Technical Decision Brief

Centralized vs. Decentralized Planning in Multi-Robot Task Allocation

B. Joshua McConkie
Prepared for Information and Decision Algorithms (IDeA) Laboratories

July 15, 2026

A practical framework for initial planner selection in multi-agent research

Executive Summary

Efficient multi-robot task allocation (MRTA) is a multi-agent planning problem with applications across robotics domains, including search and rescue, manufacturing, and underwater exploration, and with strong connections to operations research. The large number of available algorithms and methods can make it difficult to select an appropriate starting point when designing an effective, robust task planner. Because the best approach depends on contextual factors, there is no single answer to the question, "Which algorithm is best?" To assist emerging researchers in selecting an effective initial class of algorithms, this report recommends when to begin research with a centralized or decentralized approach. It draws on current MRTA literature and experiments to compare the conditions under which centralized and decentralized approaches are preferable, based on solution quality, runtime, communication feasibility, robustness to failure, and scalability.

Recommendation
When an MRTA research problem is low- to medium-scale and conducted in a controlled environment with reliable centralized communication infrastructure and low uncertainty, the researcher should begin with a centralized approach. Otherwise, if the problem is large-scale, lacks reliable communication with a central planner, or involves high uncertainty, a decentralized approach should be preferred as a starting point. Figure 1 summarizes this recommendation as a three-factor decision framework.

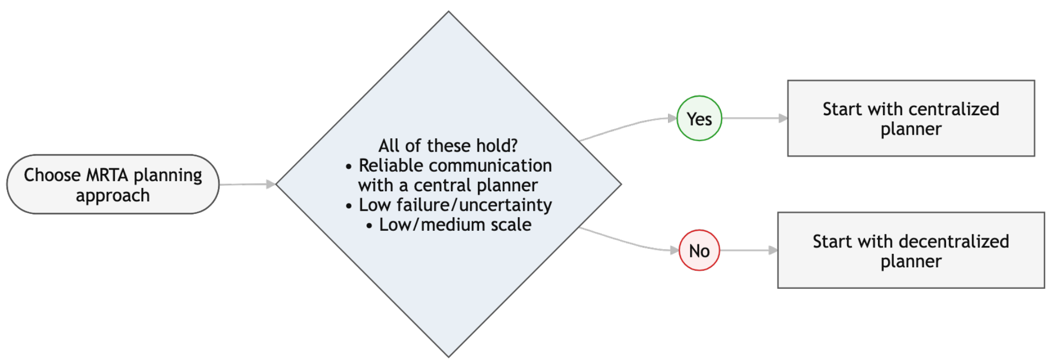

Figure 1: MRTA Algorithm Decision Framework

This brief is not intended to replace existing MRTA surveys. Instead, it translates selected findings from the MRTA literature into a practical framework for choosing between centralized and decentralized planners in early-stage multi-agent research.

1 Introduction

In multi-robot systems, a mission often consists of a set of tasks that must be distributed among the robots. The problem of efficiently distributing these tasks is known as Multi-Robot Task Allocation (MRTA). This allocation is carried out by an algorithm, or "planner." In general, planners can be divided into two classes: centralized and decentralized. The best allocation approach depends on task structure, assignment type, and domain constraints (Gerkey & Matarić, 2004; Nunes et al., 2017). Choosing the wrong approach can reduce solution quality, increase computation time, or make a system unviable (Mahato et al., 2023). Thus, selecting the right approach is a critical step for anyone investigating solutions to multi-agent control problems. This report examines current research on MRTA and the trade-offs between centralized and decentralized task allocation across various settings, and recommends when each approach is best suited for multi-robot/multi-agent task allocation research.

2 Methodology

This report uses a targeted, selective review of peer-reviewed MRTA literature. Sources were identified through Scopus and online search engines. Studies were selected when they explicitly reported results relevant to one or more of the evaluation criteria: solution quality, runtime, communication requirements, robustness to failure, and scalability. Examples were sought across different application settings to examine how operating conditions affected the relative performance of centralized and decentralized methods. The review was intended to assemble representative comparative evidence rather than exhaustively identify all relevant MRTA studies.

Searches combined terms related to multi-robot task allocation, centralized and decentralized planning, and each evaluation criterion.

3 Criteria

Although solution quality and runtime are the primary measures of algorithmic performance, planner selection also depends on the conditions under which the system operates. This report therefore compares selection of centralized and decentralized methods based on three additional criteria: centralized communication feasibility, robustness to failure, and scalability. These factors recur throughout the literature and help explain differences in solution quality and runtime across applications (Gielis et al., 2022; Jamshidpey et al., 2026; Poudel et al., 2023). In this report, scale refers primarily to the number of robots and tasks or subtasks involved in the allocation problem.

4 Solution Analysis

Centralized and Decentralized Methods

Centralized methods use a single agent to plan allocations for the rest of the network. Such algorithms perform optimization well under full information. These methods can outperform distributed methods because centralized planners in a controlled environment have global access to all available data (Geng et al., 2019). Decentralized methods are characterized by a network of multiple agents, each making decisions based on local information. Decentralized approaches have become a more powerful alternative in recent years, demonstrating robustness across many applications (Quinton et al., 2023).

Solution Quality

Centralized approaches often have an advantage in solution quality when they have access to global information. In search-and-rescue task allocation experiments, Geng et al. (2019) used a centralized algorithm as a benchmark for other methods because it had access to all available information. Their modified central particle swarm optimization (MCPSO) algorithm outperformed all tested distributed algorithms. This supports the use of centralized algorithms when full information is available. Wang et al. (2024) demonstrated another example of the solution quality of centralized methods in a controlled environment. Their underwater multi-robot path-planning experiment tested a centralized solver. This approach consistently found globally optimal solutions under the tested assumptions. The actual usefulness of these models depends on how closely their assumptions align with an implementation scenario, including the presence of communication barriers, energy constraints, and changing conditions.

In a multi-robot additive manufacturing experiment, Poudel et al. (2023) found that the centralized algorithms produced better solutions for small-scale problems, but the gap between centralized and decentralized solutions narrowed as scale increased. Thus, centralized solution-quality advantage may diminish as problem size grows.

Runtime

In Geng et al.'s (2019) search-and-rescue study, the tested centralized MCPSO method outperformed all others in runtime. This is evidence that centralized methods can also be quicker than the alternative in full-information scenarios.

However, Poudel et al. (2023) found that as the scale of their experiments increased, their centralized planner's computation time increased dramatically, whereas the decentralized planner's did not. This indicates that neither centralized nor decentralized planning is inherently better in terms of runtime; the preferred approach depends on the problem scale and operating conditions. This is illustrated in non-static environments as well. When new tasks are introduced mid-execution, a good planner must be able to make reassignments quickly. Decentralized algorithms are preferred when repeated allocation is necessary (Bagchi et al., 2024).

Centralized Communication Feasibility

Consider MRTA problems in hostile situations with time and energy constraints. Mahato et al. argue that in disaster response, exploration, and hostile environments, centralized network infrastructure may be unstable or unavailable, making decentralized task allocation necessary. Within such decentralized systems, their communication-aware decentralized method reduced both energy costs and runtime compared with other distributed approaches (Mahato et al., 2023). These results support viewing the availability of reliable centralized infrastructure as a planner-selection criterion.

Centralized methods are more justified in scenarios where information can consistently be passed through a single point. Wang et al. illustrate this advantage under strong idealized assumptions: although they acknowledge the communication barriers present in underwater environments, their centralized model assumes ideal communication conditions and globally available task and AUV information. This contrast highlights the difference between performance under idealized models and the constraints of real-world deployment.

Robustness to Failure and Uncertainty

Should a centralized planning agent fail, the entire multi-agent network would no longer receive proper allocation. Distributed systems reduce dependence on a single central planner and are therefore more resilient against concentrated attacks or failures on a single decision-making node (Shorinwa et al., 2023). In a study on multi-robot ground-sweep coverage, simulations found that while centralized approaches significantly outperformed decentralized approaches in solution quality and runtime, decentralized systems were preferable for scalability and fault tolerance (Jamshidpey et al., 2026).

Poudel et al. also demonstrated a limitation of centralized planning under execution time uncertainty. Variations in print times caused execution to diverge from the generated plan. In contrast, the decentralized planner was less dependent on a fixed global schedule and handled the discrepancies with local reassignment (Poudel et al., 2023). This example displays potential flexibility of decentralized planning in a multi-robot system operating under uncertainty.

Scalability

In multi-robot additive manufacturing experimentation, centralized methods incurred significant penalties in solution runtime, whereas distributed methods maintained comparatively stable computation time. The solution quality gap between approaches also narrowed as the problem grew larger (Poudel et al., 2023). The same principle is supported by Jamshidpey et al.'s (2026) research on sweep coverage. They explicitly identified scalability as a strength of decentralized systems.

Additionally, scalability interacts with communication overhead. More robots and tasks can increase the information exchanged between agents, raising the time and energy required for decentralized allocation (Mahato et al., 2023). Thus, scalability affects not only computation time but also the demands placed on the communication architecture.

5 Conclusion and Recommendation

Choosing the correct MRTA planning approach often involves a trade-off between the theoretical optimality of centralized coordination and the adaptability of decentralized planning. Centralized solutions capitalize on global information within a controlled setting. Decentralized methods can be more robust in less-controlled settings.

Emerging researchers should begin new MRTA studies by classifying their problem based on the three factors: centralized communication feasibility, presence of uncertainty/failure risk, and scale. A centralized planner is generally the better initial choice for low- to medium-scale problems in controlled, low-failure settings with reliable central communication. A decentralized planner is the stronger starting point for settings that are large-scale, uncertain, failure-prone, or where central communication is infeasible. Following this framework enables researchers to focus on candidate algorithms more likely to be useful in their experiments.

References

Bagchi, M. J., Nair, S. B., & Das, P. K. (2024). On a dynamic, decentralized, energy-aware technique for multi-robot task allocation. Robotics and Autonomous Systems, 180, Article 104762. https://doi.org/10.1016/j.robot.2024.104762

Geng, N., Meng, Q., Gong, D., & Chung, P. W. H. (2019). How good are distributed allocation algorithms for solving urban search and rescue problems? A comparative study with centralized algorithms. IEEE Transactions on Automation Science and Engineering, 16(1), 478–485. https://doi.org/10.1109/TASE.2018.2866395

Gerkey, B. P., & Matarić, M. J. (2004). A formal analysis and taxonomy of task allocation in multi-robot systems. The International Journal of Robotics Research, 23(9), 939–954. https://doi.org/10.1177/0278364904045564

Gielis, J., Shankar, A., & Prorok, A. (2022). A critical review of communications in multi-robot systems. Current Robotics Reports, 3, 213–225. https://doi.org/10.1007/s43154-022-00090-9

Jamshidpey, A., Wahby, M., Allwright, M., Zhu, W., Dorigo, M., & Heinrich, M. K. (2026). Centralization vs. decentralization in multi-robot sweep coverage with ground robots and UAVs. Artificial Life and Robotics, 31(1), 3–24. https://doi.org/10.1007/s10015-025-01049-7

Mahato, P., Saha, S., Sarkar, C., & Shaghil, M. (2023). Consensus-based fast and energy-efficient multi-robot task allocation. Robotics and Autonomous Systems, 159, Article 104270. https://doi.org/10.1016/j.robot.2022.104270

Nunes, E., Manner, M., Mitiche, H., & Gini, M. (2017). A taxonomy for task allocation problems with temporal and ordering constraints. Robotics and Autonomous Systems, 90, 55–70. https://doi.org/10.1016/j.robot.2016.10.008

Poudel, L., Elagandula, S., Zhou, W., & Sha, Z. (2023). Decentralized and centralized planning for multi-robot additive manufacturing. Journal of Mechanical Design, 145(1), 012003. https://doi.org/10.1115/1.4055735

Quinton, F., Grand, C., & Lesire, C. (2023). Market approaches to the multi-robot task allocation problem: A survey. Journal of Intelligent & Robotic Systems, 107, Article 29. https://doi.org/10.1007/s10846-022-01803-0

Shorinwa, O., Haksar, R. N., Washington, P., & Schwager, M. (2023). Distributed multirobot task assignment via consensus ADMM. IEEE Transactions on Robotics, 39(3), 1781–1800. https://doi.org/10.1109/TRO.2022.3228132

Wang, H., Li, Y., Li, S., & Xu, G. (2024). Research on multiple AUVs task allocation with energy constraints in underwater search environment. Electronics, 13(19), 3852. https://doi.org/

10.3390/electronics13193852