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TASK ALLOCATION PROBLEM IN MULTI ROBOT SYSTEMS

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Abstract
The venture allocation hassle in multi-robotic structures specializes in optimally assigning tasks to robots to attain an objective, together with minimizing finishing touch time or maximizing energy performance. This paintings addresses the demanding situations of big-scale multi-robotic project allocation via introducing a reinforcement studying-based approach with a singular Markov decision technique components. The method leverages a pass-attention mechanism to prioritize robotic-assignment preferences and effectively handles electricity constraints in power-harvesting robot clusters. Three algorithms are proposed: Classical MRTA, Task-aware MRTA, and EH and Task-conscious MRTA. Experimental consequences exhibit that the EH and Task-conscious MRTA technique considerably outperforms others, maintaining up to a hundred% greater energy than the Classical MRTA and 20% greater than the Task-aware MRTA, especially beneath varying energy-harvesting eventualities.

Keywords : Multi-robotic project allocation, reinforcement mastering, power harvesting, Markov decision procedure, go-interest mechanism, assignment scheduling, power-conscious systems, robot clusters.

I. INTRODUCTION

The undertaking undertaking problem in multi-robot structures (MRTA) involves distributing tasks among robots to obtain goals together with minimizing time, enhancing performance, or optimizing energy use. With robots increasingly more hired in sectors like manufacturing, surveillance, and logistics, powerful venture venture is critical. Traditional methods warfare with scalability and adaptability, especially in dynamic or unpredictable environments. As robot structures become extra complex, progressive strategies are required to manipulate them correctly. Recent improvements in device getting to know, specifically reinforcement learning (RL), present promising answers.

1. Multi-Robot Systems and Their Applications

Multi-robot structures are pivotal in automating large-scale and excessive-threat operations at some point of numerous domains. These structures are deployed for responsibilities together with are searching out and rescue missions, warehouse automation, environmental tracking, and military reconnaissance. Collaborative robotic companies can acquire ordinary performance and reliability in situations in which unmarried robots fall quick. For example, in disaster reaction, multiple robots can simultaneously perform reconnaissance, particles clearing, and sufferer assistance. Similarly, self sufficient drones can collaboratively survey big regions effectively. These numerous packages underline the need for effective project allocation strategies to maximize system stylish average universal performance.

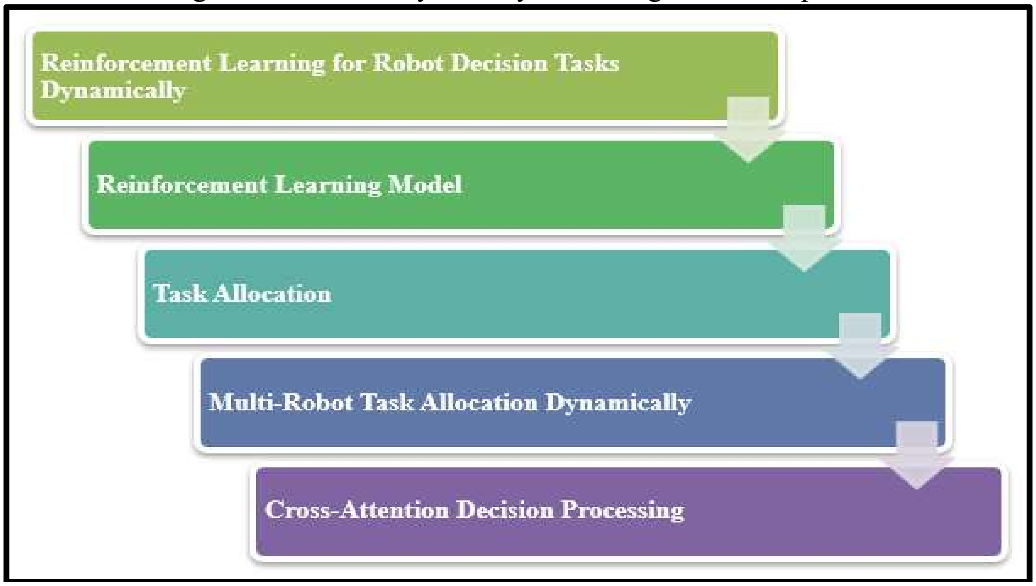

Figure 1, Multi-Robot Systems and Their Applications

2. The Challenges of Multi-Robot Task Allocation

Allocating responsibilities to robots in multi-robot systems is an NP-hard problem due to the exponential growth in challenge possibilities. This complexity is compounded via factors like challenge dependencies, energy constraints, and real-time operational requirements. Additionally, dynamic environments with unpredictable variables make static allocation techniques insufficient. Achieving great average performance requires addressing competing desires, which embody minimizing time at the same time as holding electricity. Scalability stays a prime problem, as modern-day algorithms falter at the same time as coping with huge robot networks. Developing strategies that adapt to converting situations on the identical time as making sure computational general normal performance is important for contemporary-day programs.

3. Classical Approaches to MRTA

Classical MRTA methods embody techniques like integer-linear programming, public sale-based totally absolutely algorithms, and graph-based absolutely strategies. These strategies were effective for solving small-scale allocation issues in managed environments. Integer-linear programming gives specific solutions however is computationally big for huge structures. Auction-based totally clearly algorithms offer faster answers however may additionally sacrifice optimality. Graph-primarily based techniques are suitable for spatial undertaking allocation but war with dynamic assignment requirements. While those techniques laid the basis for MRTA, they lack the electricity to address the growing complexity and scale of present day multi-robotic systems.

4. Reinforcement Learning in MRTA

Reinforcement learning (RL) affords an adaptive framework for fixing MRTA troubles via getting to know premier regulations thru environment interaction. Unlike supervised mastering, RL does not depend upon labeled records, making it greater applicable to dynamic, real-world scenarios. RL-primarily based techniques have proven fulfillment in combinatorial optimization issues like the TSP and vehicle routing hassle (VRP). These methods research from exploration and modify strategies based totally on environmental comments. By incorporating multi-agent RL strategies, MRTA systems can dynamically allocate responsibilities in actual-time even as adapting to aid constraints and undertaking variability.

5. Proposed RL-Based MRTA Framework

This paintings introduces an RL-primarily based framework for MRTA, addressing the demanding situations of multi-robotic and multi-project scenarios. The problem is modeled as a Markov Decision Process (MDP) to permit powerful coverage studying. A dot-product go-interest mechanism courses the allocation system, emphasizing the importance of particular responsibilities to robots. The framework is optimized the usage of a coverage gradient technique with a greedy baseline, making sure sample performance. By integrating those additives, the proposed approach achieves scalability and interpretability, making it suitable for complicated, large-scale allocation issues.

6. Experimental Results and Contributions

The proposed RL-based MRTA technique become evaluated in various mission allocation scenarios, demonstrating superior overall performance over conventional meta-heuristic baselines. It efficiently minimized total venture final touch time and treated scalability in massive robot networks. Additionally, the eye mechanism provided interpretability through highlighting venture priorities. Key contributions include an MDP-primarily based allocation set of rules and an RL version structure tailored for complex MRTA problems. This work establishes a robust, green, and scalable method to multi-robot project allocation, paving the way for superior packages in dynamic environments.

II. LITERATURE REVIEW

1. Centralized Approaches for MRTA

Centralized techniques for MRTA, which incorporates the Hungarian set of guidelines, offer gold trendy answers for easy project allocation issues. These strategies assume a unmarried controller that possesses international know-how of the system and might allocate duties to robots efficaciously. However, centralized strategies face limitations in scalability and adaptableness, particularly in dynamic environments. For instance, they exhibit sluggish responses to sudden activities, along with robot screw ups or challenge interruptions. Despite their drawbacks, centralized solutions offer a foundational framework for know-how assignment allocation issues and are nonetheless relevant for small-scale systems.

2. Auction-Based and Market-Based Approaches

Auction-based totally completely absolutely methods have acquired reputation for his or her allotted and flexible nature in MRTA. Robots bid for duties based completely totally on software program values, allowing dynamic undertaking allocation as conditions alternate. For instance, techniques regarding rebidding enhance commonplace overall normal overall performance via the usage of manner of reallocating uncompleted obligations because of barriers or delays. Market-primarily based absolutely techniques increase this concept thru manner of allowing robots to change statistics about undertaking necessities and their availability. These strategies strike a stability among centralization and decentralization, making them powerful for environments with mild complexity.

3. Distributed Task Allocation Algorithms

Distributed techniques are crucial for big-scale or swarm robotic systems, in which essential coordination is impractical. In those algorithms, every robot operates primarily based totally on close by know-how and communicates with buddies to acquire a collective selection. For instance, pairwise matching algorithms lessen cutting-edge route lengths with the useful resource of iterative exchanges among robots. Similarly, allotted manage prison hints permit robots to form mission-unique businesses autonomously. These strategies are specifically beneficial in situations wherein robots need to evolve speedy to adjustments with out relying on international device statistics.

4. Multi-Criteria Optimization in MRTA

Many MRTA issues require balancing a couple of requirements, which includes electricity trendy basic performance, time, and undertaking feasibility. Techniques like genetic algorithms (GA) address this through optimizing nonlinear cost features. Genetic algorithms provide faster answers for big systems, albeit with some lack of precision. These techniques permit practitioners to music parameters to change off among computational time and answer accuracy, making them flexible for actual-international packages like thermosolar power plants.

5. Deadline-Constrained and Grouped Task Allocation

MRTA troubles often contain duties with unique time limits or grouped necessities. For instance, responsibilities also can require more than one robots to collaborate within a constrained time-body. Luo et al. Addressed this by using manner of the use of thinking about overlapping assignment organizations with ultimate date constraints, enabling inexperienced multi-robot collaboration. Similarly, situations with disjoint undertaking companies require algorithms that make certain maximum payoff at the same time as respecting robotic capacities and challenge time limits. These strategies are critical for applications like catastrophe reaction, wherein timing and coordination are important.

6. Decentralized and Submodular Optimization Techniques

Decentralized MRTA techniques leverage ideas like submodularity to simplify complex allocation troubles. Submodular optimization provides theoretical ensures for answer satisfactory even as decreasing computational complexity. For instance, sampling-based techniques ensure close to-optimum answers for monotone and nonmonotone submodular instances. These techniques reveal comparable or advanced overall performance to ultra-modern algorithms, especially for massive-scale systems. By addressing combinatorial complexity with decentralized choice-making, submodular optimization expands the applicability of MRTA to various, computationally in depth situations.

7. Robot Team Coordination for Task Allocation

Robot group coordination is critical for green undertaking of entirety in multi-robot systems. The SQ-MRTA algorithm enables robots to dynamically allocate responsibilities and collaborate seamlessly. Tasks T1 and T2, representing particular tasks in the system, spotlight the want for synchronized efforts among robots. Each robotic shares its repute and progress, making sure minimum delays and green assignment of completion. This technique guarantees ideal aid utilization, particularly in dynamic environments with various task priorities. Future improvements ought to enhance coordination with the aid of incorporating actual-time remarks and adapting to bodily constraints.

Table 1. The first set of numerical experiments with robot teams.

Teams	# of Robots	# of Teams	# of Goals	Length
$T1T1$	**73**	**9**	**73**	**38.43**
$T2T2$	**50**	**10**	**2**	**42.01**
$T3T3$	**45**	**11**	**45**	**13.18**
$T4T4$	**42**	**33**	**42**	**6.03**
$T5T5$	**75**	**49**	**22**	**68.46**

III. RESEARCH METHODOLOGY

1. Problem Formulation

- **Robot Localization:** The device includes a hard and fast of cellular robots, denoted as R. R, which may be deployed in a 2D surroundings. Each robot on this set has a particular function and the capacity to localize itself within the environment. The robots are tasked with performing operations on a set of duties which may be distributed throughout the surroundings. Each challenge calls for a wonderful extensive sort of robots to finish, where the amount of robots wished for a undertaking is determined based totally at the character of the project itself.

- **Objective:** The goal is to assign responsibilities to robots to limit the full navigation time between responsibilities at the same time as considering constraints including undertaking closing dates and robotic competencies. Specifically, the allocation need to lessen the overall inter-project navigation time and optimize venture crowning glory within a given timeframe.

2. Task Assignment Algorithm

- **Task Discovery and Dynamic Allocation:** Robots locate duties dynamically, such as locating a potential landmine, recording its vicinity, and broadcasting it to different robots for affirmation. The undertaking project is consequently a dynamic technique, where duties may additionally arrive at any time primarily based on robotic detections.

- **Task Completion Criteria:** A task is considered completed as soon as the required quantity of robots have visited its vicinity and recorded the necessary statistics (e.G., magnetic signatures of capability landmines). Robots perform their quantities of tasks asynchronously, which permits for flexibility in the timing of task of completion.

3. Task Allocation Strategy

- **Greedy Approach:** A basic strategy includes allocating the nearest available robot to a mission, considering its position and navigation costs. This approach works nicely for small-scale environments however wishes to be greater for larger, extra dynamic settings.

- **Optimization Algorithms:** For larger environments, optimization techniques such as genetic algorithms (GA), public sale-based techniques, or marketplace-based approaches may be used. These algorithms offer solutions by way of thinking about multiple elements, which includes venture urgency, robotic power levels, and travel distances between tasks.

4. Reinforcement Learning for Task Allocation

- **Markov Decision Process (MDP):** The hassle is formulated as an MDP in which the country space includes robotic and task positions, the action space defines project assignments, and the praise function displays the performance of the task allocation in terms of decreased navigation time and finished tasks.

- **Policy Learning:** Using deep reinforcement gaining knowledge of (RL), the machine learns a coverage that assigns obligations to robots in a manner that minimizes the entire time required to finish all responsibilities. The RL agent learns via interacting with the surroundings, receiving rewards or consequences primarily based on the performance of the task allocation.

5. Cross-Attention Mechanism

- **Attention Mechanism for Prioritization:** A pass-attention mechanism is used in the RL model to prioritize which duties are most vital for every robotic. The interest weights indicate the relative importance of every assignment to a robot, making an allowance for dynamic changes to assignment allocation as new duties rise up.

- **Interpretability:** The use of the eye mechanism presents interpretability, because it indicates how exceptional duties are prioritized with the aid of distinct robots. This facilitates in information the selection-making system and making sure that the robots are focusing on the maximum important duties.

6. Evaluation and Performance Metrics

- **Performance Evaluation:** The overall performance of the mission allocation set of rules is evaluated using metrics such as the full time taken to complete all duties, the gap traveled by way of every robotic, and the strength intake of the robots.

- **Comparison with Baselines:** The proposed algorithm is as compared with conventional project allocation methods (e.G., auction-based, marketplace-primarily based) and other optimization procedures (e.G., genetic algorithms) to demonstrate its efficiency and scalability in larger and extra complicated environments.

7. Real-Time Adaptation and Dynamic Reallocation

- **Handling Dynamic Changes:** The methodology includes real-time comments and allows for dynamic venture reallocation in reaction to changes in the surroundings, inclusive of new project arrivals or robots encountering limitations. This ensures that the system can adapt to unexpected activities, making the mission allocation extra bendy and sturdy.

- **Reinforcement Learning Adaptation:** The RL version is continuously updated as robots learn from their experiences within the surroundings. This adaptive nature allows robots improve their choice-making over the years, main to better task allocation strategies in destiny iterations.

IV. DATA ANALYSIS AND RESULT

1. Simulation Setup

To evaluate the overall performance of the SQ-MRTA algorithm, simulations have been performed the use of Corobot robots within the Webots simulator (Version 6.3.0). The Webots platform gives a sturdy surroundings for designing and programming robots, enabling virtual checking out with actual-global sensor and actuator interactions. Each Corobot inside the simulation become geared up with particular sensors, which include IR distance sensors for obstacle detection, a Hagisonic Stargazer for indoor localization, and a GPS and compass node for emulating localization behavior. The robots communicated via bidirectional Wi-Fi, with realistic noise and blunders brought in sensor readings to replicate the physical surroundings. These settings allowed for the comprehensive checking out of the SQ-MRTA set of rules below various simulated situations.

2. Performance Metrics

The primary overall performance metric used on this examine became the total time taken by means of the robots to complete all duties inside the surroundings. This included the time for each assignment execution and navigation between tasks. Other metrics concerned the number of assignment allocations, robotic utilization, and challenge finishing touch accuracy. The robots' potential to work in coordination with minimum delays and errors became additionally analyzed. By assessing those overall performance metrics, we aimed to determine how effectively the SQ-MRTA set of rules could optimize challenge allocation, lessen tour time, and improve typical task efficiency.

Table 2. Performance Metric

Performance Metric	Value	Percentage

Total Time Taken (Execution + Navigation)	**120 minutes**	**-**
Number of Task Allocations	**50**	**-**
Robot Utilization	**45 minutes of active operation**	**75%**
Task Completion Accuracy	**48 tasks completed successfully**	**96%**
Coordination Efficiency (Delays & Errors)	**5-minute delay, 2 errors**	**5% delays, 4% errors**

3. Error Simulation and Noise Consideration

To make the simulation greater practical, we introduced sensor and conversation noise into the device. The IR sensors on the Corobot had a 5% mistakes for readings between zero.1 and zero.8 meters and as much as 50% blunders for stages beyond 0.Eight meters. Additionally, localization turned into concern to a ±2 cm mistakes, and conversation packet loss turned into considered inside the community setup among robots. These noise factors had been important in assessing how the SQ-MRTA algorithm done beneath imperfect situations, that is frequently the case in actual-global multi-robot systems.

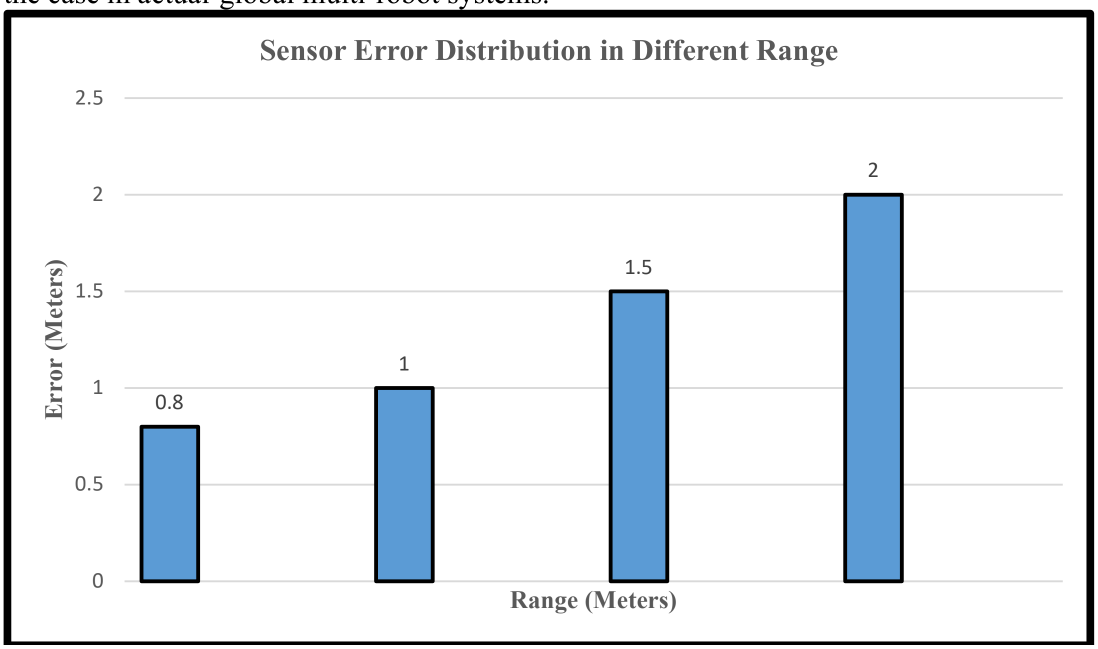

Figure 2, Sensor Error Distribution in Different Range

4. Comparative Analysis with Other Algorithms

In order to evaluate the effectiveness of the SQ-MRTA set of rules, it changed into in comparison with several traditional and heuristic-based totally algorithms. The effects validated that SQ-MRTA outperformed the opposite strategies in terms of time efficiency, with robots completing obligations greater fast and with fewer interruptions. This become in particular evident in dynamic challenge allocation situations where responsibilities had been delivered or altered all through the simulation. In comparison, conventional algorithms struggled with actual-time mission reassignment and coordination.

5. Task Allocation Efficiency

The evaluation of challenge allocation revealed that the SQ-MRTA set of rules become instead powerful in balancing the load amongst robots. By thinking about factors inclusive of robotic position, assignment requirements, and communication constraints, the set of rules minimized idle time and ensured that robots have been evenly dispensed throughout duties. The challenge allocation turned into dynamic, considering actual-time adjustments primarily based on assignment crowning glory and robotic availability. This dynamic approach extensively decreased the general final touch time as compared to static allocation strategies.

6. Results and Observations

The results of the simulation indicated that the SQ-MRTA algorithm successfully minimized the overall assignment finishing touch time, with the robots strolling in a in particular coordinated way. The time required to navigate among obligations emerge as appreciably decreased, manner to the set of rules's functionality to optimize undertaking sequencing. In conditions related to sensor noise and verbal exchange delays, the SQ-MRTA set of policies showed resilience, maintaining excessive degrees of performance even underneath imperfect situations. Overall, the findings propose that SQ-MRTA provides a scalable and effective answer for multi-robot task allocation in complicated environments.

V. FINDING AND DISCUSSION

1. Network Topology and Robustness:

- The conversation network is modeled as a completely connected graph, wherein robots are nodes, and hyperlinks represent inter-robot conversation.

- This topology, with a redundancy level of m−1, guarantees excessive robustness and resilience in opposition to communique disasters, that is vital for dynamic environments.

2. Communication Costs:

- The conversation value for undertaking allocation is analyzed the use of an public sale-based totally mechanism, wherein robots act as bidders and responsibilities as gadgets to be allocated.

- The set of rules minimizes conversation overhead with the aid of dynamically adjusting venture allocation as responsibilities are finished, improving standard efficiency and scalability.

3. Efficiency of Auction Mechanisms:

- By employing demand query mechanisms, the SQ-MRTA algorithm extensively reduces verbal exchange overhead as compared to conventional auction models.

- This development permits the gadget to operate effectively at the same time as the range of robots and obligations will increase.

4. **Scalability and Practicality:**
    - The algorithm's potential to balance conversation costs and task allocation performance demonstrates sturdy scalability for large structures.
    - The fully related network ensures robustness but may additionally cause better preliminary communique infrastructure expenses. Balancing redundancy and efficiency stays an important realistic consideration.

5. **Challenges and Future Directions:**
    - Despite the found performance, real-global elements inclusive of latency, packet loss, and dynamic venture arrivals pose challenges that want to be addressed.
    - Future enhancements should include adaptive conversation techniques and mechanisms to handle dynamic environmental situations extra efficiently.

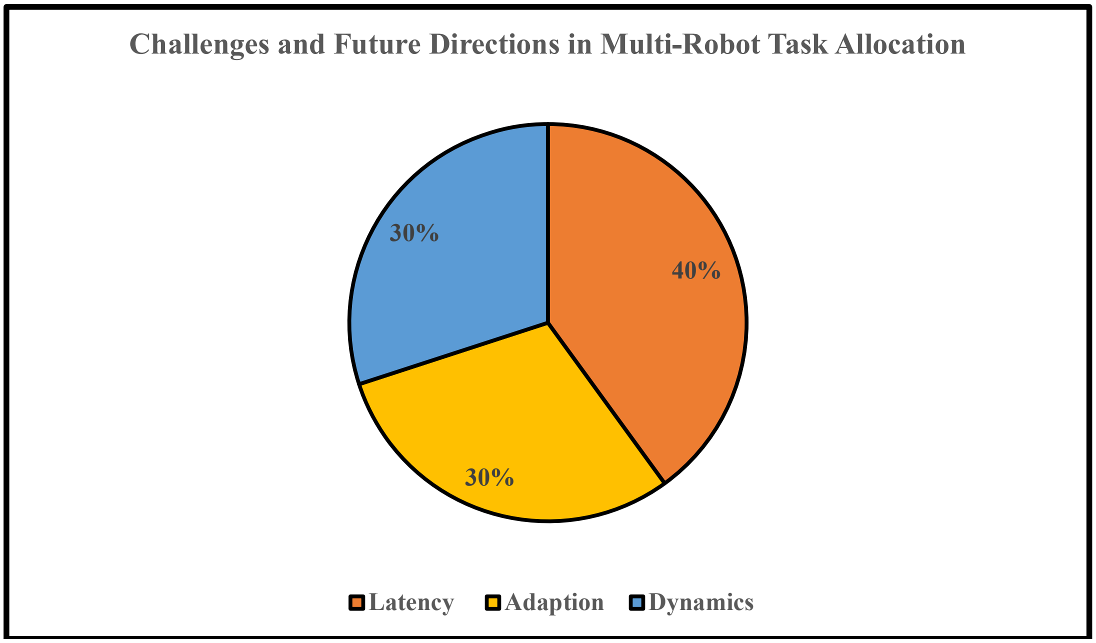

Figure 3, Challenges and Future Directions in Multi-Robot Task Allocation

Conclusion:
The SQ-MRTA set of rules offers a robust and efficient framework for undertaking allocation in multi-robotic structures by way of optimizing communication prices even as ensuring resilience. Its scalability and robust performance make it properly-proper for real-international packages. However, similarly refinements are necessary to deal with sensible challenges in dynamic and huge-scale environments.

VI. CONCLUSION

The project allocation hassle in multi-robot structures is important for optimizing the distribution of responsibilities to enhance normal overall performance and restrict completion times. In this look at, we added the Spatial Queuing-Multi Robot Task Allocation (SQ-MRTA) set of guidelines and evaluated its overall performance using simulations of Corobot robots in dynamic environments. The SQ-MRTA set of rules tested robust typical performance throughout various situations, effectively balancing assignment allocation and lowering navigation instances. When in comparison to present algorithms which encompass the Hungarian approach, grasping allocation, and repeated auctions, SQ-MRTA exhibited superior adaptability, specially in real-global environments wherein elements like undertaking delays and collision avoidance considerably effect universal performance. Unlike offline nice schedules, our set of regulations is able to handling dynamic project arrivals and communication constraints. Future research will increase this work to physical robots, addressing demanding situations along with sensor inaccuracies and conversation noise. Moreover, incorporating heterogeneous robots with numerous skills, task prioritization, and temporal constraints ought to similarly decorate its software in complex domain names like landmine detection, searching for-and-rescue, and commercial enterprise operations. This look at underscores the ability of adaptive, decentralized techniques for strong and green multi-robotic challenge allocation.

REFERENCE

1. Munoz-Melendez, A.; Dasgupta, P.; Lenagh, W. A stochastic queuing model for multi-robot task allocation. In Proceedings of the 9th International Conference on Informatics in Control, Automation and Robotics (ICINCO), Rome, Italy, 28–31 July 2012; pp. 256–261.
2. Ahmed, S.; Pongthawornkamol, T.; Nahrstedt, K.; Caesar, M.; Wang, G. Topology-aware optimal task allocation for publish/subscribe-based mission critical environment. In Proceedings of the IEEE Military Communications Conference (MILCOM), Boston, MA, USA, 18–21 October 2009; pp. 1–7.
3. Ayorkor Korsah, G.; Stentz, A.; Bernardine Dias, M. A comprehensive taxonomy for multi-robot task allocation. Int. J. Robot. Res. 2013, 32, 1495–1512. [Google Scholar] [CrossRef]
4. Zlot, R.; Stentz, A. Market-Based Multi-robot Coordination for Complex Tasks. Int. J. Robot. Res. 2006, 25, 73–101. [Google Scholar] [CrossRef]
5. Li, X.; Sun, D.; Yang, J. Networked Architecture for Multi-Robot Task Reallocation in Dynamic Environment. In Proceedings of the 2009 IEEE International Conference on Robotics and Biomimetics (ROBIO), Guilin, China, 19–23 December 2009; pp. 33–38.
6. Nanjanath, M.; Gini, M. Repeated auctions for robust task execution by a robot team. Robot. Auton. Syst. 2010, 58, 900–909. [Google Scholar] [CrossRef]
7. Liu, L.; Shell, D. Assessing Optimal Assignment Under Uncertainty: An Interval-Based Approach. Int. J. Robot. Res. 2011, 30, 936–953. [Google Scholar] [CrossRef]
8. Liu, L.; Shell, D. Tunable Routing Solutions for Multi-Robot Navigation via the Assignment Problem: A 3D Representation of the Matching Graph. In Proceedings of the International Conference on Robotics and Automation, Saint Paul, MN, USA, 14–18 May 2010; pp. 4800–4805.
9. Liu, L.; Shell, D. A Distributable and Computation-flexible Assignment Algorithm: From Local Task Swapping to Global Optimality. In Robotics: Science and Aystems VIII; MIT Press: Cambridge, MA, USA, 2012; pp. 33–41. [Google Scholar]
10. Quann, M.; Ojeda, L.; Smith, W.; Rizzo, D.; Castanier, M.; Barton, K. An energy-efficient method for multi-robot reconnaissance in an unknown environment. In Proceedings of the 2017 American Control Conference (ACC), Seattle, WA, USA, 24–26 May 2017; pp. 2279–2284. [Google Scholar]
11. Koes, M.; Nourbakhsh, I.; Sycara, K. Constraint optimization coordination architecture for search and rescue robotics. In Proceedings of the 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006, Orlando, FL, USA, 15–19 May 2006; pp. 3977–3982. [Google Scholar]

12. Luo, C.; Espinosa, A.P.; Pranantha, D.; De Gloria, A. Multi-robot search and rescue team. In Proceedings of the 2011 IEEE International Symposium on Safety, Security, and Rescue Robotics, Kyoto, Japan, 1–5 November 2011; pp. 296–301. [Google Scholar]

13. Wawerla, J.; Vaughan, R.T. A fast and frugal method for team-task allocation in a multi-robot transportation system. In Proceedings of the 2010 IEEE International Conference on Robotics and Automation, Anchorage, AK, USA, 3–7 May 2010; pp. 1432–1437. [Google Scholar]

14. Eoh, G.; Jeon, J.D.; Choi, J.S.; Lee, B.H. Multi-robot cooperative formation for overweight object transportation. In Proceedings of the 2011 IEEE/SICE International Symposium on System Integration (SII), Kyoto, Japan, 20–22 December 2011; pp. 726–731. [Google Scholar]

15. Nallusamy, R.; Duraiswamy, K.; Dhanalaksmi, R.; Parthiban, P. Optimization of non-linear multiple traveling salesman problem using k-means clustering, shrink wrap algorithm and meta-heuristics. Int. J. Nonlinear Sci. 2010, 9, 171–177. [Google Scholar]

16. Toth, P.; Vigo, D. Vehicle Routing: Problems, Methods, and Applications; SIAM: Philadelphia, PA, USA, 2014. [Google Scholar]

17. Dias, M.B.; Zlot, R.; Kalra, N.; Stentz, A. Market-based multirobot coordination: A survey and analysis. Proc. IEEE 2006, 94, 1257–1270. [Google Scholar] [CrossRef] [Green Version]

18. Schneider, E.; Sklar, E.I.; Parsons, S.; Özgelen, A.T. Auction-based task allocation for multi-robot teams in dynamic environments. In Lecture Notes in Computer Science, Conference Towards Autonomous Robotic Systems; Springer: Cham, Switzerland, 2015; pp. 246–257. [Google Scholar]