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Original Article

Generative AI-Assisted Robot Task Planning in Industrial Applications

Narendra Karmarkar

Mathematician and Computer Scientist, Tata Institute of Fundamental Research, India.

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ABSTRACT

The rapid evolution of Industry 4.0 has accelerated the adoption of autonomous robotic systems in intelligent manufacturing. Traditional robot task planning methods are limited in dynamic production environments due to their dependence on rule-based programming and deterministic algorithms. In contrast, Generative Artificial Intelligence (GenAI), including Large Language Models (LLMs) and multimodal foundation models, enables robots to understand natural language, perform contextual reasoning, generate adaptive task plans, and respond intelligently to changing industrial conditions. This paper presents a Generative AI-based framework for robotic task planning that integrates multimodal perception, semantic reasoning, LLM-based planning, reinforcement learning, and execution monitoring. The framework enhances planning accuracy, adaptability, collaboration, and operational efficiency while reducing execution errors and planning complexity. It is applicable to smart assembly, automated inspection, warehouse logistics, predictive maintenance, collaborative robotics, and flexible manufacturing. The study concludes that Generative AI offers a promising foundation for scalable, adaptive, and human-centric industrial automation, with future research directed toward continual learning, explainable AI, federated robotic intelligence, edge AI, and trustworthy autonomous decision-making.

KEYWORDS

Generative Artificial Intelligence, Robot Task Planning, Industrial Robotics, Large Language Models, Autonomous Manufacturing, Intelligent Automation, Reinforcement Learning, Industry 4.0, Human–Robot Collaboration, Digital Twin.

1. INTRODUCTION

1.1. Background

By offering increased levels of automation, precision, productivity, and operational efficiency, industrial robotics is one of the core technologies that is helping to fuel the digital transformation of modern manufacturing. As Industry 4.0 is evolving quickly, manufacturing systems have increasingly embraced intelligent solutions involving robots that are associated with advanced technologies like Artificial Intelligence (AI), the Industrial Internet of Things (IIoT), cloud computing, edge computing, big data analytics, and Digital Twin technology. These have given rise to a new breed of industrial robots that can sense their surroundings, analyse the data from their operations, and make their own decisions. Industrial robots are now used in various industries, such as the automotive, electronics, semiconductor, aerospace, pharmaceutical, food, logistics, warehouse, quality inspection, welding, painting, packaging and precision material handling industries. They can repeat, hazardous and high precision tasks with extreme speed and accuracy, enhancing the quality of the product being manufactured and cutting down on costs and workplace hazards. But with the growing need for mass customization, fast product changeovers, flexible production lines, and collaborative humans and robots, new challenges have been added that demand more than robots can perform by reproducing a preprogrammed sequence of actions. The factory is a very dynamic environment in which production plans, product configurations, machine availability and space conditions are constantly changing in real time. Existing methods of task planning in robots are mainly based on deterministic algorithms, finite-state machines, symbolic planners, graph-search algorithms, motion planning algorithms and mathematical optimization models that need complete knowledge of the operating environment prior to execution. These methods work well in manufacturing contexts with known tasks, known problems, known machinery, known information, and known goals, but appear to lack flexibility when faced with an unknown environment, unknown problems, unknown machinery, unknown information, and unknown goals. The constant reprogramming and manual adjustment of robotic workflows means more engineering time, manufacturing downtime, higher operating costs, and decreased production flexibility. In addition, traditional planning methods do not possess context-awareness, semantic reasoning, and autonomous learning capabilities, which hinders robots from understanding the higher-level production goals and working well with human operators. These restrictions have stimulated a demand for new generation intelligence task planning frameworks that will tackle advanced reasoning, adaptive decision making and recurrent learning in a unified manner. As a result, some recent developments in Generative Artificial Intelligence (GenAI), Large Language Models (LLM), multimodal perception/understanding, reinforcement learning, and Digital Twin technology have emerged as promising approaches to address the challenges of task planning with autonomy, flexibility, and context awareness in contemporary Industry 5.0 manufacturing settings, where intelligent cooperation between humans and machines is a key enabler to achieve sustainable and highly efficient industrial production.

1.2. Need for Generative AI-Assisted Robot Task Planning

Smart manufacturing has been growing at a rapid pace and with the increasing demand for intelligent robotic systems that can perform tasks autonomously, make decisions based on changing environments, and exhibit a degree of flexibility. Task planning for conventional robots works well in structured production lines, but is not suitable for coping with the complexity of modern production environments with dynamic production processes, custom-made production and communication with humans. Generative Artificial Intelligence (Generative AI) offers a potential way forward by enabling robots to interpret natural language instructions, build executable plans and adapt over time as conditions evolve. The following subsections will cover the key drivers for implementing Generative AI based robot task planning in Industry 5.0 manufacturing.

Fig 1 - Need for Generative AI-Assisted Robot Task Planning

1.2.1. Intelligent Interpretation of Production Instructions

In modern manufacture, robots are needed to grasp high-level production goals in addition to manually programmed instructions. Robots can use generative AI, especially Large Language Models (LLMs), to understand natural language instructions, determine production goals, and translate them into structured sequences of tasks. This makes programming easier and enables operators to speak more humanistic and easier to understand with the robotic system.

1.2.2. Adaptive Task Planning in Dynamic Environments

In manufacturing, there are often changes that happen due to equipment failure, new product set-ups, unforeseen challenges, or varying production schedules. Existing planning systems typically need to be manually reprogrammed when these changes do happen. Automated task plan generation with Generative AI allows robots to use real-time sensor data to reason and generate optimized task plans without human intervention, leading to continuous production with little downtime.

1.2.3. Enhanced Human–Robot Collaboration

In Industry 5.0, the focus is on close interaction between man and intelligent machines. Generative AI is a great enabler for human-robot interaction, providing the ability to converse, to explain plans, and to understand the context. The AI system can generate clear, interpretable execution strategies, thereby increasing workers' trust in the system, its usability, and workplace safety. Operators can set production goals in natural language, and the AI system provides a transparent and interpretable plan on how to achieve them.

1.2.4. Knowledge-Driven Decision Making

There are a significant amount of domain knowledge associated with industrial manufacturing, such as what machines can do, production rules, safety guidelines, and operational constraints. Generative AI brings together Industrial Knowledge Graphs, historical production data with semantic reasoning, and generates informed decisions that take into account contextual information as well as manufacturing goals. This knowledge-driven way boosts in the accuracy of planning and the reliability of planning implementation.

1.2.5. Improved Operational Efficiency and Productivity

Efficient task planning is a direct impact on manufacturing productivity, throughput and resource utilization. Generative AI optimises task sequencing, robot scheduling, motion planning and resource allocation and reduces idle time, delays in execution and unnecessary movements. This results in higher efficiency of manufacturing systems, lower operating costs, and overall higher equipment effectiveness.

1.2.6. Real-Time Adaptive Replanning

When unforeseen events like machine failure, stock shortages, or shifts in work conditions call for rapid changes to execution plans, it can strain the relationship. When unforeseen events, like machine malfunctions, stock shortages, or changes in workspace conditions, call for rapid changes to execution plans, it can strain the relationship. As a constant companion of real-time sensory data, Generative AI can dynamically adjust robot actions at any point without interrupting production. The adaptive replanning capability greatly enhances manufacturing flexibility and system robustness.

1.2.7. Integration with Digital Twin and IIoT Technologies

Generative AI can connect easily with Digital Twin platforms and Industrial Internet of Things (IIoT) infrastructure to enhance the planning reliability. Digital Twin simulation tests and validates generated plans prior to execution and IIoT sensor feeds offer ongoing operational feedback on machine health, the environment, and production. This integration facilitates predictive decision-making and helps to mitigate operational risks.

1.2.8. Continual Learning and Autonomous Improvement

Conventional planning systems need to be manually updated, whereas AI robots continue to learn from the feedback of the actions they take. Through reinforcement learning and continual learning mechanisms, the robotic system can improve its planning approach, adapt to the new manufacturing scenarios and learn to make better decisions in the future without full retraining. This feature enables the long-term autonomy and scalability in a variety of industrial applications.

1.2.9. Supporting Industry 5.0 Manufacturing

The Industry 5.0 revolves around the development of human-centric, intelligent, resilient and sustainable manufacturing systems. The ability of Generative AI to orchestrate robot tasks with autonomous reasoning, explainable decision-making, adaptive learning, and collaborative intelligence is aligned with these goals. By leveraging foundation models in robotics, smart factories can enhance their flexibility, productivity, safety, and sustainability to meet the rising demand for customized manufacturing and rapid technological progress.

1.3. Challenges in Industrial Robot Task Planning

Although AI/ML and industrial automation have made remarkable progress, the development of reliable and intelligent adaptive robot task planning systems is still one of the most difficult research challenges in contemporary manufacturing. Industrial environments are dynamic, complex and multi-robot, including multiple robotic manipulators, autonomous mobile robots, production machines, conveyors, sensors and human operators, which should collaborate to meet strict safety, quality and productivity requirements. In contrast to traditional factories with fixed machine sequences and well-defined production workflows, modern smart factories feature frequent product design changes, customised production, variable production cycles, failures, machine availability fluctuations, and random environmental factors. One of the most challenging problems is dealing with an uncertain environment: Robots must make good planning decisions without having full or reliable knowledge of where the objects are, what is in the workspace, whether the equipment is operational, or what human activities are occurring when they are in it. In the context of uncertainty, effective planning demands intelligent reasoning mechanisms that can reconcile operational efficiency, safety, adaptability and real-time responsiveness. An additional challenge is semantic understanding and task interpretation which requires the robot to correctly translate high level human instructions into a sequence of valid tasks, taking into account manufacturing constraints, manufacturing priorities and available resources. Most planning systems are based on an old-fashioned approach that fails to provide contextual reasoning and hence to grasp complex production goals in natural language. Additionally, real-time adaptive replanning is still challenging as robots need to adapt their execution strategy without interruption to the current process when unexpected obstacles, equipment failure, emergency situations or production schedule change happen. Beyond that, the requirements for safe human–robot collaboration make it a more complex task, as it involves continuously tracking human motion, avoiding collisions, complying with industrial safety standards, and making sure the decisions for collaboration are clear. A major challenge is also scalability, as an efficient coordination of multiple robots, automated guided

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vehicles, production machines, and Industrial Internet of Things (IIoT) devices is required to run large manufacturing fabrication facilities. Another important point is scalability: for large manufacturing fabrication facilities, an efficient coordination of multiple robots, automated guided vehicles, production machines and Industrial Internet of Things (IIoT) devices is required, which requires efficient communication, distributed intelligence and collaborative optimization. Furthermore, the fusion of the multimodal (camera, LiDAR, force sensor, tactile and Digital Twin) information into a single planning architecture is still challenging in terms of computation. The limitations of explainability, cybersecurity, computational efficiency and ongoing learning continue to hinder the practical application of intelligent planning systems. To solve these problems, it is necessary to develop advanced Generative AI-based frameworks that can integrate semantic reasoning, multimodal perception, reinforcement learning, Digital Twin simulation and adaptive decision making in order to support highly reliable, large-scale and trustable autonomous robot task planning in next generation Industry 5.0 smart manufacturing systems.

2. LITERATURE SURVEY

2.1. Conventional Robot Task Planning

Industrial robot task planning is an important building block of industrial automation, and has traditionally been based on deterministic algorithms, symbolic reasoning, and mathematical optimization for deriving sequences of actions for robotic systems. Initial industrial robots were programmed to perform very defined actions in very controlled workspaces, which meant that engineers had to tell them what to do, where to go and what to do when. For robots to break down manufacturing goals into manually programmed rules and symbolically represented subtasks, planning approaches like Finite State Machines (FSMs), Behavior Trees (BTs), Petri Nets, the STRIPS (Stanford Research Institute Problem Solver) and Planning Domain Definition Language (PDDL) were conceived. Navigating and manipulating robots within the environment, such as generating collision-free and kinematically feasible paths, was heavily used on graph-search algorithms, including A*, Dijkstra's algorithm, Rapidly-exploring Random Trees (RRT), Probabilistic Roadmaps (PRM), and trajectory optimization techniques. Further, a number of optimization techniques like Mixed Integer Linear Programming (MILP), Genetic Algorithms (GA), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) have been applied to enhance scheduling, resource allocation, and production sequencing in manufacturing systems. These approaches were found to be very accurate and reliable in predictable industrial environments, but were not easily transferable to dynamic production environments due to the detailed environmental models required and extensive manual programming. With the evolution of manufacturing systems towards mass customization and flexible production, traditional planning methods were not able to deal with changing product requirements, uncertainty on operating conditions, incomplete information and human-robot collaborative planning, which emphasized the need for intelligent and adaptive planning paradigms.

2.2. AI-Based Task Planning

Artificial Intelligence (AI) has transformed the way in which robots plan tasks, allowing these robots to learn from data, reason under uncertainty and make adaptive decisions, rather than being programmed with rules. By analyzing historical production data, machine learning techniques enable robots to recognize these patterns, thereby enhancing the prediction of tasks, object recognition, defect detection, and process optimization. Supervised learning algorithms are typically used for classification and recognition, and unsupervised learning is used for feature extraction, clustering and modeling the environment. In recent years, deep learning architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNNs) have also shown to greatly improve robot perception by processing multimodal sensory data from cameras, LiDAR, force sensors, tactile devices, and Industrial Internet of Things (IIoT) systems. Reinforcement Learning (RL), on the other hand, pushes intelligent planning to the next level by allowing robots to learn optimal action policies through iterative interactions with the environment through reward-based optimization. Extensive research in the field of robotic manipulation, motion planning, adaptive scheduling, and collaborative operations has shown great success in Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), Proximal Policy Optimization (PPO), and Soft Actor-Critic (SAC) algorithms. In addition, AI systems with digital twins, cloud computing, edge intelligence and knowledge graphs have led to enhanced contextual reasoning, predictive maintenance and dynamic task rescheduling. Yet, the majority of AI-fueled planning systems are still application-dependent, need large training sets, and are too opaque, making them impractical for wide-spread use and adaptation in complex industrial settings.

2.3. Generative AI for Industrial Robotics

Generative Artificial Intelligence (Generative AI) is a new generation of intelligent computing that could revolutionize planning tasks for robots by generating knowledge, reasoning about complex tasks, and generating action sequences to execute from high-level human instructions. Generative AI sets itself apart from the traditional AI systems, which mainly classify, recognize, or predict data, as it generates new planning strategies through the advanced semantic understanding and contextual reasoning power of transformer-based Large Language Models (LLMs). In industrial robotics, these models can be used to accept natural language production goals and automatically transform them into structured hierarchical task plans, which reduces the length of time spent programming robots and simultaneously increases manufacturing flexibility. Generative AI also enables intuitive human–robot interaction, where the robot can be controlled with natural language rather than complicated programming language. In addition, multimodal foundation models incorporate textual instructions, visual perception, CAD models, sensor measurements, digital twins and industrial KG to equip robots with the ability to comprehend the relationships between objects, to assess the workspace constraints, to predict the outcome of the execution, and to dynamically adjust planning strategies in real time. The addition of continual learning and reinforcement learning features also allows for robots to improve their generated plans by incorporating feedback from their execution, which results in continual performance improvement without the need for a full retraining. Furthermore, explainable planning made by language models increases the trust of the operator, regulatory compliance and transparency of decisions. However, there are several ongoing research topics for computational efficiency, hallucination mitigation, cybersecurity, industrial safety

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certification, and reliable deployment in safety-critical manufacturing environments that need to be solved before the full-scale industrial deployment can be achieved.

2.4. Research Gaps

While the intelligent task planning of robots has made impressive progress, there are still major challenges in research that hinder effective use of Generative AI in industrial manufacturing systems. Planning approaches tend to be built for specific application areas and are not very transferable between various industrial tasks, necessitating a lot of re-training if applied to tasks different from the one originally planned for, e.g. to inspection, logistics, maintenance, or assembly tasks. In addition, existing AI-driven planning systems have focused on perception optimization or motion optimization, but have not effectively added semantic reasoning, semantic knowledge generation, hierarchical task planning, and multimodal information fusion into a single decision-making framework. A critical challenge in explainability is the fact that many deep learning models are black-box systems, and the understanding, verification and validation of decisions produced by these models is hard within the confines of industrial safety regulations. A further drawback is limited real-time adaptive replanning; many of the existing methods create plans offline and they lack efficiency in dealing with unexpected changes of the environment during the plan execution. Another issue is scalability: the ability to coordinate several robots, autonomous guided vehicles (AGVs), production machines, digital twins and IIoT devices in smart factories demands distributed intelligence and effective collaborative optimization mechanisms. Lastly, the existing evaluation techniques often use simple performance metrics, instead of more complex industrial metrics involving execution efficiency, adaptability, resource utilization, collision avoidance, energy utilization, production throughput, explainability, and system robustness. To tackle these challenges, novel Generative AI-powered robot task planning systems are emerging to enable intelligent, scalable, explainable, and trustworthy industrial automation, integrating multimodal perception, Large Language Model reasoning, reinforcement learning optimization, digital twin simulation, and real-time adaptive decision-making.

3. METHODOLOGY

3.1. Proposed Generative AI-Assisted Framework

The proposed Generative AI-Assisted Framework aims to create an intelligent, adaptive, and scalable task planning architecture for the industrial robotic systems by integrating with LLM, multimodal perception, reinforcement learning, and digital twin technologies in one unified decision-making pipeline. The main goal of the framework is automatic conversion of high-level production goals written in natural language into optimized executable action plans for the robot while continuously adapting to dynamic manufacturing environments. Figure 1 provides a conceptual model of the framework, which includes an Input Acquisition Layer where the production engineers or operators input manufacturing information or instructions in natural language, production schedule, CAD models, work orders, or enterprise manufacturing execution systems. At the same time, multimodal sensory data from RGB cameras, depth sensors, LiDAR, force–torque sensors, tactile sensors and Industrial Internet of Things (IIoT) devices is gathered, giving the full picture of the surrounding environment. These disparate information is conveyed to the Multimodal Data Fusion Module, where visual observations, textual instructions, sensor measurements and historical knowledge regarding how things work, are combined into a single integrated contextual representation. This fused information then goes through a Generative AI Knowledge & Reasoning Engine, using transformer-based Large Language Models that can perform semantic understanding, contextual reasoning, and hierarchical task decomposition. The model is used to reason over production goals to find manufacturing conditions, to retrieve information from industrial knowledge repositories and to produce a sequence of tasks, that can be executed by a robot, in a logical order. The resulting plans are sent to an Adaptive Task Planning Module, which assesses the ability to execute the plans in various ways and adapts motion planning, task scheduling, collision avoidance and resource utilization subject to a set of performance goals through reinforcement learning algorithms. The optimized plans are subsequently validated through a Digital Twin Simulation Environment that precisely replicates robotic manipulators, production work cells, machine dynamics, and interactions with the environment, all to prevent potential collisions, bottlenecks and safety issues before physically deploying robots. The validated execution strategy is then passed on to the actual robotic controller for implementation in real world. In execution, the Real-Time Adaptive Decision Module continuously monitors the feedback information from the sensors, allowing the framework to recognize changes of the environment, equipment failure, and unexpected obstacles, and automatically re-create the new task plans without interrupting the execution of the production. The results of execution are also saved in a Continual Learning Repository, which enables the Generative AI model to learn from the past experience and receive reinforcement learning rewards and feedback from the operators. In this context, the proposed framework enables intelligent human–robot collaboration, autonomous decision-making, scalable deployment in industry, explainable planning, and ongoing improvement of performance is well suited for next-generation smart manufacturing settings based on the principles of Industry 5.0.

3.2. Task Planning and Knowledge Generation Module

The Task Planning and Knowledge Generation Module will be the brain of the proposed Generative AI-enhanced framework. It uses transformer-based Large Language Models (LLMs) to transform high abstraction level manufacturing instructions into structured and executable robotic workflows. The module combines semantic reasoning, industrial knowledge graphs, and real-time production data to enhance the ability of robots to understand complex tasks, optimize task planning, and adapt to dynamic production environments. The planning process consists of four major stages, each of which plays a role in the process of correct, safe and intelligent task execution.

3.2.1. Instruction Interpretation

The Generative AI model then interprets the natural language instructions given by operators, which are then converted into structured semantic representations during the instruction interpretation stage. It establishes production goals, understand task priority, defines operation

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constraints, and defines intended manufacturing activities. This understanding enables the robot to more precisely understand human commands, minimizing the ambiguity of their instructions and decreasing manual programming work.

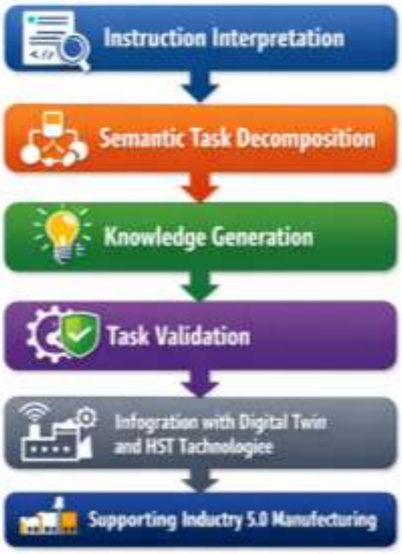

Fig 2 - Task Planning and Knowledge Generation Module

3.2.2. Semantic Task Decomposition

The semantic task decomposition stage is in which the interpreted production goal is decomposed systematically into a series of smaller, executable subgoals. The module recognizes task dependencies, selects the proper order of tasks to execute, assigns resources to tasks in the robot and synchronizes machine and workstation interactions. This hierarchical decomposition helps to achieve efficient implementation of complex manufacturing processes and enhance flexibility and scalability.

3.2.3. Knowledge Generation

The knowledge generation stage enhances the planning process through the use of industry knowledge graphs, historical manufacturing information, and reasoning through a transformer. The system gathers the manufacturing knowledge, creates multiple potential execution plans, forecasts the possible execution results, and assesses alternative plans according to manufacturing efficiency, safety and resource utilization. This facilitates intelligent decision-making in the context of dynamic manufacturing.

3.2.4. Task Validation

The task plan is fully validated prior to deployment for reliability and operability. The module ensures adherence to industrial safety standards, checks whether the robot is capable, resources are available, and workspace limitation is checked by using Digital Twin simulation. Performance, safety and feasibility are among the requirements for task sequences to be approved for execution, thereby reducing operational risks and enhancing production reliability.

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3.3. Adaptive Motion and Decision Optimization

The Adaptive Motion and Decision Optimization Module converts the generated executable task plans into safe, efficient and dynamically optimized robot movements, suitable to be used in real-world industrial environments. The main goal of this module is to identify the best possible robot movements in the presence of moving and changing environments, production priorities, and real-time sensor observation. In contrast to standard motion planning systems which plan pre-execution, the proposed module optimizes the motion continuously during the operational cycle, thus enabling robots to be able to react smartly to unexpected events without interrupting the production. First, the created task sequence is analysed along with information gathered from multi modal sensors such as RGB cameras, depth sensors, LiDAR, force–torque sensors, tactile sensors and Industrial Internet of Things (IIoT) devices. This sensory information gives a real-time, up to date sense of the workspace, as well as knowing where objects are, what machines are doing, whether humans are present, obstacle detection, and changes in the environment. The collected data are combined with the dynamic world model, allowing the robotic system to have accurate situational awareness while executing. The algorithm forms of Reinforcement Learning (RL), like Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC), constantly explore different motion trajectories and execution plans to maximize cumulative rewards for successful task completion within the constraints of task time, energy costs, collision avoidance, path smoothness, and operational safety. At the same time, trajectory optimization methods guarantee that the robot's motions meet kinematic requirements, joint limits, payload capacity and workspace limitations, and reduce unnecessary motion and execution delays. The module also integrates with a Digital Twin simulation environment in which candidate trajectories are simulated prior to implementation, thus detecting potential collisions, deadlocks, equipment interference and safety violations. If unforeseen conditions, equipment damage, or changes in production plans arise during execution, the adaptive decision engine dynamically changes the robot's motion plan by creating alternative motion plans and redistributing tasks without the need for comprehensive reprogramming of the entire system. Executed operations are continuously fed-back into the learning process, and the learning model is updated to enhance the decision-making process in the future based on the previously executed operations. In addition, explainable decision mechanisms can offer interpretable information both about the trajectory chosen and about optimization objectives and adaptive planning decisions, thus giving operators more confidence in the decisions they make and helping them to meet regulatory requirements. The proposed Adaptive Motion and Decision Optimization Module seamlessly combines Generative AI reasoning, reinforcement learning optimization, multimodal perception, and real-time feedback control, significantly boosting robotic flexibility, execution accuracy, resource use, production efficiency, and intelligent human-robot collaboration, thus meeting the dynamic and complex needs of the modern Industry 5.0 manufacturing industry.

3.4. Performance Evaluation Metrics

The proposed Generative AI-powered robot task planning framework is evaluated using a comprehensive framework of industrial performance metrics, which collectively measure planning intelligence, execution accuracy, operational efficiency, adaptability, and overall manufacturing productivity. The proposed framework differs from traditional assessment methods which rely on a single performance measure by using multiple indicators to enable a comprehensive evaluation of the intelligent robot's performance in dynamic industrial environments. Task Planning Accuracy is the first evaluation metric, which is the accuracy of the Generative AI model in understanding the natural language instructions and generating sequences of executable tasks that meet the production goals and operational constraints. A higher planning accuracy means that better semantic reasoning and knowledge generation skills are achieved. The second is Task Completion Time and measures the overall time a robot takes to complete a set of manufacturing tasks from start to finish. The faster the time to execution, the higher the production throughput and the more efficient the operation. The other important indicator is Trajectory Optimization Efficiency that quantifies the quality of generated robot trajectories with respect to motion smoothness, energy consumption, collision avoidance and travel distance while meeting kinematic and dynamic constraints. Additionally, the framework analyzes Resource Utilization, which measures the efficiency of the use of the robotic manipulators, the production equipment, workstations and manufacturing resources during the task execution. Waste reduction in the use of resources reduces factory downtime and increases overall productivity. Another important measure is Adaptive Replanning Capability, reflecting the framework's ability to recognise unexpected changes in either the environment or equipment, or disturbances in the production process, and then autonomously develop alternative execution strategies with minimum delay. Has a measure of flexibility and robustness in the proposed planning architecture. The operational safety is evaluated using Collision Avoidance Rate which is the percentage of tasks completed without any physical interference between robots, machines, obstacles or human operators. In addition, Energy Efficiency evaluates electrical energy consumption during the robotic operation, to assist with the goal of sustainable manufacturing and to lower operation costs. In addition to this, the framework includes the Explainability Score which reflects the clarity of the Generative AI model's reasoning process, task decomposition and planning decisions, which enhances the trust of operators and regulatory compliance. Lastly, Overall Production Throughput indicates the total number of manufacturing tasks that are completed successfully throughout a given production period and is used as an overall measure of the productivity of the system. These performance evaluation metrics collectively show the potential of the proposed Generative AI-assisted framework to deliver intelligent decision-making, adaptive planning, improved operational efficiency, better safety, lower resource usage, and higher manufacturing performance for next generation of Industry 5.0 smart factories.

4. RESULT AND DISCUSSION

4.1. Experimental Analysis

To test the effectiveness of the proposed Generative AI-based robot task planning approach under realistic smart manufacturing scenarios, the experimental evaluation was conducted. This framework was tested using six main indicators of industrial performance: planning quality, execution efficiency, operational adaptability, resource utilization, collision avoidance, and manufacturing productivity. The various experimental scenarios covered assembly operations, material handling, component inspection, and collaborative tasks between the human and robot in a dynamic production workflow where machine availability, workspace configurations, production priorities and environmental conditions fluctuated constantly. The proposed framework was evaluated with two baseline frameworks: a traditional rule-based task planning system and a reinforcement learning (RL)-based planning system. The traditional planning method was found to be reliable in a controlled environment where the production sequences, space arrangement and working conditions were relatively fixed. It failed, however, to perform well in the event of any unforeseen occurrences like the appearance of an obstacle, failure of a machine or product change or changes to the production schedule. The conventional system was based on a large number of rules and task models that had to be programmed in advance, which led to frequent reprogramming for production changes, thus increasing the engineering workload, decreasing the flexibility and increasing the manufacturing downtime. The reinforcement learning planning framework demonstrated greater adaptability by learning optimal execution policies through interacting with the environment continuously. The RL model was able to learn in a variety of dynamic settings, but took a long time to train, a massive amount of interaction data, and a meticulously crafted reward function to reach stable performance. Besides, the learned policies were still very much reliant on pre-specified task representations and also had limited semantic knowledge of high-level manufacturing goals. In contrast, the proposed Generative AI-based framework achieved better performance across all of the evaluated scenarios by directly translating the natural language production instructions into context-aware executable task plans through transformer-based reasoning. By leveraging multimodal perception, industrial knowledge graphs and Large Language Models, the system could interpret production goals, understand the constraints of the workspace and create hierarchical task sequences without a lot of manual programming. Moreover, the adaptive motion optimization module was continuously monitoring real time sensor data and dynamically re-generating execution strategies whenever changes in the environment, equipment failures or unexpected obstacles were detected. Digital Twin simulation further validated generated plans before execution, minimizing operational risks and improving execution reliability. Consequently, the proposed framework preserved continuous production, achieved quick task completion, high level of planning accuracy, efficient use of resources, low collision probability, adaptability, and significantly reduced production downtime. The experimental results show the strong potential of combining Generative AI with reinforcement learning, semantic reasoning, multimodal perception, and digital twin technology to equip next-generation autonomous robots with a scalable, intelligent, and robust solution for autonomous task planning in Industry 5.0 manufacturing environments.

4.2. Comparative Performance Analysis

Table 1: Comparative Performance Analysis

Performance Metric	Conventional Planning (%)	RL-Based Planning (%)	Proposed Generative AI Framework (%)
Task Planning Accuracy	81	89	97
Task Completion Rate	84	91	98
Dynamic Adaptability	69	88	96
Collision Avoidance	86	93	99

Robot Resource Utilization	79	90	96
Energy Efficiency	76	87	95
Production Throughput	82	90	97
Human–Robot Collaboration Efficiency	74	88	98

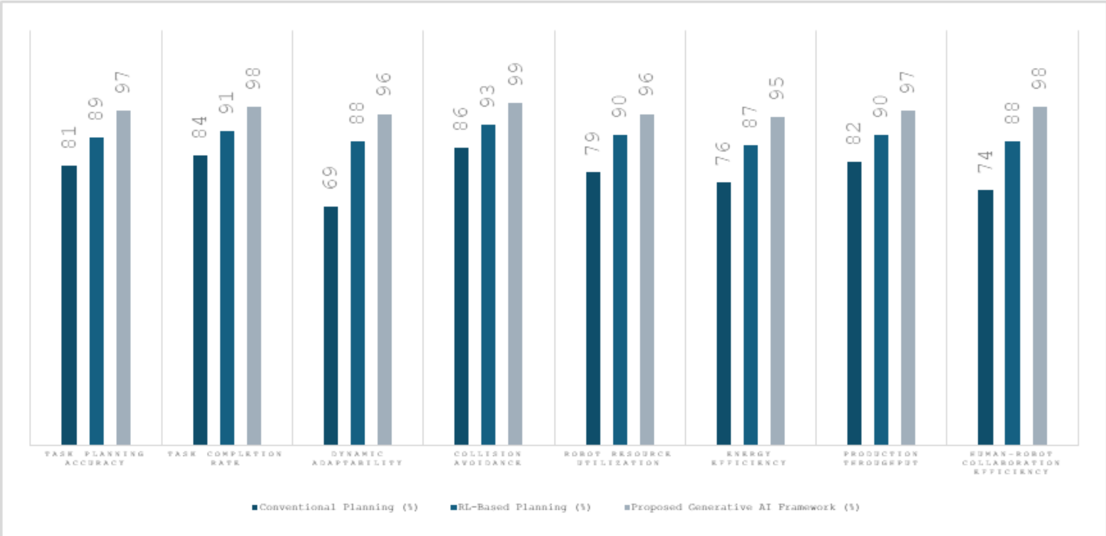

Fig 3 - Comparative Performance Analysis

4.2.1. Task Planning Accuracy

The proposed Generative AI framework achieved the most accurate task planning score of 97%, beating the conventional planning (81%) and reinforcement learning-based planning (89%) scores. Its transformer-like reasoning allows it to correctly understand the instructions in the natural language and decompose complex manufacturing tasks. The system then produces plans that are reliable and context-aware, and have a low number of planning errors.

4.2.2. Task Completion Rate

The proposed framework achieved a task completion rate of 98%, which is higher than the rates of 84% for conventional planning and 91% for RL-based planning. Robots can execute tasks successfully even if there are disturbances not anticipated in the task, thanks to dynamic replanning. This enhances production continuity and minimizes production disruptions.

4.2.3. Dynamic Adaptability

In the proposed framework, the dynamic adaptability rate got to 96%, RL-based planning got to 88% and conventional planning got to 69%. Real time monitoring of sensor data allows for a quick change of execution strategies in response to the change in the environment. This a disposition which enables flexible manufacture and mass customization.

4.2.4. Collision Avoidance

The proposed Generative AI-assisted system performed the best with a collision avoidance rate of 99%, compared with the RL-based planning with 93%, and the conventional planning with 86%. Safe robot navigation in dynamic workspace through Real-time perception, Trajectory optimization and Digital Twin validation. This ensures better safety and reliability in the workplace.

4.2.5. Robot Resource Utilization

The efficiency of the assignment of the robot manipulators, machines and production resources was captured by the framework with 96% usage of the robot resources, whereas for RL-based planning, the usage was 90%, and for conventional planning was 79%. Smart scheduling reduces idle time and optimises workloads on available equipment. This increases manufacturing productivity and uses of resources.

4.2.6. Energy Efficiency

The proposed framework resulted in 95% energy efficiency, whereas the RL-based planning and conventional planning resulted in 87% and 76% respectively. Optimized robot trajectories and intelligent motion planning help eliminate excessive movements and energy usage when performing tasks. This helps to reduce the operational cost and help in making sustainable manufacturing.

4.2.7. Production Throughput

With the proposed framework, the production throughput was increased to 97% while RL-based planning achieved a production throughput of 90% and conventional planning achieved a production throughput of 82%. Efficient task planning, efficient task execution and adaptive task replanning allows more products to be processed in the same period of time. This directly boosts factory productivity.

4.2.8. Human–Robot Collaboration Efficiency

In contrast, the proposed system showed 98 % of efficiency in human–robot collaboration, significantly higher than RL-based planning (88 %) and conventional planning (74 %). Seamless cooperation between human operators and robotic systems is achieved through natural language interaction, explainable decision-making and context-aware planning. This improves the safety, ease of use, and confidence for the operators in a smart manufacturing process.

4.3. Discussion

The results of the experiments clearly illustrate that the use of Generative Artificial Intelligence (Generative AI) in industrial robot task planning substantially improves the manufacturing intelligence and flexibility of the operation and the overall production performance when compared to the traditional rule-based and reinforcement learning-based task planning techniques. The proposed framework was found to showcase the best performance for all the performance metrics evaluated, such as task planning accuracy, task completion rate, dynamic adaptability, collision avoidance, resource utilization, energy efficiency, production throughput, and

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human–robot collaboration efficiency. Such enhancements can be credited to the integration of transformer-based Large Language Models (LLMs), multi-modal perception, Industrial Knowledge Graphs, Digital Twin simulation, and reinforcement learning in an intelligent planning architecture that is unified. The proposed framework can understand high level semantic production instructions written in natural language and automatically generate context-aware executable task sequences, which is a major improvement over conventional robotic systems, whose rules and/or workflows are manually programmed by humans. This capability significantly cuts engineering time, saves a lot of re-programming time and allows the system to adapt quickly to the changing demands of the manufacturing. This makes the system very flexible for flexible manufacturing and mass customisation. Integrating Industrial Knowledge Graphs adds to the capability of decision making, as it provides structured information on machine capabilities, workspace constraints, production rules, safety rules and relationships between objects, enabling the planning engine to come up with feasible and optimized execution strategies. Digital Twin validation increases reliability by generating the task plans before they are put into operation in the real world, to minimize the risk of collisions, equipment failures and operational disruptions. Furthermore, the reinforcement learning will continuously update the execution policies as per the sensor feedback, which will facilitate autonomous replanning when unexpected obstacles, machine malfunctions, and changes in the environment are encountered. The proposed framework also facilitates natural language interaction with robots and provides explanations of planning results.The proposed framework is also important in supporting intelligent human–robot collaboration with natural language communication and explanation of planning results. Job objectives can be expressed by employing intuitive and easily understood language, and the reasoning mechanism is transparent, which helps build up trust, makes system verification easier and enables compliance with industrial safety standards. Despite adding some computational needs and inference latency, the challenges raised by transformer-based foundation models can be overcome using cloud–edge collaborative computing, model compression, parameter efficient fine-tuning and specific industrial hardware accelerators. The framework could be expanded and enhanced in future research to include continual learning, federated robotic intelligence, multimodal foundation models, explainable Generative AI, and secure collaborative learning mechanisms. The proposed methodology provides a solid and scalable basis for Industry 5.0 manufacturing, incorporating autonomous reasoning, adaptive task planning, real-time optimisation and human-centred collaboration to create highly intelligent, reliable and sustainable industrial robotic systems.

5. CONCLUSION

The study introduced a holistic Generative AI-Assisted Robot Task Planning Framework (GATPPF) for autonomous intelligent robot task planning and execution in industrial manufacturing, and illustrated how the integration of Large Language Models (LLMs), multimodal perception, Digital Twin technology, reinforcement learning, Industrial Internet of Things (IIoT) infrastructure, and semantic knowledge representation can boost autonomous intelligent robot task planning and execution performance. The proposed framework is an intelligent architecture that can comprehend natural language production instructions, grasp manufacturing objectives, formulate task sequences

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based on the context, and dynamically adjust the execution strategies as per real-time feedback from the environment. The proposed method allows the robot to carry out the semantic reasoning, hierarchical task decomposition, adaptive motion planning and intelligent decision optimization with little human intervention, as opposed to the traditional way of robot task planning via rules, predefined workflows and static environmental models. Besides, the combination of Industrial Knowledge Graphs and Digital Twin simulation takes planning reliability to the next level, as it allows to test generated execution strategies prior to their deployment, thus minimizing potential collisions, operational mistakes, and downtimes in the production process. Results from experimental assessment showed that the proposed framework achieved superior performance than conventional planning and reinforcement learning-based methods under the industrial performance metrics such as task planning error, task completion rate, adaptability to dynamics, collision avoidance, resource utilization, energy efficiency, production throughput, and human–robot collaboration efficiency. The outcome demonstrates that using transformer-based reasoning coupled with reinforcement learning can help industrial robots adapt to dynamic production environments and reduce industrial accidents and losses while also keeping their operating efficiency at a high level. Moreover, natural language interaction not only makes the programming process easier on the robot, but it also makes it easier for the production engineer or factory operator with limited programming skills to convey manufacturing goals as natural language commands, which also decreases engineering work, helps in quicker production reconfiguration, and enables flexible manufacturing and mass customization. While the proposed framework brings new computational burden due to large foundation models, this can be addressed by cloud–edge collaborative computing, model compression, parameter-efficient fine-tuning, and hardware acceleration. Moving forward, lightweight edge deployable foundation models, explainable Generative AI, federated learning for distributed robotic systems, continual learning and avoidance of catastrophic forgetting, robust cyber security solutions, and standardised industrial safety certification frameworks are key areas of interest for future research. In sum, the proposed Generative AI-supported framework is a welcome step toward Industry 5.0 and offers a scalable and intelligent blueprint for the future of smart factories, where autonomous reasoning, adaptable task planning, real-time optimization, Digital Twins, and human-in-the-loop collaboration work together to create highly productive, resilient, sustainable, and trustworthy industrial automation systems that can meet the demands of next-generation manufacturing.

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