# Distributed Adaptive Macroscopic Ensemble Task Allocation of Heterogeneous Robot Teams in Dynamic Environments

Extended Abstract

Victoria Edwards
The GRASP Laboratory, University of Pennsylvania
Philadelphia, USA
vmedw@seas.upenn.edu

M. Ani Hsieh
The GRASP Laboratory, University of Pennsylvania
Philadelphia, PA
mya@seas.upenn.edu

## ABSTRACT

Robot teams that build highly predictive models of environments like the ocean require effective methods to collect sensor data. A robot team can collect this data, but the challenge is continuously assigning robots to informative sampling locations. Existing methods design specialized solutions for individual robots that lack the necessary flexibility. Instead, recent extensions allow macroscopic ensemble allocation to adapt with environmental changes, but currently relies on impractical centralized assumptions. To address the need for centralization, we introduce a heterogeneous formulation with unmanned aerial vehicles and a communication task where a small portion of the surface team ferries information between robots performing spatially distributed sampling tasks. We show a distributed adaptive macroscopic allocation solution with similar performance to the centralized strategy.

## KEYWORDS

Environmental Monitoring; Macroscopic Ensemble Modeling; MRTA

**ACM Reference Format:**
Victoria Edwards and M. Ani Hsieh. 2025. Distributed Adaptive Macroscopic Ensemble Task Allocation of Heterogeneous Robot Teams in Dynamic Environments: Extended Abstract. In *Proc. of the 24th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2025), Detroit, Michigan, USA, May 19 – 23, 2025*, IFAAMAS, 3 pages.

## 1 INTRODUCTION

To build representative and predictive models of environments like the ocean, it is necessary to collect multiple data samples at similar times and different spatial locations [4]. To achieve this we use robot teams equipped with sensors to augment data collection [12]. However, this requires effectively assigning robots to informative sampling locations, [9], a variant of the well known Multi Robot Task Allocation Problem (MRTA) [5]. Microscopic approaches solve a resource optimization problem for each individual robot and have scalability issues with increased team size or environmental complexities. In contrast, macroscopic methods can be used to efficiently assign populations of robots to spatially distributed tasks to achieve team-wide coordination [3]. Nevertheless, this paper addresses prior centralized assumptions in [2], and presents a distributed adaptive macroscopic allocation solution to the MRTA problem.

This work is licensed under a Creative Commons Attribution International 4.0 License.

*Proc. of the 24th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2025), Y. Vorobeychik, S. Das, A. Nowé (eds.), May 19 – 23, 2025, Detroit, Michigan, USA.* © 2025 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org).

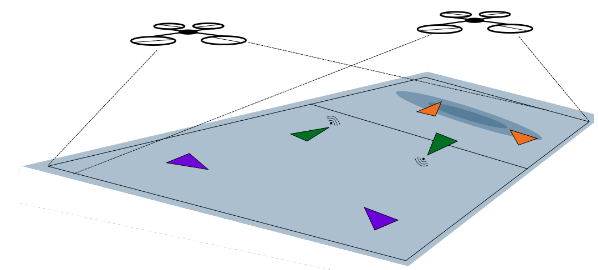


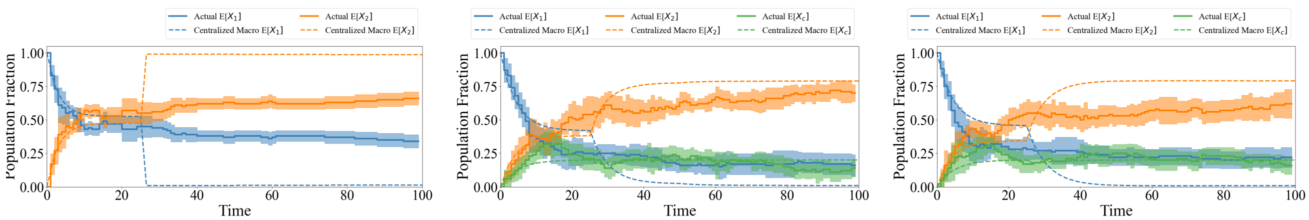
**Figure 1: Distributed adaptive macroscopic allocation uses a communication task (green triangles) to share data between robots in different task regions (orange and purple triangles) and UAVs providing team-wide task assignment estimates.**

Recently, we introduced an adaptive macroscopic ensemble approach to achieve responsive task assignment to dynamic environments [2]. However, this prior work relies on robots maintaining a fully connected communication network at all times. This is fine for laboratory settings, but it is not practical for deployed robot teams performing environmental monitoring. There are two challenges to break this assumption. Firstly, each robot needs additional information beyond its own measurements to maintain a congruent representation of the environment, a problem that can be exacerbated by changing environmental conditions. Secondly, each robot requires an estimate of the team-wide task assignment to use as allocation model feedback [11].

We present a distributed adaptive macroscopic allocation framework for robot team task assignment in dynamic environments, shown in Figure 1. The contributions of this work are 1) Incorporating a communication task into the adaptive macroscopic ensemble modeling to ensure local data is spread throughout the team helping to more accurately assign team resources. 2) Using a UAV to provide team-wide assignment estimates for responsive allocation of robots on the surface monitoring environments like the ocean. Our results show that our distributed approach performs comparably to centralized macroscopic assignment and supports that a communication task helps when communication is limited.

## 2 PRIOR WORK & METHOD SUMMARY

Each robot has a local environment model and macroscopic model extending the centralized solution in [2]. To ensure congruent environment and team models, we require the team to share data samples. Distributed approaches for multi-robot coordination often use highly flexible opportunistic communication strategies [1], *e.g*,




**(a) No Communication Task** **(b) Communication Task 1** **(c) Communication Task 2**

**Figure 2: Average results for the distributed adaptive macroscopic task allocation. Each plot contains the centralized macro-continuous solution to the model (dashed line) and the average population counts over 10 simulation trials (sold line).**

robots share data when nearby, or form more structured mobile sensor networks composed of robots [6]. Due to the size and changing conditions of the environment, opportunistic strategies may leave some robots isolated for extended periods of time. Likewise, sensor networks may require a prohibitively large number of robots to ensure that a continuous mesh can be created between all robots. An alternative solution is to have a subset of the team dedicated to a communication task where robots assigned to this task can focus on effectively sharing data throughout the team [10]. Our solution expands the solution presented in [2], and introduces a communication task to the macroscopic ensemble allocation model.

Several different distributed methods have been proposed to estimate the global task assignment in macroscopic ensemble modeling [8]. These methods assume that all robots performing a task go to a central task location and that the time between changing task assignment will not matter. Consequently, these approaches will not work in monitoring tasks in dynamic environments since robots have the potential to be spread throughout the assigned task regions, and the responsiveness of the team assignment is dependent on having a global team-wide assignment estimate. To address the problem of team-wide estimates, we employ an unmanned aerial vehicle (UAV), [7], to provide high level data of the environment and an estimate of the number of robots executing each task.

## 3 RESULTS

Given $M = 2$ task regions, Environment 1 has sparse information moving from top to bottom in task region 2. We assume that robots move faster than the dynamic process of interest and collect a snapshot of data which includes data from the UAV, local samples collected, and any communicated measurements. Our proposed approach introduces a communication task. In this work, robots performing a communication task have two options: communication task 1 (Comm 1) has robots switch between task regions and communication task 2 (Comm 2) has robots form a sensor network.

Figure 2 shows the average task population counts over 10 simulation trials (solid lines, standard deviations are shaded regions) for each communication method and compare this to an example ideal centralized model distribution (dashed lines). The centralized model distribution incorporates all data from the UAV and each member of the robot team and updates the macroscopic model parameters at fixed intervals of 25 seconds. Figure 2a shows the no communication task most often experiences the worst case for our method and evenly splits the team between the two task regions. This happens because robots in task region 1 do not come within opportunistic communication range of robots in task region 2. In Figure 2b and 2c, the addition of a communication task behavior sees the populations more closely match the ideal centralized solution.

## 4 CONCLUSION

We present a distributed adaptive macroscopic allocation method which assigns robots to regions in the environment based on relative task region importance. Our top-down approach easily incorporates an added communication task to overcome limitations when communication is restricted throughout the team. Similarly, an overhead UAV is used to provide coarse environment estimates and global estimates of the team task assignment which is used as feedback to the macroscopic model. Our results show similar performance to centralized adaptive macroscopic allocation.

## REFERENCES

[1] Fernando Cladera, Zachary Ravichandran, Ian D. Miller, M. Ani Hsieh, C. J. Taylor, and Vijay Kumar. 2023. Enabling Large-scale Heterogeneous Collaboration with Opportunistic Communications. arXiv:2309.15975 [cs.RO]

[2] Victoria Edwards, Thales C. Silva, and Ani M. Hsieh. 2025. Adaptive Macroscopic Ensemble Allocation for Robot Teams in Dynamic Environments. *Under Review* (2025).

[3] Karthik Elamvazhuthi and Spring Berman. 2019. Mean-field models in swarm robotics: a survey. *Bioinspiration & Biomimetics* 15, 1 (nov 2019), 015001. https://doi.org/10.1088/1748-3190/ab49a4

[4] Christopher B Field, Vicente Barros, Thomas F Stocker, and Qin Dahe. 2012. *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change.* Cambridge University Press.

[5] Brian P Gerkey and Maja J Matarić. 2004. A formal analysis and taxonomy of task allocation in multi-robot systems. *The International Journal of Robotics Research* 23, 9 (2004), 939–954.

[6] Bing Li, Shengjie Zhao, Ruiqin Miao, and Rongqing Zhang. 2021. A survey on unmanned aerial vehicle relaying networks. *IET communications* 15, 10 (2021).

[7] Chang Liu, Jin Zhao, and Nianyi Sun. 2022. A review of collaborative air-ground robots research. *Journal of Intelligent & Robotic Systems* 106, 3 (2022), 60.

[8] T William Mather and M Ani Hsieh. 2011. Distributed robot ensemble control for deployment to multiple sites. *Robotics: Science and Systems VII* (2011).

[9] Derek A Paley and Artur Wolek. 2020. Mobile sensor networks and control: Adaptive sampling of spatiotemporal processes. *Annual Review of Control, Robotics, and Autonomous Systems* 3 (2020), 91–114.

[10] Hannes Rovina, Tahiya Salam, Yiannis Kantaros, and M. Ani Hsieh. 2020. Asynchronous Adaptive Sampling and Reduced-Order Modeling of Dynamic Processes by Robot Teams via Intermittently Connected Networks. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* 4798–4805.

[11] Thales C. Silva, Victoria Edwards, , and Ani M. Hsieh. 2022. Proportional Control for Stochastic Regulation on ALlocation of Multi-Robots. *Distributed Autonomous Robotics Systems (DARS)* (2022).

[12] Yoonchang Sung, Zhiang Chen, Jnaneshwar Das, Pratap Tokekar, et al. 2023. A Survey of Decision-Theoretic Approaches for Robotic Environmental Monitoring. *Foundations and Trends® in Robotics* 11, 4 (2023), 225–315.