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A Systematic Literature Review on Multi-Robot Task Allocation

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Muti-Robot system is gaining attention and is one of the critical areas of research when it comes to robotics. Coordination among multiple robots and how different tasks are allocated to different system agents are being studied. The objective of this Systematic Literature Review (SLR) is to provide insights on the recent advancement in Multi-Robot Task Allocation (MRTA) problems emphasizing promising approaches for task allocation. In this study, we collected scientific papers from five different databases for MRTA. We outline the different approaches for task allocation algorithms, classifying them according to the methods, and emphasizing recent advances. In addition, we discuss the function of uncertainty in task allocation and typical coordination techniques utilized in task allocation to identify gaps in the literature and suggest the most promising ones.

CCS Concepts: • **Computing methodologies** → **Artificial intelligence**; **Distributed artificial intelligence**; **Cooperation and coordination**;

Additional Key Words and Phrases: Real-time task allocation, multi-robot system, dynamic environment, systematic literature review, task coordination, multiple agents

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1 Introduction

Autonomous robots that are capable of perceiving their surroundings, making decisions based on their observations or previous learning, and subsequently performing actions or manipulations can play a crucial role in various civil applications. Most of these real-world scenarios involve a distributed system. When there are multiple robots in an environment to work in a distributed

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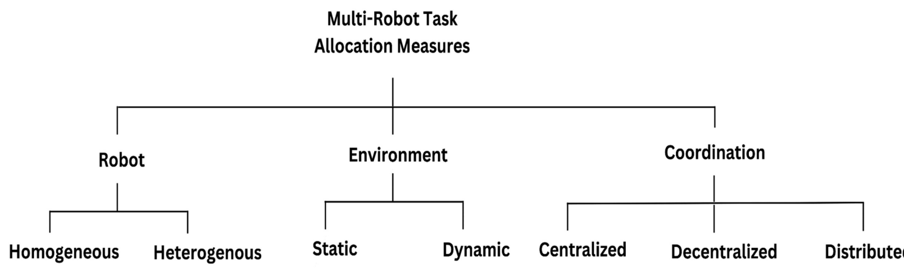


Fig. 1. Multi-robot task allocation measures.

system, it primarily requires communication and cooperation to accomplish a shared objective, such as raising each member's performance within a group to obtain the best possible performance. **Multi-Robot Task Allocation** (**MRTA**) is the process of effectively distributing tasks to a group of robots in a coordinated way. It is a significant issue in Multi-Robot Systems, which involves managing several robots to accomplish a common goal. The problem of task allocation arises frequently in situations where a set of tasks is too intricate for a single robot to handle, and multiple robots are necessary. One instance is in warehouse automation, where transporting goods from one location to another may require the participation of multiple robots.

In general, an MRTA system aims to achieve an efficient assignment of tasks to robots by considering various characteristics such as the robots' capabilities, task requirements, and system efficiency. This process of MRTA involves three important factors to be considered: robot, environment, and coordination, as shown in Figure 1. According to the capability robots can be classified as homogeneous and heterogeneous. An example of homogeneous robots is a swarm of miniature robots used for environmental monitoring or searching operations. Each robot in the swarm has the same sensors, actuators, and computing capabilities, and they work together to accomplish tasks such as mapping an area or searching for survivors. Heterogeneous robots are typically used for tasks that require different types of robots to work together to achieve a common goal. A team of robots used for manufacturing or assembly tasks is an example for heterogenous robots. This team of robots can have different capabilities like welding or painting. Similarly, tasks can also be considered homogeneous or heterogeneous based on the kind of team of robots required to complete a particular task.

The MRTA environment can be either a dynamic or static environment. In an environment that is static in nature, tasks are allocated to robots in advance before they begin to execute them. This process is known as task allocation [52] . This method works well in situations when the tasks are predetermined and the robots are either immobile or have restricted movement. In contrast, dynamic task allocation involves the real-time assignment of tasks to robots as they carry out their activities [25]. Different algorithms, like swarm-based, consensus-based, or reinforcement learning-based approaches, can be used for dynamic task allocation. During work allocation, the robots can interact with one another in a dispersed, centralized, or decentralized manner. There are several ways to accomplish multi-robot work allocation, including heuristic, market-based, and optimization-based techniques. Nonetheless, because of the growing utilization of MRS in diverse fields, this area is undergoing continuous research and development, with many encouraging solutions being proposed and tested.

Recently a lot of literature surveys had been done on the basis of the MRS and task allocation. We provide the summary of the contributions made in this **systematic literature review** (**SLR**).

— Table 1 compares our SLR with the other reviews to understand the relevance of our study. We could also understand that most of the studies were general reviews. The contents in

Table 1. A Comparison of Our Study with State-of-the-Art Research and a Justification for the Novelty of Our Work

Source	Review Topic	Survey Type	Years Included	Quality Assessment	Potential Gaps
[31]	Multi-Robot Task Allocation	General	Not Specified	No	Yes
[67]	Market Approaches to MRTA	Systematic	2006–2020	Yes	Yes
[69]	Dynamic Task Allocation Strategies for MRTA	General	Not Specified	No	Yes
[29]	Application MRS in Agriculture	General	Not Specified	No	Yes
Our Work	Multi-Robot Task Allocation	Systematic	2013–2024	Yes	Yes

Table 1 clearly specify that there has been no SLR done on the MRTA problem, available considering the quality assessment as a factor.

— Also, our approach to the SLR is unique and ensures a comprehensive and up-to-date overview (past 11 years). Unlike many previous surveys that performs the literature review on a specific methods like market based or optimization based methods our study deviates from the norm and reviews most of the approaches used for MRTA. This study gives a comparison between the approaches including the learning based approach for MRTA.
— In the context of the robots, environment, and coordination, our study gives a comparison explicitly between different combination on the type of robots, environment, and coordination used in the scientific papers which is done for the first time to the best of our understanding.
— This SLR also gives an insight into the strategies and different parameters that can be used to develop an algorithm that's both scalable and adjusts to dynamic MRTA environment.

The article is structured as follows. Section 2 discusses the research approach and the methodology followed to conduct the SLR. Then, we answer the four research questions formulated in Section 3. The answer to first question explains the classification of different papers based on the approaches used. Second question answers the taxonomies of MRTA. Third question discusses various factors involved in MRTA framework. Fourth question answers different evaluation metrics used. The fifth question answers the challenges of the current MRTA strategies. Section 4 describes the novelty of our study and the future direction for the research in MRTA. Section 5 describes the summary and key conclusions.

2 Research Approach

There are general literature reviews exclusively focusing on different approaches to MRTA. We chose to carry out a systematic study examining the existing works and the contributions made in the scientific papers published from 2013 to 2024. While searching the databases for this SLR study, majority of works on task allocation are undertaken for aerial, ground, and underwater robots. Our paper takes into consideration only the ground robots. This article performs an SLR based on the methodology inspired by PRISMA [59], which involves formulating 1. Searching criteria 2. Inclusion/ Exclusion Strategy 3. Quality Assessment 4. Data collection and analysis. The process in PRISMA is illustrated in Figure 2. There are various approaches to perform an SLR like Kitchenham [27] but Prisma approach is a widely used methodology for conducting systematic reviews and meta-analyses of quantitative studies. It provides a framework for the transparent reporting of the study methods and results, and includes guidelines for the identification, screening, and selection of relevant studies.

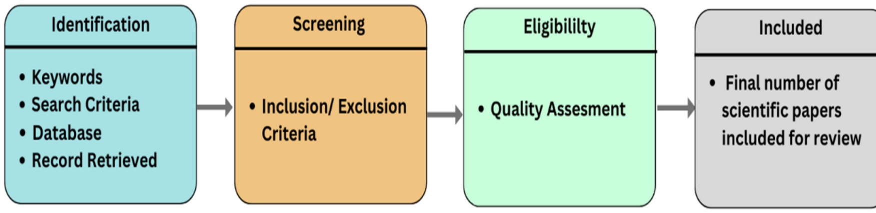


Fig. 2. The process involved in SLR.

Table 2. Sources and Search Strings Used in This Study

Database	URL	Search String
Scopus	https://www.scopus.com	*("Multi-Robot System" OR "Multi Agent System") AND ("Task Allocation")*
IEEE Xplore	https://ieeexplore.ieee.org	*"Multi-Robot" AND "Task Allocation"*
ACM Digital Library	https://dl.acm.org	[[All: *"multi robot"] OR [All: "multi agent "]] AND [All: "task allocation"]*
Science Direct	https://www.sciencedirect.com	*"Multi Robot System" AND "Task Allocation"*
Google Scholar	https://scholar.google.com	*"Multi Robot System" AND "Task Allocation"*

2.1 Searching Criteria

The information collection strategy specially tailors to the databases Scopus, ACM Digital Library, IEEE Xplore, Science Direct, and Google Scholar. Journals, conference papers, and book chapters published in the area of the MRS were the key focus of the search. The strings used to search for the scientific papers in each of the database are given in Table 2. To start with we had 339 scientific papers collected from the database and 64 papers were collected through references. After removing the duplicate records, we had 241 records that's being selected for title screening. After screening the title, 188 scientific papers were chosen for the screening of abstracts. In the abstract screening, for those records illustrating human–robot interaction for task allocation, only the robot kinematics or hardware implementations were removed, and 113 papers were selected for full-text download and reading. After reading the papers 78 scientific papers were selected for review.

2.2 Data Sources

There are several search engines and scientific databases available online. Our study particularly collected the data from the following databases. The study used various search engines and scientific databases, including Scopus, IEEE Xplore, ACM Digital Library, Science Direct, and Google Scholar. Scopus is a comprehensive bibliographic database with enriched articles from various fields. IEEE Xplore offers access to over five million full-text papers from widely cited electrical engineering, computer science, and electronics publications. ACM Digital Library provides a comprehensive bibliographic database for computing literature. Science Direct covers 24 topic areas and Google Scholar allows searching across various disciplines.

2.3 Inclusion and Exclusion Criteria

The paper inclusion criteria involved those papers from the database ranging from 2013 to 2024 and whose publication stage is final. We have limited our search to scientific papers in the English

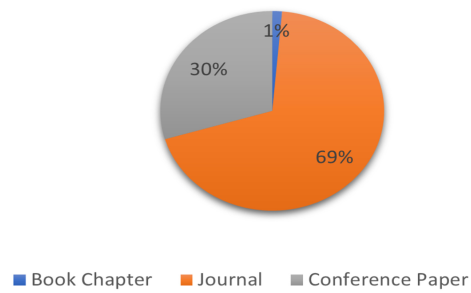


Fig. 3. Distribution of scientific papers over different types.

language. The scientific papers explaining both theoretical and algorithmic approaches for task allocation with practical implementations are included. Those works that have comparisons or experimental results were included.

At the initial stage, paper exclusion criteria involved (i) Scientific papers with subject areas other than computer science and engineering; (ii) Those papers whose title are not related to MRS were excluded. A total of 339 papers were collected based on the initial screening. After performing the abstract screening those papers that doesn't discuss about task allocation in MRS and those that concentrate on task allocation using human–robot interaction were eliminated and a total of 188 papers were selected. From those papers selected, we devised the further criteria for excluding the scientific papers involved (i) Scientific papers focusing on robot kinematics only. (ii) Studies not on ground robots are excluded. This rigorous screening helped to identify 78 papers that were used to carry out this SLR. Table 5 describes the distribution of publication types per year spanning from 2013 to 2024. Out of the 78 scientific papers, 26 are published as conference papers and 51 as journal papers. Figure 3 shows the distribution of scientific papers over different publication types. The process of collecting the scientific papers and analysis is illustrated in Figure 4. Records that are of journals, conference papers, and book chapters are collected. This study considered only those papers in the field of computer science mathematics and engineering. This work thoroughly reviewed 78 papers and divided them into learning-based, market-based, clustering-based, optimization-based, and other approaches. Comparisons were made among the techniques used in each approach to provide a mapping. This study also classifies the papers on the basis of the taxonomy, constraints, and their real-world applications.

2.4 Quality Assessment

The papers selected after the inclusion and exclusion criteria are again validated using six quality assessment questions. As shown in Table 3, a customized Quality Assessment system was formulated to achieve the goal of SLR. According to the Quality assessment questions formulated each paper can score up to six points. We have assigned three points: Yes, No, Partial. A total score of one is given if all the features are present (Yes - 1), a score zero is given for the features absent (No - 0) and a total score of 0.5 is given for the features that are partially present (Partial -0.5). The results of the papers validated using the quality assessment system are shown in Table 4.

2.5 Results

The Prisma approach provides a rigorous and transparent framework for carrying out systematic reviews and meta-analyses, ensuring that the resulting conclusions are based on a comprehensive and unbiased evaluation of the available evidence. The purpose of this survey is to compile the best research on MRTA. To offer critical knowledge of the MRTA problem for a collection of autonomous ground robots.

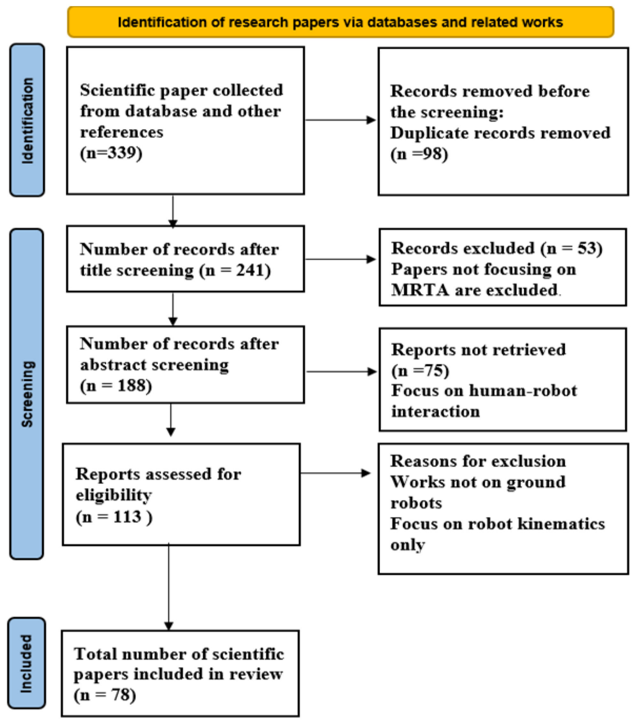


Fig. 4. Flow chart for the search and inclusion process.

Table 3. Quality Assessment Questions

SL. No.	Quality Assessment Question	Score		
QA1	Does the study clearly state objectives of research and address significant issues in MRTA?	Yes	No	Partial
QA2	Are the methods and algorithm explained sufficient in detail for replication?	Yes	No	Partial
QA3	Are the different parameters used in MRTA approach properly defined and justified?	Yes	No	Partial
QA4	Does the study performs comprehensive evaluation including the performance metrics?	Yes	No	Partial
QA5	Does the study mention any future directions for the researchers on MRTA problem?	Yes	No	Partial

3 Research Questionnaire

In this SLR, data from the chosen studies that satisfy the inclusion criteria are gathered using a research questionnaire.

RQ1: What are the different approaches adopted in an MRTA framework?

The objective of addressing this research question is to derive a categorization of the approaches chosen for MRTA in different papers. This kind of classification helps to identify the different algorithms or techniques used for task allocation in each approach. It also helps to answer the question, how different approaches are efficient than others for certain types of task allocation

Table 4. Papers Validated Using Quality Assessment Questions

Study Reference	QA1	QA2	QA3	QA4	QA5	Score Yes/No/Partial
[3, 4, 7, 11, 12, 14, 17, 18, 19, 20, 21, 24, 28, 34, 37, 38, 39, 41, 42, 46, 50, 52, 53, 54, 55, 56, 57, 65, 66, 72, 74, 75, 80, 82, 83, 84, 86, 87, 88]	1	1	1	1	1	5
[2, 6, 7, 8, 9, 10, 25, 30, 35, 36, 40, 43, 44, 45, 47, 48, 55, 63, 64, 70, 73, 76, 78, 79]	1	1	1	1	0	4
[5, 32, 47, 58, 85]	1	1	1	0.5	0	3.5
[1, 12, 13, 16, 23, 51, 60, 61, 77, 81]	1	1	1	0	0	3

Table 5. Distribution of Publications from 2013 to 2024

Publication Type	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	**Total**
Book Chapter	0	0	0	0	0	1	0	0	0	0	0	0	1
Journal	1	4	2	2	0	3	3	0	3	3	2	3	26
Conference Paper	4	5	9	3	1	9	3	3	6	5	2	1	51
Total	5	9	11	5	1	13	6	3	9	8	4	4	**78**

scenarios. Various task allocation strategies are discussed in different papers selected for study which includes learning based, market based, optimization based, clustering based and some other approaches. Table 6 summarizes the techniques or algorithms used in each paper.

In clustering, the aim is to partition the input data into discrete set structures. The input data or the tasks are divided into a specific number of clusters. The clustering approach assigns these groups of tasks to each robot instead of giving each robot a single task. As an outcome, fewer tasks need to be assigned. Also, computational complexity is minimized. Clustering approaches aim to minimize travel distance and maximize task coverage by grouping tasks effectively that are evaluated by clustering quality and distance traveled which makes this approach more suitable for exploration tasks . However, the optimal clustering of tasks and how the tasks can be clustered in a hierarchical clustering approach is to be explored more. These approaches simplify task allocation but may struggle to handle dynamic changes in the environment. Future research should focus on dynamic clustering techniques and online adaptation to continuously adjust clusters based on new data.

The goal of an optimization-based strategy is to choose the optimal solution from the set of available solutions. These solutions are restricted using certain constraints and according to the objective function the optimal solution is identified from the set of available solutions. The objective function is defined as the ultimate goal of the system. The MRTA in a dynamic environment is considered as combinatorial optimization problem and is solved using different algorithms like genetic algorithm [28], and particle swarm optimization [7]. Optimization approaches in MRTA focus on minimizing objectives such as time, energy, and workload balance through mathematical models like linear and mixed-integer programming. Most of the optimization approaches take single-objective optimization because it is difficult to model a fitness function for multi-objective optimization. Some of the optimization algorithms have poor robustness to uncertainties which is another factor to be considered [53]. This approach is more suitable for solving well-defined and

Table 6. Different Approaches to MRTA

Study Reference	Technique/Algorithm	Approach
[52]	Shapley value clustering algorithm (SVCA)	Cluster Based
[25]	Group Agent Partitioning	
[12]	Based on consensus-based distributed task allocation algorithm	
[32]	Voronoi Diagram-Based , K-Means Algorithm	
[73]	Consensus-Based Bundle Algorithm (CBBA)	
[2]	Cluster first consensus based strategy	
[48]	K-means clustering	
[40]	Auction Algorithm	Market Based
[80]	Improved Auction Algorithm	
[72]	Extended auction algorithm	
[88]	Firefly algorithm, quantum genetic algorithms and artificial bee colony optimization	
[26]	Distributed auction algorithm	
[35]	Sequential single-item auctions	
[34]	Auction-based algorithm	
[23]	Gini coefficient-based method with market-based mechanism	
[36]	Multihop-based auction algorithm	
[20]	Based on sequential single item auctions	
[14]	Consensus Based Parallel Auction and Execution Algorithm	
[78]	Extended sequential single item auction	
[49]	Distributed auction-based algorithm	
[74]	The consensus-based bundle algorithm	
[45]	Linear integer programming	
[24]	Contract Net protocol	
[47]	Gated Recurrent Unit, Multi-layer Perceptron	Learning Based
[19]	Deep Reinforcement Learning	
[77]	Heterogeneous Graph Attention Network	
[66]	Capsule Attention-based Mechanism	
[64]	Encoder Decoder Architecture with cross attention mechanism	
[3]	Graph Neural Network (GNN)	
[51]	Q-Learning , Convolutional layers and a GRU	
[50]	Deep Reinforcement Learning	
[11]	Graph Convolutional Neural Networks	
[30]	Resilient Mobile Ad hoc NETwork (MANET)	Network Based
[60]	Mixed-integer quadratic program	Optimization Based
[41]	Centralized Hungarian method	
[23]	Bin Maximum Item Doubled Packing .	
[8]	Particle swarm optimization (PSO) algorithm	
[44]	Group theory and Optimization duality theory	
[42]	Genetic algorithm with Pass-by insertion and 2-nearest-neighbor swapping	
[7]	Particle Swarm Optimization	
[43]	Group theory and the optimization duality theory	

(Continued)

Table 6. Continued

Study Reference	Technique/Algorithm	Approach
[76]	Integer Programming	Optimization Based
[55]	Mixed-integer quadratic program (MIQP)	
[53]	Graph-based optimal path-planning and Integer Linear Programming,	
[28]	A genetic algorithm (GA), A* algorithm .	
[61]	Constraint based optimization as quadratic program	
[39]	Particle Swarm Optimization	
[85]	Heuristic based	
[84]	Differential Evolution for multimodal problems	
[75]	Fuzzy Optimization	
[15]	Spatial Queueing, Voronoi partitioning	Spatial Queuing Approach
[38]	Spatial Queuing technique	
[70]	Linear temporal logic (LTL)	Automata learning
[16]	Learning automata theory and ant colony optimization algorithms	

static problems and focuses on theoretically optimal or near-optimal solutions. Some of the metrics used for the evaluation of this approach include optimality, and computational time which explains how near the solutions are to the theoretical best and how much computation is necessary. The optimization approach requires more computational power and is less adaptable to changing environments. To achieve a balance between this adaptability and computational efficiency, future works should focus more on investigating the hybrid models that could combine optimization techniques with clustering or learning-based approaches that would facilitate the MRTA to be able dynamically to adjust and re-optimize in response to changing circumstances that would increase the application of these techniques in the environment that are more complex and dynamic. Additionally, there are only a few works with multi-objective optimization in real-time that can balance the tradeoff between various competing goals like minimizing energy consumption and maximizing task completion rates.

Adapting the human trading behaviour, Market-Based approaches are able to handle extremely combinatorial optimization problem. Each robot in the team is informed about the tasks and asked to submit bids by an auctioneer robot. Based on its capacity to complete the tasks, each individual robot in the team formulates a bid before sending it to the auctioneer robot. The auctioner robot chooses the robots with the lowest bids for the task execution. The market based approach can be classified into Single item auctioning and combinatorial auctioning. Various researchers have explored these methods in different ways in their studies. In general, most of the task allocation problems based on market based approach result in minimum travel time. But in an environment with no or lossy communication this approach seems to be weak in performance. They are flexible and scalable but may not achieve global optima, necessitating adaptive market mechanisms, and incentive models for improved cooperation.

Recent approach to MRTA is using learning-based approach that makes use of deep learning algorithms based on graph, **graph neural networks (GNNs)**, graph convolutional network. Most of the learning approaches rarely demonstrate generalization to larger-scale problem scenarios than those employed for training. This characteristic is especially important because real-world MRTA problem frequently require modeling scenarios whose costs increase with the number of tasks and robots. Given the environmental and communicational certainties, as well as the potential for new tasks to emerge during the operation, a sequential decision-making strategy is preferred which

Table 7. A Comparison on Different Approaches to MRTA

	Clustering	Optimization	Market-Based	Learning-Based
Advantage	Simplifies task allocation and reduces complexity	Provides optimal solutions, well-suited for static	Flexible, scalable, decentralized	Adaptable, learns, and improves over time
Limitations	May not account for dynamics well	Computationally intensive, less adaptable	May not yield global optima, and needs effective bidding	Requires training time, initially sub-optimal
Best case	Logical tasks	Well-defined, static problems	Dynamic environments with varying tasks	Complex and uncertain environments
Future works	Dynamic clustering, online adaptation	Hybrid models, real-time optimization	Adaptive market mechanisms, incentive models	Transfer learning, meta-learning

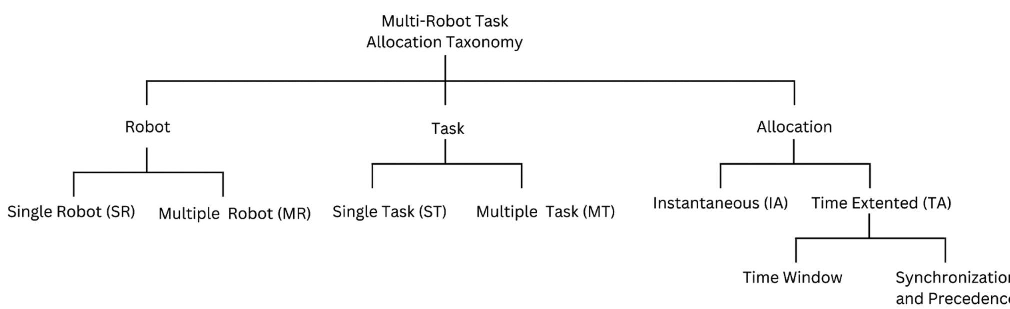


Fig. 5. Taxonomy A for MRTA.

can be attained using learning based approach [66]. Table 7 gives a comparison between all the approaches. To an extent when compared to other approaches scalability is one of the key feature of the learning based approach.The learning-based techniques optimize different task allocation algorithms by continuously improving performance through learning rates, adaptability, and convergence metrics. Even though this approach requires significant amount of training and has an initial sub-optimal performance, they can adapt well to complex environments.

RQ2: How can the papers be classified according to MRTA taxonomy?

This research question aims to determine the taxonomy for MRTA problem which helps in differentiating the MRTA problems into different classes according to their complexity.

In this study we found three taxonomies such that each MRTA problem can be categorized into any of these classes specified in the taxonomy. For simplicity lets name these classes as Taxonomy A, Taxonomy B , Taxonomy C. The authors of [22] propose a taxonomy for MRTA issues that is built on three axes. Robots are categorised along the first axis according to how many tasks they can perform at once or for a single task. The second one divides tasks into those that should be assigned to multiple robots at once or to only one robot. The third one considers how tasks are allocated to robots while taking into account both present and future information. Taxonomy A is shown in Figure 5.

Hence, ST-SR-IA, ST-SR-TA, ST-MR-IA, ST-MR-TA, MT-SR-IA, MT-SR-TA, and MT-MR-IA are the eight problem classes that are identified. Although this taxonomy does an excellent job of covering most MRTA issues, it leaves out issues with linked utilities and time limitations on tasks and robots. So, it was necessary to suggest a taxonomy that takes these restrictions into account. The authors of the paper [33] added an additional level to Taxonomy A that represents the level of interaction among robots and the tasks. There are two levels in this taxonomic hierarchy. Taxonomy A's proposed classes are included in the second one. The first one consists of the following four tasks and robot interdependency levels which is illustrated in Figure 6.

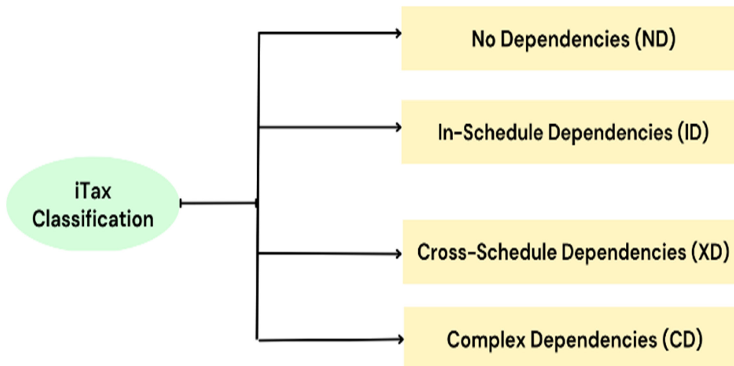


Fig. 6. Taxonomy B for MRTA.

Table 8. MRTA Taxonomy Specified

Study Reference	Taxonomy
[21, 46, 52]	ST-SR-TA-XD
[60, 82, 88]	ST-MR-IA
[12, 74, 77, 81, 84, 87]	ST-SR-TA
[15, 38, 64, 79]	ST-MR-TA
[14, 24, 32, 43, 44, 45, 84]	ST-SR-IA
[57, 66]	ST-SR-TA-ID
[2, 48]	MT-SR-IA
[85]	MT-MR-IA
[3]	ST-MR-TA-ID
[83]	MT-MR-TA

- No Dependencies (ND): It applies to ST-SR-IA and ST-SR-TA issue classes and states that the usefulness of a robot for a task is independent of all other factors.
- In-Schedule Dependencies (ID): ST-SR-TA, MT-SR-IA, and MT-SR-TA issue classes are covered. The utility of a robot for a task only depends on its schedule.
- Cross-Schedule Dependencies (XD): It addresses all eight problem classes and states that a robot's usefulness for a task depends not just on its own schedule but also on the schedules of other robots.
- Complex Dependencies (CD): In this situation, schedules are dynamic and impact a robot's suitability for a task in addition to its own and other robots' schedules; this covers the eight problem classes.

Taxonomy C can be considered as an extension of Taxonomy A as shown in Figure 5. The taxonomy A Time-extended assignment (TA) has been divided into two by the authors of [62]. This action enables the imposition of the following timing limits on tasks: The first class is Time extended: Time Window, enables considering time windows as a kind of temporal constraint.The next one is, Time extended: Synchronization and Precedence that enables consideration of synchronization and precedence constraints. Table 8 shows the taxonomy specified in the papers selected for the study.

The taxonomy for MRTA can be further extended relating to the assignment of tasks which can be online, offline, and iterated assignment. The distribution of tasks that are predetermined and can be allocated before the robots' mission begins is known as offline assignment. Thus, this kind of tasks is perfect when the surroundings are predictable and the task can be planned ahead of time. Notably, offline approaches are inappropriate for dynamic situations since they are unable to accommodate the addition of additional tasks as the operation progresses. The distribution of upcoming tasks is the subject of iterated assignment. The method assigns the robots to complete the remaining tasks after adding a new work, relieving them from their prior tasks without verifying if the task has been completed previously. The distribution of upcoming tasks is another aspect of online assignments. However, robots accept new tasks after completing previously assigned ones, they do not cancel previously assigned tasks.

RQ3: Are there any other factors considered in an MRTA problem?

This research question aims at identifying the other factors involved in an MRTA framework. It enables to discuss how the authors set up the experiments by combining these factors. RQ3.1, RQ3.2, and RQ3.3 answers the research question RQ3.

RQ3.1: What are the type of agent, environment, coordination used in MRTA framework ?

An MRTA framework should take into account a number of factors, including the kind of agent being employed, the kind of environment in which the robots are anticipated to carry out the task allocation, and the manner in which the robots communicate or coordinate with one another. There are two distinct kinds of robots: heterogeneous and homogeneous. A homogeneous robot system has robots of the same type and capabilities but a heterogeneous set of robots will have a variety of capabilities. [88] Homogeneous robots are robots that are identical in terms of their hardware, software, and capabilities. These robots can perform similar tasks and can easily communicate with each other since they share the same characteristics. In MRS with homogeneous robots, the task allocation problem is relatively simple since all the robots can perform the same tasks with the same level of efficiency. [15] Task allocation in heterogeneous multi-robot systems can be approached in different ways. One approach is to assign tasks based on the capabilities of the robots. In this approach, each robot is assigned a task that it is capable of performing efficiently. A further approach is to consider the system's overall performance while accounting for the workload and capacities of every robot. In this approach, a centralized or distributed algorithm could be used to allocate tasks to the robots based on their capabilities and workload. Table 9 shows the distribution of works considering these factors.

In an MRS, there are three types of coordination techniques, centralized, decentralized, and distributed coordination. Every other agent in the system has a connection to a single central agent in the centralized method [38]. The central agent guides the individual agents to complete the tasks in the multi-robot environment based on the information it gets from other agents. The decentralized method eliminates the need for a central node to oversee the entire task allocation procedure [36]. Decentralized MRTA is particularly useful in situations where a central coordinator is not practical or desirable, such as in large-scale systems or in situations where there is no clear hierarchy or leadership among the robots. By allowing the robots to work together and coordinate their actions in a decentralized manner, it is possible to achieve high levels of efficiency and flexibility, while minimizing the need for centralized control. Being in a decentralized system the robots can manage environmental changes. Distributed MRTA is an approach to task allocation that involves multiple robots working together to divide and complete a set of tasks without the need for a central coordinator. In a distributed system [14], to optimize task allocation and accomplish the overarching objective, each robot communicates and coordinates with its neighboring robots. The environment itself may remain unchanged while tasks are assigned, i.e., it may be static. It may be dynamic, meaning that changes in the surroundings could result

Table 9. Type of Agent, Environment, and Coordination Used in Different Papers

Reference	**Agents**		**Environment**		**Coordination**		
	Homogeneous	Heterogeneous	Static	Dynamic	Centralised	Decentralised	Distributed
[87]		✓		✓			✓
[30]	✓		✓		✓		
[88]	✓			✓			
[18]	✓		✓				
[26]		✓		✓			✓
[12]		✓	✓				✓
[35]		✓				✓	
[74]		✓		✓			✓
[80]		✓		✓			
[41]		✓					✓
[13]	✓			✓		✓	
[25]	✓			✓		✓	
[40]	✓		✓				
[56]		✓	✓				
[47]	✓			✓	✓		
[52]					✓		
[34]				✓		✓	
[23]	✓			✓			
[79]		✓		✓	✓		
[9]		✓		✓			
[5]		✓		✓	✓	✓	
[8]	✓			✓			
[57]			✓			✓	
[44]	✓			✓		✓	
[38]	✓			✓		✓	
[17]	✓			✓			
[15]		✓		✓			✓
[7]	✓			✓			
[43]	✓			✓			
[65]	✓				✓		✓
[58]	✓			✓	✓		
[19]	✓			✓	✓	✓	
[76]		✓		✓		✓	
[36]				✓		✓	
[55]		✓		✓	✓		
[77]		✓		✓		✓	
[66]		✓	✓			✓	
[3]		✓	✓				
[20]	✓			✓		✓	
[86]	✓			✓		✓	
[54]		✓	✓				
[14]		✓		✓			✓
[78]	✓			✓		✓	

(Continued)

Table 9. Continued

Reference	Agents		Environment		Coordination		
	Homogeneous	Heterogeneous	Static	Dynamic	Centralised	Decentralised	Distributed
[28]	✓		✓		✓		
[70]		✓					✓
[49]		✓					✓
[32]		✓	✓				
[61]		✓		✓		✓	
[39]	✓			✓		✓	
[10]		✓		✓			
[73]							✓
[4]	✓		✓		✓		
[16]		✓		✓		✓	
[6]	✓					✓	
[24]	✓						✓
[37]	✓			✓			✓

from dynamic challenges. Since the environment is static in a static setting, the robots may usually assign tasks using simpler algorithms. One possible approach to assign tasks to the robots would be to employ a centralized algorithm that takes into account their workload and capabilities. Another option is to utilize a distributed algorithm that would let the robots cooperate to determine the best way to divide up the tasks. Because these algorithms presume that the environment remains constant, the robots may perform their tasks without worrying about abrupt changes, which makes them potentially useful. In a dynamic setting, more advanced algorithms are required to manage the conditions that are always changing. For instance, as obstacles or new tasks become available, real-time adjustments may be necessary to the task assignment. In this scenario, robots may require modifications to their respective task allocation strategies through integrating sensing, planning, and communication. In dynamic contexts, algorithms are usually more intricate and may use methods like predictive control, dynamic programming, and reinforcement learning.

RQ3.2: Which constraints apply to the MRTA Problem?

One of the other factors that can be considered for MRTA is the constraints. These constraints are generally categorized into environment constraints, task constraints, and robot constraints. The environment in which task allocation is performed by the robot has a substantial effect on the task allocation. Suppose there are obstacles or walls or other robots in the environment, it can affect the ability of the robot for completing the task allocation process. Also, the type of tasks to be completed can influence the task allocation process. Different tasks may require robots with varying capabilities. Tasks can have different priority levels as well which will influence the order in which they are allocated to the robots for execution. Furthermore, to complete specific tasks, numerous robots may need to collaborate. The task allocation method may also be subject to constraints imposed by the robots themselves. For example, there can be limitations on the robot's speed, sensing capacity, or carrying capability. In addition, the completion of certain tasks may necessitate the collaboration of multiple robots. The robots themselves can also impose constraints for task allocation. For example, the robots may have different capabilities or limitations, such as speed, carrying capacity, and sensing capabilities. Table 10 gives the distribution of papers in which some of the constraints taken into consideration

Table 10. Constraints on MRTA

Study Reference	Constraints
[56, 87]	Spatial Constraints
[12, 18, 56, 74, 77, 78, 87]	Temporal Constraints
[23, 61, 87]	Energy Constraints
[30]	Network Constraints
[36, 68, 70, 79, 83]	Resource Constraints
[44]	Communication Constraints

(a) Temporal Constraints : Temporal constraints describes the duration of time with which a task must be performed. It is common to use intervals to express time. You could represent the temporal constraints on tasks using intervals. If not, temporal constraints can be represented as weighted arcs in graphs termed "Simple Time Networks," where nodes indicate time points and arcs express constraints. In this task network [56], each vertex represents a task, and each edge represents a temporal constraint. Additionally, an ordering constraint such as $a_j \longrightarrow a_i$ indicates a temporal relationship between two tasks, where a_i must be completed before a_j can begin.

(b) Spatial Constraints : Spatial constraints are an important consideration in MRTA, as the efficacy and efficiency of the robot team can be significantly influenced by them. Spatial constraints refer to physical limitations on the movement and placement of robots in the environment, such as obstacles, narrow passages, or limited space. The environment in Graph-based methods is represented in the form of a graph, where nodes denote locations and edges denote potential connections between them. This approach enables the algorithm to take into account spatial constraints by restricting the movement of robots to certain edges or nodes.

(c) Energy Constraints : Energy constraints specifies the limitations on energy utilized by a robot while its performing task execution. In case of real time application where the environment can be dynamic or unknown, the energy constrains are very much important. Robots must be able to execute the task even with limited energy. Reference [61] describes a task allocation strategy that allocates task priorities to the robots with heterogenous abilities.

(d) Resource Constraints: In the MRTA problem, the term "resource" has been employed to denote the consumable provisions that the robot employs during operation, as well as its capabilities, including its sensors and actuators. Each robot has different abilities, thus when the task calls for the execution of numerous capabilities, they should cooperate to complete the task by drawing on one another's resources. Finding the best robot coalition formation for jobs that call for various combinations of robot resources is the solution to the MRTA problem confined by this sort of resource. [36] Focus on task allocation using market based approach. Here the task allocation depends on the bid value which is generated based on expected cost for task. This method reduces the unexpected increase in cost of task allocation.

(e) Communication Constraints: Communication constraints refer to limitations on the ability of robots to communicate with each other in a multi-robot system [30]. These constraints can arise due to various factors such as limited bandwidth, communication delays, signal interference, and physical obstacles in the environment. The performance of the system can be significantly influenced by communication constraints, particularly when the robots are required to coordinate their actions to achieve a common objective.

Table 11. Objective Functions Specified in the Papers

Study Reference	Objective Function
[47]	Minimize task execution time
[60]	Minimizing the energy consume by the robots
[81]	Minimize task execution time
[13]	Maximize expected pure reward
[41]	Minimizing the cost of task assignment
[87]	Minimize the amount of energy consumed by the robots,Reduce cost associated with robots,Maximize the rewards, Minimize the distances and time travelled by the robots
[88]	Allocate the highest possible number of tasks.
[12]	Reduce the survivor's waiting time and the overall distance travelled by robots.
[74]	Maximize task assignment
[34]	Minimize both the completion time of tasks and resource utilization
[79]	Maximize both the tasks completed and the utilization of resources
[44]	Minimize communication between robots
[38]	Minimize both distance and time needed to fulfill all task requirements.
[42]	Minimize the cost associated with energy consumption, operating time, and distance traveled
[17]	Optimization of travel time
[65]	Minimize the time the last task is completed
[76]	Neutralize the intruders with minimal resources while minimizing both the total fuel utilized and the distance traveled
[36]	Minimizing the task completion time
[77]	Minimize over all task completion time
[66]	Minimize task completion time
[64]	Minimize the total time taken to complete task
[3]	Minimize Completion Time of all Task
[86]	Efficient sharing of workload and minimize the distance travelled.
[78]	Minimizing the completion time and minimizing the fuel consumption for different application domains.
[28]	Task completion time was to be minimum
[49]	Maximize the overall payoff of allocating robots with tasks
[61]	Minimization of the cost of assignment
[39]	Maximize the completion time for a single task by a robot, and to maximize the total completion time across all tasks performed by the robot
[2]	Maximize the number of survivors who are affect the utility of a robot for a task, wait time minimization, and Minimize the distance travelled.
[48]	Minimize travel distance
[85]	Minimize sum of path cost
[45]	Maximize profit
[24]	Maximize the number of victims that are rescued

RQ3.3: What would be the different objective functions in MRTA problem?

MRTA is the process of allocating tasks to a group of robots in a manner that optimizes a specific objective function. The objective function defines the metric that the allocation algorithm tries to optimize, such as minimizing the time taken to complete all tasks or maximizing the overall efficiency of the robot team. In MRTA, objective functions are employed to assess the quality of various allocation strategies and drive the algorithm toward the optimal solution. Different funtions used in the scientific papers are given in Table 11. Common objective functions used in

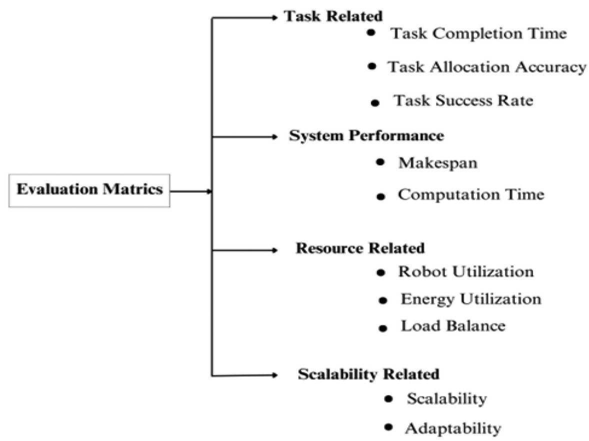


Fig. 7. Key evaluation metrics in MRTA.

MRTA include Makespan which aims to minimize the time taken to complete all tasks. Minimize energy consumption,this objective function aims to minimize the energy consumption of the robot team during task execution. Maximize overall efficiency aims to maximize the overall efficiency of the robot team by assigning tasks to robots with the highest efficiency or minimizing the number of idle robots. The objective of the maximize task completion rate is to increase the number of tasks that are completed within a particular time.

RQ4: What are the kinds of experiments carried out along with the evaluation metrics used and how do they vary for different approaches?

In order to determine the performance of the MRTA system there are some evaluation metrics that effectively measure the individual and collective performance of the robots in the system. These evaluation metrics can be widely categorized into task-related, system performance-related, Resource-related, and Scalability metrics. Figure 7 shows the key evaluation metrics used in MRTA. Table 12 gives the evaluation metrics used in the selected papers as well as the type of experiment, real-time (R) or simulation (S) is carried out.

(a) Task Completion Time: This metric measures the efficiency of task execution. It is the time taken to complete the individual tasks.
(b) Task Allocation Accuracy: It defines the degree to which the tasks are allocated to most suitable robots.
(c) Task Success Rate: It indicates the percentage of completed tasks.
(d) Makespan: It measures the overall system efficiency by calculating the total task completion time.
(e) Computation Time : It can be considered as the time required by the underlying algorithm to process and determine the optimal or feasible solutions to MRTA problems.
(f) Robot Utilization: This metric defines the percentage of times robots are actively engaged in completing a task.
(g) Energy Utilization: This metric is employed in an energy-constrained environment and calculates the amount of energy utilized by the robots during task execution.
(h) Load Balance: This measure looks at how equally the tasks are divided among the robots and assesses the balanced utilization of resources.

Table 12. Evaluation Metrics and Type of Experiment Used in Different Papers

Reference	Maximum No. of robots	Maximum No. of tasks	Scalability	Adaptability	Evaluation metrics	Method	R\S
[52]	15	45	No	No	Completion Time Of Tasks	Cluster	S
[46]	–	128	Yes	–	Computation Time And Scalability	Optimization	S
[47]	6	–	No	No	Computational Time	Learning	S
[56]	25	30	Yes	No	Computation Time, Coverage Percentage, Makespan, Travel Time, Task Planning Nodes Expanded, Task Planning Nodes Visited, Task Allocation Nodes Visited, Average Number Of Concurrent Tasks	Cluster	S
[40]	4	150	–	–	Task Completion Time	Market-Based	S
[81]	3	–	–	–	Total Distance Travelled		R \S
[25]	12	–	No	No		Cluster	R\S
[13]	9		Yes	No	Computation Time		S
[41]	–	–	–	–	Convergence, Converging Speed, Optimality	Optimization	S
[80]	10	50	No	Yes	Travel Distance, Load Balance, Completion Time.	Marlet-Based	S
[72]	10	50	–	–	Task Completion Time	Market-Based	S
[87]	10						S
[30]	10	2518.68	–	–	Total Number Of Tasks		R\S
[88]	180	750	No			Market-Based	S
[18]	4	28	Yes	–	Number Of Tasks That are Scheduled, Distance Robots Travelled,Makespan	Optimization	S
[74]	14	64	–	Yes	Number Of Tasks Allocated With Time Constraints	Market Based	S
[34]	11	–	Yes	Yes	Total Number Of Tasks Completed, Average Communications Per Task, Resource Management Time With A Different Number Of Robots, Resource Consumption With A Different Number Of Robots	Market-Based	S
[79]	5	50	–	–	Number Of Completed Tasks, Resource Consumption On Each Task	Optimization	S
[57]	31			–	Travel Time, Number Of Tasks Completed, Computation Time		S

(Continued)

Table 12. Continued

Reference	Maximum No. of robots	Maximum No. of tasks	Scalability	Adaptability	Evaluation metrics	Method	R\S
[42]	–	–	Yes	–	Task Completion Time, Computation Time	Optimization	R
[58]	16		No		Number Of Tasks Completed		S
[19]	2	5	Yes	–	Task completion rate Navigation efficiency Scalability	Learning	S
[76]				Yes	Task Assignment Accuracy Task Completion Time Scalability Computational Efficiency Solution Optimality Adaptability	Optimization	S
[77]			Yes	Yes	Task completion time Task assignment accuracy Scalability Computational efficiency Resource utilization Scheduling efficiency	Learning	S
[66]			Yes	Yes	Task completion rate Task assignment accuracy Scalability Computational efficiency Resource utilization Convergence speed	Learning	S
[64]	–	–	Yes	Yes	Makespan	Learning	
[32]					Tasking time, computation time, coverage ratio, and segmented area	Cluster	S
[2]					Convergence, distance travelled.	Cluster	S
[48]					Travel time, search time, scalability	Cluster	S
[51]	64	–	Yes	–	Task success rate	Learning	–
[61]	10	2			Task Assignment Accuracy	Optimization	S
[85]			Yes		Computational time	Optomization	S

(i) Scalability: This refers to the capacity of the algorithm or system to continue operating as the number of robots or tasks grows.
(j) Adaptability: This denotes the capacity to deal with sudden changes in the task requirements or surroundings.

From the analysis we could conclude that most of the studies like [46, 52, 72] focus on a single evaluation metrics like the task completion time or computation time, ignoring other aspects like the resource or energy utilization and coordination complexity. A single metric evaluation may result in an incomplete understanding of the overall efficiency or effectiveness of the MRTA system. It is also evident that real-time experiments are very much limited and most of the works use simulation environments for the evaluation,thereby limiting the usability of MRTA systems in

Table 13. Applications of MRTA Problems

Study Reference	Application
[7, 8, 10, 48, 58, 79]	Exploration
[1, 26, 28, 40, 46, 47]	Industrial Application
[34]	Delivery Mission
[5, 13, 18, 19, 41, 43, 44, 49, 55, 57, 70 80, 81, 87, 88]	Generic
[70]	Office Activities
[15, 38]	Landmine Detection
[32]	Agricultural Spraying
[2, 4, 12, 25, 65, 74, 78]	Search And Rescue
[6, 20, 23, 24, 30, 53, 60, 85]	Surveillance
[56]	Routing Problem
[35, 68]	Cleaning
[72]	Pavement Detection
[17, 39, 86]	Intelligent Warehouse
[54]	Delivery Problem
[42]	Inspection
[76]	Perimeter Defence Problem
[14]	Healthcare Facilities

time-sensitive scenarios requiring quick decision-making. In MRTA research [13] fault tolerance receives little attention which is a critical component for resistance against robot failures. MRTA systems run the danger of losing functionality under difficult circumstances without evaluating reliability. Often undervalued in MRTA studies is adaptability to dynamic surroundings and changing task needs.Only a few, such as [46] and [48], explicitly address this, highlighting a gap in understanding how systems handle dynamic changes. Without assessing adaptability, it is difficult to gauge how well MRTA systems can manage real-world scenarios that demand frequent adjustments.

RQ5: Where the MRTA problem can be applied in the real-time scenarios?

This research question discusses the various applications of the MRTA problem. It also identifies the standards of Real-World Experiments of MRTA problem. The MRTA problems have practical applications in various real-world situations. Following are some of the applications discussed in various studies included for the review. Overall, as shown in Table 13 MRTA has numerous real-time applications and can improve the efficiency and effectiveness of many complex systems.

RQ6: What are the challenges and limitations of current studies?

This research question aims to identify the challenges in the MRTA problem and the limitations of the current study. This will help in identifying the potential gaps in this area of research. Table 14 shows the distribution of papers specifying these limitations.

(a) **Motion Planning** in MRTA refers to the process of generating collision-free paths for each robot as it moves to complete its assigned tasks. This is an important consideration in the design of MRS, as collisions between robots can lead to wasted effort and reduced efficiency. With the implementation of MRTA for the applications that doesn't require tight coupling between the robots, motion planning is not troublesome. But for the cases where more complex robot to robot interaction is there planning collision free

Table 14. Challenges in MRTA Problem

Study Reference	Challenges
[17, 18, 25, 63]	Motion Planning
[3, 17, 19, 25, 56]	Dynamic or Uncertain Environment
[13, 41, 57, 74]	Computational Time

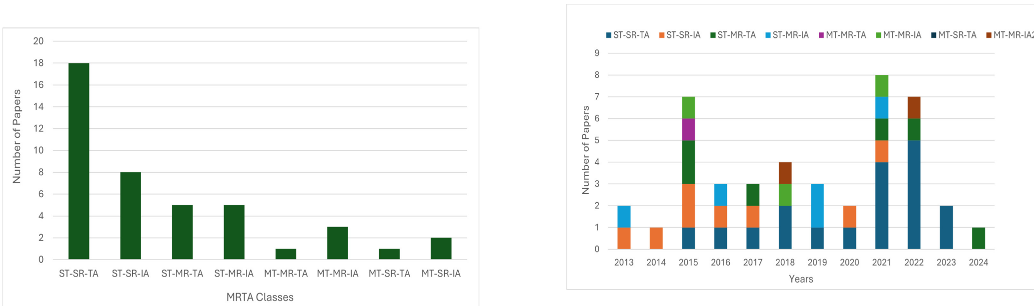
pathways is important. For instances mobile manipulators working in an environment to accomplish household tasks that require cooperative manipulation require motion planning avoiding collision between the robots and other obstacles. Even though there are more sophisticated motion planners [2, 71] for mobility, collision free path planning for teams of heterogeneous robots that have complex interactions to accomplish a task is still an open challenge.

(b) **Dynamic or uncertain environment** MRTA can become more challenging in dynamic or uncertain environment as the robots must adjust to uncertain environment and respond to new information in real-time. For example, in a warehouse environment where goods are constantly being moved around, the robots must be able to quickly adjust their paths and avoid collisions with other moving objects. Spatial, temporal or resource constraints along with uncertain environment is a difficult problem to approach. Different approaches can be employed in the design of MRTA systems in order to solve these difficulties. Online planning and replanning is one method whereby the robots constantly modify their course of action depending on new information and environmental changes. Though computationally costly, this method can be more resistant to environmental changes.Reinforcement learning is one of the machine learning methods used to let the robots learn from their experiences and change their actions with time. Learning from past interactions helps the robots to get more effective and efficient while carrying out assignments within a dynamic surroundings. With recent techniques like learning automaton [16], deep learning [66] or machine learning, only a small few works had able to handle the MRTA in dynamic or uncertain environment.

(c) **Computational Time** is a crucial factor to take into account when designing MRTA because the time needed to allocate tasks and set up paths can have a direct effect on the system's efficacy and efficiency. In most of the studies, the computation time of the experiment grows when the total number of agents grows.Parallel processing or distributed computing enable the system to process information and generate solutions in parallel across multiple processors or computers [13]. When it comes to distributed computation the complexity of the algorithms varies greatly with the complexity of the scenarios. There is always a tradeoff between the computational time and quality of the solutions. The computational time in [74] implies the number of iterations which, in turn, is determined by the processing and communication speed of the robots. Limiting the computational time while retaining the quality of the solution, and deployment in more realistic testing circumstances is another challenge to be dealt with in MRTA problem.

4 Discussions and Findings

It is evident from Figure 8(a), most of the research works focus on the problems that fall under the classes ST-SR-TA and ST-SR-IA. This is because most of the MRTA applications in the real-world belong to this category. Also, there are only a few works that consider the task dependencies explained in iTax taxonomy.



(a) Distribution of scientific papers on MRTA classes.

(b) Number of papers on MRTA classes published in different years.

Fig. 8. MRTA classes based on iTax taxonomy.

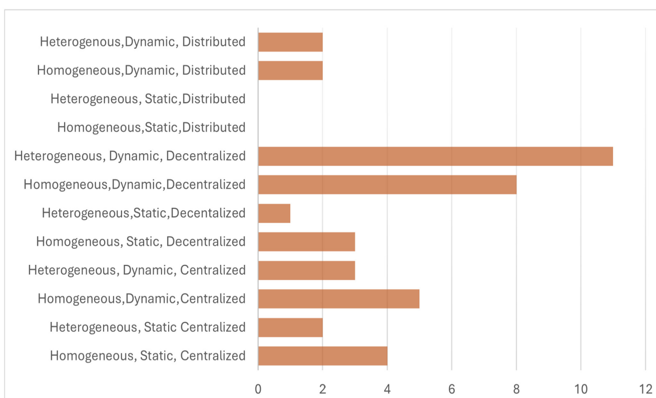


Fig. 9. Number of papers with a combination of types of robots, tasks, and coordination.

Figure 8(b) shows the distribution of MRTA classes over different years. Research works on ST-SR-TA problems has increased over the past few years and there is a lack of research that falls under other MRTA classes. The analysis of different factors of MRTA problem, that is, type of robots, tasks, and coordination used, shows that works with distributed coordination are less when compared to centralized and decentralized. Especially, those with a combination of heterogeneous robots, dynamic environment, and distributed coordination. Figure 9 shows the comparison on the number of papers on different combinations of these factors. Figure 10 filters the previous analysis on objective functions. It shows the distribution of number of papers that deals with some important objective functions. It is found that most of the works deal with optimizing the completion time of the tasks. Only a very few works has been done on the minimizing the communication between the robots and load balance. Moreover, there are only few works that considers multiple objective functions. Figure 11 shows the real-world applications of the MRTA problems. It is found that most of the works are generic meaning they do not mention any specific application. Almost 19% of the works concentrate on the application of MRTA in surveillance scenarios.

4.1 Future Research Direction

From the review conducted we have found some potential gaps as follows: (a) Develop a task rescheduling or reallocation strategy; (b) Nonconvex obstacle avoidance; (c) Task Allocation

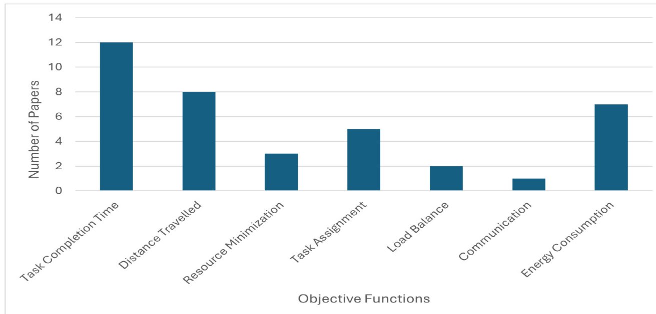


Fig. 10. Distribution of scientific papers over objective functions.

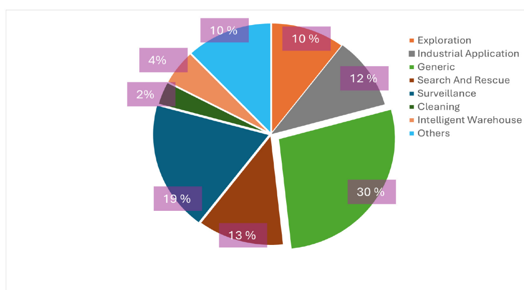


Fig. 11. Distribution of scientific papers over different applications.

considering resource and energy constraints; (d) Taxonomy Complex Dependency (CD) and Cross Schedule Dependency (XD) to be explored.

Task rescheduling or reallocation strategy: The environment that is dynamic or uncertain as well as situations where goals could change asynchronously and unexpected throughout execution like they might be in hostile settings. The two obvious objectives for study are to develop plans that take known run-time exceptions into account and to develop rapid replanning algorithms [47] that can adjust to unforeseen changes during the execution of task.

Nonconvex obstacle avoidance: The obstacles in the environment may be non-convex, meaning that they cannot be represented as simple geometric shapes such as circles or rectangles [14]. Nonconvex obstacle avoidance and dynamic priority changes of the targets is a problem to be solved. Deep reinforcement learning or neural networks allow the robots to learn how to navigate around non-convex obstacles. By training the robots on a variety of environments and obstacle configurations, they can learn to recognize and avoid non-convex obstacles in real-time. This further helps in dealing with scenarios like disaster management wherein heterogeneous tasks and heterogeneous robots [86] are to be deployed.Hybrid approaches, which integrate various trending techniques, are becoming a promising solution for multi-robot systems that need to handle nonconvex obstacle avoidance and dynamic priority changes. Robot's ability to navigate complex environments and dynamically adjust task priorities based on environmental feedback can be improved by integrating attention mechanisms with Deep Reinforcement Learning algorithms. This will improve the overall performance and adaptability of multi-robot system in dynamic settings.

Complex Dependency (CD) and Cross Schedule Dependency (XD): Our study shows that there is a lack of study and deployment of multi-robots in complex scenarios. To be precise, contributions can be made for the situations considering complex dependencies or cross schedule dependencies since the working of MRS requires more coordination and cooperation between the robots. One of the promising future research directions is to develop a Hierarchical- Decentralized coordination framework that allows autonomous robots to handle intra-group dependencies on their own and higher-level systems in the framework to handle inter-group dependencies. Such a framework will delve into the dynamic adaptation of varying robot capabilities and task dependencies. **Multi-Agent Reinforcement Learning** (**MARL**) with Dependency Awareness can be explored to develop a hierarchical MARL framework to handle different levels of task dependencies, addressing both spatial and temporal dimensions of coordination. Future research can also focus on GNNs to enhance multi-robot systems by modeling and learning task dependencies, thereby improving the prediction and management of complex task interactions. This includes developing real-time GNN algorithms that process streaming data from robots, allowing for adaptive and responsive task coordination and allocation in dynamic environments. Additionally, investigating GNN-based communication strategies can optimize how information is propagated across the robot network, reducing communication overhead while maintaining effective coordination. This integrated approach aims to improve the efficiency and scalability of MRS in managing complex, interdependent tasks. We have observed that there are only very few works out of 78 papers selected for the review that performs real-time experiments [1, 4, 5, 20, 25, 47, 61]. Bridging the gap between real time and simulation experiment is still an open problem.

5 Conclusion

This SLR was meant for providing a critical analysis of the 78 papers published on the topic MRTA. The selected papers ranged 11 years from 2013 to 2024. Examining these works has given an understanding of several approaches and strategies applied for MRTA. The real-time applications of MRS make this topic a major focus of research importance.It also shows that there are only a very few works implemented in real-time indicating there is a need to overcome the limitations of implementing the simulated works in the real world. The SLR concludes that the MRTA problem is still crucial and challenging. To the best of our understanding, this survey also gives an active research direction in MRTA.

To conclude, MRTA is an interesting concept with enormous potential in several applications.Many times over conventional single robot systems, the usage of several robots offers scalability, flexibility, and higher efficiency. It can also lower the possibility of human error and offer improved coverage of the task area. Still, the field of MRTA presents numerous more concerns to be solved. These comprise creating effective algorithms for assigning tasks and coordination, best use of resources, handling uncertainty and dynamic surroundings, and guarantees of system security and privacy. Even though there are difficulties in addressing many challenges in MRTA the study in this field is expanding fast. MRTA thus has the potential to transform many different industries, including search and rescue, disaster response, industrial automation, and many more.

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