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RoboVineSim: A Simulation Tool for Human-Robot Collaboration in Vineyard Harvesting

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Abstract

In agricultural tasks, manual grape harvesting remains a labor-intensive activity facing challenges of efficiency, labor shortages, and sustainability. To this end, tailor-made robotic systems have been designed with the capabilities to transfer heavy boxes, navigate vineyard terrains, communicate, accurately locate, and safely interact with humans. The introduction of collaborative robotic fleets alongside human workers in large-scale vineyard harvesting effectively presents a Multi-Robot Task Allocation (MRTA) problem, where the real-world domain possesses characteristics that, when combined, pose a challenging research endeavor and align with open issues in MRTA research. Here, we present RoboVineSim, a simulation tool that can capture any vineyard area using geographical data and model the behavior of humans and robots in the environment. In addition, we have established the necessary mechanisms to facilitate the development of novel MRTA methods in this domain.

1 Introduction

Agricultural Robotics [Duckett *et al.*, 2018] present new opportunities that already transform the landscape of agricultural operations. The technological capabilities of robotic platforms are harnessed in a wide range of field applications [Bechar and Vigneault, 2017]. Such platforms may require human monitoring and intervention, while others are targeted for Human-Robot Collaboration (HRC) environments where human workers coexist and collaborate with robots [Yerebakan and Hu, 2024]. In the context of harvesting applications, the current roadmap for HRC research calls for principled designs that tackle safety, functionality, and interface design (in that order) [Adamides and Edan, 2023]. In particular, the functionality aspect aligns with the task allocation mechanism for the robotic fleet. For HRC in vineyard harvesting, we are interested in expanding the capabilities of a flexible robotic platform [Conejero *et al.*, 2025] that helps humans harvest grapes by undertaking the transportation task.

Figure 1: Simulation environment with online visualization of robots and humans.

The robotic fleet consists of four-wheeled mobile robots designed to transport boxes. Each robot is equipped with the necessary hardware and software to safely detect, track, and follow a human worker along a vineyard row, while maintaining reliable communication with a centralized system.

However, scheduling this multi-robot system efficiently presents a challenge, as we need to account for human-imposed uncertainty about timings and heterogeneity between them, e.g., depending on their expertise, as shown from field tests [Conejero *et al.*, 2025]. To advance the capabilities of the technology, this HRC environment can be formulated as a Multi-Robot Task Allocation (MRTA) problem [Khamis *et al.*, 2015]. The development and evaluation of solution methods require a capable and flexible simulation environment, and, to the best of our knowledge, existing work on related problems [Seyyedhasani *et al.*, 2020; Peng *et al.*, 2022] relies on ad hoc simulators with limited extensibility and limited open-source availability.

To this end, we propose RoboVineSim[1] (ROBOtic VINEyard SIMulator), a novel simulation tool that models key components of a real-world vineyard setting—including hu-

[1]A demonstration video presentation is available at: https://drive.google.com/file/d/1tuQ6yXjyhbvODIMu6n8QYOPWJMTe4KEZ.

mans, robots, and the environment—and translates them into an MRTA problem. What distinguishes it from related work is that it: a) incorporates Geographical Information System (GIS) data capturing any arbitrary vineyard layout; b) supports configurable assumptions regarding robots and humans, by specifying robots' kinematics and task-specific characteristics, and how humans' performance evolves over time according to their fatigue levels [Yao *et al.*, 2024]; and c) is compatible with any task allocation algorithm that can operate in an online manner, receiving and allocating new tasks. Robots navigate the environment autonomously, conforming to its topological layout and following their task sequence, with routes updated automatically as new tasks arrive. Figure 1 shows the simulator's graphical user interface.

From a research perspective, RoboVineSim offers substantial benefits that extend the specific agricultural application for robotics. Our simulator can be used as a benchmark environment for MRTA research, as the setting poses well-known challenges, including scalability (controlling large robotic fleets across vast areas), flexibility (operating in open environments that adapt to sudden changes), incorporation of uncertainty, and need for dynamic task allocation. Benchmarks in the literature that encompass a combination of the aforementioned elements are scarce [Quinton *et al.*, 2023]. Furthermore, by modeling a challenging real-world environment and with the field-testing opportunities presented by the existing robotic platform [Conejero *et al.*, 2025], this endeavor is also geared towards novel MRTA methods that bridge the gap between simulation-based evaluation and field deployment.

2 Problem Description

We model our MRTA problem as one consisting of parallel rows of grapes, and we consider each human $h_i, i \in [0, H-1]$ of the harvesting team to be located in a different row, harvesting grapes with a rate of $f_i(t)$ weight unit per time unit at each discrete time-step t. This element introduces: (a) the heterogeneity of humans in terms of performance (function is unique to each human), along with uncertainty in the case $f_i(t)$ follows some probability distribution. Harvesting sessions typically span many hours, during which human fatigue builds. This aspect is investigated in manufacturing processing research [Yao *et al.*, 2024; Asadayoobi *et al.*, 2023], which shares conceptual similarities with our domain of interest, and should affect the form of $f_i(t)$.

To make efficient use of an available robotic fleet, we formulate an MRTA problem to determine robots' behavior by assigning tasks to them. A robot $r_k, k \in [0, R-1]$ assigned for a task τ_{ij} of human h_i performs the following consecutive actions in order to execute it:

1. start from a station s_l and navigate the vineyard to reach h_i (r_4 in Figure 2);
2. follow h_i until a certain amount of weight is collected; (r_1, r_5, r_8 in Figure 2); and
3. return to the closest station and unload the full box. (r_7 in Figure 2)

Afterwards, robot r_k is available for a new task. If there are no pending tasks, it remains at the station (r_0, r_2, r_3, r_6 in

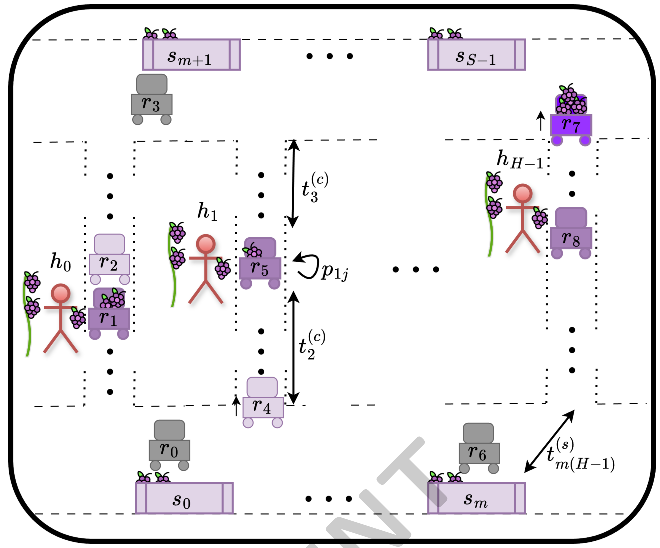

Figure 2: MRTA problem formulation capturing different travel times.

Figure 2). Each robot maintains a sequence of tasks (illustrated in Figure 3) that is updated online based on a task allocation mechanism.

Reflecting our current objective, successive tasks $\tau_{i(j-1)}, \tau_{ij}$ of human h_i should be ideally executed without any intervening delay. As robots handle transportation tasks, humans can concentrate solely on grape collection without interruptions caused by robot delays.[2] Essentially, when the robot assigned with $\tau_{i(j-1)}$ is about to leave human h_i and exit, a second robot assigned with task τ_{ij} should be there already to replace it. Since vineyard rows are narrow, we do not allow robots to cross paths within a row to prevent collisions or deadlocks. This means that we have constraints regarding how robots should navigate the vineyard, which are also part of the MRTA formulation. In Figure 2, we see additional timing information that is needed to accurately represent this problem. These involve various *travel* (time to navigate between key locations) and *processing* (time human h_i needs to fill up the box to capacity) times.

Humans work with different rates, and fatigue is expected to gradually increase their processing times over extended operations. At a given time-step, over a long planning horizon, a set of tasks need to be assigned, each with distinct processing time, and time precedence constraints on successive tasks $\tau_{i(j-1)}, \tau_{ij}$. Based on the established taxonomy of MRTA problems [Quinton *et al.*, 2023], we can classify our problem as SR-ST-TA:SP, XD (Single-task Robot, Single-robot Task, Time-extended Assignment with Synchronization and Precedence constraints and Cross-Schedule Dependencies). The environment is also dynamic, and we have uncertainty about how it evolves, an element that stems from the collection rate $f_i(t)$ of humans, which in turn can be modeled by human fa-

[2]Instead of the typical makespan objective in scheduling problems. Naturally, more elaborate criteria involving multiple goals (e.g., energy efficiency) and soft constraints (e.g. respecting human fatigue limits) can be examined.

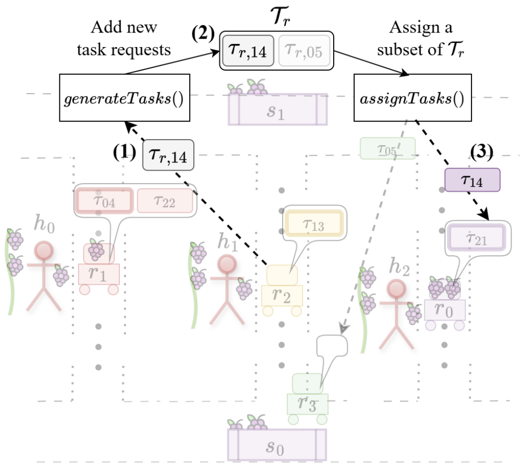

Figure 3: Task generation and allocation in RoboVineSim: (1) $generateTasks()$ creates new task request $\tau_{r,14}$, (2) it is appended to the set $\mathcal{T}_r$, and (3) $assignTasks()$ allocates it to a robot.

tigue models [Yao *et al.*, 2024]. Moreover, tasks gradually appear online according to adjustable conditions. Based on the robotic platform's capabilities [Conejero *et al.*, 2025], we can assume global connectivity without communication issues. However, our simulation environment does not restrict the development of decentralized methods, assuming only local communication (fully distributed based on proximity or any type of hierarchical structure) among robots. In addition, we can also draw similarities with Flexible Job-Shop Scheduling Problems with Sequence-Dependent Setup Times [Shen *et al.*, 2018]. Based on the notation of such problems, each human acts as a *job* with successive *operations* (tasks) and each robot as a *machine*.

3 Assigning Tasks to Robots

In our simulation environment, we have a discretized time-step length. At each time-step, two main methods $generateTasks()$, $assignTasks()$ are called with access to a data structure containing each robot's online information and current schedule. Thereby, we assume a centralized system that communicates with all robots and has access to their information, as indicated in Figure 3. More specifically, we have a set of *task requests* $\mathcal{T}_r$, where $generateTasks()$ can append new tasks $\tau_{r,ij}$ according to user-defined conditions. Each entry is a tuple with the following information: $\tau_{r,ij} = \langle h_i, j, t_{ij,e}, p_{ij} \rangle$, where h_i: human associated with the task; j: the jth task of h_i; $t_{ij,e}$: earliest start time of task; and p_{ij}: duration of task (estimate in the case of uncertainty). Then, $assignTasks()$ needs to allocate each element to a robot. Notably, task requests can remain unallocated until a deadline (according to the earliest start time $t_{ij,e}$ of $\tau_{r,ij}$).

Inside $assignTasks()$, we implement a Sequential Single-Item (SSI) auction [Dias *et al.*, 2006] to exemplify our tool, and form a simple bidding function $b_k(\tau_{r,ij})$ based on the time robot r_k expects to finish $\tau_{r,ij}$. Naturally, other classic methods based on Mixed-Integer Linear Programming (MILP) or Metaheuristics [Chakraa *et al.*, 2023], could also be considered by appropriately processing the set $\mathcal{T}_r$ and (re-)scheduling tasks online according to a frequency term. Decentralized methods, such as the Consensus-based Auction Algorithm [Choi *et al.*, 2009] and its extensions, could also be adopted. This can be accomplished by implementing $assignTasks()$ with restricted information access and communication among robots based on a decentralized scheme.

4 Additional Aspects

Capture Vineyard Areas with GIS Software. We can prepare an appropriate input file based on any vineyard's geographical data. By prescribing key points of interest (row entries, station and intermediate point positions wherever needed), we can directly construct a topological map for our problem and, assuming GPS-enabled robots, command them accordingly. QGIS software [QGIS Development Team, 2026] is used for this procedure. With UTM coordinates and certain assumptions, we can then measure distances accordingly. Another useful feature of working with geographical data is that we can parse satellite and aerial landscape views to our visualizer, as illustrated in Figure 1, and display robots' and humans' online behavior.

Robot Navigation in the Vineyard. Robots navigate the constructed vineyard network using assumed kinematics and projected UTM coordinates, enabling us to estimate travel time data for each robot. To prevent deadlocks in vineyard rows, robots maintain the same direction alongside a row. A direction change can only be triggered when a robot enters the row, provided the row contains at most one robot at that time. In such cases, the robot already inside is notified and adjusts its exit direction and the nearest station accordingly. As a result, a robot attempting to enter an occupied row from the wrong direction may be forced to wait at the entry point. This highlights the importance of efficient and informed task allocation, as robots may end up waiting in queues.

Configuration File. A main configuration file prescribes the human and robotic fleet along with their characteristics and initializes the environment according to the GIS data.

5 Conclusions and Future Work

We presented the development of RoboVineSim, a research-focused simulator designed as an expansive tool that supports research on MRTA methods for tackling HRC in similar environments. Furthermore, by calibrating our assumptions regarding the robots, e.g. the hardware being part of a specific robotic platform as the one developed in [Conejero *et al.*, 2025], along with how humans operate and how their fatigue evolves in this environment [Yao *et al.*, 2024], we can provide a complete framework for sustainable agriculture in HRC, advancing the capabilities of robotic infrastructure in terms of coordination and online adaptation.

Future work endeavors involve operating alongside ROS2 [Macenski *et al.*, 2022] and Gazebo [Agüero *et al.*, 2015] to gain insight into the actual hardware characteristics of the robotic fleet, assessing aspects such as communication delays and robot kinematic calibration, ultimately resulting in a proper end-to-end platform. Furthermore, we are working to model and understand the impact of human fatigue on the design of MRTA methods.

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References

[Adamides and Edan, 2023] George Adamides and Yael Edan. Human–robot collaboration systems in agricultural tasks: A review and roadmap. *Computers and Electronics in Agriculture*, 204:107541, 2023.

[Agüero *et al.*, 2015] Carlos E. Agüero, Nate Koenig, Ian Chen, Hugo Boyer, Steven Peters, John Hsu, Brian Gerkey, Steffi Paepcke, Jose L. Rivero, Justin Manzo, Eric Krotkov, and Gill Pratt. Inside the virtual robotics challenge: Simulating real-time robotic disaster response. *IEEE Transactions on Automation Science and Engineering*, 12(2):494–506, 2015.

[Asadayoobi *et al.*, 2023] Negin Asadayoobi, Sharareh Taghipour, and Mohamad Y. Jaber. Optimising stochastic task allocation and scheduling plans for mission workers subject to learning-forgetting, fatigue-recovery, and stress-recovery effects. *Expert Systems with Applications*, 229:120524, 2023.

[Bechar and Vigneault, 2017] Avital Bechar and Clément Vigneault. Agricultural robots for field operations. part 2: Operations and systems. *Biosystems Engineering*, 153:110–128, 2017.

[Chakraa *et al.*, 2023] Hamza Chakraa, François Guérin, Edouard Leclercq, and Dimitri Lefebvre. Optimization techniques for multi-robot task allocation problems: Review on the state-of-the-art. *Robotics and Autonomous Systems*, 168:104492, 2023.

[Choi *et al.*, 2009] Han-Lim Choi, Luc Brunet, and Jonathan P How. Consensus-based decentralized auctions for robust task allocation. *IEEE transactions on robotics*, 25(4):912–926, 2009.

[Conejero *et al.*, 2025] Maria Nuria Conejero, Hector Montes, Jose Maria Bengochea-Guevara, Laura Garrido-Rey, Dionisio Andújar, and Angela Ribeiro. A collaborative robotic fleet for yield mapping and manual fruit harvesting assistance. *Computers and Electronics in Agriculture*, 235:110351, 2025.

[Dias *et al.*, 2006] M. Bernardine Dias, Robert Zlot, Nidhi Kalra, and Anthony Stentz. Market-based multirobot coordination: A survey and analysis. *Proceedings of the IEEE*, 94(7):1257–1270, 2006.

[Duckett *et al.*, 2018] Tom Duckett, Simon Pearson, Simon Blackmore, and Bruce Grieve. *Agricultural Robotics: The Future of Robotic Agriculture*. EPSRC UK Robotics and Autonomous Systems (RAS) Network, United Kingdom, June 2018.

[Khamis *et al.*, 2015] Alaa Khamis, Ahmed Hussein, and Ahmed Elmogy. *Multi-robot Task Allocation: A Review of the State-of-the-Art*, pages 31–51. Springer, 2015.

[Macenski *et al.*, 2022] Steven Macenski, Tully Foote, Brian Gerkey, Chris Lalancette, and William Woodall. Robot operating system 2: Design, architecture, and uses in the wild. *Science Robotics*, 7(66):eabm6074, 2022.

[Peng *et al.*, 2022] Chen Peng, Stavros Vougioukas, David Slaughter, Zhenghao Fei, and Rajkishan Arikapudi. A strawberry harvest-aiding system with crop-transport collaborative robots: Design, development, and field evaluation. *Journal of Field Robotics*, 39(8):1231–1257, 2022.

[QGIS Development Team, 2026] QGIS Development Team. *QGIS Geographic Information System*. QGIS Association, 2026.

[Quinton *et al.*, 2023] Félix Quinton, Christophe Grand, and Charles Lesire. Market approaches to the multi-robot task allocation problem: a survey. *Journal of Intelligent & Robotic Systems*, 107(2):29, 2023.

[Seyyedhasani *et al.*, 2020] Hasan Seyyedhasani, Chen Peng, Wei jiunn Jang, and Stavros G. Vougioukas. Collaboration of human pickers and crop-transporting robots during harvesting – part i: Model and simulator development. *Computers and Electronics in Agriculture*, 172:105324, 2020.

[Shen *et al.*, 2018] Liji Shen, Stéphane Dauzère-Pérès, and Janis S. Neufeld. Solving the flexible job shop scheduling problem with sequence-dependent setup times. *European Journal of Operational Research*, 265(2):503–516, 2018.

[Yao *et al.*, 2024] Bitao Yao, Xinyu Li, Zhenrui Ji, Kun Xiao, and Wenjun Xu. Task reallocation of human-robot collaborative production workshop based on a dynamic human fatigue model. *Computers & Industrial Engineering*, 189:109855, 2024.

[Yerebakan and Hu, 2024] Mustafa Ozkan Yerebakan and Boyi Hu. Human–robot collaboration in modern agriculture: A review of the current research landscape. *Advanced Intelligent Systems*, 6(7):2300823, 2024.