Intelligent robotic systems in Industry 4.0: A review

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Journal of

Advanced Manufacturing Science and Technology

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Received 12 January 2024; revised 20 January 2024; accepted 25 January 2024

Abstract

As Industry 4.0 continues to transform the landscape of modern manufacturing, the integration of intelligent robotic systems has emerged as a pivotal factor in enhancing efficiency, flexibility, and overall productivity. The Integration of intelligent robotic systems within the framework of Industry 4.0 represents a transformative shift in advanced manufacturing systems. The integration of intelligent robotic systems in Industry 4.0 has significantly reduced production costs while simultaneously improving product quality. The intelligent decision-making capabilities of robotic systems in Industry 4.0 have played a pivotal role in minimizing downtime in order to enhance productivity in process of part manufacturing. Intelligent robotic systems in Industry 4.0 has not only increased production efficiency but has also contributed to a more sustainable and eco-friendly manufacturing environment through optimized resource utilization. This review explores the key aspects, benefits, and challenges associated with the deployment of intelligent robotic systems in Industry 4.0. The review analyze the cutting-edge advancements in artificial intelligence, machine learning, and sensor technologies that contribute to the evolution of intelligent robotic systems in Industry 4.0. The discussion extends to emerging trends in intelligent robotic systems including digital twin, blockchain, Internet of Things, artificial intelligent and the integration of advanced analytics for real-time decision support systems. Challenges and considerations surrounding the implementation of intelligent robotic systems in Industry 4.0 are thoroughly examined, ranging from technical hurdles to ethical and societal implications. Finally, the review concludes with a forward-looking perspective on the future trajectory of intelligent robotic systems in Industry 4.0. As a result, the study can provide a roadmap for researchers and industry professionals to navigate the evolving landscape of intelligent robotics in the era of Industry 4.0.

Keywords: Intelligent Robotic, Industry 4.0, Automation, Efficiency of part production

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Peer review under responsibility of Editorial Committee of JAMST

DOI: 10.51393/j.jamst.2024007

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1. Introduction

The fourth industrial revolution, or "industry4.0," is defined by the use of digital technology, automation, and data sharing in production processes. To improve productivity, adaptability, and flexibility in industrial environments, intelligent robotic systems are developed. The integration of intelligent robotic systems within the context of Industry 4.0 has ushered in a new era of smart manufacturing, transforming traditional production processes [1]. Industry 4.0 has brought about a paradigm shift in which intelligent robotic technologies are essential to changing the industrial operations environment. The implementation of Industry 4.0, the fourth industrial revolution defined by automated, intelligent, and linked production processes, has made intelligent robotic systems essential [2]. Intelligent robotic systems in Industry 4.0 are characterized by their adaptability to changing manufacturing demands. Through advanced sensors and learning algorithms, these systems can dynamically adjust their behavior, tooling, or programming to accommodate variations in product specifications or production requirements [3]. This adaptability contributes to the development of flexible manufacturing systems capable of handling diverse tasks and products.

The concept of human-machine collaboration is at the forefront of Industry 4.0, and intelligent robotic systems play an advanced role in realizing this vision. These systems facilitate seamless interaction between human workers and machines, promoting a collaborative work environment. Human input becomes an integral part of the learning process for robots, enhancing overall productivity and adaptability [4]. Intelligent robotic systems equipped with advanced vision systems contribute to quality control and inspection tasks in manufacturing. These systems ensure consistent and precise inspection, leading to improved product quality and adherence to stringent quality standards [5]. The adaptability of intelligent robotic systems in Industry 4.0 is commendable, allowing for seamless customization to meet the specific needs of our diverse manufacturing tasks. Moreover, incorporating advanced robotics into our industrial framework has streamlined workflows, enabling quicker turnaround times and boosting overall productivity [6].

In manufacturing and logistics, autonomous guided vehicles (AGVs) and drones are used for material handling and transportation, enhancing efficiency in warehouses and production facilities. Robots equipped with vision systems and AI can autonomously inspect and assess the quality of products, identifying defects and ensuring high standards. Intelligent robotic systems are often equipped with sensors that collect and transmit real-time data. These robots can interact with other devices and systems thanks to the Internet of Things (IoT) integration, which makes the manufacturing environment smooth and networked [7]. Digital twins, virtual replicas of physical systems, enable simulation and testing of robotic processes before they are implemented. This reduces the risk of errors and aids in optimizing workflows. Industry 4.0 relies on cyber-physical systems where physical processes are controlled and monitored in real-time. Intelligent robotic systems are integral components of this paradigm, contributing to the efficiency and agility of manufacturing operations. Intelligent robotic systems contribute to the automation of material handling and logistics within the supply chain, leading to improved inventory management and reduced lead times [8]. Large amounts of data produced during industrial operations may also be processed and analyzed by these systems using data analytics. Predictive maintenance, process optimization, and quality control are made possible by this data-driven methodology.

Artificial intelligence (AI) aids in anticipating equipment malfunctions and planning maintenance tasks in advance of a breakdown, minimizing downtime and boosting overall equipment efficiency. AI and ML algorithms are used by intelligent robotic systems to help them adapt and learn from their experiences [9]. This adaptability is valuable in optimizing production processes and improving efficiency over time [10]. So, the integration of intelligent robotic systems in Industry 4.0 is transforming traditional manufacturing practices, offering greater flexibility, efficiency, and responsiveness to the dynamic demands of the modern industrial landscape. Advances in intelligent robotic systems and sensor technologies in Industry 4.0 is shown in the Fig.1 [11].

AI and ML algorithms enable robots to learn from data, adapt to changing conditions, and improve their performance over time. This adaptive learning capability is essential for handling dynamic and unpredictable manufacturing environments. Intelligent robotic systems are designed to optimize energy consumption and resource utilization. This focus on efficiency aligns with sustainable and environmentally friendly manufacturing practices.

Meta-heuristic algorithms for assessing the collapse risk of steel moment frame mid-rise buildings is presented by Karimi Ghaleh Jough and Şensoy [12] in order to provide a better risk management strategy in steel moment frames. Steel Moment-Resisting Frame Dependability via Interval Analysis using the FCM-PSO Method is studied by

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Peer review under responsibility of Editorial Committee of JAMST
DOI: 10.51393/j.jamst.2024007
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Karimi Ghaleh Jough and Şensoy [13] to enhance accuracy and decrease execution time in calculation of siesmic fragility curves. Assessment of out-of-plane behavior of non-structural masonry walls using FE simulations is presented by Karimi Ghaleh Jough and Golhashem [14] in order to reduce self-weight axial compression of the walls with modern lightweight masonry units. Uncertainty analysis through development of seismic fragility curve for an SMRF structure using an adaptive neuro-fuzzy inference system based on fuzzy C-means algorithm is implemented by Karimi Ghaleh Jough and Beheshti Aval [15] to incorporate epistemic uncertainty and increasing calculation accuracy. Road map to BIM use for infrastructure domains: Identifying and contextualizing variables of infrastructure projects is presented by Ghasemzadeh et al. [16] to identify and prove the existing lack of using BIM for infrastructure projects. Epistemic Uncertainty Treatment Using Group Method of Data Handling Algorithm in Seismic Collapse Fragility is presented by Karimi Ghaleh Jough et al. [17] to increase accuracy and precision of the outputs as well as power with the same computational time compared to aforementioned methods. Uncertainty Interval Analysis of Steel Moment Frame by Development of 3D-Fragility Curves Towards Optimized Fuzzy Method is presented by Karimi Ghaleh Jough and Ghasemzadeh [18] to enhance accuracy and reduce execution time in driving the 3D-fragility curves. The contribution of steel wallposts to out-of-plane behavior of non-structural masonry walls is investigated by Karimi Ghaleh Jough [19] to provide smaller modification factors in masonry walls with wallpost.

Fig. 1. Advances in intelligent robotic systems and sensor technologies in Industry 4.0 [11].

Soori et al. [20-23] proposed virtual machining methods for improving and assessing CNC machining in virtual settings. Soori et al. [24] provided an overview of recent advancements in friction stir welding techniques in order to analyze and improve performance in the component production process using welding processes. Soori and Asamel [25] investigated the use of virtual machining technology to reduce residual stress and displacement inaccuracy during five-axis milling operations for turbine blades. Soori and Asmael [26] investigated possibilities of virtualized machining methods to monitor and lower the cutting temperature while milling things that are challenging to cut. Soori et al. [27] suggested the implementation of a sophisticated virtual machining technique to enhance surface properties during turbine blade five-axis milling operations. Soori and Asmael [28] developed virtual milling procedures to lower dislocation error in impeller blade five-axis milling operations. Soori [29] presented virtual invention as an attempt to examine and improve the part production process in virtual settings.

Soori and Asmael [30] Presented a summary of recent developments from literature to evaluate and improve the parameter approach for machining process optimization. To enhance energy consumption efficiency, data availability and quality throughout the supply chain, and component manufacturing precision and reliability, Dastres et al. [31] proposed a review of RFID-based wireless manufacturing systems. Soori et al. [32] investigated the use of artificial intelligence and machine learning to CNC machine tools in order to increase efficiency and profitability in component production processes. In order to enhance the functionality of machined parts, Soori and Arezoo [33] examined the subject of residual stress measurement and reduction in machining operations. To enhance the integrity of the surface and reduce residual stress while grinding Inconel 718, Soori and Arezoo [34] recommended employing the Taguchi optimization approach to determine the ideal machining settings. To prolong the life of the cutters used in machining processes, Soori and Arezoo [35] investigated various approaches for tool wear prediction algorithms. Soori and Asmael [36] examined the use of computer-assisted process planning to increase component manufacturing method efficiency. Dastres and Soori [37] examined how to utilize advancements in web-based decision support systems to provide solutions for data warehouse administration through support for decision-making. Dastres and Soori [38] examined uses of artificial neural networks to investigate methods to implement them to increase the efficacy of products. Dastres and Soori [39] suggested using communication systems in environmental issues to reduce the detrimental impacts of technology development on natural disasters. To improve the internet security of networks and data, Dastres and Soori [40] suggested the secure socket layer.

To improve network security protocols, Dastres and Soori [41] provided a review of the most current developments in network threats. To expand image processing systems' potential for a variety of purposes, Dastres and Soori [42] examined systems for image processing and analysis. Dimensional, geometrical, tool deflection, and thermal defects have been modified by Soori and Arezoo [43] to improve accuracy in 5-axis CNC milling processes. Recent developments in published articles are examined by Soori et al. [44] in order to evaluate and enhance deep learning, machine learning, and artificial intelligence's effects on advanced robots. Soori and Arezoo [45] created a virtual machining system application to investigate if the tool life and cutting temperature throughout milling operations are influenced by the cutting parameters. Soori and Arezoo [46] investigated how coolant affected the cutting temperature, surface roughness, and tool wear when turning Ti6Al4V alloy. A review of recent advances from published publications is conducted by Soori[47] in order to investigate and modify composite constructions and materials. Soori et al. [48] studied how to improve quality control and streamline part production operations in industry 4.0 smart factories by utilizing the Internet of Things. To reduce the amount of wear on cutting tools while drilling, Soori and Arezoo [49] proposed a virtual machining system. Soori and Arezoo [50] reduced surface roughness and residual stress to raise the overall quality of products made with abrasive water jet cutting. In order to improve the precision of five-axis milling operations for turbine blades, Soori [51] calculates and compensates for deformation errors. Soori and Arezoo [52] studied the application of the finite element approach in CNC machine tool modification in order to assess and improve accuracy in CNC machining processes and components. Soori et al. [53] studied several energy use optimization techniques in order to assess and optimize energy consumption in industrial robots. Soori et al. [54] examined the negative and positive aspects of virtual manufacturing systems in order to assess and improve the part production process in Industry 4.0. In order to develop the supply chin management in advanced manufacturing, artificial neural networks are studied by Soori et al. [55].

This comprehensive review synthesizes the current knowledge base on intelligent robotic systems within the context of Industry 4.0, shedding light on their transformative potential, challenges, and future directions. By providing a nuanced perspective on the intersection of robotics and the fourth industrial revolution, this review aims to contribute to the ongoing discourse and foster advancements that propel manufacturing and production industries into a new era of efficiency, adaptability, and innovation.

2. Connected automation

Intelligent robotic systems play a central role in Industry 4.0 by being seamlessly connected to other components in the manufacturing ecosystem [56]. They communicate with sensors, machines, and other robots to enable a highly interconnected and automated production environment [57]. Intelligent robotic systems serve as the backbone of this connectivity, facilitating seamless communication between machines, sensors, and the broader manufacturing ecosystem [58]. This interconnected automation enhances overall operational efficiency and responsiveness. In this context, Intelligent Robotic Systems leverage connected automation to enhance efficiency, flexibility, and responsiveness in industrial processes [59]. Here are some key aspects of connected automation in Intelligent Robotic Systems in Industry 4.0:

1. Interconnected Devices and Systems: Intelligent Robotic Systems in Industry 4.0 are characterized by the interconnectivity of devices and systems. Robots, sensors, actuators, and other manufacturing equipment are connected to a network, enabling seamless communication and information exchange [60].
2. Industrial Internet of Things (IIoT): Industry 4.0's networked automation is based on IIoT. Real-time data is gathered by sensors built into production machinery and robotic systems, which offer insights into the operation and condition of the machines. This data is then utilized for decision-making and optimization [61].
3. Data Analytics and Machine Learning: The data generated by connected robotic systems is analyzed using advanced analytics and machine learning algorithms [63]. This allows for predictive maintenance, process optimization, and the identification of patterns that can improve overall efficiency and reduce downtime [63].
4. Collaborative Robots (Cobots): Connected automation facilitates the deployment of collaborative robots or cobots. These robots can work alongside human operators, and their actions can be synchronized with other machines in the production line. This collaborative approach enhances flexibility and adaptability in manufacturing processes [64].
5. Real-time Monitoring and Control: With connected automation, operators can monitor and control robotic systems in real time. This capability is essential for making quick adjustments to production processes, addressing issues promptly, and optimizing the use of resources.
6. Remote Maintenance and Diagnostics: Connected automation enables remote monitoring and diagnostics of robotic

systems. Maintenance issues can be identified early, and in some cases, problems can be resolved remotely, reducing the need for physical interventions and minimizing downtime.

7. Cybersecurity Measures: Given the increased connectivity, cybersecurity is a critical consideration. Industry 4.0 implementations must incorporate robust cybersecurity measures to protect against potential threats and ensure the integrity of data and operations [65].

8. Digital Twins: Digital twins are digital copies of real-world processes or systems. Digital twins can be utilized for testing, modeling, and optimization in the context of intelligent robotic systems, enabling a better comprehension of the behavior and functionality of the system. [66].

9. Supply Chain Integration: Connected automation extends beyond individual factories to integrate with the broader supply chain. This integration enables better coordination and synchronization of production processes across different stages of manufacturing [67].

10. Adaptive and Agile Manufacturing: The connected automation in intelligent robotic systems supports adaptive and agile manufacturing processes. Systems can quickly adapt to changes in demand, reconfigure production lines, and optimize resource utilization based on real-time data.

Operation model of cloud manufacturing is shown in the Fig. 2 [68].

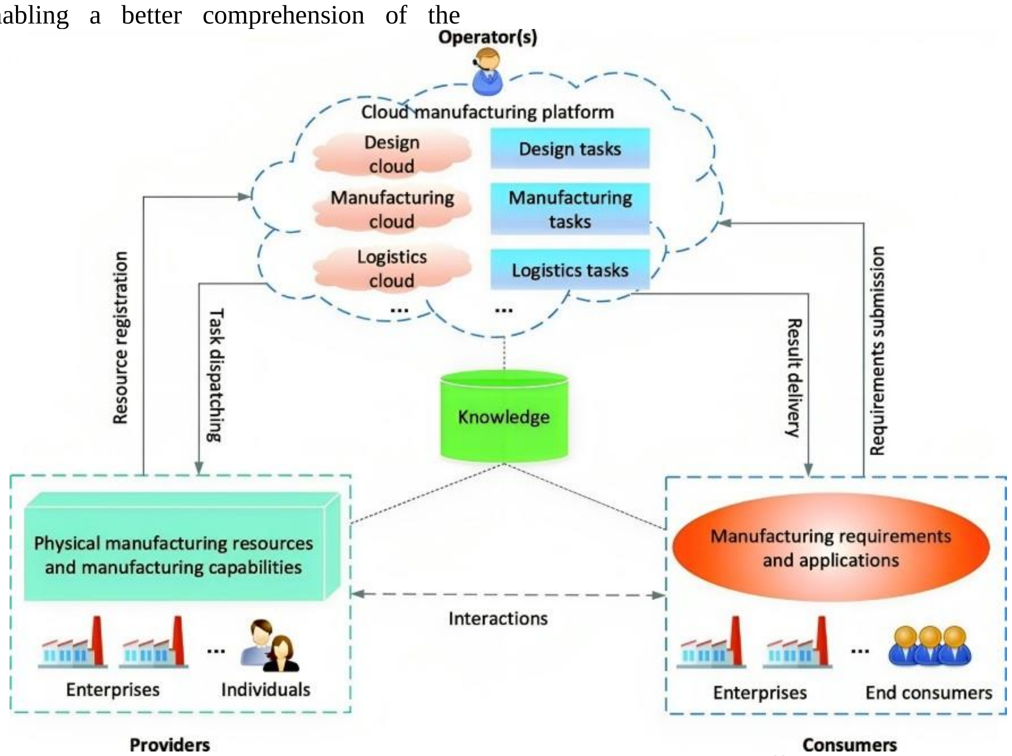

Fig. 2. Operation model of cloud manufacturing [68].

In conclusion, connected automation is a fundamental aspect of Intelligent Robotic Systems in Industry 4.0, contributing to increased efficiency, flexibility, and responsiveness in manufacturing processes. The integration of digital technologies and connectivity not only enhances the capabilities of individual robotic systems but also enables a more holistic and interconnected approach to industrial automation.

3. Data-driven decision making

Industry 4.0 leverages intelligent robots to collect and analyze vast amounts of data from various sources. This data-driven approach allows for real-time decision-making, predictive maintenance, and continuous optimization of manufacturing processes [69]. Here's how data-driven decision-making is applied in this context:

1. Data Collection and Sensors: Sensors and IoT Devices: Intelligent Robotic Systems gather data in real time from the production environment using a variety of sensors and Internet of Things devices. These sensors can include cameras, temperature sensors, pressure sensors, and more [70]. Data Streaming: Continuous data streaming from these sensors provides a comprehensive view of the production process, equipment status, and environmental conditions [71].

2. Data Processing and Analytics:

Collected data is processed using big data analytics tools to identify patterns, trends, and anomalies. This enables a deeper understanding of the production processes and system performance [72]. Also, machine learning models can be applied to predict equipment failures, optimize production schedules, and improve overall system efficiency based on historical data and real-time inputs [73].

3. Predictive Maintenance: It is possible to anticipate equipment failures using data analytics before they happen. This minimizes the impact on production and permits preventive maintenance, which cuts downtime. Maintenance schedules may be modified to reduce costs and extend the life of robotic systems by examining past data [74].
4. Process Optimization: Data-driven insights enable continuous monitoring of robotic system performance. Deviations from optimal performance can be quickly identified and addressed. Intelligent robotic systems can adapt their behavior based on real-time data, optimizing their actions in response to changing conditions [75].
5. Quality Control: Cameras and sensors can be used for real-time quality inspection. Data analytics help identify defects or deviations from quality standards, enabling immediate corrective actions. Data-driven decision-making supports the implementation of statistical process control methods to maintain consistent product quality [76].
6. Supply Chain Integration: Data analytics can be applied to predict demand fluctuations, allowing for better inventory management and production planning. Integrating data from the supply chain provides end-to-end visibility, helping organizations make informed decisions regarding logistics, inventory, and resource allocation [77].
7. Human-Robot Collaboration: Data-driven insights can be used to optimize the collaboration between human workers and robotic systems, ensuring efficient and safe coexistence in the workplace [67]. Analytics can identify areas where human workers may need additional training or support to work effectively with Intelligent Robotic Systems [78].

In summary, real-time and historical data are leveraged to optimize processes, improve performance, and make well-informed decisions that result in greater productivity, decreased costs, and decreased efficiency in Intelligent Robotic Systems in Industry 4.0. For Industry 4.0 technologies to be fully utilized in manufacturing and other industrial applications, this strategy is essential.

4. Collaborative robotics

Collaborative robotics, or cobots, is significant in the context of Industry 4.0 and Intelligent Robotic Systems. The fourth industrial revolution, or Industry 4.0, is defined as the incorporation of digital technologies, data exchange, and automation into manufacturing processes [79]. These robots can collaborate with human workers to improve production settings' flexibility, safety, and productivity [80]. Here's how collaborative robotics contributes to intelligent robotic systems in Industry 4.0:

1. Human-Robot Collaboration (HRC): Robots built for collaboration are intended to operate side by side with humans in a shared workspace. By working together, industrial processes become more flexible and people and robots can play to each other's strengths [81]. The ability of cobots to operate safely in proximity to humans without the need for physical barriers enables a more dynamic and adaptable production environment [82].
2. Flexibility and Adaptability: In Industry 4.0, there is a growing need for flexible and adaptable manufacturing systems. Collaborative robots are designed to be easily reprogrammed and redeployed, making it easier for manufacturers to adapt to changes in production demands or shifts in product lines [83].
3. Sensors and Perception: Cobots are equipped with advanced sensors and perception technologies, such as vision systems and force/torque sensors. These features enable them to perceive their environment, recognize objects, and react to changes in real-time, enhancing their ability to work alongside humans safely [84].
4. Data Integration and Analytics: Intelligent Robotic Systems in Industry 4.0 leverage data integration and analytics to optimize manufacturing processes. Collaborative robots generate a wealth of data during operation, which can be analyzed to improve efficiency, predict maintenance needs, and optimize production workflows [85].
5. Interconnected Systems: Collaborative robots are part of the interconnected network of smart devices and systems in Industry 4.0. They can communicate with other machines, robots, and systems, facilitating seamless

coordination and collaboration within the manufacturing environment [86].

6. Skill Augmentation: Cobots are meant to complement human abilities, not to take their place. Labor-intensive or repetitive activities can be performed by them, freeing up human workers to focus on more challenging but important duties like creativity, judgment, and problem-solving.

7. Adaptive Manufacturing: With the ability to adapt to changing production requirements, collaborative robots contribute to the concept of adaptive manufacturing [87]. This allows companies to respond quickly to market demands, customize products efficiently, and maintain a competitive edge.

8. Safety Standards and Regulations: Collaborative robots adhere to stringent safety standards and regulations to ensure the well-being of human workers. This includes features such as force limiting, speed monitoring, and collision detection to prevent accidents and injuries [88].

In summary, collaborative robotics is a key enabler of Intelligent Robotic Systems in Industry 4.0, offering increased flexibility, adaptability, and the ability to work collaboratively with human workers. This integration of advanced robotics contributes to more efficient and responsive manufacturing processes in the evolving landscape of Industry 4.0.

5. Adaptive manufacturing

Intelligent robotic systems are capable of adapting to changes in production requirements. The capacity of manufacturing systems to dynamically modify and improve their operations in response to real-time data, feedback, and changing conditions is known as "adaptive manufacturing" [89]. In the context of Intelligent Robotic Systems, this involves the use of advanced robotics and intelligent automation technologies to create flexible, responsive, and efficient manufacturing processes [90]. Through advanced sensors and learning algorithms, these robots can adjust their behavior, tooling, or programming to accommodate variations in product specifications or demand. Here are some key aspects of adaptive manufacturing in Intelligent Robotic Systems within Industry 4.0:

1. Real-time Data Analytics: Intelligent Robotic Systems are equipped with sensors and data analytics capabilities to gather and analyze real-time data from the manufacturing environment [91]. So, data from sensors, cameras, and other sources enable the system to make informed decisions and adapt to changes in the production environment [92].

2. Machine Learning and Artificial Intelligence: Artificial intelligence and machine learning algorithms are used in adaptive manufacturing to anticipate and react to changes in the production process. These systems have the ability to recognize trends in previous data, learn from them, and make decisions on their own to improve efficiency and streamline procedures [93].

3. Flexible Automation: Robots are designed to handle a variety of tasks and can be easily reprogrammed or reconfigured to adapt to changes in product specifications or production requirements [94].

4. Human-Robot Collaboration: Industry 4.0 encourages more human-robot cooperation in the production setting. Robots and humans may work together seamlessly thanks to adaptive manufacturing systems, which can modify processes to suit the preferences and skill levels of human operators [95].

5. Predictive Maintenance: Adaptive manufacturing systems incorporate predictive maintenance capabilities, leveraging data analytics to predict when equipment or robots are likely to fail. This proactive strategy enhances overall system dependability, lowers maintenance costs, and minimizes downtime [96].

6. Communication and Connectivity: Intelligent Robotic Systems are part of a connected ecosystem where devices, machines, and systems communicate with each other. This connectivity allows for the exchange of real-time information, enabling adaptive manufacturing systems to respond quickly to changes in demand, supply chain disruptions, or other factors [97].

7. Digital Twins: Digital twin technology creates virtual replicas of physical systems, including robots and manufacturing processes. These digital twins can be used for simulation, testing, and optimization, allowing for proactive adjustments to the manufacturing process before changes are implemented in the physical environment.

8. Customization and Batch Size Flexibility: Efficiency in managing small batch sizes and customisation is made possible by adaptive manufacturing. Production schedules and product standards may be instantly changed by robots, enabling more responsive and customer-focused manufacturing [98].

In summary, adaptive manufacturing in Intelligent robotic systems plays a vital role in Industry 4.0 by leveraging real-time data, artificial intelligence, flexible automation, and connectivity to create agile and efficient manufacturing processes. This approach is essential for meeting the demands of a rapidly changing and dynamic industrial landscape.

6. Predictive maintenance

The predictive maintenance capabilities of intelligent robotic systems contribute to increased reliability and reduced downtime. By monitoring their own health and performance, these systems can predict potential issues and schedule maintenance activities proactively. Industry 4.0 utilizes intelligent robots equipped with sensors to monitor their own health and performance [99]. Predictive maintenance algorithms analyze this data, allowing for proactive maintenance to prevent unexpected downtime and improve overall equipment effectiveness. This results in enhanced equipment reliability and overall operational efficiency [100]. Here's how predictive maintenance is applied in Intelligent Robotic Systems within the Industry 4.0 framework:

1. Data-driven Insights: Massive volumes of data are produced by intelligent robotic systems' sensors, actuators, and other networked devices. The purpose of gathering and analyzing this data is to learn more about the functionality and condition of the robotic systems [101]. Machine learning algorithms are employed to detect patterns and anomalies in the data, helping to predict potential issues before they lead to system failures.
2. Condition Monitoring: Predictive maintenance relies on continuous monitoring of the condition of robotic components. Sensors attached to various parts of the robot collect real-time data on factors such as temperature, vibration, and power consumption [102]. By comparing current conditions with historical data, algorithms can identify deviations and predict when a component is likely to fail.
3. Predictive Analytics: Advanced analytics, such as artificial intelligence and machine learning, are used to evaluate past data and forecast robotic system performance in the future. When estimating when maintenance is necessary, predictive models include a number of variables, including component deterioration, usage patterns, and environmental considerations.
4. Reduced Downtime: By arranging maintenance tasks at the best times, predictive maintenance reduces unscheduled downtime. Robotic systems can function more dependably and contribute to higher productivity in industrial processes by resolving possible problems before they become serious ones [70].
5. Cost Reduction: Predictive maintenance is cost-effective compared to traditional reactive or scheduled maintenance approaches. It helps in avoiding unnecessary maintenance activities and reduces the likelihood of costly breakdowns. Maintenance tasks can be planned and executed efficiently, optimizing the use of resources and minimizing operational costs [103].
6. Remote Monitoring and Diagnostics: Industry 4.0 enables remote monitoring of robotic systems, allowing technicians and engineers to assess the condition of robots from a distance. In case of an identified issue, remote diagnostics can be performed, and appropriate actions can be taken, reducing the need for on-site interventions [104].
7. Integration with IoT and Cloud Computing: Intelligent robotic systems that use predictive maintenance make use of cloud computing and the Internet of Things (IoT) to process and store data in real-time. Cloud-based platforms make it easier to combine data from various robotic systems, which allows for more thorough analysis and improved prediction models [105].

Predictive maintenance based on industrial asset management in industry 4.0 is shown in Fig. 3 [106].

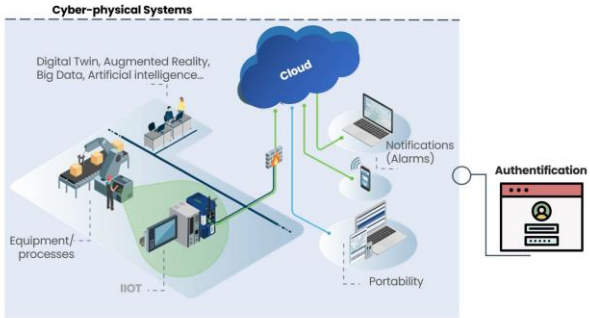

Fig. 3. Predictive maintenance based on industrial asset management in Industry 4.0 [106].

In summary, Industry 4.0's predictive maintenance inside intelligent robotic systems is a technology- and data-driven strategy that seeks to improve industrial robotic operations' dependability, efficacy, and affordability. It leverages advanced analytics, condition monitoring, and real-time data to predict and prevent failures, ultimately contributing to improved overall system performance.

7. Autonomous navigation

Industry 4.0 embraces intelligent robotic systems with autonomous navigation capabilities. These robots can navigate through dynamic environments, avoiding obstacles and optimizing their paths for efficient material handling and logistics within smart factories [96]. Here are key aspects related to autonomous navigation in Intelligent robotic systems in Industry 4.0:

1. Sensors and PerceptionTo sense their surroundings, intelligent robotic systems employ a variety of sensors, including inertial, radar, LiDAR, and cameras. Several sensors' worth of data are combined using sensor fusion techniques to provide a complete picture of the environment [108]. Computer vision algorithms enable robots to interpret visual information, recognize objects, and navigate based on the analysis of images or video feeds [108].
2. Mapping and Localization Algorithms: Robots can map their surroundings and identify their own location inside it at the same time thanks to simultaneous localization and mapping procedures. This is essential for navigation in dynamic environments. Advanced localization algorithms, such as Monte Carlo Localization (MCL) or Kalman filtering, are used to estimate the robot's position accurately [109].
3. Path Planning and Decision Making Algorithms: These algorithms help robots determine the most efficient route from one point to another while avoiding obstacles. As a result, the robots can move in working schedules by avoiding obstacles and optimizing their paths during working conditions [110].
4. Obstacle Avoidance and collision detection algorithms: Robots need the ability to dynamically adapt their paths to avoid obstacles. This involves real-time decision-making based on sensor data.
5. Communication and Collaboration by Interconnected Systems: In Industry 4.0, robotic systems often need to collaborate with other machines and systems. Communication protocols, such as OPC UA (Open Platform Communications Unified Architecture), facilitate seamless information exchange between different components of the manufacturing ecosystem [111].
6. Machine Learning and AI by Reinforcement Learning: AI techniques, such as reinforcement learning, can be employed to enable robots to learn optimal navigation strategies in complex and dynamic environments. Algorithms trained on previous data can forecast possible obstructions, malfunctions in equipment, and other elements that might affect navigation [112].
7. Safety and Complianceby Collision Avoidance: Implementing safety measures, such as collision detection and avoidance systems, is critical to prevent accidents and damage to both the robotic system and its surroundings [82].
8. Compliance with Regulations: Robotic systems must adhere to industry and safety regulations governing autonomous navigation in industrial settings in order to enhance safety in working conditions.
9. Real-time Monitoring and Adaptability by IoT Integration: Internet of Things (IoT) technologies enable real-time monitoring of robotic systems. This data can be used to make on-the-fly decisions and adapt navigation strategies based on changing conditions [113].
10. Energy Efficiency by Optimized Routes: Autonomous navigation systems can optimize routes not only for time efficiency but also for energy conservation, contributing to overall sustainability in manufacturing [92, 114].

Fig.4 illustrates smart manufacturing using AGV technology integrated into module manufacture [115].

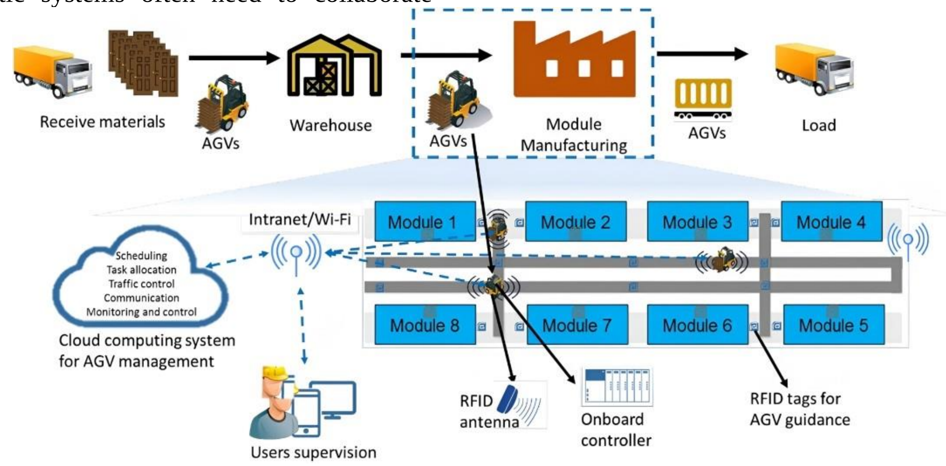

Fig. 4. Smart manufacturing using AGV technology integrated into module manufacture [115].

In conclusion, autonomous navigation in Intelligent robotic systems is a multifaceted domain that combines advanced sensing, perception, decision-making algorithms, and collaboration with other Industry 4.0 technologies. These capabilities are essential for creating agile, adaptive, and efficient robotic systems in modern industrial settings.

8. Human-Machine collaboration

Industry 4.0's transition to human-robot collaboration is best shown by the incorporation of collaborative robots, or cobots. These robots work alongside human operators, enhancing productivity, safety, and flexibility. Intelligent robotic systems facilitate seamless collaboration between humans and machines. Human workers can interact with robots through intuitive interfaces, and robots can learn from human input, creating a synergistic and efficient work environment [116]. The synergy between humans and robots creates a harmonious work environment, where each complements the strengths of the other. Here are key aspects of human-machine collaboration in intelligent robotic systems within Industry 4.0:

1. Cobots (Collaborative Robots): Collaborative robots are designed to work alongside human workers in a shared workspace. These robots are equipped with advanced sensors and programming to ensure safe and efficient collaboration. They can perform tasks that are either too dangerous or monotonous for humans, allowing the workforce to focus on more complex and creative aspects of their jobs.

Working procedures for collaboration according to by ISO 10218-1/2 is shown in the Fig. 5 [117].

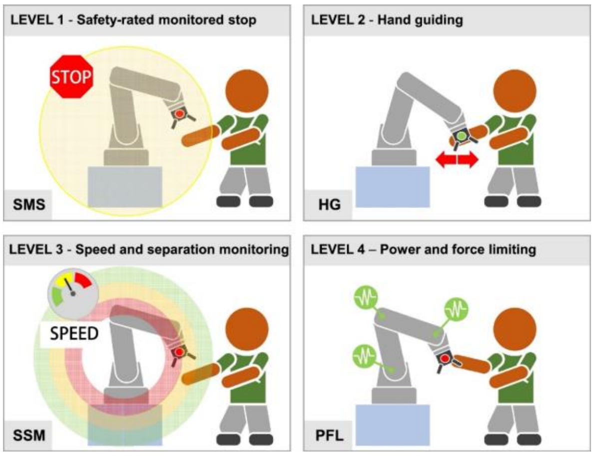

Fig. 5. Working procedures for collaboration according to by ISO 10218-1/2 [117].

2. Skill Augmentation: Intelligent robotic systems can augment human capabilities by taking over repetitive and physically demanding tasks. This collaboration enhances overall productivity and quality while reducing the risk of human error. Workers can focus on tasks that require critical thinking, problem-solving, and creativity [118].
3. Human-in-the-Loop Systems: Industry 4.0 emphasizes real-time data and connectivity. Human workers can be actively involved in decision-making processes through human-in-the-loop systems. Intelligent robotic systems gather and analyze data, while humans provide contextual understanding, make complex decisions, and handle non-routine situations.
4. Adaptive Automation: Intelligent robotic systems in Industry 4.0 are designed to be adaptive. They can learn from human operators, adapt to changes in the environment, and continuously improve their performance [119]. This adaptability is crucial in dynamic manufacturing environments where processes and requirements may change frequently.
5. User-Friendly Interfaces: The collaboration between humans and machines is facilitated by user-friendly interfaces. Human operators need to interact with intelligent robotic systems seamlessly. Intuitive interfaces, augmented reality, and natural language processing contribute to effective communication between humans and machines [120].
6. Data Sharing and Integration: In a smart factory environment, data is a key asset. Human-machine collaboration involves sharing and integrating data from various sources. This data exchange enables better decision-making, predictive maintenance, and optimization of manufacturing processes.
7. Continuous Training and Education: As technologies evolve, continuous training and education become essential for both human workers and intelligent robotic systems. Workers need to be familiar with the operation and programming of these systems, and the systems themselves need updates and improvements to stay relevant [121].
8. Ethical Considerations and Safety: Human-machine collaboration should be designed with ethical considerations in mind. Safety measures must be in place to protect human workers, and ethical considerations, such as job displacement, need to be addressed through thoughtful design and implementation [122].

Fig.6 depicts the self-driving framework for mobile robots, which are devices outfitted with human security features [123].

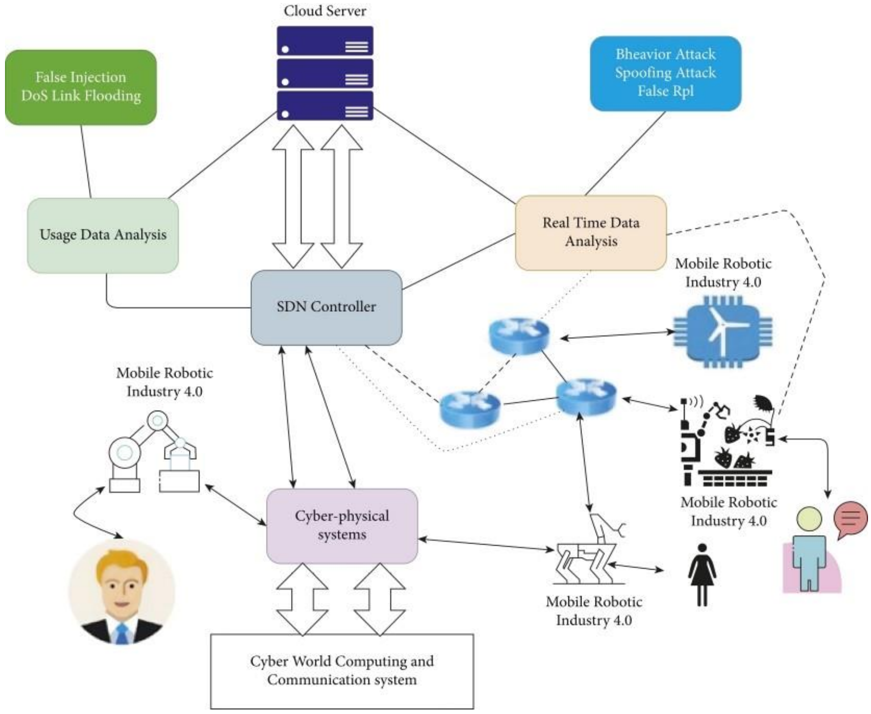

Fig. 6. the self-driving framework for mobile robots, which are devices outfitted with human security features [123].

In conclusion, the collaboration between humans and intelligent robotic systems in Industry 4.0 is a dynamic and evolving field. It has the potential to revolutionize manufacturing processes, enhance efficiency, and create safer and more flexible working environments. As technology continues to advance, the key is to find the right balance between automation and human intervention, ensuring a harmonious and productive collaboration.

9. Flexible manufacturing systems

Within the context of Industry 4.0's intelligent robotic systems, Flexible Manufacturing Systems (FMS) are essential. Industry 4.0 is known for its flexible manufacturing processes, which are greatly enhanced by intelligent robotic systems. Robots with intelligence help create flexible manufacturing systems that can swiftly adjust to shifting demands for output [92, 124]. These systems can adapt to changes in production requirements, allowing for quick reconfiguration and efficient handling of diverse tasks, from small-batch production to customized manufacturing [125]. These systems excel in small-batch or customized production scenarios, supporting the trend towards personalized and on-demand manufacturing [126]. Here's how Flexible Manufacturing Systems are integrated into Intelligent robotic systems in the Industry 4.0 paradigm:

1. Interconnected Systems: FMS in Industry 4.0 are characterized by interconnected systems where various components, including robotic systems, sensors, and machines, communicate seamlessly through the Internet of Things (IoT) and other communication protocols. Robotics within FMS can receive real-time data from other connected devices, enabling them to adapt to changing conditions, optimize production schedules, and make informed decisions [127].
2. Adaptive Automation: Intelligent robotic systems in Industry 4.0 are designed to be adaptive, capable of adjusting their behavior based on real-time data and feedback. FMS contributes to this adaptability by allowing robots to switch between tasks, reconfigure production lines, and adjust to variations in demand or resource availability.
3. Collaborative Robotics: FMS often incorporate collaborative robots (cobots) that can work alongside human operators. These robots are equipped with advanced sensors and vision systems, allowing them to interact safely with human workers. Collaborative robots enhance flexibility in manufacturing by easily adapting to new tasks and working in close proximity to humans without compromising safety [87, 128].
4. Data-Driven Decision-Making: FMS generate a vast amount of data from sensors, machines, and robots. Intelligent Robotic Systems leverage this data for predictive maintenance, process optimization, and

quality control. Advanced analytics, machine learning, and artificial intelligence algorithms analyze this data to make informed decisions, identify patterns, and continuously improve manufacturing processes [129].

5. Real-Time Monitoring and Control: FMS in Industry 4.0 enable real-time monitoring and control of manufacturing processes. Robotics within these systems can be monitored remotely, and adjustments can be made in real time to optimize performance, reduce downtime, and enhance overall efficiency [130].

6. Modular and Scalable Systems: FMS are often designed to be modular and scalable, allowing for easy integration of new robotic technologies or the reconfiguration of existing systems to meet changing production requirements. The dynamic character of Industry 4.0 is in line with the production system's increased adaptability and flexibility thanks to its modular design.

7. Human-Machine Collaboration: FMS facilitate effective collaboration between human workers and robots. Intelligent Robotic Systems are designed to understand and respond to human input, making it easier for workers to interact with and supervise robotic processes.

The Flexible Manufacturing System using intelligent robotic systems is shown in Fig. 7 [131].

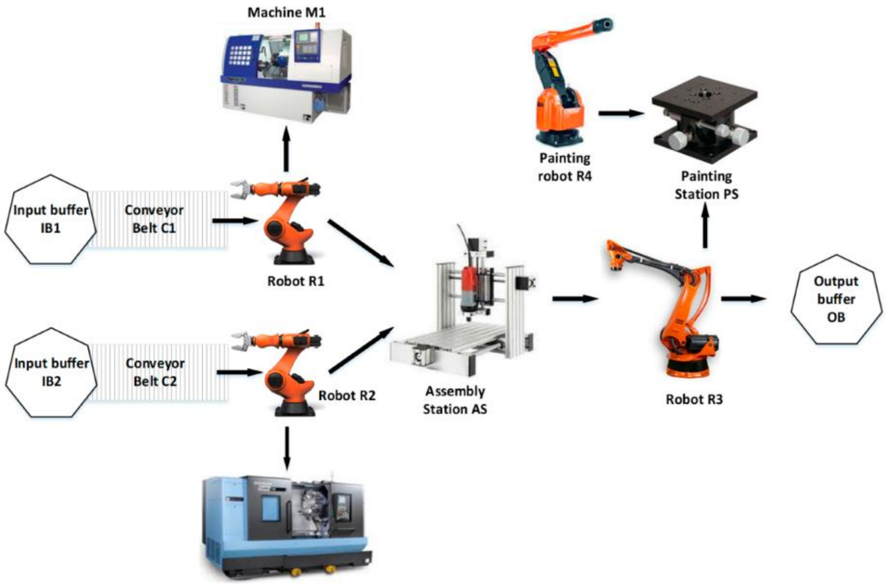

Fig. 7. Flexible Manufacturing System using intelligent robotic systems [131].

In summary, the integration of Flexible Manufacturing Systems with Intelligent Robotic Systems in Industry 4.0 results in adaptive, data-driven, and interconnected manufacturing environments that can quickly respond to changing conditions, optimize efficiency, and enhance overall productivity.

10. Advanced assembly lines by Intelligent Robotic Systems

In the context of Industry 4.0, assembling lines in intelligent robotic systems entails integrating cutting-edge technology to provide more adaptable, effective, and intelligent production processes [96]. Here's an overview of how assembling lines are impacted by intelligent robotic systems in Industry 4.0:

1. IoT (Internet of Things): Assembling lines in Industry 4.0 are equipped with sensors and connected devices. These sensors collect real-time data on various parameters such as temperature, pressure, and product quality. This data is then analyzed to optimize the assembly process, predict maintenance needs, and ensure product quality.

2. Big Data and Analytics: The data collected from IoT sensors and other sources are analyzed using big data analytics. This helps in identifying patterns, optimizing production schedules, and making informed decisions to enhance the efficiency of the assembly line [132].

3. Machine Learning and AI: Artificial intelligence and machine learning algorithms are used by intelligent robotic systems to enhance decision-making. This covers quality assurance, adaptive learning for ongoing assembly process optimization, and predictive maintenance of robotic equipment.

4. Digital Twin Technology: Digital

twins are virtual copies of physical systems, a notion introduced by Industry 4.0. Before making modifications to an assembly line in the real world, manufacturers can use digital twins to mimic and evaluate its performance in a virtual setting [133]. This helps in reducing downtime and optimizing the overall system.

5. Augmented Reality (AR): AR is used in Industry 4.0 to provide assembly line workers with real-time information, instructions, and guidance. AR glasses or devices can overlay digital information onto the physical workspace, aiding workers in performing tasks more efficiently and accurately [134].
6. Blockchain Technology: Blockchain is employed for secure and transparent transactions in the supply chain. It helps in tracking the provenance of components, ensuring product quality, and maintaining a secure record of transactions throughout the manufacturing and assembly process [135].
7. Human-Machine Collaboration: Industry 4.0 encourages seamless collaboration between humans and machines. Workers are involved in more complex decision-making processes, problem-solving, and supervision, while robots handle repetitive and dangerous tasks. This enhances overall productivity and job satisfaction.

In summary, assembling lines in the context of Industry 4.0 leverage a combination of robotics, IoT, analytics, AI, and other advanced technologies to create more efficient, flexible, and intelligent manufacturing processes. The main points of emphasis are human-machine cooperation, data-driven decision-making, and flexibility.

11. Quality control and inspection

Quality control and inspection play crucial roles in ensuring the reliability and efficiency of intelligent robotic systems in the context of Industry 4.0. Robotic systems equipped with intelligent vision systems ensure high-quality manufacturing by performing precise and consistent quality control and inspection tasks. They can identify defects, measure dimensions, and ensure compliance with quality standards [136]. Here are several aspects related to quality control and inspection in intelligent robotic systems within the Industry 4.0 framework:

1. Sensors and Data Acquisition: Intelligent robotic systems are equipped with various sensors, such as cameras, force sensors, and other specialized devices, to collect real-time data during the manufacturing process [137]. These sensors provide information about the quality of raw materials, intermediate products, and the final output, contributing to comprehensive quality control.
2. Data Analytics and Machine Learning: Advanced analytics and machine learning algorithms are used to examine the gathered data in order to find trends, abnormalities, and possible flaws. The manufacturing process may be made more efficient overall by using machine learning models that are taught to anticipate and avoid faults [138].
3. Automated Inspection: Intelligent robotic systems can perform automated inspection tasks using computer vision and image processing techniques. Robots equipped with vision systems can detect defects, measure dimensions, and ensure that products meet specified quality standards.
4. Collaborative Robots (Cobots): Collaborative robots complement human workers by fusing robotic accuracy with human experience to improve quality control. Cobots may be trained to carry out sophisticated inspection duties, freeing up human personnel to concentrate on more difficult areas of decision-making [79].
5. Real-time Monitoring and Feedback: Industry 4.0 emphasizes real-time monitoring of manufacturing processes. Intelligent robotic systems can provide instant feedback on quality issues, allowing for quick adjustments and minimizing the production of defective products.
6. Integration with Quality Management Systems (QMS): To ensure compliance with rules and industry norms, intelligent robotic systems are included into larger quality management systems. Logging and using data produced by robotic systems can facilitate traceability, auditability, and ongoing enhancement [139].
7. Predictive Maintenance: Intelligent robotic systems can employ predictive maintenance algorithms to anticipate equipment failures and prevent unplanned downtime, contributing to sustained quality in manufacturing.
8. Human-Machine Collaboration: Human workers collaborate with intelligent robotic systems to conduct quality inspections, combining the creativity and problem-solving abilities of humans with the speed and precision of robots [118, 140].
9. Remote Inspection and Quality Assurance: Industry 4.0 facilitates remote monitoring and quality assurance, enabling experts to inspect and ensure the quality of products and processes from anywhere in the

world [136].

10. Cybersecurity Measures: Given the increased connectivity in Industry 4.0, robust cybersecurity measures are crucial to protect the integrity of data and prevent tampering that could compromise the quality control process [141].

Health monitoring of the manufacturing environment using the AI is shown in the Fig. 8 [142].

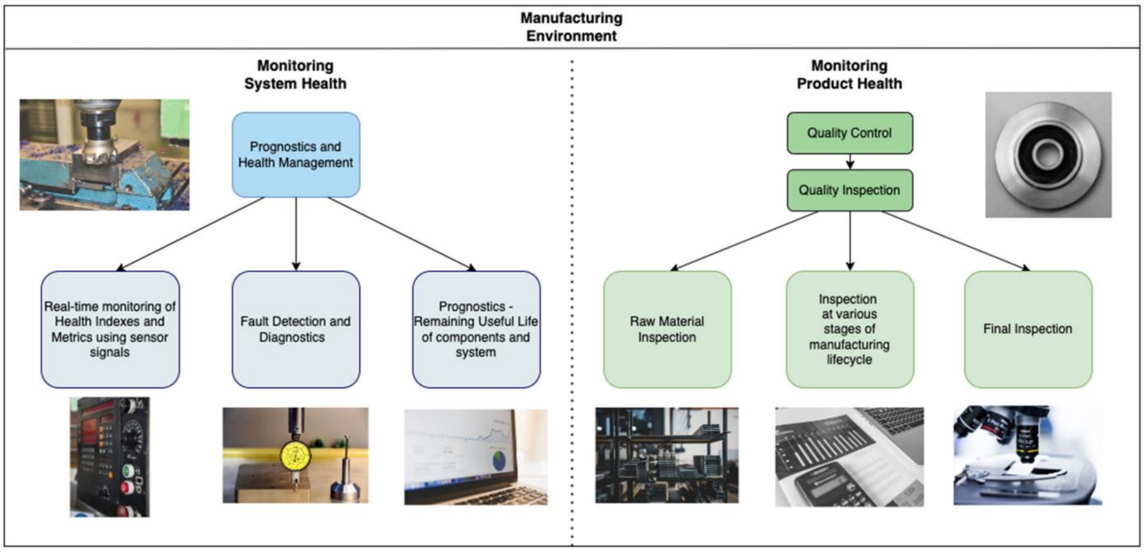

Fig. 8. Health monitoring of the manufacturing environment using the AI [142].

In summary, the integration of intelligent robotic systems with advanced technologies in Industry 4.0 enhances the quality control and inspection processes, leading to improved product quality, reduced defects, and increased overall efficiency in manufacturing.

12. Data-driven decision making

Industry 4.0 is distinct in that it relies heavily on data-driven decision-making, and intelligent robotic systems are essential to this paradigm. Large volumes of data are gathered, processed, and analyzed in real-time by these systems thanks to sophisticated sensors and analytics [143]. The insights derived from this data enable proactive decision-making, predictive maintenance, and continuous process optimization [69, 144]. Here's how data-driven decision-making contributes to the effectiveness of Intelligent Robotic Systems in Industry 4.0:

1. Sensor Data and Monitoring: Intelligent Robotic Systems are equipped with various sensors that collect real-time data from the manufacturing environment. Data from sensors, such as temperature, pressure, and position, are continuously monitored to ensure optimal performance and identify any anomalies or deviations from the expected parameters.
2. Predictive Maintenance: Data analytics can be applied to the sensor data to predict when robotic systems or equipment are likely to fail. Predictive maintenance helps in scheduling maintenance activities proactively, reducing downtime and minimizing unexpected breakdowns [146].
3. Performance Optimization: By analyzing data generated by robotic systems during operation, manufacturers can identify opportunities to optimize performance and efficiency. Data-driven insights can lead to adjustments in robotic processes, cycle times, and resource utilization for improved productivity.
4. Quality Control: Intelligent Robotic Systems can be integrated with machine vision systems to inspect and analyze the quality of products during and after production. Data-driven decision-making ensures that any deviations from quality standards are identified and addressed in real-time, reducing defects and enhancing overall product quality [146].
5. Adaptive Manufacturing: Data analytics enable adaptive manufacturing processes, where robotic systems can dynamically adjust their operations based on real-time data. This adaptability allows manufacturers to respond quickly to changes in demand, product specifications, or supply chain disruptions [147].
6. Energy Efficiency: Data-driven decision-making helps optimize energy consumption in robotic systems. By analyzing energy usage patterns and identifying opportunities for efficiency improvements, manufacturers can reduce operational costs and minimize environmental impact [148].
7. Supply Chain Integration:

Data-driven insights from robotic systems can be shared with other components of the supply chain in real-time. This integration facilitates a more responsive and interconnected manufacturing ecosystem, allowing for better coordination and synchronization across the entire value chain [4, 149].

8. Continuous Improvement: Data analytics provide a foundation for continuous improvement in robotic systems and manufacturing processes. Historical data can be analyzed to identify trends, patterns, and areas for enhancement, enabling manufacturers to make informed decisions for ongoing optimization.

9. Risk Mitigation: Risks related to robotic operations can be identified and mitigated with the use of data-driven decision-making. Robotic system safety and dependability are guaranteed by proactive risk management that is based on data analysis and reduces the possibility of interruptions. [150].

Fig.9 displays a study of intelligent decision-making utilizing industrial technology powered by big data [151].

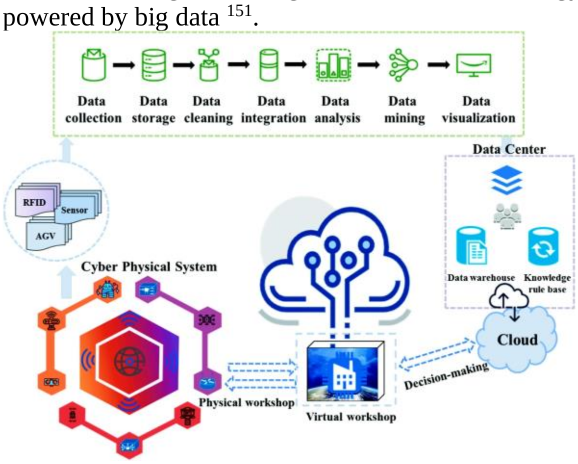

Fig. 9. Intelligent decision-making utilizing industrial technology powered by big data [151].

In summary, data-driven decision-making in Intelligent Robotic Systems within the framework of Industry 4.0 is essential for achieving efficiency, quality, adaptability, and overall operational excellence in manufacturing processes. Analyzing real-time data generated by robotic systems empowers manufacturers to make informed decisions that drive continuous improvement and innovation in the evolving landscape of industrial automatic systems.

13. Blockchain and cyber–physical integration

Cloud Blockchain ensures secure and tamper-resistant communication channels between cyber-physical systems and intelligent robotic devices in Industry 4.0. This enhances the integrity and confidentiality of data transmitted within the manufacturing ecosystem [152]. Through blockchain, the control and coordination of intelligent robotic systems can be decentralized, allowing for a distributed ledger that records and verifies commands and transactions. This mitigates the risk of a single point of failure and enhances system resilience. All data generated by intelligent robotic systems, including performance metrics, maintenance records, and production data, can be stored immutably on the blockchain [153]. This ensures data integrity, making it resistant to unauthorized tampering and manipulation. Blockchain facilitates efficient resource utilization by creating a transparent and decentralized ledger for resource allocation and utilization. Intelligent robotic systems can autonomously negotiate and optimize resource usage based on the shared blockchain ledger [154].

Furthermore, Blockchain's transparent and traceable nature assists in quality assurance by recording the entire manufacturing process. This includes the actions of intelligent robotic systems, ensuring that quality standards are met and providing a reliable audit trail. Blockchain can be used for decentralized identity management, ensuring that each intelligent robotic system and cyber-physical entity has a verifiable and secure identity. This helps in preventing unauthorized access and facilitating secure interactions [127]. Blockchain enhances the cybersecurity resilience of intelligent robotic systems by reducing vulnerabilities associated with centralized databases. The decentralized and cryptographic nature of blockchain makes it more challenging for malicious actors to compromise the integrity of the system. Cyber-physical systems and digital twins are integrated, as seen in Fig. 10 [155].

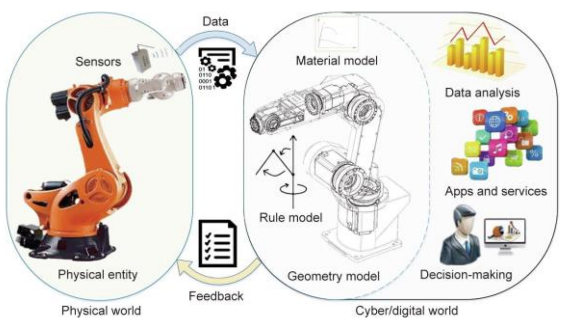

Fig. 10. Digital twins and cyber-physical systems are integrated [155].

In summary, Industry 4.0's integration of blockchain technology with cyber-physical systems improves the security, openness, and effectiveness of intelligent robotic systems. This combination guarantees a reliable and robust base for the next generation of smart production settings.

14. Artificial Intelligence (AI) integration

The infusion of artificial intelligence into robotic systems amplifies their capabilities. Machine learning algorithms enable robots to learn from experience, recognize patterns, and make autonomous decisions. Computer vision enhances their perception, enabling tasks such as object recognition, quality control, and complex manipulation [75]. Artificial intelligence (AI) technologies, such as computer vision and machine learning, are integrated into intelligent robotic systems to improve their performance. Robots are now capable of object recognition, experience-based learning, and complicated pattern-based decision-making thanks to this integration [156]. Here are several ways AI is integrated into Intelligent Robotic Systems in Industry 4.0:

1. Machine Learning for Robot Control: Machine learning algorithms enable robots to adapt to variations in their environment. They can learn from experience and adjust their movements or tasks accordingly, improving efficiency and adaptability [61]. AI helps in integrating data from various sensors on robots, such as cameras, LiDAR, and other environmental sensors. This enables robots to perceive and understand their surroundings more accurately [157]. AI algorithms, particularly machine learning (ML) techniques, enable robots to adapt their control strategies based on the changing environment and varying task requirements. This adaptability is essential for handling diverse tasks in dynamic manufacturing environments. AI aids in the processing of data from several sensors (including touch, lidar, and image sensors) to produce a thorough knowledge of the robot's environment [158]. This enhanced perception allows robots to navigate and interact with their environment more effectively [156].

2. Predictive Maintenance: Robotic sensor data can be analyzed by AI systems to forecast when maintenance is necessary. Predictive maintenance reduces downtime and increases robotic system longevity by seeing any problems before they become serious [159]. AI-powered analytics can predict equipment failures and schedule maintenance activities proactively. By analyzing data from sensors and historical performance, robots can notify operators of potential issues, minimizing downtime and optimizing maintenance schedules [160].

3. Collaborative Robots (Cobots): AI enables robots to work collaboratively with humans. Machine learning algorithms can be employed to allow robots to understand human actions and intent, making it safer and more efficient for humans and robots to work together in shared workspaces [79].

4. Quality Control: Real-time quality control may be achieved by integrating AI-powered vision systems with robotic arms. These systems are capable of measuring measurements, spotting flaws, and making sure the goods fulfill the required quality requirements.

5. Autonomous Navigation: AI algorithms, such as simultaneous localization and mapping (SLAM), enable robots to navigate autonomously within dynamic environments. This is particularly important in manufacturing facilities where the layout may change, and robots need to adapt to new surroundings [92, 161].

6. Data Analytics and Optimization: AI facilitates the analysis of large datasets generated by robotic systems. This data can be used to optimize manufacturing processes, identify bottlenecks, and improve overall efficiency. Also, AI facilitates the seamless integration of robotic systems with other components of Industry 4.0, such as Enterprise Resource Planning (ERP) systems, to create a connected and efficient manufacturing ecosystem [162].

7. Cognitive Robotics in Problem-Solving and Decision-Making: AI enables robots to make decisions and solve problems autonomously. This is particularly useful in scenarios where robots need to navigate complex environments, handle uncertainties, and make real-time decisions to optimize manufacturing processes [146].

8. Natural Language Processing (NLP): Integrating NLP with robotic systems allows them to understand and respond to human commands or queries. This is useful in human-robot collaboration scenarios and facilitates easier interaction between humans and robots [163].

9. Human-Robot Collaboration: AI facilitates safe and intuitive collaboration between robots and human workers. Cobots equipped with AI can understand human gestures, speech, and actions, making them more responsive to human input and enhancing their ability to work alongside humans on the factory floor.

10. Digital Twins: AI is used to create digital twins of physical systems, including robotic systems. This involves creating a virtual model that mirrors the behavior and performance of the physical robot. This digital representation can be used for simulation, testing, and optimization.

11. Cyber-Physical Systems (CPS): AI helps in the development of intelligent

cyber-physical systems where the physical components (robots) are tightly integrated with computational and communication capabilities. This integration enhances overall system performance and responsiveness [164].

12. Security and Anomaly Detection: AI can be employed for detecting anomalies in the behavior of robotic systems, helping to identify potential security threats or malfunctions. This is crucial for maintaining the integrity of the entire industrial ecosystem.

13. Supply Chain Optimization by Smart Logistics: AI helps optimize the movement of goods within the manufacturing facility. Intelligent robotic systems can use AI algorithms to plan and execute logistics tasks efficiently, improving the overall flow of materials and reducing lead times [165].

14. Learning from Experience: By employing reinforcement learning and other learning algorithms, robots can learn from their experiences and improve their performance over time. This is valuable for tasks that involve a degree of variability or require adaptation to changing conditions [166].

15. Quality Control by Visual Inspection: AI-powered vision systems enhance the precision and speed of quality control processes. Robots with computer vision capabilities are able to recognize deviations, abnormalities, and flaws in real time, guaranteeing that only top-notch goods finish the manufacturing line.

16. Big Data Analytics: AI tools process large volumes of data generated by robotic systems, enabling manufacturers to gain insights into production processes, identify patterns, and make data-driven decisions for process optimization [167].

The architecture of reinforcement learning-based robot learning in intelligent robotic systems is shown in Fig. 11 [168].

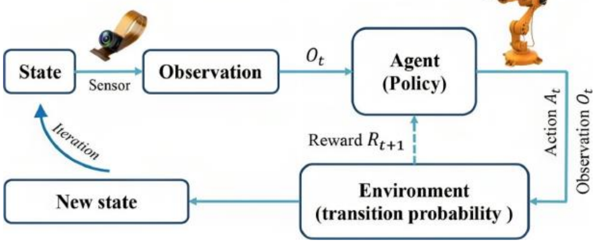

Fig. 11. Architecture of reinforcement learning-based robot learning in intelligent robotic systems [168].

In summary, the integration of AI in Intelligent Robotic Systems in Industry 4.0 brings about significant improvements in adaptability, efficiency, collaboration, and decision-making, contributing to the transformation of manufacturing and industrial processes. In conclusion, the integration of AI in Intelligent Robotic Systems is a key enabler of Industry 4.0, providing robots with advanced capabilities to operate autonomously, adapt to changing conditions, and contribute to the overall efficiency and competitiveness of modern manufacturing processes [169].

15. Digital twin integration

Within the context of Industry 4.0, digital twin integration in Intelligent Robotic Systems is essential for improving productivity, efficiency, and decision-making processes. Intelligent robotic systems are frequently included in digital twin ideas, which generate a virtual model of the robot and its operations [170]. The integration of intelligent robotic systems with the digital twin concept is a notable trend which can provide a virtual representation of the robotic system allows for simulation, optimization, and testing in a virtual environment before implementation in the physical world [171]. This allows for simulation, optimization, and monitoring of the robot's performance in a virtual environment before implementation in the physical world. This not only improves system design but also aids in continuous improvement and innovation [172]. Here's how digital twin integration contributes to Intelligent Robotic Systems in the context of Industry 4.0:

1. Virtual Representation of Physical Systems: Digital twins generate virtual models of real-world robotic systems. This comprises intricate representations of the whole manufacturing area as well as the individual robots and their parts [173]. These virtual models are continuously updated with real-time data from sensors on the physical robots, providing an accurate and up-to-date representation of the system.

2. Real-time Monitoring and Analytics: Digital twins enable real-time monitoring of robotic systems. Sensors on robots collect data, and this data is sent to the digital twin for analysis. Analytics tools process this data to identify patterns, anomalies, and performance metrics, allowing for predictive maintenance and optimization of robotic operations [174].

3. Simulation and Testing: Before implementing changes or upgrades to the physical robotic system, digital twins allow for simulation and testing in a virtual environment. This helps in identifying potential issues, optimizing processes, and ensuring that modifications will have the desired impact without causing disruptions in the actual production environment [175].

4. Predictive Maintenance: Digital twins are used to continually monitor the state of robotic components, making it feasible to forecast when maintenance is required. By resolving possible problems before they become serious ones, predictive maintenance lowers downtime and raises the overall dependability of robotic systems.

5. Optimized Workflows and Processes: The examination of manufacturing workflows and procedures is made possible by digital twins. Manufacturers may determine the most economical and effective ways to run robotic systems by modeling various scenarios. This optimization can lead to improved cycle times, resource utilization, and overall productivity [176].

6. Data-driven Decision Making: The integration of digital twins provides a wealth of data that can be used for informed decision-making. Machine learning algorithms can be applied to analyze historical data, identify trends, and suggest improvements, contributing to the continuous improvement of Intelligent Robotic Systems.

7. Collaborative Robotics (Cobots): Collaborative robots (cobots) can be more easily incorporated into production processes with the help of digital twins. In order to maintain productivity and safety, these cobots may operate alongside human workers. Their behavior can be adjusted and mimicked in a digital twin environment [87].

8. Supply Chain Integration: Digital twins extend beyond the factory floor to include the entire supply chain. This integration allows for better coordination between different elements of the supply chain, improving overall responsiveness and reducing lead times.

Fig.12 illustrates the digital twin integration of intelligent robotic systems [155].

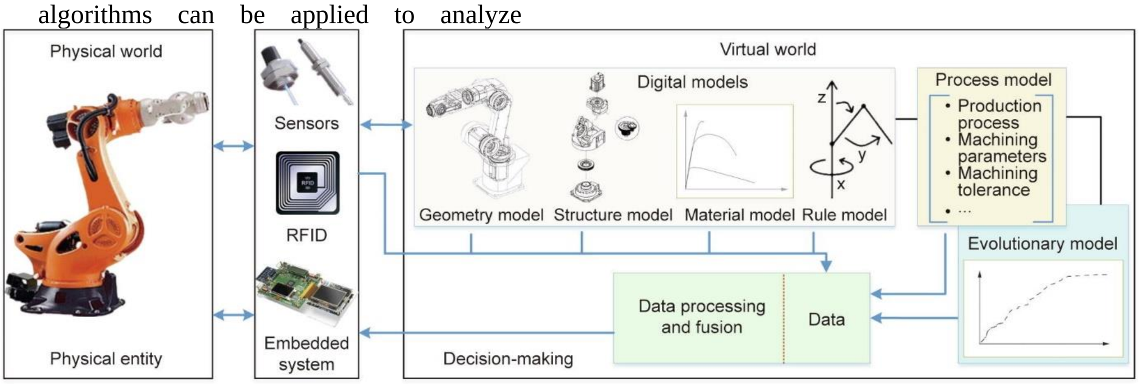

Fig. 12. Digital twin integration of intelligent robotic systems [155].

In summary, the integration of digital twins in Intelligent Robotic Systems within Industry 4.0 enables a more agile, efficient, and data-driven approach to manufacturing. It supports optimization, predictive maintenance, and informed decision-making, ultimately contributing to increased productivity and competitiveness in the rapidly evolving industrial landscape.

16. Energy efficiency in intelligent robotic systems

Industry 4.0 emphasizes sustainability, and intelligent robotic systems contribute to energy-efficient manufacturing by optimizing their movements, reducing idle times, and incorporating energy-saving features. Intelligent robotic systems in Industry 4.0 prioritize energy efficiency and sustainability [177]. Optimizing energy consumption in robotic systems not only aligns with sustainability goals but also contributes to cost savings and overall operational efficiency [132]. Through optimized movements, reduced idle times, and energy-saving features, these systems contribute to the overarching goal of creating environmentally conscious manufacturing practices [178]. Here are several key aspects to consider when addressing energy efficiency in Intelligent Robotic Systems:

1. Energy-Aware Design: energy-efficient robotic hardware components, including motors, sensors, and processors can be designed. Alos, robot components that offer high performance with lower energy consumption such as low-power processors and sensors without compromising performance can be selected [179]. This is particularly relevant for robotic systems operating in diverse environments [180]. The integration of energy harvesting technologies, such as solar panels or kinetic energy harvesters can also be implemented to supplement or replace traditional power sources [181].

2. Smart Control Algorithms: motion planning algorithms that minimize unnecessary movements and optimize trajectories to reduce energy consumption can be implemented [182]. Adaptive control algorithms that adjust the robot's behavior based on real-time data and environmental

conditions can be used to optimize energy usage in working conditions. predictive maintenance algorithms can be implemented in order to identify potential issues in robotic systems before they lead to energy-inefficient operation [183].

3. Efficient Sensing and Perception: selective sensing can be utilized to activate sensors only when needed, reducing overall power consumption. data processing and analysis closer to the source (edge computing) can be Performed to minimize the energy required for transmitting large amounts of data to a centralized system.
4. Energy Monitoring and Management: Real-time monitoring of energy consumption can be implemented to identify inefficiencies and areas for improvement [184]. Intelligent energy management systems can be used to optimize the allocation of energy resources based on the robotic system's operational requirements [183].
5. Human-Robot Collaboration: human-robot collaboration can be implemented to leverage the strengths of both humans and robots, potentially reducing the need for continuous robot operation and saving energy. Mechanisms for robotic systems can also be implemented to enter low-power or idle states during periods of inactivity.
6. Advanced Materials and Energy Storage: lightweight and energy-efficient materials in the construction of robotic components can be utilized. Advanced energy storage solutions, such as high-performance batteries or capacitors can be used, to store and release energy efficiently [185].
7. Life Cycle Analysis: A life cycle analysis can be conducted to assess the environmental impact of the robotic system, considering energy consumption during manufacturing, operation, and disposal [186].
8. Regulatory Compliance and Standards: Compliance with energy efficiency standards and regulations applicable can be considered in order to select the best robotic systems in the relevant industry.

Integrating these considerations into the design, development, and operation of Intelligent Robotic Systems can contribute significantly to achieving energy efficiency goals in the Industry 4.0 landscape [187]. It's essential to adopt a holistic approach that considers the entire life cycle of the robotic system and balances energy efficiency with performance requirements.

17. Conclusions

In A key component of Industry 4.0, the fourth industrial revolution defined by the integration of digital technologies, automation, and data sharing in production, is intelligent robotic systems. The incorporation of cutting-edge technology, including artificial intelligence, machine learning, and the Internet of Things, has enabled these robotic systems to demonstrate previously unheard-of degrees of flexibility, efficiency, and autonomy. These systems leverage advanced technologies to enhance efficiency, flexibility, and responsiveness in industrial processes. Intelligent robotic systems are designed to be interconnected with other components of the manufacturing process, creating a network where machines, sensors, and humans communicate and share information in real-time. As industries increasingly adopt smart technologies and automation, optimizing energy use in robotic systems becomes essential for sustainability, cost reduction, and overall efficiency.

As Industry 4.0 continues to unfold, the collaborative efforts between human workers and intelligent robots become increasingly essential for achieving optimal results. The human workforce finds new opportunities for skill development and creativity, as routine and physically demanding tasks are delegated to intelligent robotic counterparts. This shift allows employees to focus on strategic decision-making, problem-solving, and other high-value activities that contribute to overall business growth. The synergy between humans and intelligent robots has redefined the industrial landscape, fostering a more collaborative and dynamic work environment. With the ability to perform complex tasks with precision, speed, and reliability, IRS enhances productivity, reduces operational costs, and ensures a higher quality output. Moreover, these systems contribute to the optimization of supply chains, fostering a leaner and more responsive manufacturing ecosystem. One of the key advantages of IRS in Industry 4.0 is the enhancement of productivity through seamless collaboration between humans and machines. These systems can handle repetitive and hazardous tasks, allowing human workers to focus on higher-order activities that require creativity, problem-solving, and emotional intelligence. This not only boosts overall productivity but also improves the working conditions for employees.

Moreover, the real-time data generated by IRS enables predictive maintenance, minimizing downtime and optimizing resource utilization. This proactive approach to maintenance ensures that machines operate at peak efficiency, reducing costs and extending their lifespan. The interconnected nature of IRS also facilitates a more streamlined supply chain, fostering a responsive and agile production ecosystem. However, it is crucial to address challenges such as ethical considerations, cybersecurity threats, and the potential impact on employment. A thoughtful approach is necessary to ensure that the benefits of intelligent robotic systems are balanced with ethical considerations, and mechanisms are in place to address societal impacts, such as workforce displacement and skill transitions.

In essence, the era of intelligent robotic systems in Industry 4.0 marks a paradigm shift, where innovation converges with practical applications to redefine the future of manufacturing. As we navigate this transformative landscape, it is imperative to harness the potential of IRS responsibly, fostering a balance between technological advancement and ethical considerations. As a result, the transformative power of intelligent automation, careful consideration of ethical, social, and economic implications will be essential to navigate the path toward a harmonious integration of human and robotic capabilities in the industries of the future.

18. Future research work directions

Intelligent robotic systems are integral to the transformative vision of Industry 4.0, driving increased automation, connectivity, and adaptability in modern manufacturing environments. The ongoing research and development in this field hold the promise of even more sophisticated and capable robotic systems in the future, driving innovation and redefining the landscape of industrial manufacturing. Potential advantages extend across a wide range of industries, including manufacturing, logistics, healthcare, opening up new avenues for development and innovation. However, the adoption of IRS is not without challenges, including concerns related to ethical considerations, cybersecurity, and the impact on employment patterns. As we navigate the integration of these systems into our industries, it becomes imperative to address these challenges collaboratively, ensuring that the benefits are maximized while mitigating potential risks.

The journey towards a smart and interconnected industrial future is ongoing, and the continued refinement and integration of these intelligent systems will undoubtedly shape the trajectory of global industries for years to come. The field of Intelligent Robotic Systems in Industry 4.0 is dynamic and evolving rapidly. The concepts of future research works in applications of Intelligent Robotic Systems in Industry 4.0 can be presented as:

1. Human-Robot Collaboration Optimization: Investigate advanced algorithms and techniques to optimize human-robot collaboration in Industry 4.0 settings. This involves developing intelligent systems that can adapt to human behavior, anticipate user intentions, and dynamically adjust their actions to enhance efficiency and safety.
2. Explainable AI for Robotic Decision-Making: Address the challenge of making robotic decision-making processes more transparent and understandable. Explore methods to integrate explainable artificial intelligence (XAI) into intelligent robotic systems, allowing humans to comprehend and trust the decisions made by robots in complex industrial environments.
3. Adaptive Learning and Skill Acquisition: Research methods for enabling robotic systems to learn and acquire new skills autonomously. This involves developing adaptive learning algorithms that allow robots to continuously improve their performance based on experience, feedback, and changing environmental conditions.
4. Cyber-Physical Security for Robotic Systems: Focus on enhancing the cybersecurity of intelligent robotic systems within Industry 4.0. Explore novel approaches to protect robotic networks, communication protocols, and data exchanges, ensuring the integrity, confidentiality, and availability of information in smart manufacturing environments.
5. Robotic System Resilience: Investigate methods to enhance the resilience of robotic systems to handle unforeseen challenges and recover from failures autonomously. Research on fault-tolerant control strategies for maintaining system functionality in adverse conditions.
6. Swarm Robotics for Industrial Applications: Investigate the potential of swarm robotics in Industry 4.0, exploring the coordination and collaboration of multiple robots to perform complex tasks. This research can include developing algorithms for swarm intelligence, communication protocols, and real-time adaptation mechanisms for large-scale robotic systems.
7. Energy-Efficient Robotic Systems: Address the environmental impact of intelligent robotic systems by researching and implementing energy-efficient algorithms and strategies. This includes optimizing robotic movements, power management, and exploring alternative energy sources to reduce the ecological footprint of industrial automation.
8. Human-Centric Design for Robotic Interfaces: Focus on designing user

interfaces and interactions that enhance the user experience and increase the acceptance of intelligent robotic systems in industrial settings. Research can explore natural language processing, gesture recognition, and intuitive interfaces that enable non-experts to interact seamlessly with robotic systems.

9. Autonomous Robotic Maintenance and Self-Healing Systems: Explore the development of autonomous robotic systems capable of self-diagnosis, self-repair, and predictive maintenance. Investigate advanced sensor technologies, machine learning algorithms, and robotic architectures that enable intelligent machines to identify and address issues before they lead to system failures.

10. Global Connectivity and Collaboration of Robotic Systems: Research the integration of intelligent robotic systems into a globally connected network. This involves developing communication standards, protocols, and collaboration frameworks that enable seamless interaction and coordination among robotic systems across different industries and geographical locations.

11. Ethical Considerations in Intelligent robotic systems: Address the ethical implications of deploying intelligent robotic systems in Industry 4.0. Investigate issues related to job displacement, privacy concerns, and societal impacts. Develop guidelines and frameworks for responsible and ethical use of intelligent robotic technologies in industrial contexts.

12. Standardization and Interoperability: Work towards standardization of interfaces and communication protocols to ensure interoperability among different robotic systems and components. Explore open architecture approaches that allow seamless integration of robotic systems from various manufacturers.

13. Digital Twin Integration: For improved simulation, monitoring, and control, the integration of digital twin technology with intelligent robotic systems might be investigated. Thus, with Industry 4.0's advanced robotics systems, digital twins can improve predictive maintenance and maximize robotic system performance.

14. Machine Learning and AI for Robotics: more sophisticated machine learning algorithms can be developed for robots to adapt and learn from dynamic environments. Explore reinforcement learning techniques for robotic systems to improve their decision-making abilities.

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