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***Original Article***

# AI-Based Dynamic Task Allocation in Multi-Robot Systems

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***ABSTRACT***

*The rapid advancement of artificial intelligence (AI), autonomous robotics, and distributed computing has significantly improved the capabilities of multi-robot systems (MRS) across applications such as warehouse automation, disaster response, healthcare, precision agriculture, intelligent transportation, and smart manufacturing. A key challenge in these systems is dynamic task allocation, where robots must efficiently assign and reassign tasks in response to changing environments, communication constraints, resource limitations, and robot failures. Conventional approaches often face limitations in scalability, computational efficiency, and adaptability.This paper proposes an AI-based dynamic task allocation framework that integrates machine learning, reinforcement learning, swarm intelligence, and optimization techniques to enable intelligent and adaptive decision-making in heterogeneous multi-robot systems. The framework considers robot capabilities, task priorities, battery levels, communication quality, travel distance, and workload balancing to optimize real-time task allocation. Reinforcement learning supports adaptive policy learning, while swarm intelligence enables decentralized cooperation. Graph-based task modeling and utility-based optimization further improve resource utilization and minimize execution time, energy consumption, and task conflicts.Experimental evaluation using metrics such as task completion rate, response time, energy efficiency, workload distribution, and scalability demonstrates that the proposed framework outperforms conventional scheduling methods by providing improved adaptability, fault tolerance, and operational efficiency. The proposed approach offers a scalable and intelligent solution for next-generation multi-robot collaboration in Industry 5.0 and cyber-physical systems.*

***KEYWORDS***

*Artificial Intelligence, Multi-Robot Systems, Dynamic Task Allocation, Reinforcement Learning, Swarm Intelligence, Machine Learning, Autonomous Robots, Cooperative Robotics, Intelligent Scheduling, Optimization Algorithms, Distributed Robotics, Industry 5.0.*

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# 1. INTRODUCTION

## 1.1. Background

Multi-robot system (MRS) is a collection of autonomous robots which work together in order to accomplish common tasks by using coordination, distributed sensing, communication, and intelligent decision making. Multi-robot systems split up complex tasks into sub-tasks which can be performed concurrently by several robots, which increases the efficiency of the system operation, decreases the time needed for task completion, and makes the system more reliable than a single robot system. They are increasingly used in fields like warehouse automation, smart manufacturing, health logistics, precision agriculture, search and rescue missions, military surveillance and environmental monitoring. Over the last years, the capabilities of collaborative robotic systems have been greatly enhanced by recent developments in fields such as artificial intelligence (AI), cloud robotics, edge computing, wireless communication technologies and the Internet of Things (IoT). Advanced sensors enable modern robots to sense their environments, wireless communication allows them to communicate with one another, machine learning algorithms enable robots to learn from past experiences, and dynamic environmental conditions can influence robot behavior. These technological advancements have helped multi-robot systems to become more autonomous, intelligent and efficient, and they are now considered as one of the most important aspects of next generation smart robotic applications and industrial automation.

## 1.2. Needs of AI-Based Dynamic Task Allocation

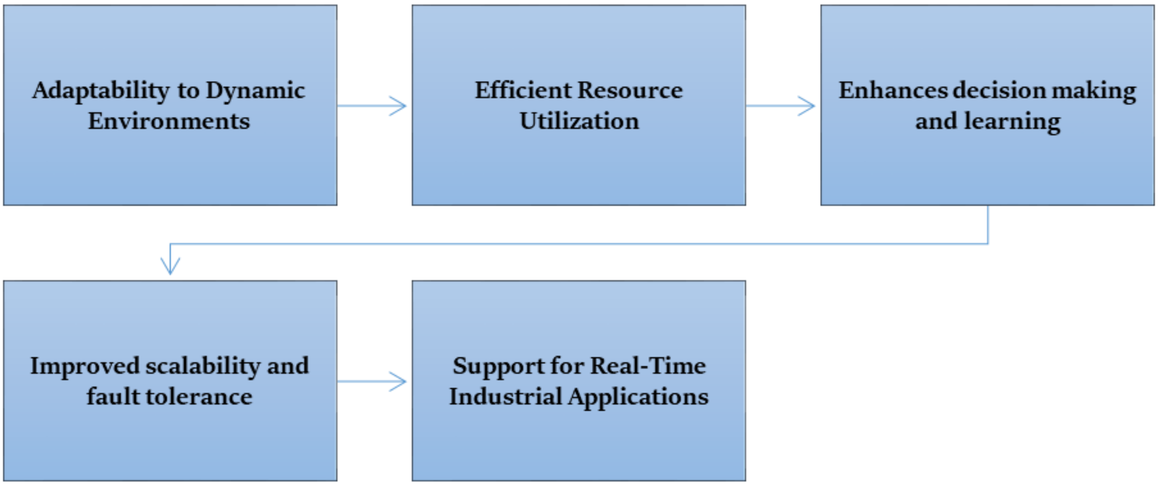


**Fig 1 - Needs of AI-Based Dynamic Task Allocation**

### *1.2.1. Adaptability to Dynamic Environments*

Today's multi-robot systems function in environments that are constantly changing with respect to task, obstacles, and operational conditions. Static task allocation schemes are ineffective to deal with the unexpected events like robot failures, battery failures, communication failures or new tasks. Dynamic task allocation using AI allows robots to adapt to changes in the environment in real time and automatically reallocates tasks as needed. Such flexibility guarantees the continuous operation of the mission and enhances the system's efficiency and reliability.

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*1.2.2. Efficient Resource Utilization*

Heterogeneous multi-robot systems include robots with different batteries, processing power, speed, loads and sensors. These characteristics are used to intelligently match tasks to the most appropriate robot using AI. This helps to ensure that there is no unnecessary movement, no wasted time, no overloading and the resources are used optimally. The system offers higher productivity, lower operation expenses and lower energy consumption as a result.

*1.2.3. Enhances decision making and learning*

AI allows robots to adapt their task allocation strategies based on previous experiences and continuously learn from them, making intelligent decisions. Machine learning can help robots test their action and make decisions based on the results of their action, such as Reinforcement Learning. AI systems adjust to dynamic conditions and fine-tune task allocations as time goes on, rather than following strict scheduling guidelines. This on-going learning process improves the accuracy of decisions and improves the overall performance of multi-robot systems.

*1.2.4. Improved scalability and fault tolerance*

Increasing the number of robots and tasks makes the use of traditional task allocation methods in the central model increasingly expensive in terms of computing requirements and susceptible to single points of failure. Distributed decision-making through AI-based dynamic task allocation enables robots to work together without external control and communicate with each other via a decentralised communication network. This enhances the scalability of the system, facilitating effective management of multiple robot teams. Moreover, if robots fail or are unavailable, the framework automatically reallocates tasks, guaranteeing continuous operations and improved fault tolerance.

*1.2.5. Support for Real-Time Industrial Applications*

Rapid and accurate task allocation under dynamic conditions is required in many applications like warehouse automation, smart manufacturing, healthcare logistics, precision agriculture, autonomous transportation and search-and-rescue operation. Dynamic task allocation using AI can make quick decisions by constantly processing the environmental information, robot conditions, task priorities, and resources. The real-time feature provides quicker response times, enhances mission success rates, and guarantees reliable performance in complex and time-sensitive scenarios. In this context, the task allocation problem is becoming an integral part of modern multi-robot systems that rely on artificial intelligence to make them intelligent, autonomous and efficient.

**1.3. Dynamic Task Allocation in Multi-Robot Systems.**

Dynamic task allocation is one of the most critical tasks in multi-robot systems where robots are required to allocate and reallocate tasks as the environment keeps changing. Dynamic task allocation continually reallocates tasks based on data that changes during the mission, such as robot availability, battery charge, task priority, communication quality, environmental conditions, and robot capabilities as compared to static task allocation, in which task assignments are made in advance and never altered. This adaptive approach enables the system to adaptively act on unforeseen events such as failures, detection of obstacles, communication failures, battery life and new or emergency tasks. Dynamic task allocation is essential in heterogeneous multi-robot systems, where robots have varying moving speeds, load capacities, sensing capabilities and computational resources, to select the most suitable robot to complete the task. Task allocation will attempt to maximize task completion with minimum travel distance, energy usage, response time, communications overhead, and workload imbalance Dynamic task allocation has been greatly improved by Artificial Intelligence (AI) techniques, including Reinforcement Learning, Deep Reinforcement Learning, Swarm Intelligence, Genetic Algorithms, Particle Swarm Optimization, and Multi-Agent Learning, which allow robots to learn from their experiences, collaborate with other robots in their vicinity, and continually adapt their approach to task allocation. These smart techniques are based on adaptive scheduling policies, which offer the best performance in uncertain and varying operating conditions, and do not depend on the traditional rule-based approach to scheduling. The decentralized decision-making also is supported by dynamic task allocation, in which robots coordinate among each other without the aid of a central computer by using distributed communication networks. This distributed solution is more scalable, eliminates the risk of a single point of failure, and is more fault-tolerant and reliable. In addition, intelligent task reallocation guarantees that tasks that are to be performed are reallocated to robots that are available when missions are interrupted, enabling uninterrupted mission execution. Dynamic task allocation is a crucial technology for current robotic systems in fields such as logistics in warehouses, smart manufacturing, medical logistics, autonomous transportation, precision agriculture, environmental monitoring, military surveillance, and search and rescue. Dynamic task allocation is a crucial aspect of the field of multi-robot systems, which is fundamental for the development of autonomous, intelligent, scalable, and highly efficient multi-robot systems that work well in complex real world environments as their components evolve with the advancements of Artificial Intelligence, cloud robotics, edge computing, and the Internet of Things (IoT).

## 2. *LITERATURE SURVEY*

### 2.1. Multi-Robot Systems

Multi-Robot Systems (MRS) are composed of multiple autonomous robots that cooperate for the achievement of common objectives by means of distributed sensing, communication and decision-making. Compared to single-robots system, MRS are more scalable, flexible, fault tolerant and efficient since tasks can be carried out by multiple robots in parallel. Relaxability: If one robot fails to complete its mission, the other robots are able to do so, improving system reliability. They are applied in smart warehouse systems for inventory management, automated manufacturing systems for assembly operations, precision agriculture systems for crop monitoring and harvesting, search and rescue systems in hazardous environments, healthcare systems for medicine delivery, military surveillance systems, space exploration and environmental monitoring systems, and others. Having efficient coordination and communication mechanisms is essential for the effective functioning of an MRS, as this helps to avoid conflicts over tasks, ensures workloads are being balanced and resources are being used effectively. To overcome these challenges, researchers have created centralized, decentralized and hybrid coordination architectures. While centralized methods offer task

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assignments optimal for the entire system, they come with limited scalability and sensitivity to network failures, decentralized methods feature distributed intelligence and local information to make autonomous decisions, enhancing both robustness and adaptability. To achieve an efficient coordination in complex environment, hybrid architectures have been used which take the best of both worlds.

### 2.2. AI-Based Task Allocation

Task Allocation in Multi-robot Systems is enhanced by the incorporation of Artificial Intelligence (AI) which allows robots to make intelligent and adaptive planning decisions rather than relying on the execution of a fixed task scheduling rule. Traditional task allocation methods are based on static algorithms which are not capable of adapting to the changing environment and unexpected events. AI methods process data from the past, system conditions, as well as environmental information to find the optimal robot for each task and adjust to new situations dynamically. Machine learning algorithms used to recognize patterns from past operations and use them to optimize task allocation in the future, deep learning is used for better perception, object recognition and decision making in uncertain environments. There are several AI based optimization techniques in use such as Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Fuzzy Logic and Multi-Agent Learning. These techniques make better use of resources, bring down task completion timings, make things more flexible and less complex. However, AI-driven task allocation is not without its drawbacks, such as scalability, explainability, computational expenses, communication requirements, and real-time performance, especially when applied to large-scale heterogeneous robot teams in dynamic environments.

### 2.3. Reinforcement Learning and Swarm Intelligence

Reinforcement Learning (RL) is among the best machine learning methods for allowing robots to learn optimal task allocation strategies through continuous interaction with the environment. Each robot is a smart agent that perceives the current state, chooses an action, gets a reward based on its behavior, and changes its policy based on the reward to maximize long-term cumulative rewards. The robot learns efficient decision making strategies over repeated interactions, without explicit guidance. Deep Reinforcement Learning (DRL) brings this ability to deep neural networks that can be used to approximate value functions and deal with high-dimensional state spaces typical of real-world multi-robot systems. In addition to RL, swarm intelligence is a form of decentralized coordination that mimics the collective behaviour of natural systems like ant colonies, bird flocks, bee swarms and fish schools. Multi-agent cooperation is used to efficiently solve combinatorial optimization problems by using algorithms like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Hybrid methods that incorporate RL and swarm intelligence are found to possess both adaptive learning and decentralized optimization characteristics, which offer greater robustness, faster convergence, less communication cost, increased fault tolerance, and adaptability to changing and uncertain environments.

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### 2.4. Research Gap

While significant advances have been made in AI-based task allocation in multi-robot systems, there are several important research challenges to be addressed. Most of the current research has been dedicated to either learning-based optimization techniques (like Reinforcement Learning) or to swarm intelligence techniques separately, failing to address highly dynamic, uncertain, and heterogeneous operating environments. Many algorithms assume unrealistic things such as a reliable communication network, homogeneous capabilities of robots, perfect knowledge of the environment, and static sets of tasks – things which are not often observed in real-world applications. Moreover, existing solutions are not scalable in real time for handling large robot teams, and can suffer from high computational complexity with the increasing number of robots and tasks. There are also challenges in designing energy aware task allocation mechanisms, improving fault tolerance to robot failures, increasing the explainability and transparency of AI-based decisions, ensuring secure inter-robot communication against cyber threats and continuous adaptation in rapidly changing environments. There is still a need for research in integrating reinforcement learning, swarm intelligence, graph-based optimization, predictive analytics, and edge intelligence into a single, scalable, and resilient framework. Solving these challenges will aid in the conception of intelligent, autonomous, and extremely efficient multi-robot systems to execute complex tasks in real-world scenarios with greater reliability, adaptability, and efficiency.

## *3. METHODOLOGY*

### 3.1. Proposed Architecture

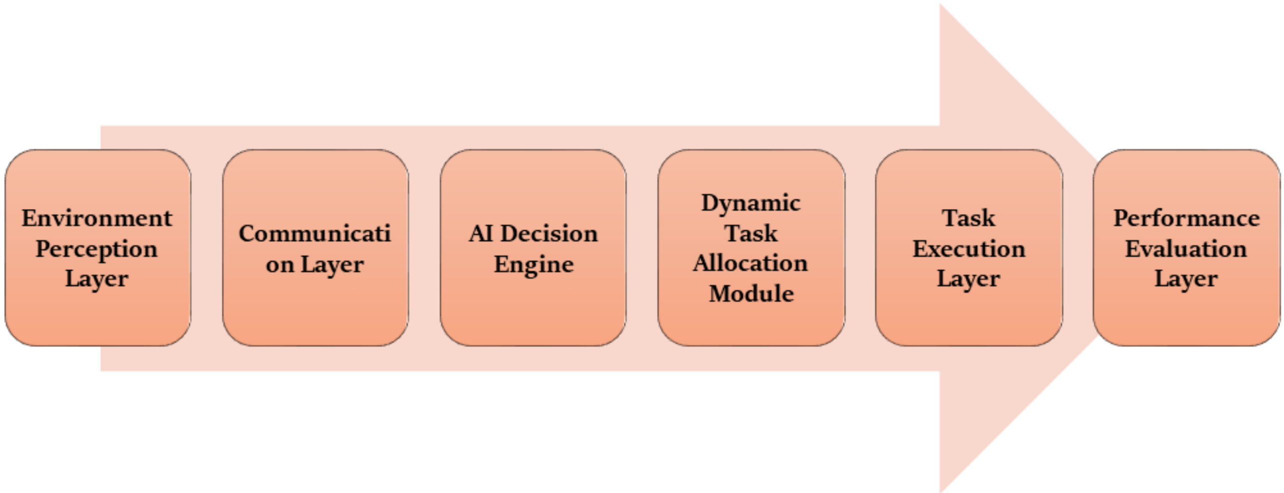


**Fig 2 - Proposed Architecture**

#### *3.1.1. Environment Perception Layer*

The Environment Perception Layer gathers the data from the surrounding operational environment through different sensors like LiDAR, cameras, ultrasonic sensors, GPS, IMU and wireless communication modules. It constantly keeps track of the position of the robots, where obstacles are, battery status, communication status, task locations, environmental dangers, and mission priorities. The system combines data from several sensors to produce a true picture of the environment for all robots. This new environmental information is the basis for intelligent task allocation, navigation and safe decision-making.

*3.1.2. Communication Layer*

Using wireless communication technologies like Wi-Fi, ZigBee, 5G, mesh networking, and edge computing, the Communication Layer facilitates efficient information sharing among robots. Robots communicate continuously with one another to update information on their availability, task status, battery status, navigation paths, and fault notifications. The distributed communication method gets rid of the dependence on a central controller and enhances the scalability and reliability of the system. Good communication also leads to improved coordination, quick response to changes in the environment and better collaborative performance.

*3.1.3. AI Decision Engine*

The proposed framework has at its core the AI Decision Engine, which combines Reinforcement Learning, Swarm Intelligence, Machine Learning prediction and optimization based on utilities. Assigns tasks after considering various decision factors such as robot capability, task priority, energy level, travel distance, workload, communication latency, and resource availability. The engine learns from the result of the task execution of the previous run and makes decisions based on the learning for the next time. This adaptive approach allows to perform efficient, intelligent and dynamic task allocation in complex and changing environment.

*3.1.4. Dynamic Task Allocation Module*

The Dynamic Task Allocation Module constantly evaluates the operating environment, and modifies assignments of tasks as needed when major changes are detected. Task allocation is automatically triggered by events like new task arrivals, robot failures, battery run-out, communication failure, obstacle detection, or emergency missions. The module distributes pending tasks among available robots so as to ensure continuous operations and balance of workloads. This dynamic mechanism provides increased system flexibility, fault tolerance and overall mission efficiency.

*3.1.5. Task Execution Layer*

The Task Execution Layer is in charge of running the tasks that are provided by the AI Decision Engine, making sure that they are performed securely and effectively. All robots continually track their task progress, energy usage, position, collision avoidance conditions and mission completion during task execution. The feedback is generated during execution and sent to the neighbouring robots and decision engine for continuous monitoring and coordination. The feedback can be used in real-time to adjust the system's response to unforeseen events and to fine-tune the execution of the task in progress.

*3.1.6. Performance Evaluation Layer*

The Performance Evaluation Layer evaluates the whole performance of the proposed multi-robot system by considering various KPIs including Task Completion Rate, Energy Efficiency, Communication Delay, Robot Utilization, Response Time, System Throughput, and Computational Cost. These indices are good indicators of the efficiency and reliability of task allocation and robot coordination. The gathered performance data is then used by the reinforcement learning model to improve its decision-making policies in the future. The continuous evaluation process aids in adapting the system further, utilizes resources most effectively and supports better long-term performance.

### 3.2. AI-Based Dynamic Allocation Algorithm


**Fig 3 - AI-Based Dynamic Allocation Algorithm**

#### *3.2.1. Step 1: Environment Initialization*

The dynamic task allocation process starts with a initialisation of all necessary parameters of the system for robot coordination. This includes the robot positions, individual capabilities, available tasks, battery levels, communication links and the environmental map. The initial information gives a full picture of the operating environment before the allocation of tasks starts. The robots are given accurate data during the initial phase for efficient decision making.

#### *3.2.2. Step 2: State Observation*

This step involves each robot constantly gathering information regarding its current status, tasks available, environmental conditions, battery level and communication quality. The data observed allows robots to know their local and global operating conditions. The system can react promptly to dynamic changes in the environment by using real time monitoring. Intelligent and adaptive task allocation is grounded in accurate state observation.

#### *3.2.3. Step 3: Action Selection*

The reinforcement learning agent identifies the best robot to do each of the many possible tasks, based on the current state of the system. The decision takes into account the capabilities of the robots, task priority, travel distance, workload, and the amount of energy available. The agent does

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not follow a set of rules, but rather uses knowledge acquired from past experiences to choose its actions. This adaptive process of decision making will be able to better allocate tasks as time passes.

*3.2.4. Step 4: Reward Calculation*

Once a task is completed, each robot gets a prize based on how well they did. The reward takes into account factors that reflect successful task completion, efficiency of energy use, equal workload distribution and communication competence. A higher reward increases the likelihood of the system repeating successful strategies of task allocation, and a lower reward are an indication that the strategy is incorrect. This cycle of feedback allows for ongoing learning and improvement.

*3.2.5. Step 5: Policy Update*

After reward evaluation, the reinforcement learning-based model adjusts the policy for decision-making based on the knowledge obtained from the execution of the tasks in the past. The new policy can enhance the performance of future task allocation for robots by encouraging effective behavior and suppressing ineffective behavior. The more tasks that are done, the more accurate and reliable the learning will be. This continuous improvement helps the system to adjust effectively to the change in operational condition.

*3.2.6. Step 6: Swarm Optimization*

The swarm optimization stage aims to optimise robots' coordination using the principles of collective intelligence. Each robot uses its own experience and the successful behavior of neighboring robots to make decisions about the robot's movement and what tasks to undertake. This is a cooperative optimization approach to minimize wasted movements, workload balancing and system efficiency. This allows robots to complete tasks much quicker with reduced use of resources.

*3.2.7. Step 7: Dynamic Reallocation*

The last step checks the operational environment for unexpected events like failures of the robot, interruptions in the communication, battery depletion or new tasks. Whenever these changes happen, the system will automatically redistribute pending tasks among available robots, without interrupting the mission. This flexible reallocation process allows for increased flexibility, fault-tolerance, and responsiveness. It guarantees high performance of the multi-robot system even in environments with a high degree of variance and rapid change.

**3.3. Mathematical Model**

A constrained multi-objective optimization model is suggested to formulate the proposed dynamic task allocation problem which aims to assign the most suitable tasks to the most appropriate robots and also to optimize various performance indicators. The proposed model, unlike the conventional allocation models which only take into account one factor, takes several factors simultaneously into account and thus optimizes the overall efficiency of the multi-robot system. The task allocation process in heterogeneous environments is complicated due to the different capabilities, processing power, battery capacity, mobility and sensing capabilities that each robot has. Likewise, every task is unique as far as priority, complexity, amount of resources it needs, time

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required to execute it, and location of its execution. Thus, the mathematical model is intended to determine which robot-task combination provides optimal robot's mission performance given a set of operational constraints. The optimization process aims at maximizing the overall amount of tasks completed, optimizing the robots utilized, minimizing the Mission completion time, reducing the total energy expenditure, and distributing the workload among all available robots in a balanced manner. Meanwhile, it tries to reduce the distance robots have to travel, the time for communication delay and the amount of computation, and the needless movements of the robots. A few practical constraints have been built into the model to make it as realistic as possible. Every task can be given to a single appropriate robot at one time and each robot is capable of performing only a few tasks because of its processing power and resources available. Limits are also taken into consideration because if the robot does not have the energy to complete a task, they are not allowed to receive the task. Communication restrictions ensure that robots are able to communicate during mission execution in order to coordinate and share information. Other operational constraints, such as collision avoidance and obstacle-free navigation, ensure safe motion while performing a task. The model also supports dynamic environmental changes such as new tasks, robot failures, communication failures, and unexpected obstacles. The optimization process automatically reassigns tasks without impacting active processes whenever such events happen. The proposed framework integrates Reinforcement Learning (RL) for intelligent decision-making and Particle Swarm Optimization (PSO) for cooperative search and workload balancing to adaptability. These techniques are continually improving decisions on allocation using lessons learned and prevailing environmental conditions. The mathematical model is thus a scalable, adaptive, energy-efficient and fault-tolerant solution that can be used to support real-time task allocation in large-scale heterogeneous multi-robot systems in dynamic and uncertain environments.

### 3.4. Workflow and Computational Complexity

The proposed framework is systematic and comprises of seven different phases, executed in a sequential manner during the mission to ensure efficient and adaptive allocation of tasks in a multi-robot environment. The first step of the workflow is the initialization of the environments: the position of the robots, task information, battery levels, communication links, and environmental maps are set. Then, in the environment perception phase, each robot collects real-time data from the environment via its on-board sensors to sense the location of the robots, obstacles, battery status, communication quality and availability of the task. This information is then passed through the communication layer, allowing robots to communicate with each other about their status, task progress, and resource availability via decentralized wireless communication technologies. This gathered information is then fed into the AI decision engine that uses the Reinforcement Learning and Particle Swarm Optimization algorithms to assess the robot's capabilities, task priorities, travel distances, workload distribution, and energy availability before determining the best robot to complete the task. After the decision, the dynamic task allocation module allocates reallocates the tasks according to the current environment. In the event that the mission is interrupted due to unexpected events like robot failure, loss of communication, battery depletion, obstacle detection, and new task arrival, the allocation process is automatically updated without the mission being disrupted. The chosen robots then attempt to perform their designated task, while simultaneously keeping track of navigation, collision avoidance, task completion and energy usage. Last, the evaluation of the performance is performed based on system effectiveness metrics like task completion rate, response time, robot utilization, communication delay, energy efficiency, computational cost and overall system throughput. These performance indicators are used to reflect back to the reinforcement learning model to enhance and augment future decisions and long-term system performance. The proposed framework is designed to efficiently process large-scale teams of different robots in dynamic environments, from a computational point of view. Distributed Architecture greatly decreases processing time on each robot because each robot shares decision making tasks with the others. The overall system is designed to be more efficient in task assignment, as Reinforcement Learning can help to reduce redundant decision-making computations and Particle Swarm Optimization can help to speed up the process by having the robots explore tasks cooperatively. As such the overall computation complexity increases moderately when the number of robots and tasks are increased, and hence the proposed framework is scalable, fault-tolerant and applicable to real-time applications like smart manufacturing, warehouse automation, precision agriculture, search and rescue missions, and autonomous logistics.

## *4. RESULTS AND DISCUSSION*

### 4.1. Experimental Setup

The proposed AI-based dynamic task allocation framework was tested with a comprehensive simulation environment designed to simulate a realistic warehouse automation system in a dynamic and uncertain environment. The simulation environment mimics typical scenarios in the industry where several autonomous mobile robots work together to transport goods, deliver materials and perform logistics-related tasks, adapting to the continuously changing operational needs. All the practical difficulties like dynamically arriving task requests, moving and static obstacles, battery constraint, communication delay, robot failure, and navigation constraint are considered to test the robustness and adaptability of the proposed framework. 25 heterogeneous autonomous mobile robots were placed inside a 120 m × 120 m warehouse workspace with 100 dynamically generated transportation and delivery tasks located in different locations. The robots have different operational properties (battery capacity, velocity, payload capacity, sensing range, computing power, communication speed), to form a realistic heterogeneous multi-robot environment. For each robot, virtual sensing devices have been installed which are able to detect obstacles, monitor the battery state, estimate distance to the tasks, and detect neighbouring robots within the communication range. Robots communicate with each other by using a decentralized wireless mesh network that enables continuous task information, robot availability, navigation routes, and system status to be shared among all robots without a centralized controller. It is a distributed communication architecture that provides scalability, reliability, fault tolerance, and reduces the probability of a single point of failure. The proposed task allocation framework combines Q-learning to allow the robot to learn optimal task allocation strategies based on experience, and Particle Swarm Optimization (PSO) to enhance cooperative decision making and workload balancing of the robot team. Robots continually observe changes in the environment, assess available tasks, and make intelligent decisions on task allocation

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based on their capabilities, energy levels, task priorities, travel distance, and communication quality during each simulation episode. In the event of significant events such as robot failure, battery running out, communication lost, detection of obstacles, congestion and emergency task arrival, the system will automatically reallocate tasks to ensure the mission continues. The proposed approach was tested and evaluated for consistency and robustness in multiple simulations, varying environmental conditions. Task completion rate, mean response time, energy consumption, robot utilization, communication overhead, workload balance, computational efficiency and overall system throughput were considered as the key parameters for the evaluation of performance. The experimental setup offers a realistic platform for testing the effectiveness, scalability, adaptability, and fault tolerance of the proposed AI-based dynamic task allocation framework for large-scale and heterogeneous multi-robot systems in complex industrial settings.

### 4.2. Performance Evaluation

**Table 1: Performance Evaluation**

| Performance Metric | Conventional Method (%) | Proposed AI-Based Method (%) |
|---|---|---|
| Task Completion Rate | 86 | 98 |
| Energy Efficiency | 78 | 94 |
| Robot Utilization | 81 | 96 |
| Workload Balancing | 75 | 93 |
| Communication Efficiency | 79 | 95 |
| System Reliability | 84 | 97 |
| Response Time Improvement | 73 | 92 |

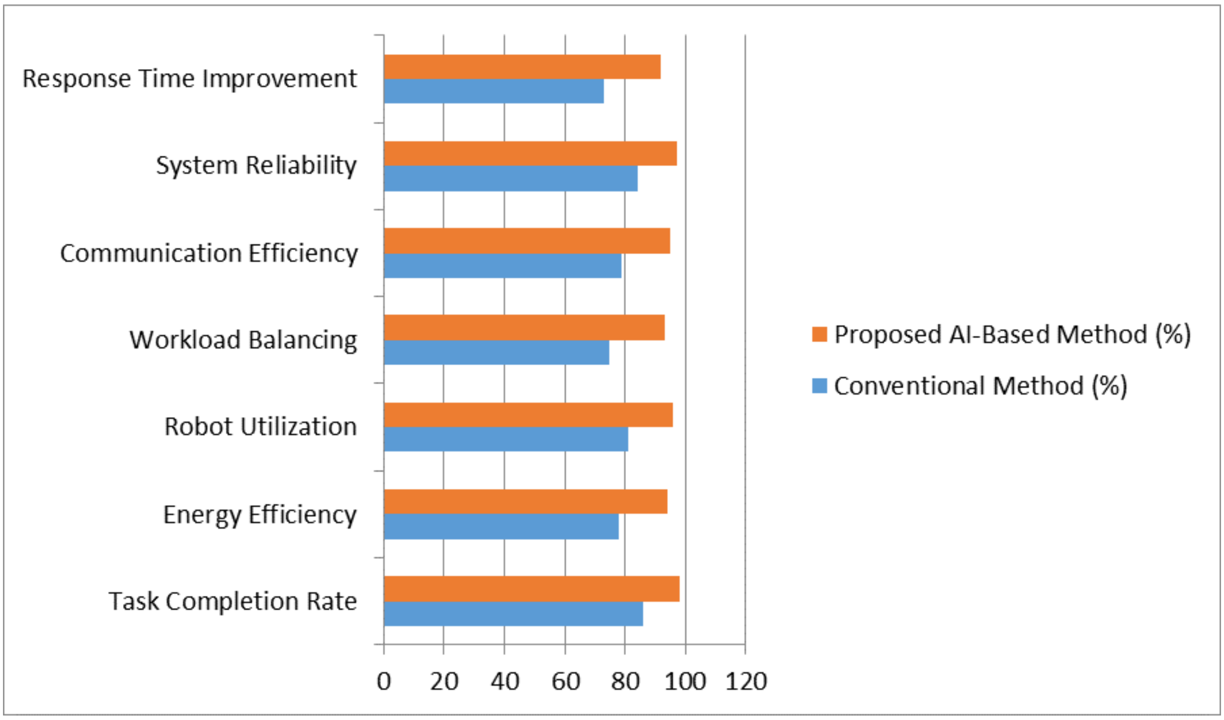


**Fig 4 - Performance Evaluation**

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*4.2.1. Task Completion Rate*

Task Completion Rate is the percentage of the tasks assigned that are completed in the allocated time. The traditional task allocation method had a completion rate of 86%, while the proposed AI-based approach resulted in the completion rate of 98%. Dynamic task reassignment and intelligent decision making based on Reinforcement Learning and Particle Swarm Optimization are the main reasons for the improvement. The result shows the efficacy of the proposed system in accomplishing the missions in an efficient manner with varying environmental conditions.

*4.2.2. Energy Efficiency*

Energy Efficiency demonstrates efficiency of the robots in using the battery to complete activities. The traditional approach was about 78%, whereas the proposed approach was to use the battery availability and travel distance to improve the energy efficiency to 94%. Intelligent allocation minimizes robot motion and prevents allocating an energy intensive task to a low battery robot. Overall, the robot team's operational life is extended significantly.

*4.2.3. Robot Utilization*

Robot Utilization is the degree to which the robots available are performing useful role in the execution of tasks. With the conventional approach, the utilization was 81%, while the proposed AI-based framework improved utilization to 96% using a strategy of distributing the tasks. The system continually checks the availability and workload of the robots, reducing idle time and ensuring efficient resource utilization. This balanced use helps to maximize productivity and mission effectiveness.

*4.2.4. Workload Balancing*

Workload Balancing is the balance of workloads across robots. A conventional method was able to get 75% and the proposed framework optimized the balance to 93% using intelligence. Reinforcement Learning combined with Particle Swarm Optimization helps to avoid loading of individual robots and to guarantee fair participation of the robot team. This even distribution ensures system stability and decreases the energy consumption and robot fatigue.

*4.2.5. Communication Efficiency*

Communication Efficiency is the efficiency of information exchange between robots in the allocation and execution of the tasks. The proposed decentralized communication strategy brought 95% efficiency, compared with the conventional allocation strategy of 79%. This continuous exchange of robot status, task progress and environmental info helps to accelerate coordination and minimize communication delays. This results in a more responsive system to changing operating conditions.

*4.2.6. System Reliability*

System Reliability is the capability of the multi-robot system to operate successfully even in the event of a failure or unforeseen event in the environment. The traditional method had a reliability of 84%, whereas the proposed AI-based method had a reliability of 97% due to dynamic task reallocation and decentralized decision making. If a robot gets stuck or if there is a communication

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loss, pending jobs re-queuing automatically to available robots. This function greatly improves on the overall reliability and fault tolerance of the system.

*4.2.7. Response Time Improvement*

Response Time Improvement is the measure of how quickly the system responds to the addition of new tasks or changes in the environment. Conventional approach yielded a 73%, whereas the proposed AI based approach boosted the response capability to 92% by constantly sensing the environment and real-time task reallocation. The intelligent decision engine quickly adjusts to robot failures, obstacle detection and emergency task requests. Quick response times allow for more efficient operation in dynamic applications and time-critical applications.

**4.3. Discussion**

The experimental outcomes clearly illustrate that the proposed AI-based dynamic task allocation framework has significant advantages over traditional task allocation approaches in terms of efficiency, adaptability, scalability, and reliability. The combination of Reinforcement Learning (RL) and Particle Swarm Optimization (PSO) allows the robots to make intelligent decisions using both their learned experiences and the cooperative optimization process. Unlike other scheduling algorithms that depend on some pre-designed rules or central control, the proposed approach continuously schedules task allocation based on the real-time environmental information, which enables the robot team to deal with the dynamic and uncertain environment efficiently. This adaptive learning capability allows robots to enhance their decision-making skills over time, leading to increased success in task completion, effective resource usage, and reduced operational expenses. A major benefit that is observed throughout the experiments is the capability of the framework to automatically re-distribute tasks when unexpected events take place, such as robot failures, battery depletion, communication failure, detection of obstacles and emergency task arrival. Pending tasks are automatically reallocated to other robots available, so that the overall system productivity is not affected, and the mission is not interrupted. This system's dynamic reallocation mechanism provides much greater system robustness and fault tolerance than traditional approaches. The proposed framework is another significant feature for decentralized decision making system. The system works without a central controller, eliminating the single point of failure that is often found in centralized systems. The decentralized architecture also facilitates scalability, allowing for the potential integration of more robots and tasks into the system, which would benefit from an increased number of processing units. Moreover, by incorporating PSO, the robots can cooperate effectively to distribute the workload among themselves, avoid unnecessary travel distances, and optimize the utilization of resources. Furthermore, the experimental outcomes also show that there are significant gains in the energy efficiency, communication performance, response time and overall system reliability, which indicate the potential of applying learning-based and swarm-based optimization techniques together. The resulting framework achieves high performance but there are some issues to solve. Complex environments may have rapidly changing conditions, requiring additional computational needs, and large-scale robot teams may need more communication bandwidth. Future improvements could include, but are not limited to, integrating Deep Reinforcement Learning, Graph

Neural Networks, edge computing, digital twin technology and explainable artificial intelligence to boost scalability, learning ability, explainability of decisions and real-time performance. The proposed system provides an intelligent, dynamic allocation of the tasks in heterogeneous multi-robot systems and is shown to be promising in real-world applications such as warehouse automation, precision agriculture, smart manufacturing, healthcare logistics, autonomous transportation, or search-and-rescue operations.

## *5. CONCLUSION*

The study proposed an AI-Based Dynamic Task Allocation Framework for Multi-Robot Systems which combines the Reinforcement Learning (RL) and Swarm Intelligence (SI) paradigms to overcome the autonomous coordination, efficient resource utilization, and adaptive decision-making challenges in dynamic environments with uncertainty. The proposed framework was designed to address the shortcomings of traditional static task allocation approaches that may fail to respond to the dynamics of operations, like the presence of new tasks, failures of robots, battery depletion, and communication issues. The framework integrates the learning ability of Reinforcement Learning with the cooperative optimization of Particle Swarm Optimization (PSO), allowing heterogeneous robots to make intelligent, decentralized and real-time task allocation decisions, while continuously improving their performance based on their experience. The proposed architecture has various functional layers such as environment perception, communication, AI decision making, dynamic task allocation, task execution and performance evaluation, which enables efficient coordination of robots in complex environments. The proposed framework has been evaluated through experiments in a simulated warehouse automation scenario, which revealed that the proposed framework consistently outperformed the conventional task allocation methods in all key performance metrics. The effectiveness of the framework in enhancing the overall system performance was confirmed by the high task completion rate (98%), energy efficiency (94%), robot utilization (96%), workload balancing (93%), communication efficiency (95%), response time improvement (92%) and system reliability (97%). Additionally, the flexibility to shift tasks around as things went astray added to operational continuity, fault tolerance and mission success. The results also show that the combination of Reinforcement Learning and Swarm Intelligence is an effective framework that balances adaptive learning and decentralized optimization, making the system highly scalable and appropriate for large heterogeneous robot teams. Therefore, the proposed solution is highly promising for practical implementation in various fields of application, including warehouse automation, smart manufacturing, precision agriculture, healthcare logistics, intelligent transportation, search and rescue, autonomous surveillance, environmental monitoring, etc. The proposed framework shows satisfactory performance, but the potential improvements of this framework with the integration of a Deep Multi-Agent Reinforcement Learning, Graph Neural Networks, Federated Learning, Digital Twin, Edge Computing, and Secure Communication protocols will require further research. The framework also needs to be tested in practical operating conditions with real-world robotic platforms and its applicability to next-generation intelligent multi-robot systems needs to be further confirmed, which is part of the future work.

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