Enhancing Quality Inspection in Zero-Defect Manufacturing Through Robotic-Machine Collaboration

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***Abstract*—The modern industrial sector is placing a growing emphasis on sustainability and efficiency. The concept of Industry 5.0 builds upon Industry 4.0, aiming to combine human skills with advanced technologies to create flexible and responsive manufacturing systems. This paper discusses Zero Defect Manufacturing (ZDM), which emphasizes the production of flawless components from the beginning. The paper introduces a pilot line for ZDM, which includes a collaborative robotic quality inspection system that integrates artificial vision and AI decision-making. The system consists of a manipulator robot, an industrial camera, an AI IoT node utilizing a segmentation algorithm for quality control based on YOLO V10, a human operator, and an Autonomous Mobile Robot (AMR) to ensure the safety of the human operator. All these components are interconnected using MQTT and ROS2. The results of the pilot line demonstrate significant improvements in quality control, reduced waste, and enhanced operational efficiency, all of which are in line with the principles of Industry 5.0.**

***Index Terms*—Human safety, Robot-machine interaction, Collaborative robots, Zero-defect, Quality control, computer vision, machine learning**

I. Introduction

Contemporary industrial efforts increasingly prioritize principles of sustainability and efficiency. Industry 5.0 seeks to revolutionize the concepts introduced by Industry 4.0 through a human-centric approach that integrates human skills with advanced technologies [1]. This approach aims to establish manufacturing systems that are flexible and responsive. Furthermore, collaboration between humans and technology is also promoted, to enhance interaction and productivity [2], addressing concerns about human obsolescence. Key enabling technologies in Industry 5.0 include energy-efficient and secure data transmission, storage, and analysis, incorporating networked sensors, scalable cybersecurity, big data management, traceability, and edge computing [3]. Additionally, advanced AI technologies such as causality-based AI, swarm intelligence, brain-machine interfaces, and informed deep learning are essential for ensuring AI systems can adapt to new conditions, handle complex data, detect product errors, and effectively align human skills with tasks [4] [5].

The principles above mentioned bring new concepts for manufacturing, regarding environmental, sustainable, and logistic perspectives. One of these concepts is Zero Defect Manufacturing (ZDM). The objective is to mitigate failures within manufacturing processes, emphasizing the production of flawless components from the outset. The strategy is divided into product-oriented and process-oriented approaches [6], focusing on defect identification in products and manufacturing equipment, respectively. Key ZDM strategies include detection, repair, prediction, and prevention of defects, ensuring continuous process improvement and significant cost reductions. The increased demand for customized products and rapid production cycles has made traditional quality control methods insufficient, necessitating sophisticated techniques for quality management. Consequently, ZDM not only enhances production efficiency and reduces waste but also reinforces customer satisfaction and loyalty by consistently delivering high-quality products.

The primary contribution of this work is to demonstrate the benefit of ZDM on industrial productivity and sustainability, achieved by the deployment of an efficient, human-safe, and

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collaborative robotic quality inspection. The system is based on the interaction of two robots and an AI-based decision-making process supported on computer vision. Additionally, enhancing safety by minimizing human operator involvement in these tasks is a key aspect of this advancement.

This work is divided into five sections. After the introduction, there is a review of related works. Subsequently, section III describes the robotic quality inspection system, including the communications. The next section describes the specific use case in a manufacturing pilot line and the experimental results for validation. Finally, a summary of the results is presented in the conclusions section.

II. Related Work

In this section, a literature review aimed at establishing the contextual framework for this work is presented. Initially, Table I outlines a set of methods and technologies that delve into the foundational principles guiding the present research. Subsequently, Table II refers to works related to the enabling technologies forming the basis for the proposed implementation system.

TABLE I
KEY CONCEPTS IN THE STATE-OF-THE-ART

Reference	Relevance for the research
Maddikunta et al. (2022) [4]	• Enabling technologies of 5.0 Industry.
Nahavandi (2019) [2]	• Human-Robot-Machine collaboration instances. • Impact in Manufacturing.
Psarommatis et al.(2020) [6]	• ZDM main concepts. • Detection algorithms in ZDM.
Psarommatis (2022) et al. [7]	• Quality control concepts and insights. • Quality control in ZDM.
Demir et al.(2019) et al. [8]	• Considerations and concerns about the collaboration and cooperation between humans and machines in Industry 5.0. • Multidimensional perspectives about a possible human-robot co-working scenario

TABLE II
ENABLING TECHNOLOGIES

Reference	Relevance for the research
Villalonga et al. (2020) [9]	• Systems interconnection, quality control and data analysis.
Leberruyer et al. (2023) [10]	• Machine learning techniques in quality control.
Tsintotas et al.(2024) [11]	• Active vision insights
Xu et al.(2024) [12]	• Machine learning approaches for ZDM
Bhattacharya, Cloutier (2022) [13]	• Deep learning algorithms to detect and identify defects.
Noor-A-Rahim et al. (2022) [14]	• Review IoT protocols.
Vithanage et al. (2021) [15]	• MQTT for IoT.

III. Inspection system for quality control in manufacturing

Quality control is essential for achieving zero-defect manufacturing. By implementing rigorous quality control, it can be ensured that each product meets standards of precision and reliability. This not only reduces the likelihood of defects reaching the customer but also minimizes waste, leading to significant cost savings and improved efficiency. Additionally, maintaining a zero-defect standard enhances a company's reputation for quality, fostering customer trust and loyalty sources of defects. By prioritizing quality control, organizations can achieve a competitive edge in the market, ensure regulatory compliance, and contribute to overall operational excellence. Effective quality control in manufacturing involves regular inspections, testing, and monitoring of the production processes. For that reason, modern quality control integrates advanced technologies to enhance precision and efficiency. These technologies enable real-time monitoring and data analysis, allowing for immediate detection and correction of quality issues.

A. System elements description

Considering the key ssues above mentioned, an inspection system for quality control is proposed in this work. The system is designed considering flexibility and adaptability to integrate with most of the manufacturing processes. It is composed of four elements: a manipulator to pick the manufactured piece from the production process, a camera to capture high-quality images of the piece, an AI-based IoT node to analyze the pieces through a visual inspection algorithm, an AI-based IoT node to analyze the pieces through a classification algorithm, and an Autonomous Mobile Robot (AMR) to move the piece to the final destination, taking into account the output from the classification algorithm, see Figure 1.

The system takes the operator into account as an important aspect. The distribution of tasks and elements was done to reduce the workload and increase the safety of the operators. This helps to decrease operator fatigue caused by repetitive tasks and improves working conditions. In terms of safety, all elements can safely work with the human (cobot) for piece picking and with the AMR for piece storage or remanufacturing.

Analyzing the role of each component in the system, the manipulator serves as the initial link between the system and the manufacturing process. Most production processes utilize various transportation methods, such as conveyor belts and autonomous robots, to transport finished pieces to the warehouse or for delivery. This way, the manipulator enhances precision, consistency, and efficiency in handling the finished

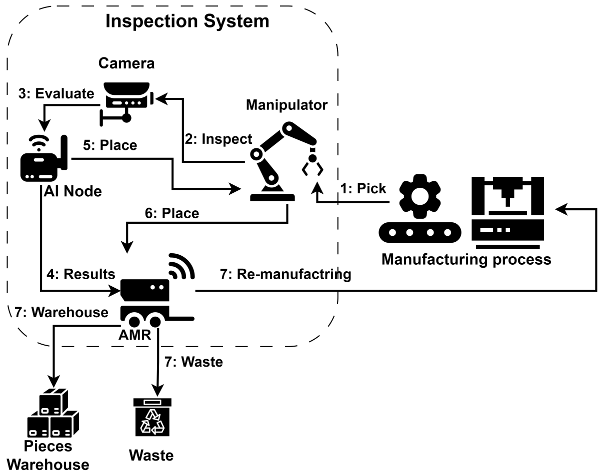

Fig. 1. Quality inspection system description.

pieces from the transportation element. The arms are equipped with advanced sensors and end-effectors, allowing them to delicately and accurately interact with objects in chaotic picking.

Once the manipulator takes the piece the next step is the visual inspection. The visual inspection is conducted through an industrial camera. The camera serves as a crucial tool for ensuring product integrity. It captures high-resolution images of products or components, providing detailed visual data for analysis. This data enables the detection of tiny defects such as cracks, scratches, dents, or color inconsistencies, which are essential for upholding product quality. The camera also allows to measure dimensions and geometrical properties with high precision.

The next step is to process and analyze the data collected from the camera. This data is analyzed in a computational node using a machine learning-based classification algorithm. The algorithm analyzes visual data to detect defects and anomalies that may be challenging for human inspectors or traditional methods to identify. By leveraging machine learning, it can be trained on extensive datasets to recognize patterns, categorize defects, and predict potential quality issues with high accuracy. One of the main advantages of using this kind of algorithm is the continuous improvement over time, by learning from new data to enhance their detection capabilities. This results in faster identification and correction of defects, reducing waste and improving overall product quality [16].

Once the piece is positioned over the AMR, the AMR uses the output from the classification algorithm to proceed to its intended destination. Depending on the classification, the AMR will take the piece to the warehouse if it's correct, to waste if it can't be fixed, or to the manufacturing process if the detected defect can be rectified through remanufacturing. The use of AMRs provides flexibility due to their ability to dynamically navigate and adapt to changes using advanced sensors. This integration into existing workflows makes them suitable for deployment in various production process layouts, enhancing operational efficiency by optimizing routes in real time for tasks like storage and delivery.

The proposed solution is designed to be flexible and adaptable, allowing for integration with various shop floor layouts. However, it is important to consider some limitations. From the manipulator's perspective, the geometry of the piece is crucial, and selecting the right grip is essential. For the camera, limitations primarily stem from environmental conditions such as illumination and visual noise. As for the classification algorithm, having a sufficient amount of high-quality data to represent the entire operational range is crucial for accurate classification. Lastly, for the AMR, while it can navigate efficiently in complex environments, there are limitations related to space and safety, especially in zones with human operators.

B. *Communications*

An efficient and reliable communication is crucial for maintaining operations and ensuring optimal performance in manufacturing processes. Adhering to industry 5.0 standards, it is essential to implement an IoT network that can efficiently obtain real-time data from various components such as sensors and smart devices. In order to select a protocol for implementing this IoT network some aspects like speed, flexibility, and scalability should be considered. Taking these aspects into account, the MQTT (Message Queuing Telemetry Transport) protocol was chosen to facilitate communication between the components of the quality control system. MQTT plays a crucial role in facilitating IoT communications within the framework of Industry 5.0, which emphasizes the integration of advanced technologies with human-centric approaches to manufacturing. MQTT is a lightweight and efficient messaging protocol designed for low-bandwidth and high-latency networks, making it perfect for connecting numerous IoT devices in industrial settings. Its capability to facilitate reliable and real-time data exchange among sensors, machines, and control systems ensures smooth operation and coordination along the production line.

Following the MQTT principles and to ensure flexibility scalability and lightweight communications a proper message structure should be defined. This message must contain all the information related to the action to be carried out. This way, the following structure for the message was defined:

- Topic: /Component/Action. The first part of the topic will identify the component where the action should be carried out. In the second one the action. This structure allows to easily track all the actions in the system.
- Payload: the payload is optional, just for messages whereas is mandatory for the action clarifications such as the results of the classification and the goal for the AMR.

IV. Case study: Zero-defect manufacturing pilot line

The pilot line selected for the system validation includes two machine tools with sensors, two manipulator robots, and two conveyor belts. The machine tools include a Deckel Maho DMC 75V Linear high-speed machining center with a CNC Siemens 840D, and an ultra-precision micromachining center Kern-Evo with a laser control Nano NT. Additionally, a collaborative robot Universal Robots UR5e and an industrial manipulator Stäubli RX90 are positioned next to the machines for operational handling. Finally, two conveyor belts are responsible for transporting the workpieces between machines.

The process implemented in the pilot lines is the manufacturing of envelopes for structural isolation. This manufacturing process is composed of several steps. First the operations of profiling the edges of the covering to eliminate imperfections. Then measurement of the height of the panel surface to calculate a compensation based on the different highs of the surface to conduct the final step cutting of the guide groove. All these operations take place in the Deckel machine tool. After this, a superficial engraving is carried out on the surface in the Kern-Evo machine tool. Finally, an AMR is introduced with the aim of transporting the piece to the delivery or remanufacturing points.

Carefully analyzing the process to guarantee the final quality, a vision-based inspection control must be conducted at the end of the operations of the first machine tool. For this, the implementation of the proposed control system is carried out. The UR5e robotic manipulator presents the four faces of the object to the camera connected to an IoT node. The selected camera for artificial vision inspection was the Allied Vision Mako G-192. As AMR a ROSbot XL HUSARION, equipped with a LiDAR RPLIDAR A2 and a stereoscopic camera Intel RealSense, is used to facilitate the transfer of manufactured pieces. Finally, as an IoT node for image processing, a Raspberry Pi 4 model B with 8GB RAM was introduced. All the elements from the pilot line and the quality control system are shown in Figure 2.

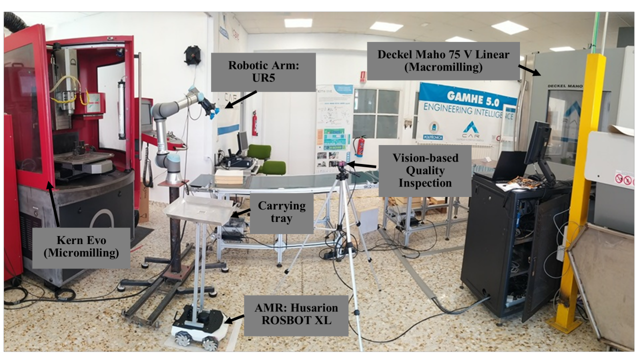

Fig. 2. Manufacturing pilot line.

Based on the evaluation of the image from the piece the decision-making process conducted on the IoT node has three outputs "COMPLAIN PIECE", "NON-COMPLAIN PIECE" and "REMANUFACTURING". Depending on the output the AMR takes the piece to the warehouse after the second machining process, takes it to the waste point, or to the first machine tool to fix the manufacturing defects. Figure 3 represents the navigation map of the AMR with the different goal points highlighted. Point 1 represents the location where the piece is placed by the collaborative robotic arm on the AMR tray. Points 2 and 3 are the two sections of storage piles, one for pieces to be repaired and the other for pieces ready for delivery, respectively. Point B indicates the charge point of the AMR.

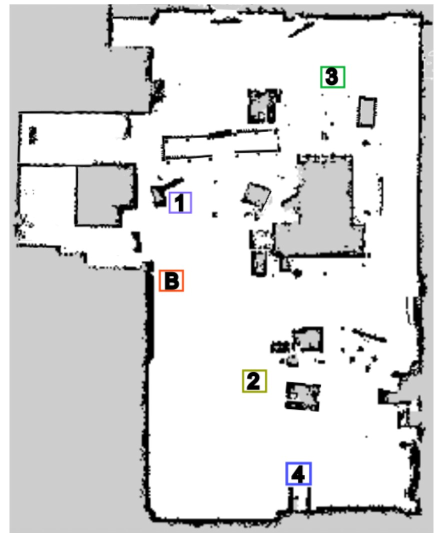

Fig. 3. Navigation map for AMR planning.

A. *Visual inspection-based decision-making*

One pivotal point in the production workflow is located in the visual inspection control. Therefore, decision-making processes are carried out based on the results of an object detection algorithm using AI. For this task, the state-of-the-art object detection algorithm YOLOv10 is used [17]. Specifically, the algorithm is trained on a custom dataset for detecting correctable and non-correctable defects on the produced items. Figure 4 shows an item that contains both types of defects, correctable and non-correctable. In this case, correctable defects refer to scratches or minor surface irregularities, while non-correctable defects refer to cracks or chipping. Information related to the results obtained for the training of the YOLOv10 algorithm on the custom dataset can be found in Table III.

TABLE III
TRAINING METRICS

Metric	Training result
Precision (P)	0.959
Recall (R)	0.970
Mean Average Precision at an Intersection over Union threshold of 0.5 (mAP50)	0.979

Additionally, Figure 5 shows the confusion matrix obtained during cross-validation.

Given the high accuracy demonstrated by the algorithm for detecting defects in the produced items, it is used as the base of the decision-making process. Figure 6 depicts how this process is carried out. First, the algorithm runs an inference on four images (one for each side of the item). Second, if a

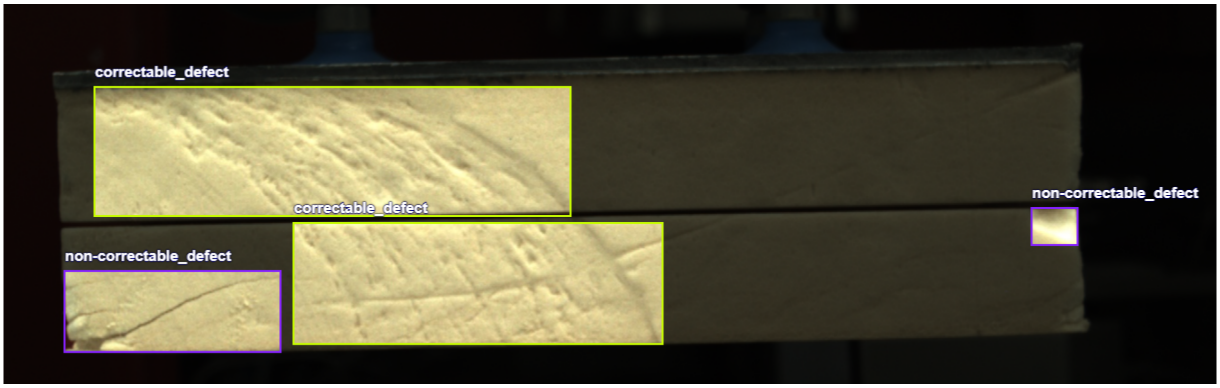

Fig. 4. Item presenting both, correctable and non-correctable defects.

non-correctable defect is detected in any of the four images, a message indicating that the current item must be removed from production is published. On the other hand, if no non-correctable defects are found, the next step is to check if any correctable defect is detected. If correctable defects are detected, a message containing a list of the item's sides that must be remanufactured (where the defects were found) is published to indicate that the current item must be sent to a previous stage of the production process. Finally, if no defects are found, a message indicating that the item is ready to be sent to the next stage of the production process is published. This way, the production workflow can be modified to handle efficiently the occurrence of defects, by removing the item from the production line and avoiding wasting time in further processing if the item has a non-correctable defect, or by timely remanufacturing the item if it has correctable defects before carrying out other operations.

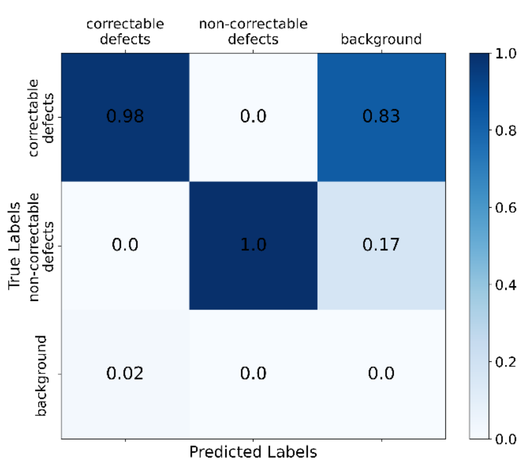

Fig. 5. Cross-validation confusion matrix.

B. Results

In order to assess the impact of the quality control system on the pilot line, several tests were conducted, with ten replicas made for each case. Table IV summarizes the system's performance. In general, the production time is not affected

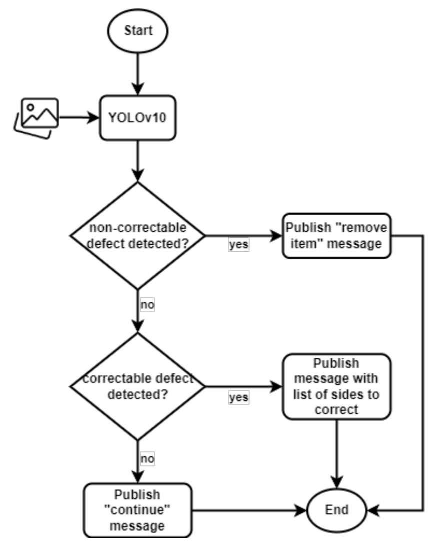

Fig. 6. Decision-making procedure.

by the introduction of the quality control system, except when the piece needs to be remanufactured, in which case the time increases. However, this increase is justified because most of the pieces detected as remanufactured will be labeled as waste, thereby increasing the defect rate.

TABLE IV
SYSTEM PERFORMANCE

Type of piece	**Total**	**Insp. accuracy**	**Prod. time increase (%)**
Good (P)	10	1	2.6
Bad (R)	10	1	2.6
Re-manufactured	10	1	7.2

On the other hand, many times an operator finds it difficult to differentiate between a piece that must be discarded and one that can be remanufactured. In this sense, the inspection algorithms, with high accuracy, are capable of improving the piece classification, reducing waste and leading to a zero-defect manufacturing process. Of course, to achieve the zero-defect goal, other aspects related to the process need to be analyzed and improved, but for sure, one of the main aspects, quality inspection, is covered.

Another aspect taken into consideration was the operator. Figure 7 shows the average operator physical activity time determined in the tests. As can be seen, in all cases the operator's physical workload was reduced when the fully automated quality control system was used. The biggest reduction occurs in the case of a piece needs to be re-manufactured (i.e., reinserted at the beginning of the pilot line to correct some defect), where the operator's physical workload was reduced from 14.46% to 8.69% (these values are expressed concerning the time that it takes the product to move from the beginning of the line to its final destination)

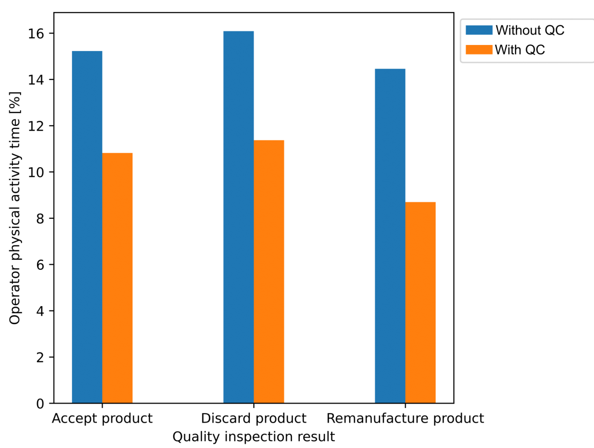

Fig. 7. Comparison of the average operator's physical workload

V. Conclusion

The introduction of a Zero Defect Manufacturing (ZDM) strategy in the GAMHE 5.0 pilot line has led to significant improvements in quality control and operational efficiency. By utilizing set of enabling technologies such as AI, machine vision, and autonomous robots, a substantial reduction in defects is achieved, minimizing waste, and guaranteeing the production of high-quality components. The robotic inspection system in the pilot line, featuring a collaborative robot and an Autonomous Mobile Robot (AMR), has effectively reduced human operator involvement, thereby enhancing safety and productivity. This system's capability to detect, categorize, and appropriately handle defective pieces has highlighted the potential of ZDM approaches in modern manufacturing environments.

In the future, research and development in Zero Defect Manufacturing and Industry 5.0 should focus on integrating advanced AI technologies such as informed deep learning and brain-machine interfaces to enhance human-machine collaboration. It is also important to expand the capabilities of the pilot line to include more complex and heterogenous manufacturing processes. Additionally, developing more robust and scalable IoT networks and cybersecurity measures will ensure the reliability and security of data transmission and analysis. By integrating sophisticated algorithms for decision-making and optimal allocation of resources, the system's efficiency and responsiveness can be further enhanced. These advancements will contribute to the broader adoption of ZDM, ultimately driving the manufacturing industry towards greater sustainability, efficiency, and human-centric innovation.

References

[1] F. Castano, Y. J. Cruz, A. Villalonga, and R. E. Haber, "Data-driven insights on time-to-failure of electromechanical manufacturing devices: A procedure and case study," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 5, pp. 7190–7200, 2023.

[2] S. Nahavandi, "Industry 5.0—a human-centric solution," *Sustainability*, vol. 11, p. 4371, 8 2019.

[3] W. M. Mohammed, M. Nejman, F. Castaño, J. L. Martinez Lastra, S. Strzelczak, and A. Villalonga, "Training an under-actuated gripper for grasping shallow objects using reinforcement learning," in *2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS)*, vol. 1, pp. 493–498, 2020.

[4] P. K. R. Maddikunta, Q.-V. Pham, P. B, N. Deepa, K. Dev, T. R. Gadekallu, R. Ruby, and M. Liyanage, "Industry 5.0: A survey on enabling technologies and potential applications," *Journal of Industrial Information Integration*, vol. 26, p. 100257, 3 2022.

[5] E. Commission, D.-G. for Research, Innovation, and J. Müller, *Enabling Technologies for Industry 5.0 – Results of a workshop with Europe's technology leaders*. Publications Office, 9 2020.

[6] F. Psarommatis, G. May, P.-A. Dreyfus, and D. Kiritsis, "Zero defect manufacturing: state-of-the-art review, shortcomings and future directions in research," *International Journal of Production Research*, vol. 58, pp. 1–17, 1 2020.

[7] F. Psarommatis, J. Sousa, J. P. Mendonça, and D. Kiritsis, "Zero-defect manufacturing the approach for higher manufacturing sustainability in the era of industry 4.0: a position paper," *International Journal of Production Research*, vol. 60, pp. 73–91, 1 2022.

[8] K. A. Demir, G. Döven, and B. Sezen, "Industry 5.0 and human-robot co-working," *Procedia Computer Science*, vol. 158, pp. 688–695, 2019.

[9] A. Villalonga, G. Beruvides, F. Castano, and R. E. Haber, "Cloud-based industrial cyber–physical system for data-driven reasoning: A review and use case on an industry 4.0 pilot line," *IEEE Transactions on Industrial Informatics*, vol. 16, pp. 5975–5984, 9 2020.

[10] N. Leberruyer, J. Bruch, M. Ahlskog, and S. Afshar, "Toward zero defect manufacturing with the support of artificial intelligence—insights from an industrial application," *Computers in Industry*, vol. 147, p. 103877, 5 2023.

[11] K. A. Tsintotas, I. Kansizoglou, F. K. Konstantinidis, S. G. Mouroutsos, G. C. Syrakoulis, F. Psarommatis, Y. Aloimonos, and A. Gasteratos, "Active vision: A promising technology for achieving zero-defect manufacturing," *Procedia Computer Science*, vol. 232, pp. 2821–2830, 2024.

[12] Z. Xu, Z. Guo, G. Zhang, X. Zhou, and Y. Zhang, "A framework for process states structural interpretation of zero-defect manufacturing," *Advanced Engineering Informatics*, vol. 60, p. 102442, 4 2024.

[13] A. Bhattacharya and S. G. Cloutier, "End-to-end deep learning framework for printed circuit board manufacturing defect classification," *Scientific Reports*, vol. 12, p. 12559, 7 2022.

[14] M. Noor-A-Rahim, J. John, F. Firyaguna, H. H. R. Sherazi, S. Kushch, A. Vijayan, E. O'Connell, D. Pesch, B. O'Flynn, W. O'Brien, M. Hayes, and E. Armstrong, "Wireless communications for smart manufacturing and industrial iot: Existing technologies, 5g and beyond," *Sensors*, vol. 23, p. 73, 12 2022.

[15] N. N. N. Vithanage, S. S. H. Thanthrige, M. C. K. P. Kapuge, T. H. Malwenna, C. Liyanapathirana, and J. L. Wijekoon, "A secure corroboration protocol for internet of things (iot) devices using mqtt version 5 and ldap," in *2021 International Conference on Information Networking (ICOIN)*, pp. 837–841, IEEE, 1 2021.

[16] Y. J. Cruz, F. Castaño, R. E. Haber, A. Villalonga, K. Ejsmont, B. Gladysz, Álvaro Flores, and P. Alemany, *Self-Reconfiguration for Smart Manufacturing Based on Artificial Intelligence: A Review and Case Study*, pp. 121–144. Springer Nature Switzerland, 2024.

[17] A. Wang, H. Chen, L. Liu, K. Chen, Z. Lin, J. Han, and G. Ding, "Yolov10: Real-time end-to-end object detection," *arXiv preprint arXiv:2405.14458*, 2024.