a fully automated inspection workflow, as shown in Figure 7 [33].

The workflow diagram of the integrated AMR–cobot inspection process, shown in Figure 8, illustrates data collection via sensors, CNN-based analysis, classification of components, and automatic integration with CMMS/ERP platforms. The AMR transports components to the inspection station, where the cobot performs a visual assessment. The captured data are processed by an AI algorithm, which classifies the inspected items as compliant (OK) or non-compliant (NOK).

Classification results are automatically transmitted to the CMMS and ERP platforms.

This hybrid robotic configuration aims to reduce human involvement in repetitive inspection tasks, enhance fault detection accuracy, and minimize response times to failures.

3.4. Performance evaluation

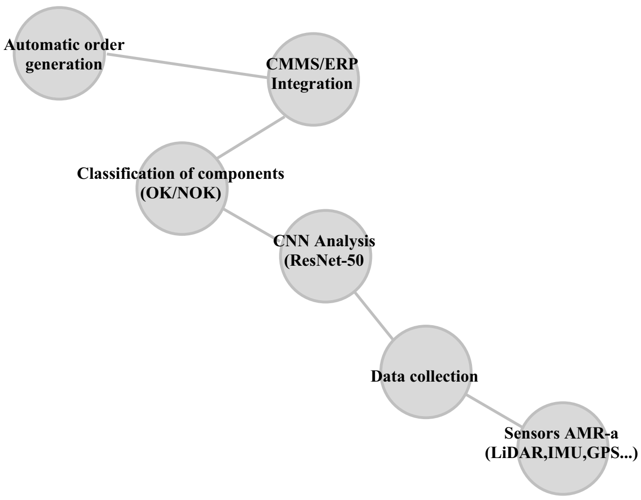
System efficiency was assessed using the following KPIs:

MTTR (mean time to repair) – the average time required to restore functionality after fault detection.
MTBF (mean time between failures) – the mean operational time between two consecutive breakdowns.
Unplanned downtime frequency – the total number of unexpected operational interruptions.

Figure 7
Autonomous mobile robot and collaborative robot equipped with multiple sensors

Source: Mobile Industrial Robots (2025). "MiR-Go Enabled Robotics MC250" product page.

Figure 8
Workflow diagram of the integrated AMR–cobot inspection process



Total downtime duration – the cumulative length of all stoppages within the observation period.
ROI (return on investment) – calculated from maintenance cost reductions and productivity gains.

3.5. Data acquisition and processing

Data were collected from three primary sources:

CMMS – automated records of failures, repair durations, and preventive maintenance actions.
ERP platform – financial and operational data related to production, procurement, and maintenance costs.
Sensor-based monitoring – IoT-enabled data streams from the AMR and cobot, including visual data, temperature readings, and vibration measurements.

The processing workflow included:

Data cleaning – removing incomplete records and correcting anomalies.
Data integration – consolidating heterogeneous datasets into a unified database via ETL (Extract, Transform, Load) processes.
Data analysis – applying statistical and ML methods to identify operational patterns and trends.

Visual datasets underwent preprocessing, including noise filtering, contrast normalization, and object segmentation [34]. AI models were trained in GPU-accelerated environments using TensorFlow and PyTorch, while results were visualized in Tableau dashboards.

Data validation was performed to ensure that measurement results were unaffected by production load changes or external variables. Control groups—production line sections without robotic integration—were monitored in parallel, allowing the isolation of effects attributable solely to the new automation technology.

4. Results and Discussion

4.1. Quantitative analysis of outcomes

The evaluation covered two consecutive six-month periods—one before and one after the robotic system deployment. Statistical validation was conducted using a paired t-test ($p < 0.05$) to determine the significance of changes in KPI values [35]. The results demonstrated a notable decrease in MTTR and a significant increase in MTBF, accompanied by a measurable reduction in total downtime. ROI analysis indicated a 32% return in the first year following implementation Table 1.

Beyond standard statistical validation using the t-test, an analysis of effect size was performed. The findings reveal a substantial impact of the robotic system implementation on key performance metrics, namely, MTTR (Cohen's $d = 1.21$) and MTBF ($d = 1.05$). Additionally, 95% confidence intervals were computed: MTTR CI95% [1.7–2.5 h], MTBF CI95% [180–240 h]. These results further substantiate the significance and robustness of the observed improvements in system performance.

Table 1
Key performance indicators (KPIs) before and after robotic system implementation

KPI indicator	Before implementation	After implementation	Change (%)
MTTR (Mean Time to Repair)	4.8 h	2.1 h	–56.3%
MTBF (Mean Time Between Failures)	120 h	210 h	+75.0%
Number of Unplanned Downtimes	15	6	–60.0%
Total Downtime Duration (h)	540	140	–74.1%
ROI in First Year	—	32%	—

The integration of the robotic system into the manufacturing process resulted in significant improvements across key performance indicators, particularly in reducing downtime and maintenance costs. Data were systematically collected over two consecutive six-month periods—before and after the robotic system implementation—allowing for a robust longitudinal evaluation of automation's impact on production continuity and enabling precise quantification of its benefits. Prior to the system's deployment, production disruptions were predominantly caused by human errors, operational inconsistencies, and maintenance irregularities, all of which negatively affected operational efficiency and output. Following the introduction of the robotic system, the production process exhibited marked stabilization, as evidenced by a substantial decrease in unplanned stoppages and enhanced overall system reliability. Furthermore, the robotics-enabled continuous monitoring of equipment conditions and the execution of PdM protocols contributed to further reductions in maintenance expenditures and associated downtime. These empirical results highlight the critical role of advanced technological integration in optimizing industrial workflows and elevating standards of operational excellence.

Graphical Illustration of Downtime Before and After Robotic System Implementation

Downtime remains a vital metric for assessing the effectiveness of automation [35]. Figure 9 presents a comparative analysis chart illustrating the total downtime, expressed in hours, across selected production lines before and after the robotic system adoption.

The graph shown in Figure 9 presents the total downtime, expressed in hours, for five production lines before and after the implementation of robots. Comparative analysis of total downtime (in hours) across five production lines before and after robotic implementation. Bars represent mean values, while error bars indicate the 95% confidence intervals. The asterisk (*) denotes a statistically significant difference ($p < 0.05$) between pre- and post-robotic implementation values. All lines recorded a significant reduction in downtime following the introduction of robotic systems.

The largest decrease was observed on Line 1, where downtime dropped from 120 to 35 h, while the smallest reduction occurred on Line 3, from 140 to 50 h. A similar trend is evident across the remaining lines, with reductions ranging from approximately 60% to 80%.

The monthly trend of total downtime (expressed in hours) before and after the implementation of the robotic system, shown in Figure 10, indicates a continuous decrease throughout the evaluation period. These results indicate that the application of robots has a direct positive impact on reducing operational interruptions and increasing production efficiency. Overall, the data in the table confirm a consistent pattern of performance improvement across all analyzed production lines.

Figure 9
Comparative analysis graph of total downtime (in hours) on five production lines before and after robot introduction (95% CI)

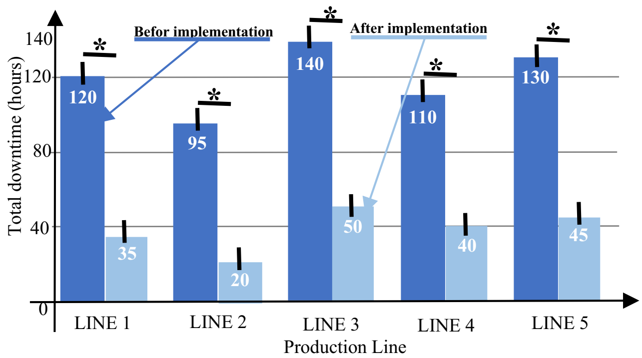
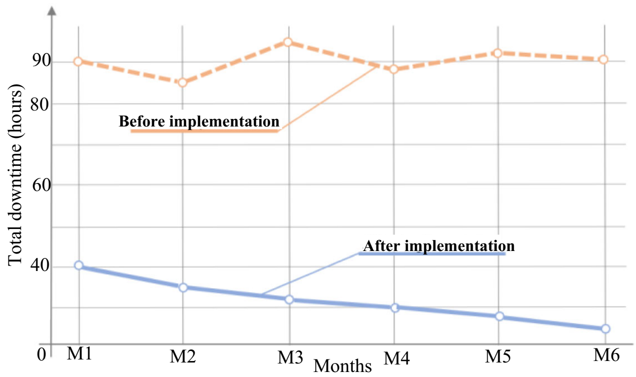


Figure 10
Monthly trend of total downtime (in hours) before and after robotic system implementation



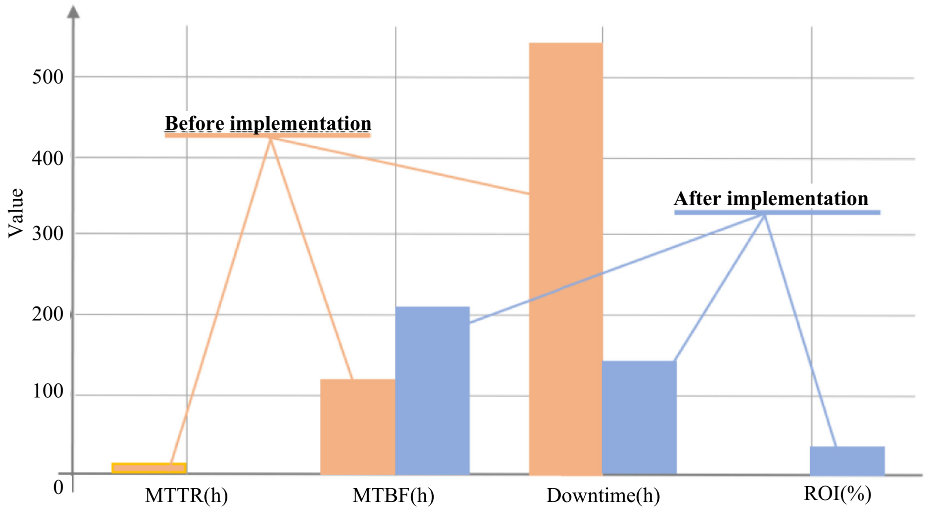
4.2. Qualitative insights and operator feedback

In addition to the quantitative metrics demonstrating the enhanced efficiency and productivity achieved through the implementation of the robotic system, this study placed significant emphasis on evaluating operator experience and subjective perceptions of the technology's integration into daily workflows. Data were collected through in-depth interviews, structured questionnaires, and focus group discussions, with a total of 42 operators surveyed. Three predominant themes were identified: (1) heightened perception of safety, (2) alleviation of work monotony, and (3) the necessity for additional training. All participants had been continuously employed at the facility for at least six months prior to the implementation of the robotic system. This ensured that respondents were familiar with the production processes both before and after the system's deployment, allowing them to provide informed and experience-based assessments of the technological integration. Moreover, correlation analysis demonstrated a significant relationship between operator satisfaction with Human–Robot Interaction (HRI) and the reduction of operational errors ($r = 0.62$, $p < 0.01$). These findings indicate that the qualitative insights are directly aligned with quantitative performance outcomes, highlighting the interplay between human factors and robotic system effectiveness.

The results of the key performance indicators (MTTR, MTBF, downtime, ROI) before and after the implementation of the robotic system, shown in Figure 11, clearly demonstrate significant improvements in operational efficiency.

The majority of operators expressed a high degree of satisfaction with the system's intuitive design and ease of use. Over 85% of respondents reported that the user interface facilitated straightforward operation without necessitating extensive technical knowledge or complicated instructions. Operators highlighted that the automation of repetitive tasks and the clear visibility of controls considerably reduced occupational stress and uncertainty, thereby fostering greater confidence in their interactions with the robotic system. Such positive reception is instrumental in mitigating resistance to technological adoption, a commonly identified barrier in manufacturing digital transformations [36]. Supporting these findings, Marino et al. [12] emphasize that clear and user-friendly

Figure 11
Comparative bar chart of key performance indicators (MTTR, MTBF, downtime, ROI) before and after robotic system implementation



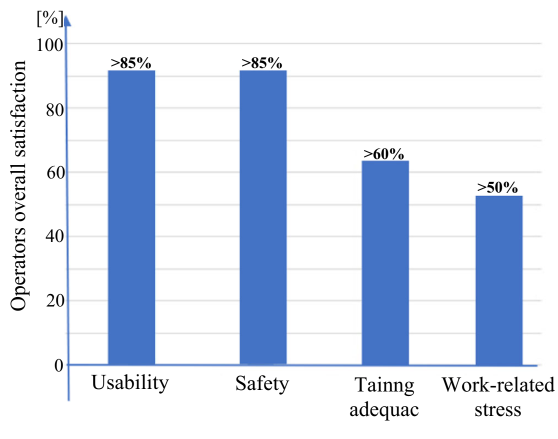
interfaces accelerate the acceptance of robotic systems and improve operator satisfaction. Safety emerged as a critical concern among operators, particularly regarding work in close proximity to autonomous robots. The necessity for seamless coordination between human workers and robotic agents often introduces apprehension and caution. However, the implementation of advanced safety protocols—including human presence detection sensors and automated emergency stop mechanisms—was reported to substantially enhance perceived workplace safety. Approximately 90% of respondents indicated increased feelings of security due to these measures, which in turn alleviated stress associated with robot proximity and fostered a more positive work environment [37]. Corroborating these observations, Saleem et al. [38] identify safety technologies such as LIDAR sensing and designated safety zones as pivotal in reducing risk perception among workers in highly automated facilities. Despite favorable evaluations of the system's simplicity, approximately 60% of operators underscored the importance of ongoing and advanced training, especially concerning robotic control, programming fundamentals, and task customization. This finding underscores the necessity of comprehensive educational programs and continuous technical support to maximize the benefits of automation technology [39]. The institution of regular training sessions, workshops, and e-learning modules is advocated to equip operators with the skills to manage unanticipated scenarios and optimize operational processes independently. Such capacity building not only elevates workforce competency but also reduces reliance on external technical services, ultimately contributing to operational cost savings and increased production flexibility. Fan et al. [40] similarly highlight the critical role of continuous education in the successful integration of cobots within manufacturing environments.

Operator feedback further revealed positive impacts on human–robot interaction quality. Participants reported a notable reduction in monotonous and physically demanding tasks, which translated into improved job satisfaction and decreased fatigue and stress during work shifts. This advancement has a direct positive effect on overall productivity and error reduction, enabling operators to concentrate on quality assurance and process optimization while delegating repetitive activities to robotic systems. Enhanced coordination between human personnel and automation technologies reflects the successful application of collaborative robotics principles in the production setting. Faccio et al. [41] similarly document that the incorporation of cobots positively influences employee motivation and satisfaction, with downstream benefits for manufacturing efficiency. Figure 12 illustrates operators' overall satisfaction with the robotic system across multiple dimensions including usability, safety, training adequacy, and impact on work-related stress. The bar chart displays that over 85% of operators rated usability and safety as highly satisfactory, while approximately 60% emphasized the need for expanded training programs.

The qualitative analysis substantiates that robotic system deployment delivers significant advantages in usability, safety, and operator satisfaction. Concurrently, it identifies essential areas for improvement through targeted training and support frameworks. This integrated approach, addressing both technological and human dimensions, is foundational for the sustainable and effective adoption of advanced automation technologies in contemporary industrial production.

While the findings of this study clearly demonstrate the positive impact of integrating mobile and collaborative robots on reducing downtime and improving operational efficiency, certain limitations must be acknowledged when interpreting the results.

Figure 12
Operators' overall satisfaction with the robotic system



First, the experimental setup involved a limited number of robotic units and was focused on a specific sector—the automotive industry—which may restrict the generalizability of the results to other industrial domains with different process requirements. Furthermore, the evaluation period was relatively short, meaning that long-term effects on performance sustainability and economic viability require further investigation. In addition, the implementation took place in a facility with a high level of digitalization and automation, which may imply that results could differ in less technologically advanced environments. Future research should include a broader range of industrial sectors, a larger number of robotic units, and extended monitoring periods to verify the stability and transferability of the observed benefits.

5. Conclusions

The results presented in this paper confirm the justification for implementing robotic systems in manufacturing processes for PdM, as production downtime is significantly reduced and operational efficiency is increased. By implementing these systems, average daily downtime is reduced by approximately 75%, which improves productivity, task execution accuracy, and workplace safety through the introduction of advanced detection and protection systems. The conducted research provides practical guidelines for the successful implementation of robotic systems in manufacturing processes, including the use of modular architectures for easier scalability, addressing technical and economic challenges, and organizing operator training programs. Although the research was conducted with a limited number of units in a pilot environment, it represents a basis for further studies in this field. Future research should focus on investigating long-term performance, integration with IoT and other smart factory systems, and application in various industrial sectors to verify and validate the results. Subsequent studies should focus on cross-sectoral validation of results and comparability in industries such as food processing and pharmaceuticals, using quantitative measures such as downtime, production quality, and operational efficiency. Likewise, long-term and scalable studies should be conducted over a period of at least 24 months, with quarterly assessments monitoring indicators such as maintenance costs, robot failure rates, and software update performance. Future development is directed toward integration with the latest technologies, such as 5G networks, digital twins, and edge AI, with the aim of improving predictive analytics, while also presenting challenges regarding system interoperability and cybersecurity. Product lifecycle assessment, taking into account economic, environmental, and social impacts, is crucial for the overall evaluation of benefits, as are automation costs. For sustainable industrial transformation, adapting the workforce through reskilling and organizational change is essential. The research in this paper provides a new demonstration of implementing a cobot and an AMR in an integrated PdM architecture. The study is original because it combines a real-time robotic inspection system with CMMS and ERP software, resulting in improved technical characteristics and direct organizational and economic benefits. This is precisely what distinguishes this research from other similar studies addressing robotics for the maintenance of manufacturing systems.

Ethical Statement

All procedures performed in this study involving human participants were conducted in accordance with relevant ethical standards. Informed consent was obtained from all participants involved in the study.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Isak Karabegovic: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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