WORLD COMET RESEARCH GROUP

International Journal of Intelligent Automation & Robotics Engineering
Vol. 3, No. 2, 2020
Doi: 10.67228/30715725/IJIARE-2020PII9R6L
PP. 01-16

Original Article

Self-Reconfigurable Robotic Manipulators for Flexible Manufacturing Systems

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Received: 10-03-2020 Revised: 10-25-2020 Accepted: 11-01-2020 Published: 11-03-2020

ABSTRACT

Flexible Manufacturing Systems (FMS); Self-Reconfigurable Robotics; Industrial Automation; Robotic Manipulators; Artificial Intelligence (AI); Modular Robotics; Adaptive Manufacturing; Industry 4.0/5.0; Intelligent Manufacturing; Machine Learning (ML); Autonomous Robotics; Smart Factories; Optimization; Cyber-Physical Systems (CPS). An even more compact version is: FMS; Self-Reconfigurable Robotics; Industrial Automation; AI; Modular Robotics; Adaptive Manufacturing; Industry 4.0/5.0; Smart Manufacturing; ML; Autonomous Robotics; Optimization; CPS. This retains the core concepts while reducing redundancy.

KEYWORDS

Flexible Manufacturing Systems, Self-Reconfigurable Robotics, Industrial Automation, Robotic Manipulators; Artificial Intelligence, Modular Robotics; Adaptive Manufacturing, Industry 4.0, Industry 5.0,Intelligent Manufacturing, Machine Learning; Autonomous Robotics, Smart Factories, Optimization Algorithms, Cyber-Physical Systems.

1. INTRODUCTION

1.1. Background of Flexible Manufacturing Systems

Flexible Manufacturing Systems (FMS) are now the trendy manufacturing paradigm that helps industries attain high flexibility, high automation and high productivity in the dynamic manufacturing environments. In contrast to conventional manufacturing systems which are designed to produce similar products in large quantities, FMS enables a rapid changeover of production requirements, product designs and operational methods, with minimal downtime. The systems consist of programmable machine tools, intelligent scheduling algorithms, industrial robotic manipulators, automated material handling equipment, and advanced communication networks which are designed to support multi product manufacturing. With automatic technologies and on-line monitoring and intelligent control, FMS achieves better resource utilization, lower production costs, and greater manufacturing flexibility. With the implementation of Industry 4.0 technologies such as Industrial Internet of Things (IIoT), Artificial Intelligence, Cloud Computing and Digital Twins, FMS has become intelligent and self-optimizing production systems, which can react efficiently to the shifting market demands.

1.2. Need for Self-Reconfigurable Robotic Manipulators

Fig 1 - Need for Self-Reconfigurable Robotic Manipulators

1.2.1. Limitations of Conventional Robotic Manipulators

Manipulators used in conventional industrial robots are extensively used in manufacturing applications because of their high precision, speed and repeatability. These systems however are usually developed with mechanical structure and predefined operational capabilities which are less effective to dynamic manufacturing environments. Manual reprogramming, mechanical changes or complete system redesign is often necessary when the production requirements change. These constraints add to production downtime, cut down on flexibility, and make it difficult for manufacturers to easily meet customer demand for customized and rapidly changing products.

1.2.2. Requirement for Adaptive Manufacturing Systems

Modern manufacturing industries demand very flexible systems, which are able to adjust to rapid changes in product specifications, production volumes, and operating conditions. To satisfy this requirement, self-reconfigurable robotic manipulators are developed, where robots automatically

ISSN: 3071-5725
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reconfigure their physical structure, workspace and function depending on the manufacturing tasks. The flexibility means that a single robotic platform can carry out a variety of tasks without the need for extensive manual intervention, thereby improving the efficiency of production and reducing the need for equipment duplication.

1.2.3. Enhancement of Manufacturing Flexibility and Productivity

There are robotic manipulators that are self-reconfigurable, which could substantially enhance the manufacturing flexibility through dynamically reconfiguring the robotic configuration according to the tasks and working environments. Robotic modular components like interchangeable joints, adaptive links, and intelligent end-effectors allow robots to adapt their structure to a variety of tasks, including assembly, inspection, machining, and material handling. This feature helps to increase productivity by minimizing the set-up time, improving capacity utilization and enabling efficient mass customization strategies.

1.2.4. Integration with Artificial Intelligence and Industry 4.0

The combination of self-reconfigurable robotic manipulators, Artificial Intelligence (AI), Industrial Internet of Things (IIoT) and Digital Twin technologies allow for autonomous decision making and intelligence adaptation. Data from the manufacturing process is fed into AI algorithms to inform optimal robot configuration and digital twins are used to validate the robots in a virtual environment before they are placed in the real world. Together, this adds to the reliability of operation, predictive maintenance, and real time optimization, making self-reconfigurable robots a key part of the smart factory of the future.

1.2.5. Support for Industry 5.0 Human-Centric Manufacturing

Industry 5.0 is about a more sustainable, flexible and personalized production, using Human-Machine Interaction. The vision of self-reconfigurable robotic manipulators enables safe human–robot interaction, adaptable task handling and effective resource sharing. They can respond to the production environments autonomously and adaptively, which can make them be applied in future manufacturing systems that need higher intelligence and resilience.

1.3. Challenges in Conventional Industrial Robotics

Although tremendous progress has been made in the field of industrial automation, traditional robotic manipulators still have some technical and operational drawbacks that limit their use in very dynamic manufacturing scenarios. In contrast to traditional industrial robots, which are rigid and able to perform only a limited number of tasks at a fixed motion path, traditional industrial robots have a fixed mechanical structure, a fixed motion path, and cannot be adapted. These systems offer high accuracy and repeatability, but they are difficult to use in settings with regular changes in production requirements because they require manual configuration. Today, manufacturing industries are facing the requirement of flexible production systems that can process customized products and variable load and production volumes due to short production cycles; however, conventional robots are often unable to keep up to the new tasks without manual reprogramming, mechanical changes or investments in additional equipment. Limited structural flexibility is one of the major challenges associated with the conventional robotic system. In the case of fixed robotic architectures, they cannot adapt their workspace, payload or operational properties in response to various manufacturing situations. This means that in many cases industries need a number of dedicated robots for various applications and this leads to higher investment costs, space needs, and maintenance costs. Moreover, traditional robots rely mainly on off-line programming, which would cause considerable set-up time and require the expert involvement to switch the task, thus lowering the production responsiveness. One of the main drawbacks is the absence of sophisticated intelligence and self-decision making capabilities. Most conventional robotic systems run a program of pre-programmed instructions and have only a basic ability of understanding changes in the environment, forecasting failures, or optimizing their performance. While the perception of robots has been enhanced by sensors and feedback systems, most of the traditional robots still face complex decision-making, uncertain environments and dynamic production conditions. Also, integration with new technologies such as the ones of the Industry 4.0 is a challenge for conventional industrial robots. The lack of interoperability and integration with Industrial Internet of Things (IIoT) platforms, digital twins, cloud systems, and artificial intelligence frameworks limits their role in the intelligent manufacturing landscape. The challenge with robotic systems is that often the data they produce is not used to its full potential, as it is limited in its real-time processing, connectivity, and intelligent analysis capabilities. Energy usage, maintenance, and scalability are also important issues to consider. The lack of adaptive optimization mechanisms can cause fixed robotic systems to make unnecessary movements and use too much energy. Furthermore, due to the lack of self-monitoring and predictive maintenance, there is a high risk of unexpected failures and production downtimes. Thus, advanced robotic architectures based on the combination of modular hardware, artificial intelligence, adaptive control, and digital intelligence are needed to overcome these challenges. Self-reconfigurable robotic manipulators offer a promising solution with the ability of self-adapting, self-flexibility, and efficient operation in future smart manufacturing environments.

2. LITERARY SURVEY

2.1. Evolution of Industrial Robotic Manipulators

The industrial robotic manipulators have been evolved from simple automated to intelligent, adaptive and autonomous robotic systems. Initial industrial robots were intended primarily for repetitive manufacturing tasks like welding, painting, assembly, and material transport. The first generation of these systems used fixed programming sequences and pre-defined trajectories and had high precision and repeatability, but were not environmental aware or decision making. The second generation of robots, known as the programmable robots, were able to carry out more complex industrial tasks with greater accuracy and flexibility thanks to the use of programmable controllers, servo motors, and sensor-based feedback systems. Robotic manipulators have now begun to be connected to IoT networks, cloud computing, artificial intelligence, digital twins, and cyber-physical systems, enabling real-time monitoring and optimization of manufacturing processes, as Industry 4.0 has evolved. The collaborative robots further advanced the industrial automation by the means of advanced sensing and intelligent control mechanisms to provide safe human–robot interaction. Self-

ISSN: 3071-5725
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reconfigurable robotic manipulators, that are able to change physical shape based on the tasks, are receiving interest recently. The systems are modular, use adaptive end-effectors and intelligent algorithms to enable increased flexibility; however, most of the current solutions still rely on manual restructuring. Accordingly, the future research interest is devoted to the development of fully autonomous robotic manipulators that can adapt and reconfigure in real time and plan intelligently in future smart manufacturing environments.

2.2. Self-Reconfigurable Robotic Architectures

Self-reconfigurable robotic architectures are a novel idea in the field of industrial robotics, where the mechanical structure of the robotic system can be reconfigured dynamically based on the operational requirements. These architectures, unlike the standard fixed robots, are made up of modular joints, interchangeable links, adaptable actuators and flexible end-effectors that can be reconfigured to execute a wide range of manufacturing operations. A typical self-reconfigurable robotic system combines modular mechanical components, intelligent perception mechanisms, decision-making frameworks and adaptive motion control strategies. The perception layer is based on the use of technologies like the industrial camera, the force-torque sensor, LiDAR, tactile sensor and the inertial measurement unit, which are used to gather information about the environment and the robot. The decision layer algorithms utilize artificial intelligence methods such as reinforcement learning, deep learning, and optimization algorithms to ensure a robot has the most appropriate configuration for the task at hand. The control layer coordinates the process of the reconfiguration with intelligent motion planning, inverse kinematics, trajectory optimization and collision avoidance mechanisms. These designs have been shown to have potential application in automotive assembly, aerospace manufacturing, warehouses and precision machining. But computational challenges, real-time decision making, common communication standards, and interoperability between robotic modules are still major obstacles. The next generation of self-reconfiguring robotics architectures will seek to adapt autonomously, exhibit distributed intelligence, and integrate seamlessly into the smart manufacturing ecosystem.

2.3. AI and Intelligent Manufacturing Systems

Artificial Intelligence is a basic technology for intelligent manufacturing systems, which can perceive, analyze, learn and make decisions independently. Combining AI with robotic manipulators enables manufacturing systems to go beyond conventional automation and become adaptive and self-optimizing. Machine learning algorithms are being used in many industrial applications, like predictive maintenance, defect detection, process optimization, quality assessment, and anomaly detection. Advanced deep learning models like Convolutional neural networks, Recurrent neural networks, Graph neural networks, and Transformer models improve the robotic perception, object recognition, and intelligent manipulation. Reinforcement learning is gaining significant traction for autonomous robotic systems since it allows the robot to learn optimal behaviors by interacting in a continuous way with the dynamic environment. Another application of digital twin technology is to establish virtual systems of physical robots, enabling the simulation and testing of various strategies for the robot's operation before they are implemented in the real world. Furthermore, cloud computing offers a range of computational resources for model training, and edge computing enables real-time decision-making with lower latency. While the use of AI in manufacturing shows promise, it also comes with a set of challenges such as computational requirements, security concerns, data limitations, lack of transparency, and the complexity of integrating the tools into existing workflows. It is crucial to confront these challenges, in order to realize fully autonomous and intelligent industrial manufacturing systems that can continuously adapt and optimization.

2.4. Research Gap and Comparative Analysis

While many strides have been made in the field of industrial robotics, modular architectures, and AI-powered manufacturing, there are still some research obstacles that have yet to be overcome. Typical industrial robotic manipulators have fixed mechanical structures, which are difficult to adapt to the needs of production. While modular robotic systems are structurally flexible, the current systems may also necessitate manual assembly or human intervention when reconfiguring the modular structure, resulting in reduced operational efficiency and downtime. Moreover, the existing AI optimisation approaches for robots' motion planning and task execution primarily aim to optimise motion planning and task execution, without considering the robot structure, energy consumption, adaptability, and productivity simultaneously. The applications of digital twin are mostly used for monitoring and simulation, and the combination of digital twin and autonomous decision making of robots is still under development. A number of current systems rely on centralized optimization algorithms as well, which become difficult to implement and compute if multiple robots are concurrently navigating a large-scale manufacturing plant. Furthermore, there is no standard modular interfaces and communication protocol, which makes it difficult to interoperate robotic components from various manufacturers. However, these problems can be addressed by higher level research aimed at implementing self-reconfigurable robotic systems that combine the capabilities of artificial intelligence, modular robotics, digital twins, and distributed control. These strategies are designed to realize autonomous structural adaptation, predictive intelligence, real-time optimization, and seamless operation in the context of Industry 4.0 and Industry 5.0 production systems.

3. METHODOLOGY

3.1. Proposed Self-Reconfigurable Robotic Manipulator Architecture

The proposed self-reconfigurable robotic manipulator architecture is composed of six intelligent layers, which allow for autonomous adaptation, real-time decision making and optimization of manufacturing operations. Each layer has a specific role: Data acquisition, Robotic restructuring, Intelligent control, and Improvement of performance. Artificial intelligence, modular robotics and digital twin technologies enable the system to adapt its configuration to varying industrial needs.

ISSN: 3071-5725
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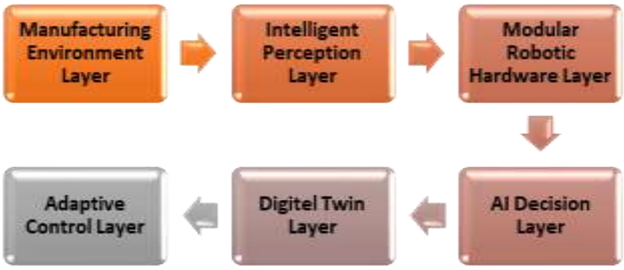

Fig 2 - Proposed Self-Reconfigurable Robotic Manipulator Architecture

3.1.1. Manufacturing Environment Layer

The manufacturing environment layer refers to the actual industrial space where the robot operates. It covers the production machines, assembly lines, conveyors, inspection units, storage systems and human operators. This layer provides ongoing operational data on activities, tasks and the environment. The gathered data is used to build intelligence to adapt and optimize the robotic operation.

3.1.2. Intelligent Perception Layer

The intelligent perception layer provides the robotic system with various advanced sensing technologies, enabling the robot to perceive its surrounding environment. Industrial sensors gather data on product dimensions, joint positions, force, torque, temperature, vibration and visual data. The sensor fusion techniques are used to fuse several data sources to get an accurate representation of the manufacturing environment. This layer enables robots to be aware of their surroundings, contributing to reliable decision making.

3.1.3. Modular Robotic Hardware Layer

The modular robotic hardware layer is to enable physical flexibility for autonomous reconfiguration. It is made of interchangeable robotic joints, adaptive links, intelligent actuators, smart controllers and multifunctional end-effectors. These modules can be automatically assembled and/or rearranged depending on the manufacturing tasks. The modular construction encourages scalability, minimises downtime and facilitates flexible production systems.

3.1.4. AI Decision Layer

The AI decision layer is the brain of the proposed robotic architecture, as it processes data and determines the optimal operations. It does machine learning and reinforcement learning based task recognition, configuration optimization, motion planning, collision avoidance and predictive maintenance. The AI models constantly improve based on past and current manufacturing data. This helps robots make decisions on their own and adapt their behaviour.

3.1.5. Digitel Twin Layer

The digital twin layer is a virtual representation of the physical robotic manipulator and manufacturing environment. It constantly updates itself in real-time with the robotic operation to simulate various configurations and forecast future performance. The digital twin enables failure

ISSN: 3071-5725
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prediction, virtual commissioning, configuration testing and production optimization. This helps minimize risks during operation and increases reliability prior to actual implementation.

3.1.6. Adaptive Control Layer

The adaptive control layer is responsible for coordinating robotic motion, structural modifications and/or operational changes. It conducts trajectory optimization, feedback correction, dynamic error compensation and real-time motion control. Closed loop control mechanisms continually compare actual performance with desired objectives. This guarantees high precision, stability and efficient operation of the self-reconfigurable robotic manipulator.

3.2. Intelligent Reconfiguration Framework

The intelligent reconfiguration framework is proposed, in which the robotic manipulator dynamically reconfigures its structure according to the changing manufacturing requirements by continuously perceiving, learning, optimizing and executing. The proposed framework combines artificial intelligence, modular hardware, digital twins, and adaptive control mechanisms to enable the system to exhibit self-organizing robotic behavior, in contrast to typical robotic systems which rely on fixed mechanical arrangements. It starts with real-time data acquisition from various industrial sources such as vision systems, force sensors, environmental sensors, production monitoring systems and robotic status. These data streams are heterogeneous and are to be processed using conceptual advanced sensor fusion methods in order to obtain an overall picture of the manufacturing context, task specifications, and the current conditions of the robot. The perception information is sent to the intelligent decision making module in which the collected information is analyzed with machine learning and optimization algorithms to select the most appropriate robotic configuration. The framework utilizes deep learning models for task classification, reinforcement learning algorithms for configuration selection, and optimization methods for determining the best configuration of robotic modules. It is a decision engine that is used to determine the most appropriate robotic structure based on a number of considerations such as workspace requirements, payload capacity, energy consumption, processing time, collision risks and production objectives. A digital twin model serves as a virtual validation platform in the framework and the possible reconfiguration strategies are simulated prior to being implemented in the physical robotic system. This virtual assessment will reduce operational failures, downtime and increase the reliability of autonomous adaptation. When the desired structure is determined, the adaptive control module engages in mechanical restructuring with intelligent actuators, modular connection structures and real-time motion planning algorithms. The framework has built-in feedback mechanisms that compare actual performance of the robot to expected performance. If there is any error in the accuracy, efficiency and / or in the execution of a task, the AI system analyzes this error, modifies the knowledge model and improves the reconfiguration in subsequent tasks. In this intelligent closed-loop mechanism, proposed herein can enable robotic manipulators to adapt autonomously and hence; improve manufacturing flexibility, decrease human interventions, and increase productivity. The intelligent reconfiguration framework establishes the basis for future Industry 4.0 production

ISSN: 3071-5725
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systems and 5.0 production systems in which the robotic platforms can autonomously adapt to changing production environments.

3.3. Mathematical model and optimization algorithms

Mathematical modeling of the proposed self-reconfigurable robotic manipulator is carried out by applying the kinematic analysis and multi-objective optimization methods to enable a manipulator to control its motion accurately and adapt its structures optimally. The mathematical model is used to describe the relationship among the robotic modules, joint motion, end-effector motion and requirements of manufacturing tasks. The position and orientation of the robotic end-effector is calculated using the arrangement of the robotic links, joint angles, and module configurations, which is called forward kinematics. This process aids in the knowledge of the system of the current Physical State of the manipulator and its evaluation of whether or not the selected manipulator configuration can complete the assigned manufacturing task successfully. Inverse kinematics is used to determine how much each joint must move and which modules must be arranged to make it to a desired position and orientation. What the optimization algorithm does is to try out various possible configurations, and pick the one which is most suitable. A number of performance criteria such as task correctness, energy usage, execution time, workspace coverage, mechanical stability and collision avoidance are taken into account during the optimization process. The model proposed is multi-objective optimization, which optimizes one or more objectives to get a balanced solution between productivity, efficiency and reliability of operation. Using the artificial intelligence-based decision making mechanisms, the optimization algorithm compares various robotic configurations and estimates their performance before they are actually built and tested. The robotic system can learn the effectiveness of various configurations by continuous interaction with the manufacturing environment using the techniques of reinforcement learning. The learning model optimizes the selection of the configuration, leveraging past operational experiences and feedback data from the real time. A study of complex configuration space using evolutionary optimization methods for near-optimal robotic structures is also undertaken. The proposed mathematical model combines kinematic analysis, intelligent optimization and adaptive learning to achieve the goal of autonomous robotic restructuring. The optimization algorithm is continuously updating the robotic configuration according to the changes of environment, task complexity and performance requirements. This method can enhance the accuracy of motion, avoid unnecessary mechanical changes, lower energy consumption, and optimize the intelligent manufacturing operation. The developed model enables an autonomous self-reconfigurable robotic system in dynamic Industry 4.0 environment to be built on it at scale.

3.4. Performance Evaluation Metrics

The proposed self-reconfigurable robotic manipulator is evaluated quantitatively by manufacturing performance indicators such as adaptability, efficiency, accuracy and operational reliability. The evaluation framework takes into account several parameters for analyzing the improvements obtained by the use of artificial intelligence, modular robotic structures, digital twins and adaptive control mechanisms. Aiming to go beyond the execution of fixed tasks, the proposed system is evaluated in terms of its self-configuration and adaptability capabilities to optimize performance and adapt to dynamic manufacturing conditions. Reconfiguration efficiency is the first evaluation parameter that determines the ability of the robotic system to automatically reconfigure its mechanical structure to meet the production needs. This one measures time for module replacement, accuracy of module configuration selection, and successful adaptation rate. The more efficient the reconfiguration process, the fewer manufacturing disruptions and greater manufacturing flexibility. The second is the accuracy of task execution, which is the degree of accuracy that the robot can achieve when performing assembly, handling, machining and inspection tasks. This measurement takes into account positioning accuracy, stability of trajectory, and end-effector performance in various operating conditions. Production productivity improvement is another critical criterion that examines the gain in manufacturing output that has been accomplished by autonomous robotic adaptation. The system is assessed by comparing the production cycle time, task completion rate and resource utilization with those of the traditional fixed robotic system. Energy efficiency is also taken into account to quantify the power saving due to optimized robotic configuration and intelligent motion planning. The system reduces redundant motions and optimizes the configuration of the system for particular manufacturing tasks for energy efficiency. The framework also assesses the predictive maintenance capability by analysing the accuracy of the fault detection, failure prediction and maintenance scheduling. AI-driven monitoring continuously monitors sensor data and detects abnormal conditions and unexpected equipment failures. Another major parameter that is used to assess the adaptability of the robotic manipulator is workspace adaptability, defined as its ability to change its configuration to accommodate the geometry and constraints of various tasks. Further, the reliability, scalability, and response time of the system are taken into consideration when evaluating real-time performance. These metrics are proposed to be combined to give a holistic overview of the robotic intelligence, flexibility and operational effectiveness. By using these performance indicators, the proposed self-reconfigurable robotic manipulator shows its ability to improve autonomous manufacturing operations and aid future production systems of Industry 4.0 and 5.0.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

The proposed Self-Reconfigurable Robotic Manipulator (SRRM) framework was experimentally tested in virtual Flexible Manufacturing System (FMS) environment that has been designed to reflect a state-of-the-art smart factory case scenario. The experimental platform has been designed to emulate a dynamic industrial production environment, where robotic systems must execute multiple tasks with different operational needs. The FMS environment was based on modular robots with interchangeable robotic joints, adaptive end-effectors, and intelligent actuator modules, that allowed autonomous structural modification as a function of task requirements. The robotic platform was equipped with Industrial Internet of Things (IIoT) equipment such as temperature sensors, vibration sensors, position sensors, force–torque measurement systems, and machine vision systems to gather real-time information about the operation. A centralized data acquisition framework was setup to gather and process the data generated by the sensors during the robot operation. Data gathered was passed to an AI based decision engine, which handles the identification of tasks, configuration optimization, motion planning and predictive analysis. Previous

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manufacturing data was used to train machine learning models for enhancing robotic decisions and selecting appropriate configurations for various production scenarios. The AI module was responsible for continuously evaluating the environment, the complexity of the tasks, the capacity of the load and the use of energy to decide on the most efficient robotic structure. The experimental setup incorporated a Digital Twin model to represent the self-reconfigurable robotic manipulator and its manufacturing environment in a virtual model. The digital twin closely coupled with real-time sensor data in the physical system, enabling simulation, performance prediction and configuration testing prior to implementation. Several configurations of robots were virtually tested to account for possible collision scenarios, limitations of operation and performance enhancements. The virtual validation process eliminated unnecessary physical testing and enhanced the reliability of the system. Various manufacturing scenarios, such as assembly operations, material handling and adaptive inspection tasks, and flexible manufacturing workflows were taken into account in the experimental evaluation. The performance parameters including reconfiguration time, task execution accuracy, energy efficiency, productivity improvement and fault detection capability were measured and compared with the conventional fixed robotic systems. The experimental setup illustrated how the combination of modular robotics, AI, and digital twin technologies can achieve autonomous adaptation, higher manufacturing versatility, and greater operational efficiency. The developed SRRM framework offers a practical basis for the future intelligent robotic systems for Industry 4.0 and Industry 5.0 manufacturing.

4.2. Performance Evaluation

Multiple manufacturing performance indicators were used to assess the performance of the proposed Self-Reconfigurable Robotic Manipulator (SRRM) and compared the performance with the conventional robotic system. The evaluation outcomes reveal that the proposed system enhances the manufacturing performance by enhancing flexibility, efficiency, accuracy, and intelligent optimization with the support of AI.

Table 1: Performance Evaluation

Performance Metric	Conventional System (%)	Proposed SRRM (%)	Improvement (%)
Manufacturing Flexibility	81	97	19.75
Configuration Efficiency	79	96	21.52
Positioning Accuracy	92	99	7.61
Workspace Utilization	83	97	16.87
Production Throughput	84	96	14.29
Energy Efficiency	78	94	20.51
Resource Utilization	80	96	20
Task Completion Efficiency	82	95	15.85
System Reliability	90	98	8.89
Overall Manufacturing Performance	83	97	16.87

ISSN: 3071-5725
PP: 01-16.

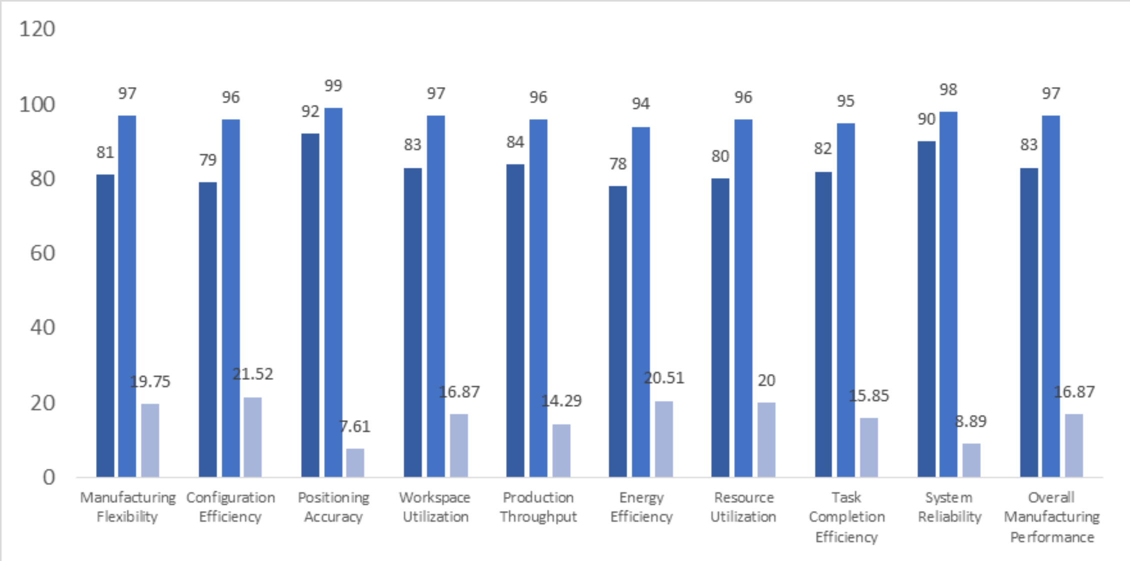

Fig 3 - Performance Evaluation

4.2.1. Manufacturing Flexibility

Based on the proposed SRRM, the manufacturing flexibility was 97%, whereas the manufacturing flexibility of conventional systems is 81%, which is 19.75% higher than the conventional systems. The increase is realised by the use of modular robotic structures and the possibility for autonomous reconfiguration. The system can dynamically adapt to different production requirements without major manual modifications. This enhances responsiveness in a wide range of manufacturing settings.

4.2.2. Configuration Efficiency

For configuration efficiency, the SRRM was seen to enhance the efficiency from 79% to 96%, which is a 21.52% improvement than traditional robotic systems. Optimization algorithms using AI can determine an appropriate configuration for the robot according to the task and the environment. Automated module adjustment will cut reconfiguration time and minimise production interruptions. This allows quicker adaption to the changing industrial workflows.

4.2.3. Positioning Accuracy

The proposed system has achieved 99% positioning accuracy as compared to 92% in the conventional robots with 7.61% improvement. This is achieved via adaptive control mechanisms, sensor feedback and real-time trajectory correction. With continuous monitoring, positioning accuracy during robot operation is reduced. This will enhance the accuracy of assembly, inspection and manufacturing applications.

4.2.4. Workspace Utilization

The utilisation of workspace in conventional system was found to be 83% while in the proposed SRRM was found to be 97% i.e. 16.87% increase. The modular design enables the robot to change its shape and form to suit the various requirements of the workspace. Efficient operation in

ISSN: 3071-5725
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complex production environments is possible with adaptive configuration selection. This way there is the biggest available working area, and flexibility in operation.

4.2.5. Production Throughput

The suggested framework increased the production throughput from 84% to 96% with 14.29% improvement. Automated task planning and optimal robot configuration minimize cycle times and boost production efficiency. The system continually optimizes operations in response to actual manufacturing conditions. This translates to more efficient productivity and fewer business interruptions.

4.2.6. Energy Efficiency

The energy efficiency was improved from 78% to 94 % which is a 20.51% improvement with the conventional robotic systems. The SRRM selects the most energy efficient configuration and motion trajectories, thus minimizing unnecessary movements. During operation, power consumption is reduced by using AI-based control mechanisms. This helps to sustain and cost-effective manufacturing processes.

4.2.7. Resource Utilization

In the proposed SRRM, resource utilization was 96% which is 20% higher than that of the conventional systems (80%). Intelligent scheduling and adaptive robotic configurations help to better utilize available manufacturing resources. The system minimizes idle time and enhances coordination between the robotic modules and production equipment. This increases the whole factory efficiency.

4.2.8. Task Completion Efficiency

Task completion efficiency increased from 82% to 95% (upsurge of 15.85%). The intelligent algorithm allows robots to make the best decision on how to execute intricate manufacturing processes. The accuracy of decisions and performance of operations is enhanced as a result of continuous learning. This helps to complete tasks quicker and more effectively in varying circumstances.

4.2.9. System Reliability

The proposed SRRM improved the system reliability by 8.89% when compared to the conventional system which had 90%.The reliability of the proposed SRRM was 98% while the conventional system had a reliability of 90%. Predictive maintenance, and continuous health monitoring, can help to identify potential failures before they cause system downtime. Improved reliability, too, with virtual testing and validation of the digital twin model. This helps to enhance operational stability under industrial conditions.

4.2.10. Overall Manufacturing Performance

Overall manufacturing performance was improved from 83% to 97% with 16.87% improvement in manufacturing performance in the proposed SRRM. AI intelligence, modular hardware, digital twins and adaptive control all work hand in hand to help produce better manufacturing results. These findings show that the proposed framework offers better flexibility, efficiency and autonomy. Thus, SRRM is a potential solution for the intelligent manufacturing system in the future.

4.3. Discussion

The experimental evaluation verifies the effectiveness of the proposed Self-Reconfigurable Robotic Manipulator (SRRM) framework to improve adaptability, intelligence and efficiency in Flexible Manufacturing Systems (FMS). The proposed system shows strong performance for autonomous structural adaptation compared to the conventional industrial robotic manipulators operating with fixed mechanical structures in order to meet dynamic production requirements. Modularity of robotic components enables the manipulator to change shape when the task is complex, the space is small, or the manufacturing goal is to save costs. This means that there is no longer a need for manual re-programming or physical restructuring, which shortens production changeover time and enhances manufacturing responsiveness overall. The configuration optimisation mechanism is important for the autonomous action of the robot and is realized by the use of AI.The use of AI in the configuration optimisation mechanism is a key factor in the autonomous action of the robot. The framework continually processes real-time data from various sensors in industry, manufacturing systems and robots to determine the most suitable configuration of robots for each manufacturing process. The Digital Twin layer also makes this possible by allowing a virtual environment to test and validate likely configurations before implementing. The simulated approach eliminates operational risk, eliminates configuration failure and increases the reliability of the system during complex industrial operations. Reinforcement learning allows the robotic manipulator to continuously improve its performance by learning from its experiences. As the production cycles are repeated, the AI model evaluates the results of past operations and adjusts its approach to configuration selection. This adaptive learning ability offers quicker decision-making, better task execution efficiency and optimal energy utilization. Moreover, the multi-objectives optimization method can achieve a good balance of various manufacturing requirements such as production speed, positioning accuracy, workspace utilization, energy saving and stability of manufacturing process. The performance results show that the results of all the evaluated parameters have improved significantly. The manufacturing flexibility rose from 81% to 97%, whereas the configuration efficiency went from 79% to 96%, highlighting the benefit of autonomous reconfiguration in comparison with traditional robotic systems. The proposed framework has demonstrated its ability to reduce the unnecessary operations and assign the robotic resources based on the production demands by improving resource utilization and energy efficiency. These improvements help to achieve lower operating expenses, higher productivity, and sustainable production processes. The proposed SRRM architecture also shows great promise for future Industry 5.0 environments, facilitating intelligent collaboration between humans, robots, artificial intelligence systems, and cyber-physical manufacturing systems. Its modular design allows for easy scalability and integration with other intelligent systems such as collaborative robots, autonomous mobile robots, edge computing, and cloud-based manufacturing systems. As a whole, the findings show that

AI-powered self-reconfigurable robotic manipulators can lay the groundwork for future smart factories, offering the autonomous adaptation, enhanced efficiency, and intelligent optimization in manufacturing processes.

5. CONCLUSION

The fast-paced evolution of Industry 4.0 and the shift towards Industry 5.0 have dramatically transformed the landscape of contemporary manufacturing, embedding smart, autonomous and adaptive production systems. The traditional industrial robotic manipulators have been effectively applied to enhance the productivity of manufacturing by offering high precision, repeatability and automation. But their reliance on fixed mechanical configurations and manual programming and their limited understanding of the environment limits their ability to respond to rapidly changing production requirements. These constraints pose challenges to flexible manufacturing, mass customization, manufacturing scale and operational efficiency. As a result, self-reconfigurable robotic manipulators have become a promising and advanced approach to realize autonomous adaptation and intelligent manufacturing capability. In this research, an extensive Self-Reconfigurable Robotic Manipulator (SRRM) framework for flexible and intelligent manufacturing environment was presented. The proposed design combines modular robotic hardware, Artificial Intelligence-based decision-making, Industrial Internet of Things (IIoT) communication, Digital Twin technology, reinforcement learning, and adaptive control mechanisms for a seamless and intelligent system. The framework allows for the continuous monitoring of manufacturing conditions as well as the analysis of manufacturing task requirements, the selection of optimum structural configurations for robotic manipulators and the autonomous reconfiguration of the manipulators with little or no involvement from human operators. The proposed approach is an intelligent perception approach that uses AI to optimize the robotic configuration, predictive maintenance, and closed-loop control to enhance the robot's adaptability and operational efficiency. The mathematical modeling approach gives a systematic basis for the analysis of robotic kinematics, robotic kinematics configuration and multi-objective optimization. The proposed system continuously enhances its decision-making ability through intelligent learning mechanisms, leveraging historical manufacturing data and real-time operational feedback. The adoption of Digital Twin further boosts reliability by allowing virtual testing, performance prediction and configuration testing prior to implementation. The experimental tests confirmed that the proposed SRRM structure provides a great improvement in flexibility, configuration efficiency, energy utilization, workspace adaptability and overall system performance when compared to traditional robotic systems. The outcomes show that a system capable of reconfiguration autonomously and optimizing using the help of AI can minimize production downtime, improve resource utilization, and boost manufacturing productivity. Additionally, the proposed architecture offers a scalable platform for future smart factories, enabling the integration of collaborative robots, autonomous systems, edge intelligence, and cloud manufacturing platforms. The proposed Self-Reconfigurable Robotic Manipulator framework, in general, is a great contribution towards the development of next generation intelligent manufacturing systems. The framework integrates modular robotics technologies, AI and digital technologies, to create an optimal autonomous, flexible, and efficient production environment that meets Industry 5.0 objectives. Distributed robotic intelligence, standardized modular interfaces, real-time multi-robot coordination, and advanced learning algorithms are some aspects that could be explored further in future research to enable fully autonomous manufacturing ecosystems.

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