MOASEI 2026: Methods for Open Agent Systems Evaluation Initiative

OBERLIN COLLEGE
LEARNING AND LABOR

Team Members

PIs

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Students

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Agenda

11:00 AM: Introduction & Background

11:20 AM: New this Competition

11:25 AM: Team Presentation

11:40 AM: Competition Results

12:00 PM: Discussions on Improvement/Revision

12:15 PM: Concluding Remarks

12:30 PM: Adjourned

Shared Notes

- https://go.unl.edu/moasei2026notes

INTRODUCTION & BACKGROUND

Open Environments

In most real-world decision-making situations, the set of agents, their types, and tasks are *not* static, but instead **change over time**

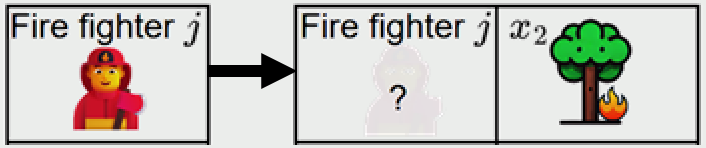
- Robots tasked with suppressing wildfires eventually run out of limited suppressant resources and must temporarily disengage to refill their supplies, or they might become damaged and leave the environment permanently
- Robotaxis transport passengers from pickup to drop off locations in a ridesharing application, where new passengers (tasks) dynamically appear based on needs and events in a city.
- In a large business organization, objectives and goals change with the market, requiring workers to adapt and prioritize work across changing sets of tasks.

Open Agent Systems

We call these challenging multi-agent environments **open agent systems.**

OASYS present novel challenges that necessitate new science in modeling, planning, **learning**, and **evaluation**.

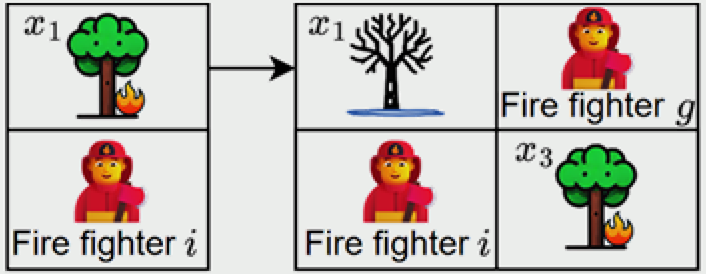
Agent Openness



Agent openness, where the set of agents in the world changes over time

- Agents disengage **temporarily** *(autonomous robotaxis recharging when low on energy)*
- New agents join over time *(new attackers entering a network in cybersecurity.)*
- Existing agents leave **permanently** *(firefighting robots become inoperable and therefore unavailable)*

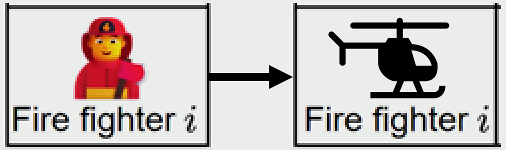
Task Openness



Task openness, where the set of tasks that agents work on change over time

- Novel tasks appear
  (Fires spreading to new locations or new ride hailing passengers appear)
- Popular tasks disappear forever
- A gradual shift in the requirements of tasks over time.

Frame Openness



Frame openness, where the frames (e.g., capabilities or preferences) of agents change over time.

- Agents learn new skills and gain new responsibilities
  (promotions of office workers)
- Robots lose abilities over time
  (e.g., damage to robots in the field)
- Agents change preferences or priorities over time

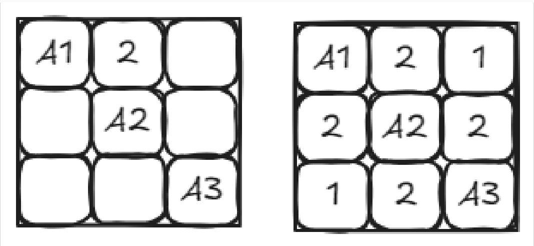
Why Investigate OASYS?

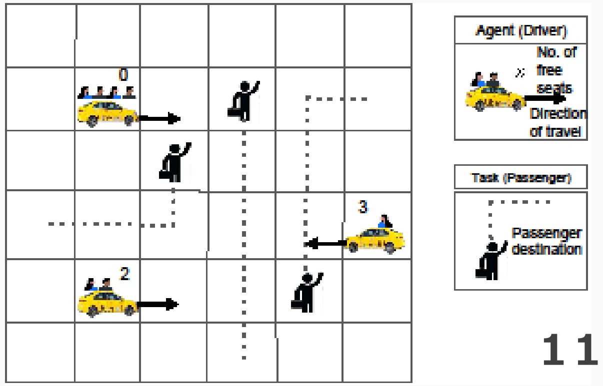
Modeling

Openness in MAS makes *modeling* challenging

A model must answer several questions:

- Represent openness
- Reason over the partially observed **presence** and **features** of agents and tasks.
- Endogenous vs Exogenous changes.
- Unbounded openness





Why Investigate OASYS?

Planning

Openness in MAS makes *planning* challenging

- The dynamic introduction and removal of agents, tasks, and types caused by openness changes the underlying problem representation during operation, resulting in complex policies.
- The amount of uncertainty the agent faces often requires more iterations to calculate the expected rewards

Together, these pose significant challenges to the efficacy and *computational scalability* of traditional planning.

Why Investigate OASYS?

Learning

Openness in MAS makes *reinforcement learning* challenging

- The added uncertainty and model/policy complexity complicates value assignment
- When should we stop training to learn stable, performant policies that are currently effective, yet adaptable?
- *Understanding where in the policy space* does an agent need to explore more versus what knowledge it can still exploit is an open problem
- Agent Openness creates the possibility of new **untrained** agents, or agents who have never interacted.

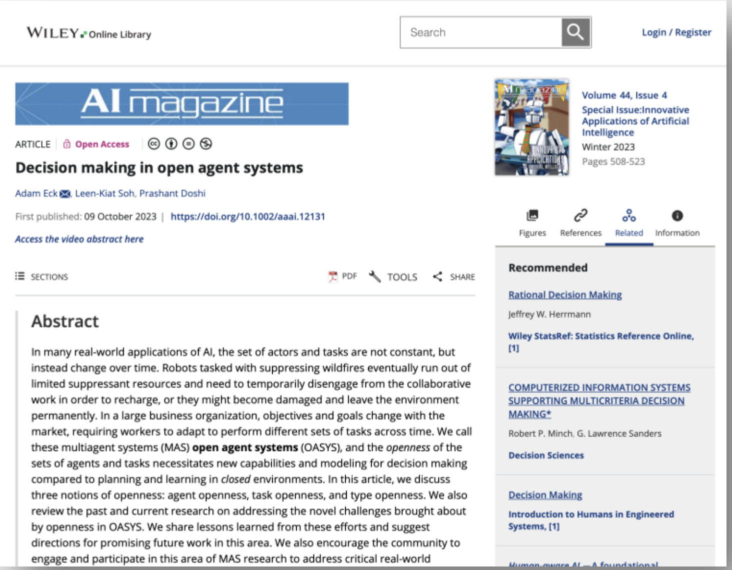
Why Investigate OASYS?

Evaluation

Openness in MAS makes *Evaluation* challenging

- External factors cannot be fully enumerated which limits conclusions from direct empirical evaluation and limits theoretical guarantees.
- Dynamic, ragged, observation and action spaces introduce significant computational overhead.

To Probe Further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Decision making in open agent systems
Adam Eck, Leen-Kiat Soh, Prashant Doshi
First published: 09 October 2023 | https://doi.org/10.1002/aaai.12131
Access the video abstract here
SECTIONS PDF TOOLS SHARE

Abstract

In many real-world applications of AI, the set of actors and tasks are not constant, but instead change over time. Robots tasked with suppressing wildfires eventually run out of limited suppressant resources and need to temporarily disengage from the collaborative work in order to recharge, or they might become damaged and leave the environment permanently. In a large business organization, objectives and goals change with the market, requiring workers to adapt to perform different sets of tasks across time. We call these multiagent systems (MAS) **open agent systems** (OASYS), and the *openness* of the sets of agents and tasks necessitates new capabilities and modeling for decision making compared to planning and learning in *closed* environments. In this article, we discuss three notions of openness: agent openness, task openness, and type openness. We also review the past and current research on addressing the novel challenges brought about by openness in OASYS. We share lessons learned from these efforts and suggest directions for promising future work in this area. We also encourage the community to engage and participate in this area of MAS research to address critical real-world

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Special Issue:Innovative Applications of Artificial Intelligence
Winter 2023
Pages 508-523

Figures References Related Information

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RECAP MOASEI 2025

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Evaluation Tracks

(AO/TO) Wildfire Fighting

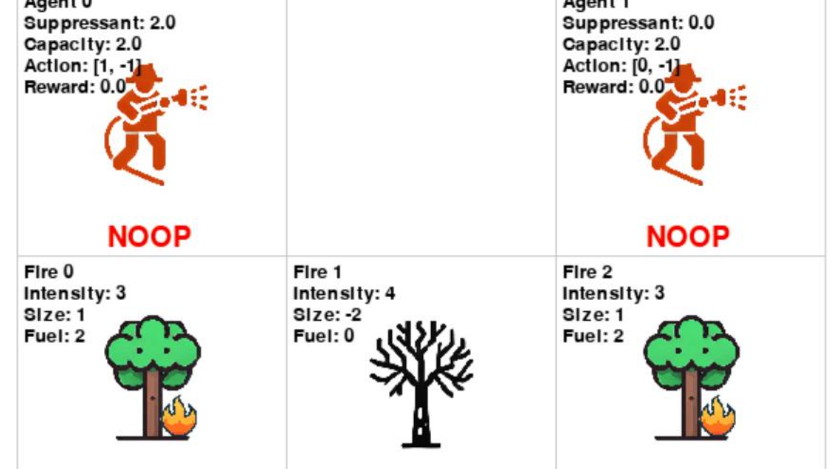
Agents collaborate with limited resources to fight fires of varying sizes. Fires spread between cells and may randomly ignite.

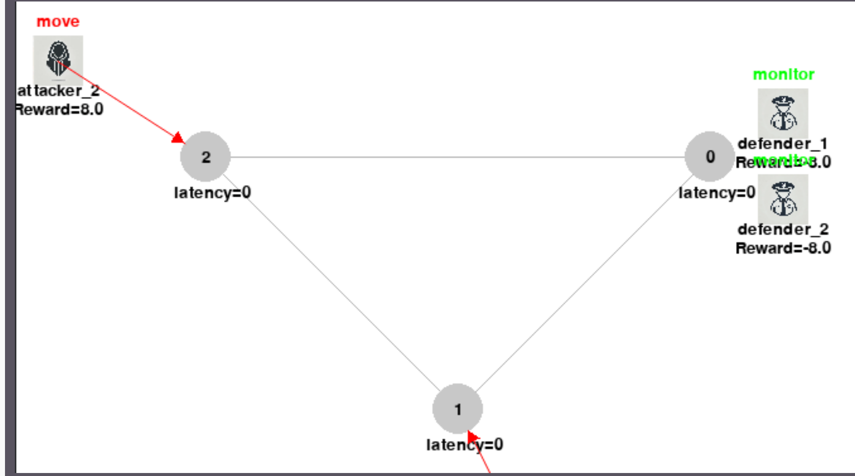
(AO) Cyber Security

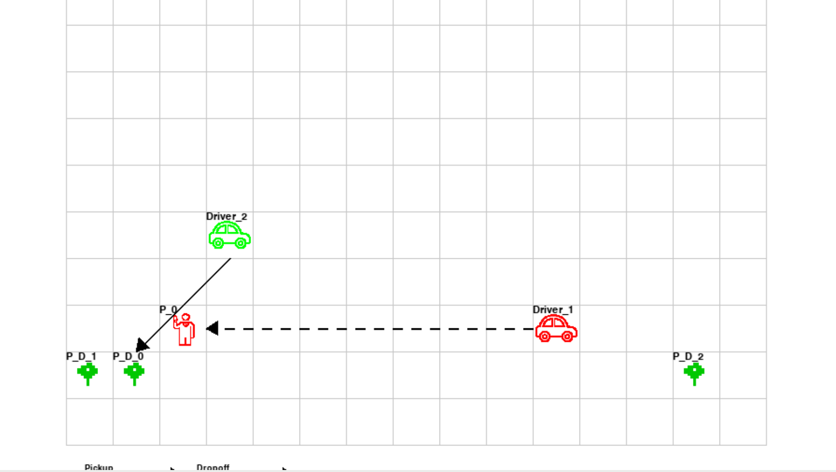
Agents compete against a changing team of heuristic attackers to protect nodes.

(TO) Ride-Sharing

Agents coopetitively deliver passengers to maximize individual fares earned while minimizing time passengers are waiting.







Summary of Competitors

2/3 tracks active

11 teams registered

4 teams submitted

Teams	Approaches	Tracks
Zana-Cyber (Winner)	Uses a weighted scoring function to focus on the most critical tasks.	Cyber Security
University of Tehran (Winner)	Uses a grid representation combined with historical observations to prioritize tasks.	Wildfire Fighting
Markov Mayhem (Winner)	Leverages GNNs to handle openness by modifying observations into flexible graph-structured data.	Wildfire Fighting
Bit Student (Honorable Mention)	Uses an iterative process sampling from LLM models to continuously improve upon a baseline policy.	Wildfire Fighting

Methodology - Wildfire

Evaluation Metrics

- rewards

Simulation Setup

- 256 evaluation runs / configuration

Baselines Compared

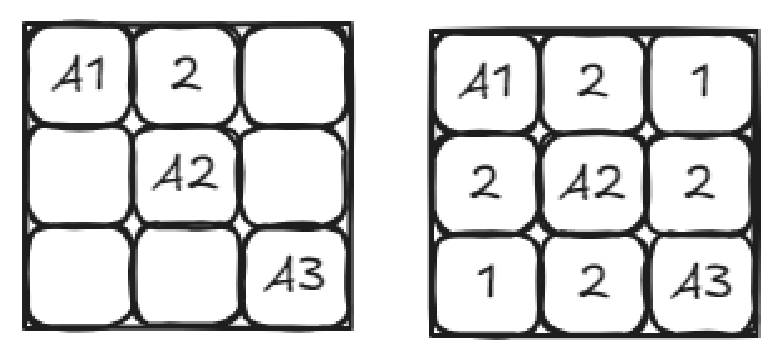
- **noop** – agents take no actions
- **random** – agents take random actions
- **smallest** – agents attack the fire closest to being put out
- **largest** – agents attack the task closest to burning out

Evaluation Procedure

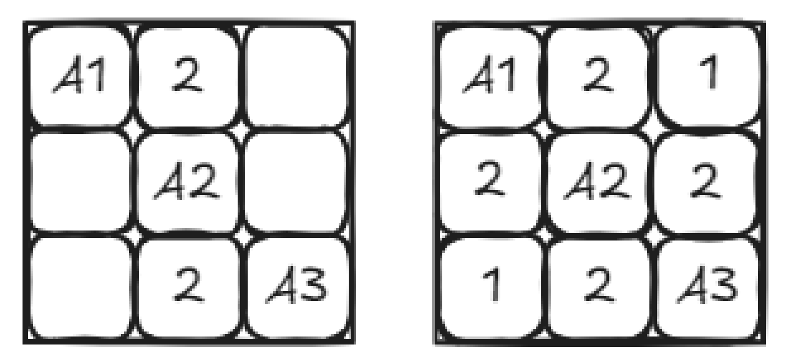
1. Each team’s solution tested on same 256-seed set per configuration
2. Collected average and variance across 256 total trials
3. Visualizations generated after all evaluations for post-hoc analysis

Wildfire

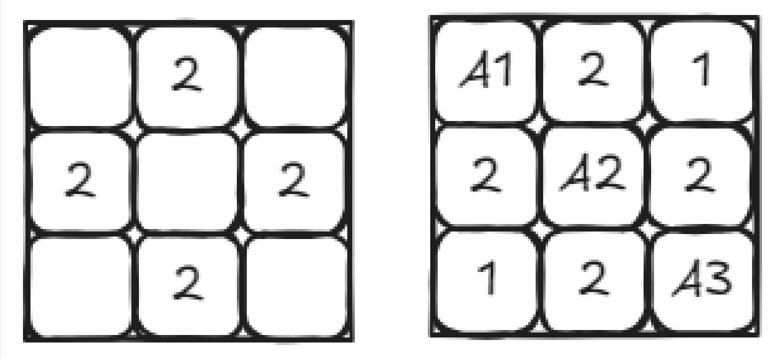
Configurations



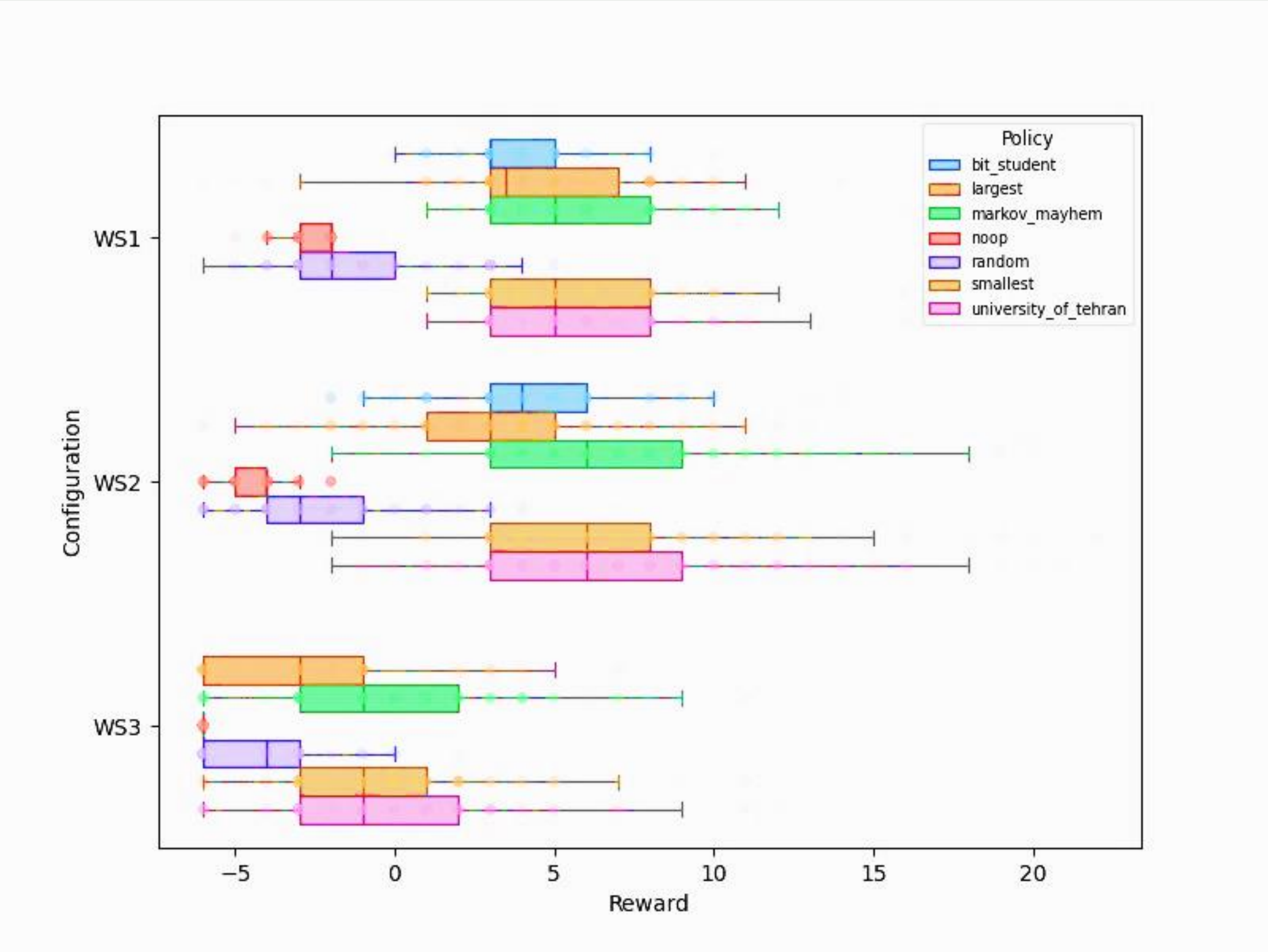
WS1
- base spread rate: 0.1
- random ignition probability: 0.05
- single initial fire, all agents present



WS2
- base spread rate: 0.5
- random ignition probability: 0.25
- two initial fires, all agent present

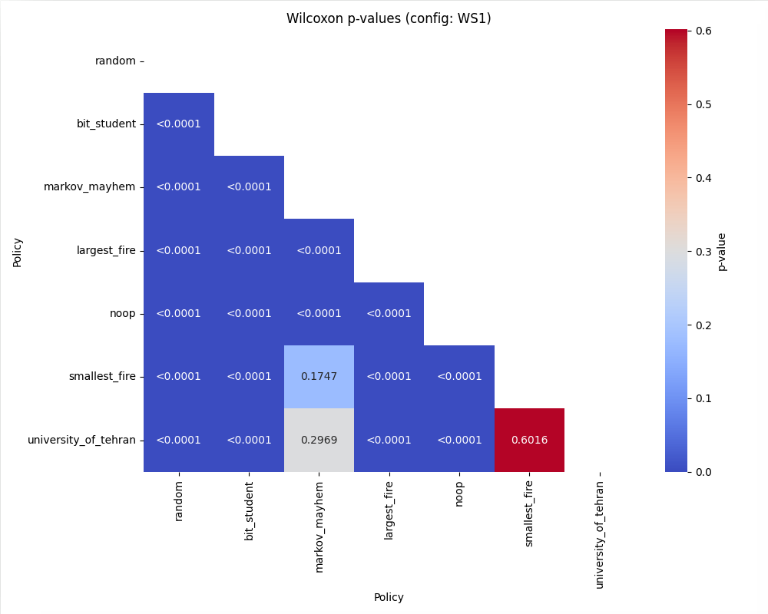


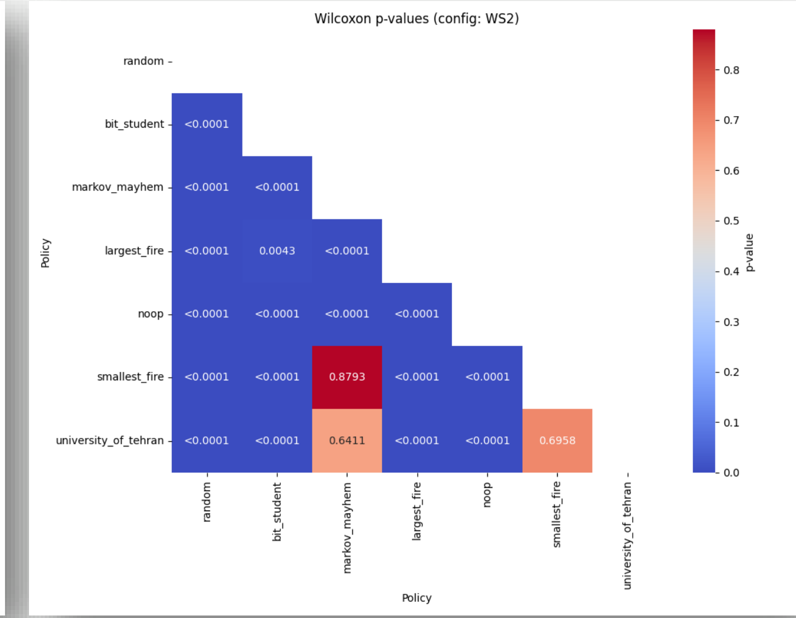
WS3
- base spread rate: 0.5
- random ignition probability: 0.25
- four initial fires, no agents present

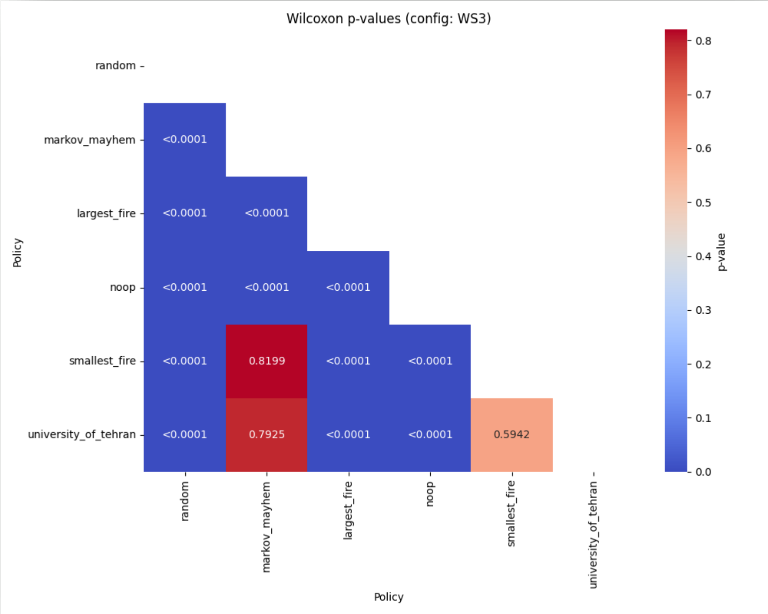


Wildfire

Competition Results





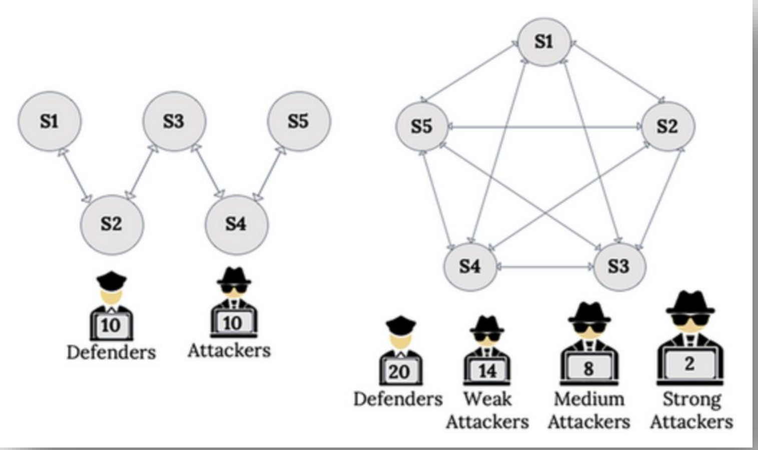


No statistically significant differences between the University of Tehran and Markov Mayhem

Wildfire

Wilcoxon test for statistical significance

Methodology - Cybersecurity



Evaluation Metrics

- rewards

Simulation Setup

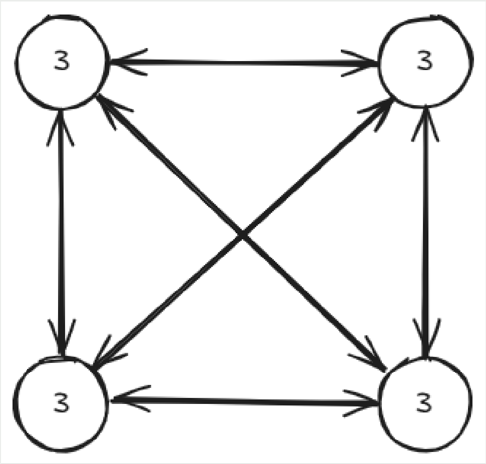
- 256 evaluation runs / configuration

Baselines Compared

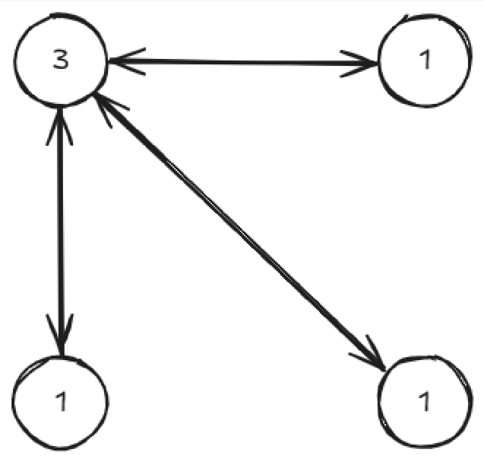
- **noop** – agents take no actions
- **random** – agents take random actions
- **exploited** – agents patch the node which is most exploited for 3 consecutive steps, then retarget
- **patched** – agents patch the node which is closest to completely patched for 3 consecutive steps, then retarget

Evaluation Procedure

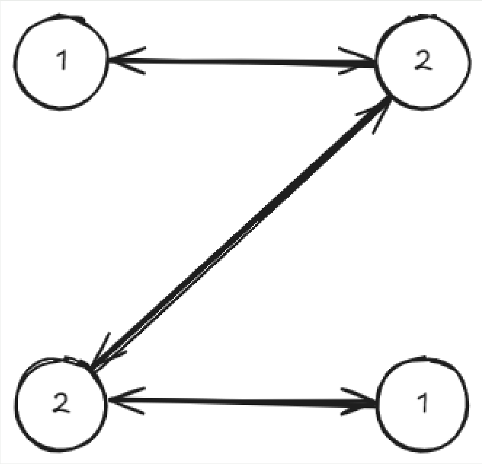
1. Each team’s solution tested on same 256-seed set per configuration
2. Collected average and variance across 256 total trials
3. Visualizations generated after all evaluations for post-hoc analysis



CS1
- persist probability: 0.5
- return probability: 0.25
- fully-connected network



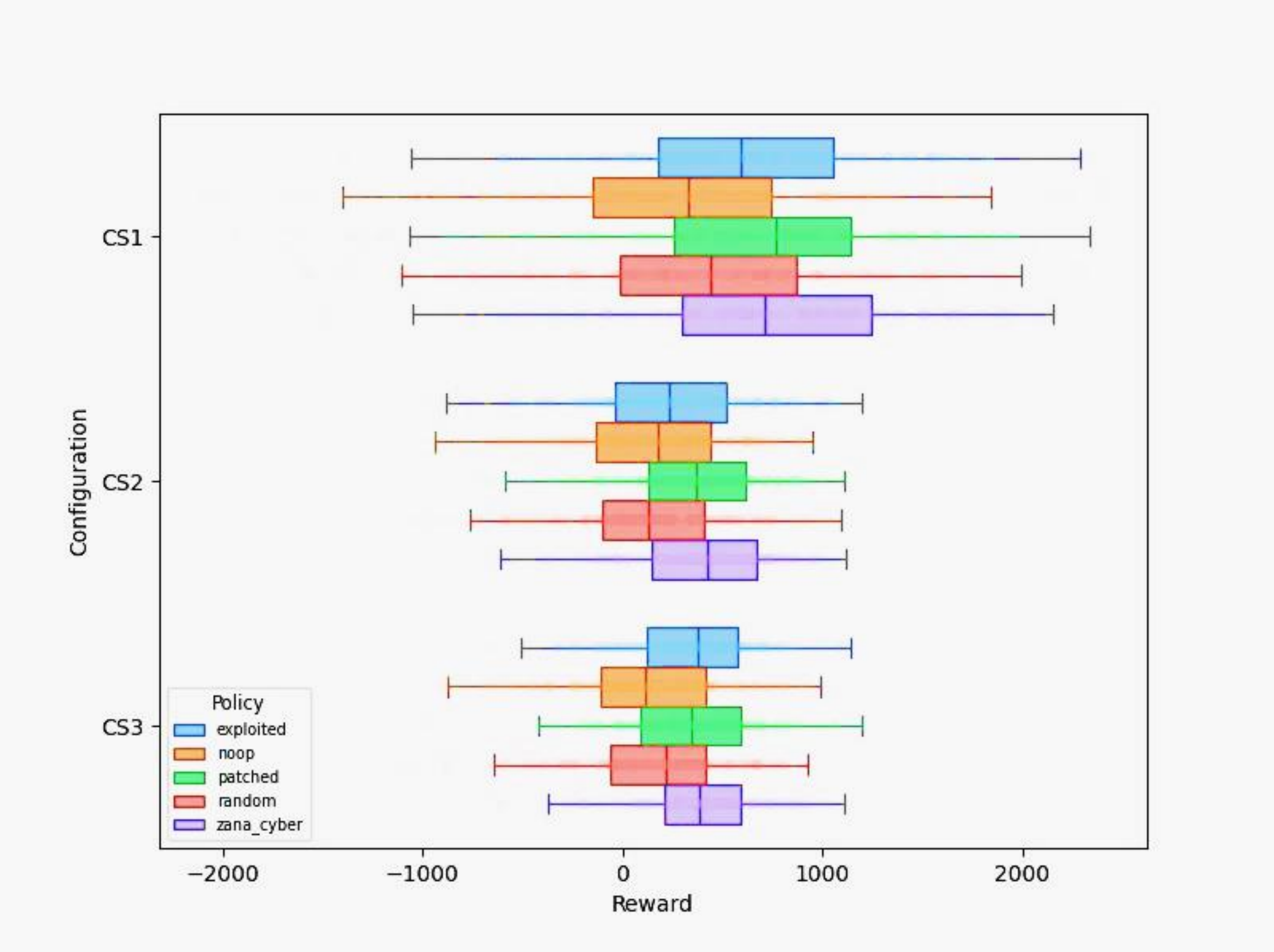
CS2
- persist probability: 0.5
- return probability: 0.25
- central-node network



CS3
- persist probability: 0.5
- return probability: 0.25
- linear network

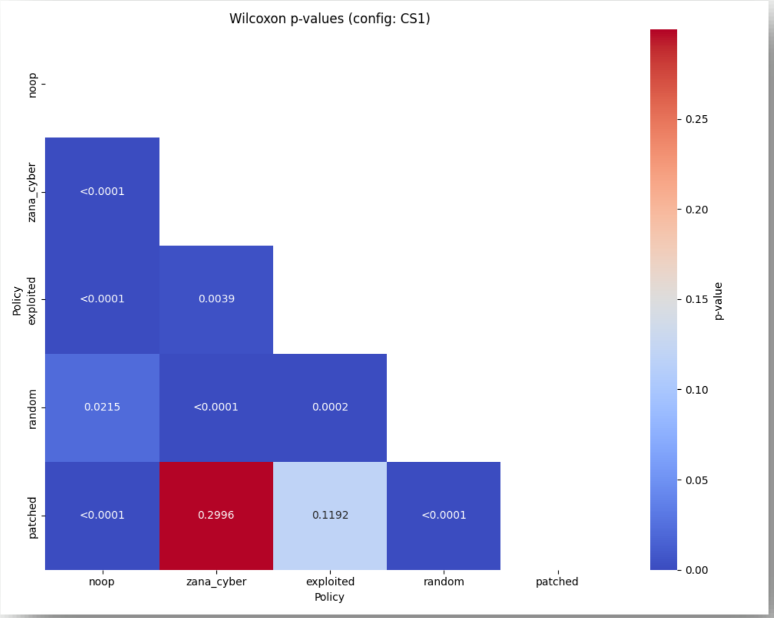
Cybersecurity

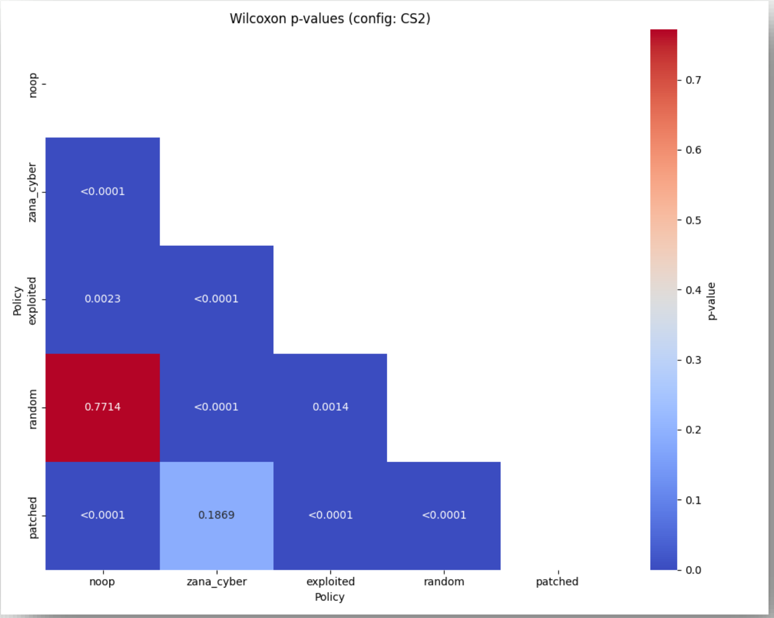
Configurations

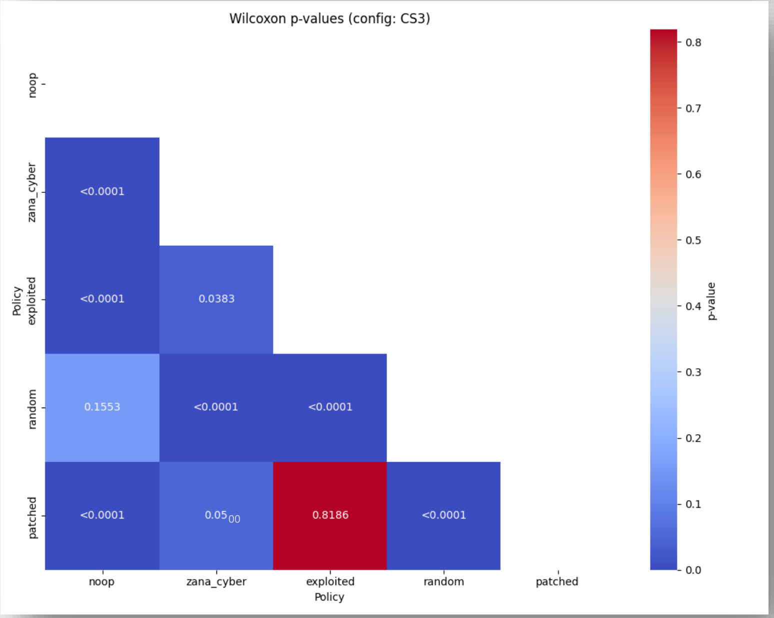


Cybersecurity

Competition results







Zana Cyber has statistically significant difference with patched (most competitive baseline) in CS3 (p = 0.0500)

Cybersecurity

Wilcoxon test for statistical significance

MOASEI 2026

Changes from last MOASEI

FRAME OPEN WILDFIRE

We introduced **Frame Openness** into our evaluations through agent **equipment states** in the Wildfire bonus track.

METRICS

We introduce new measures,
total task-completions, mean task completion time, and mean value of tasks completed.

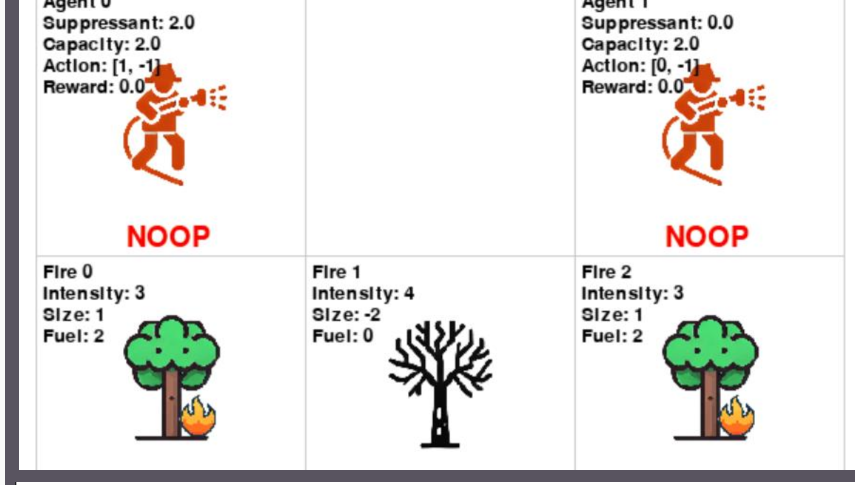
Evaluation Tracks

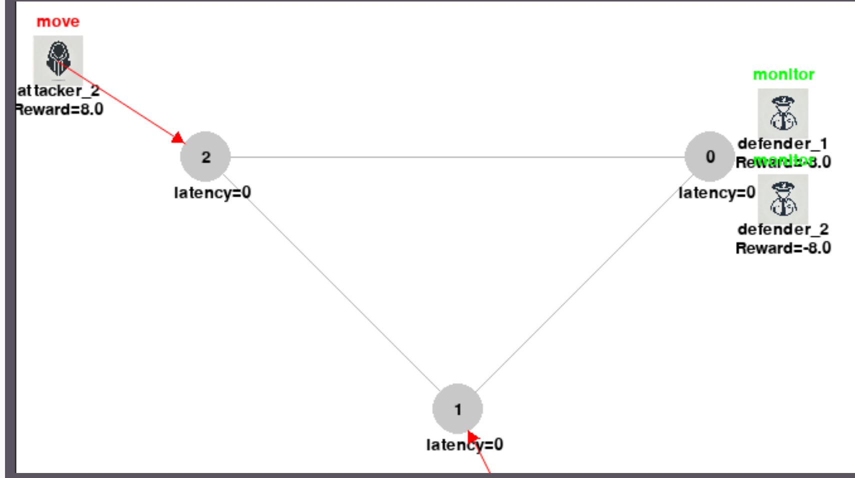
(AO/TO) Wildfire Fighting
Agents collaborate with limited resources to fight fires of varying sizes. Fires spread between cells and may randomly ignite.

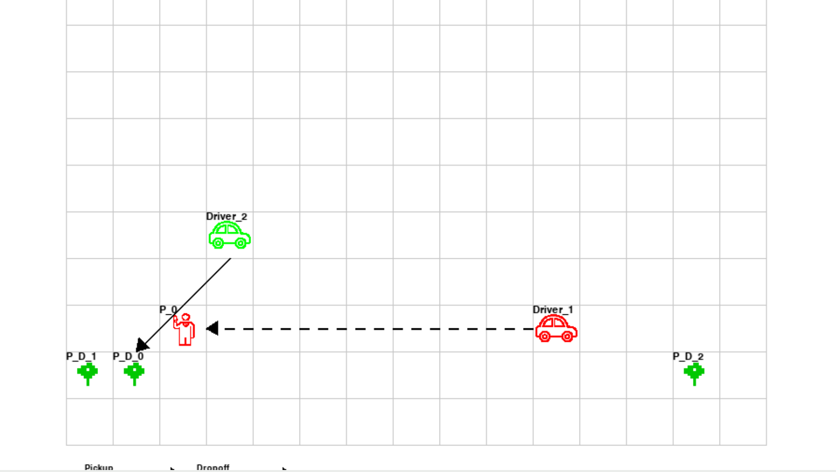
(AO/TO/FO) Bonus Wildfire Fighting
Agents have changing tank sizes and ranges which influence their duration in the environment and the tasks they can reach.

(AO) Cyber Security
Agents compete against a changing team of heuristic attackers to protect nodes.

(TO) Ride-Sharing
Agents coopetitively deliver passengers to maximize individual fares earned while minimizing time passengers are waiting.







Summary of

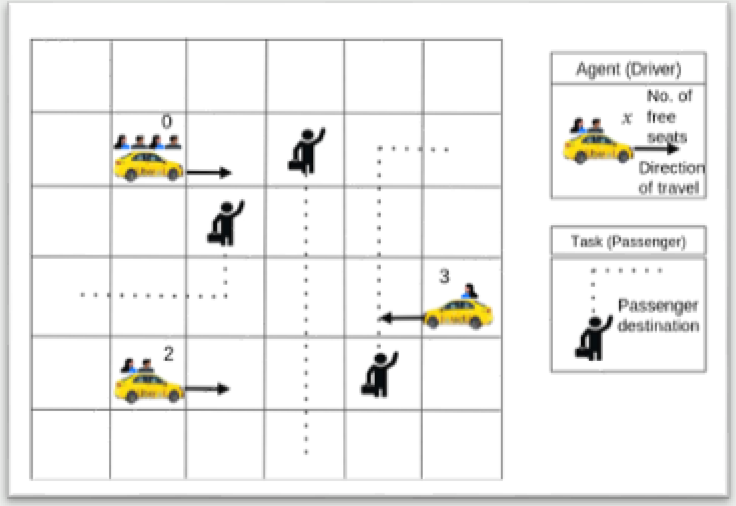
1/4 active tracks

8 teams registered

1 team submitted

Teams	Approaches	Domains
DLC (Winner)	A planning approach which solves an optimal routing problem across agents. Replanning when new passengers enter the environment.	Rideshare

Methodology – Ride-Sharing



Evaluation Metrics

- Rewards, Completed Tasks, and Wait/Riding Time

Simulation Setup

- 256 evaluation runs / configuration

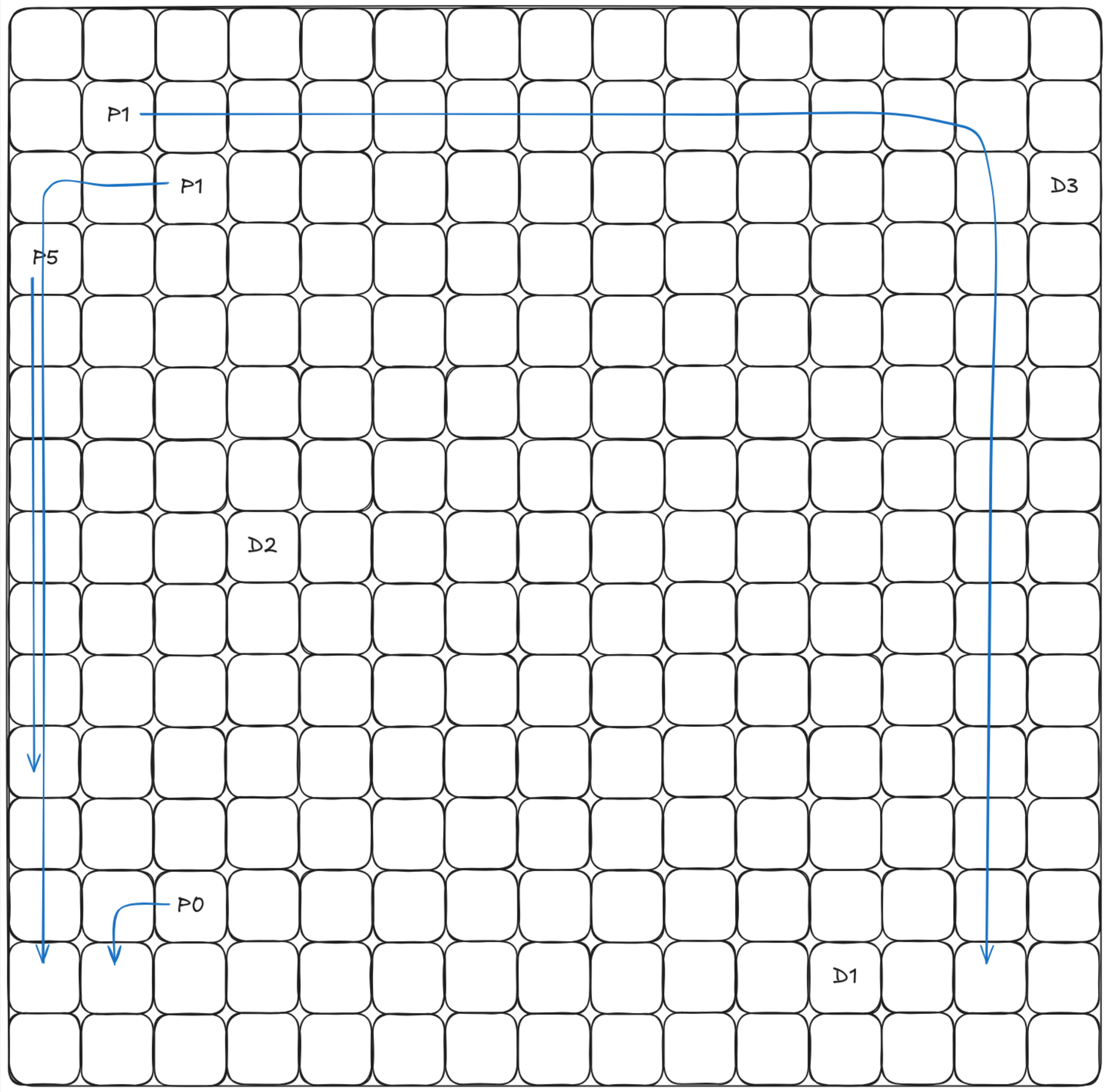
Baselines Compared

- **No-Op** – agents take no actions
- **Random** – agents take random actions
- **FIFO** – Agents *act* on the longest waiting passenger, sampling if tied.
- **Greedy**– Agents *act* on the shortest total distance passenger (agent->passenger->destination)
- **TFocus** – Agents "commit" to a passenger once selected.
- **TGlobal** – Agents always follow their heuristic, dynamically re-evaluating which passenger to serve

Evaluation Procedure

- Each team's solution tested on same 256-seed set per configuration
- Collected average and variance across 256 total trials
- Visualizations generated after all evaluations for post-hoc analysis

15x15 grid



Agents = (13,11), (8,3), (2,14)

Passengers = 70, 65, 65
sampled similarly to MOHITO [1]

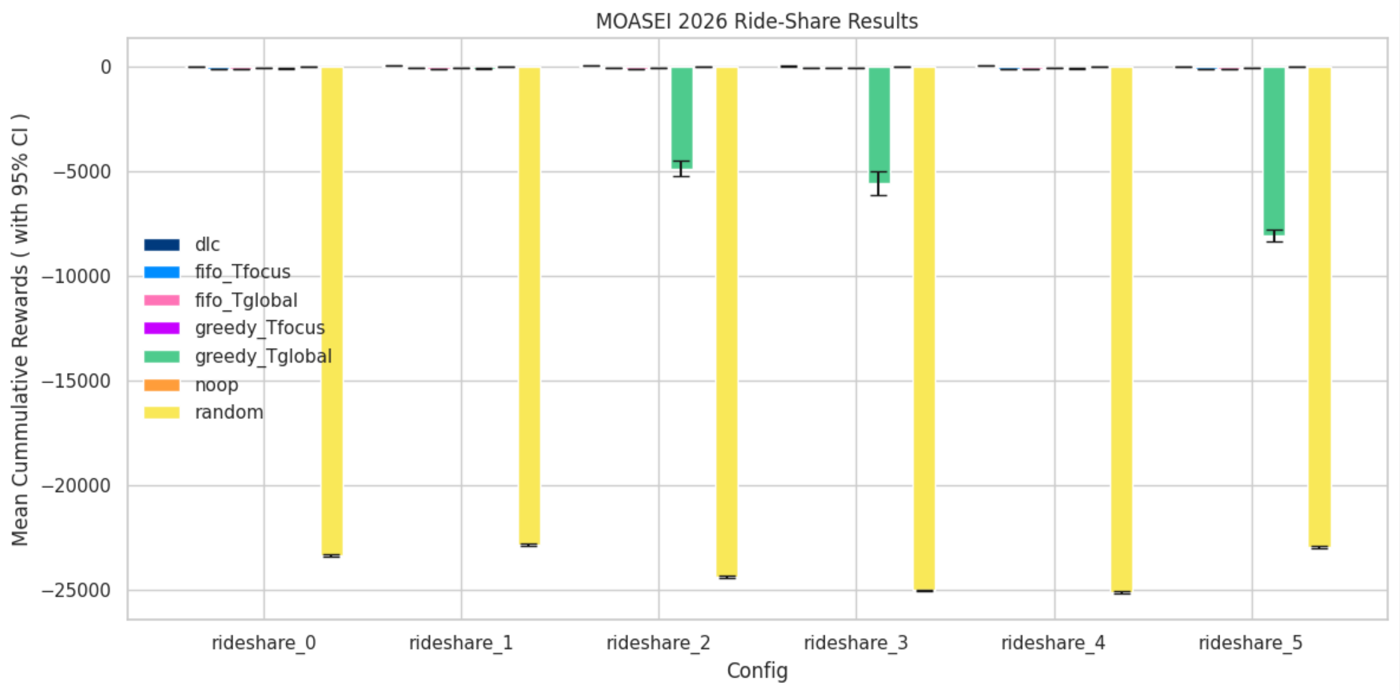
Ride-Share

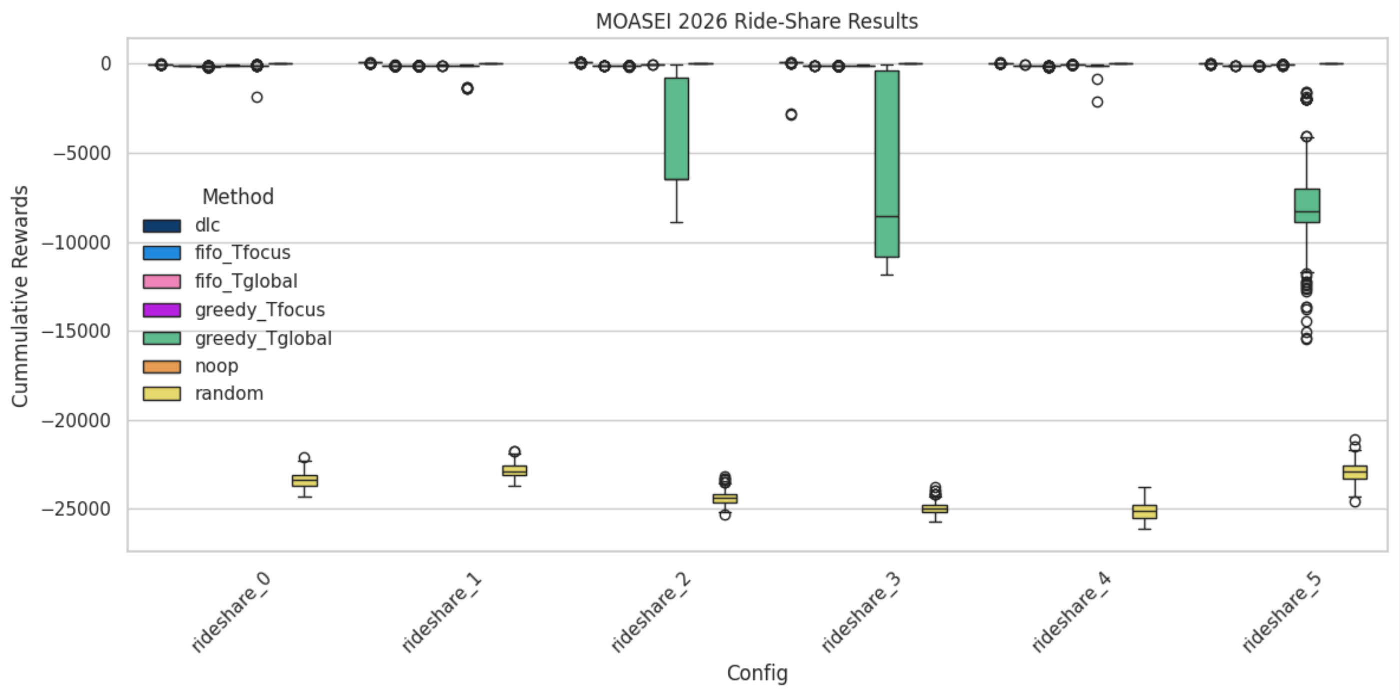
Configurations

TEAM PRESENTATION

DLC

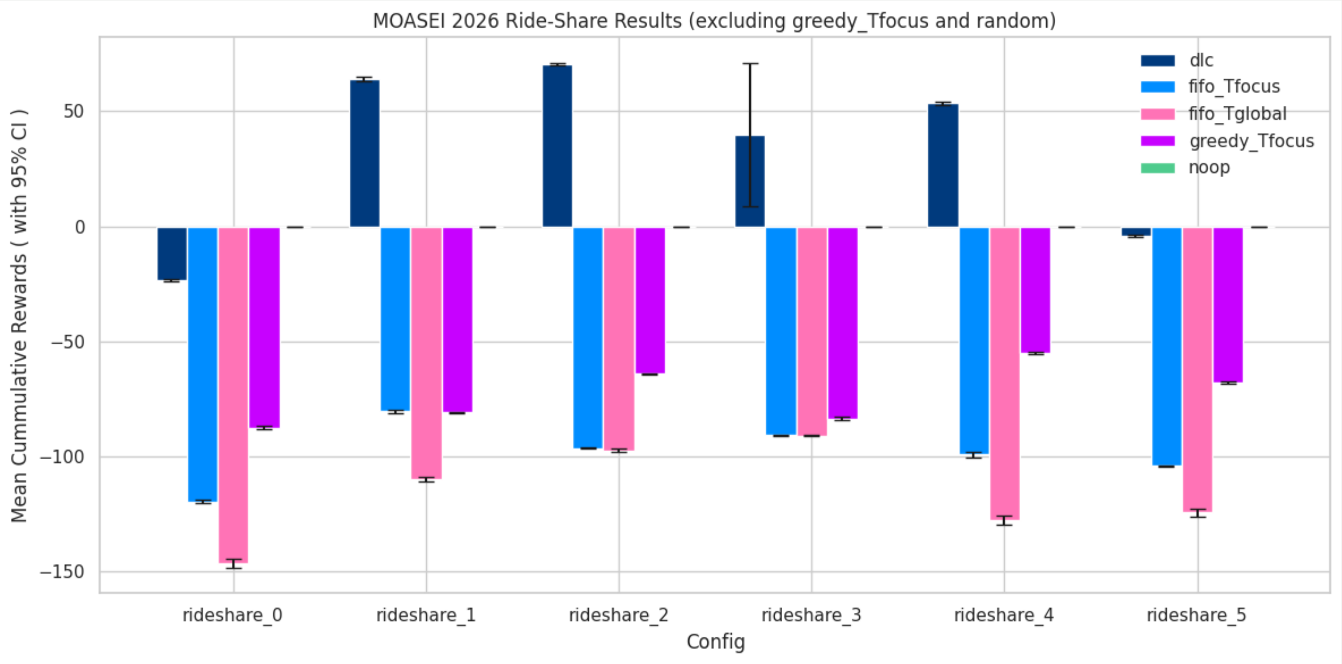
COMPETITION RESULTS

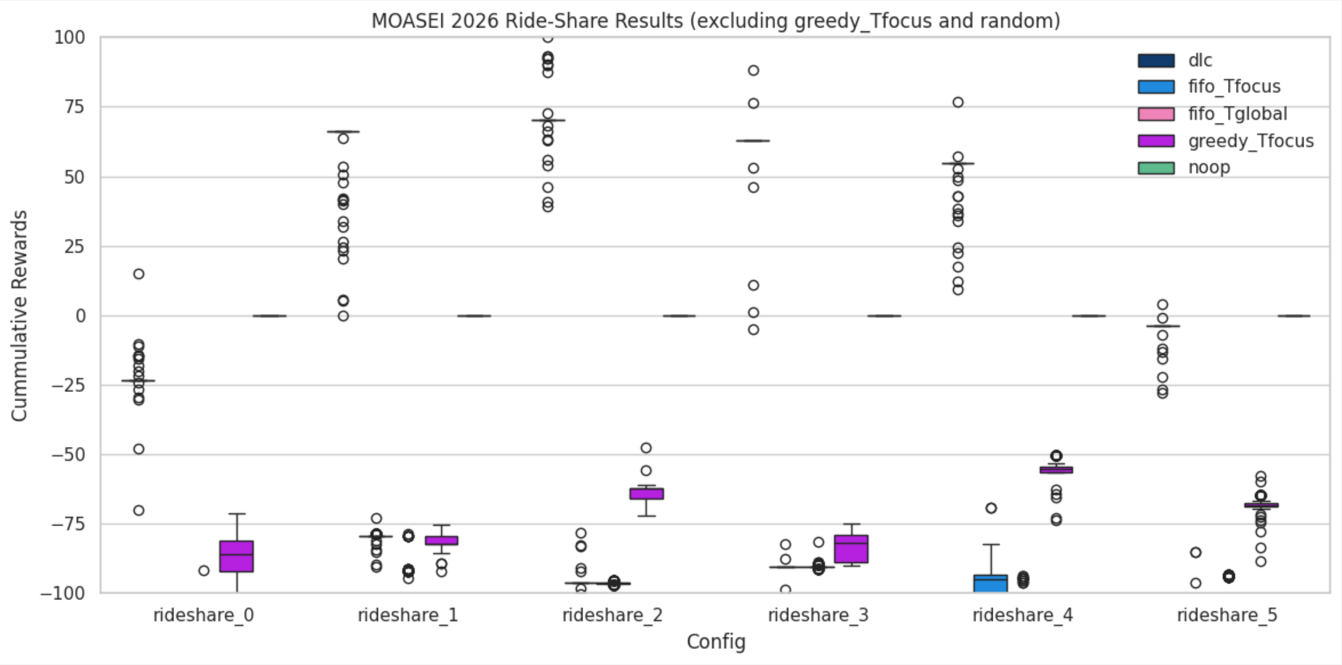




Rideshare

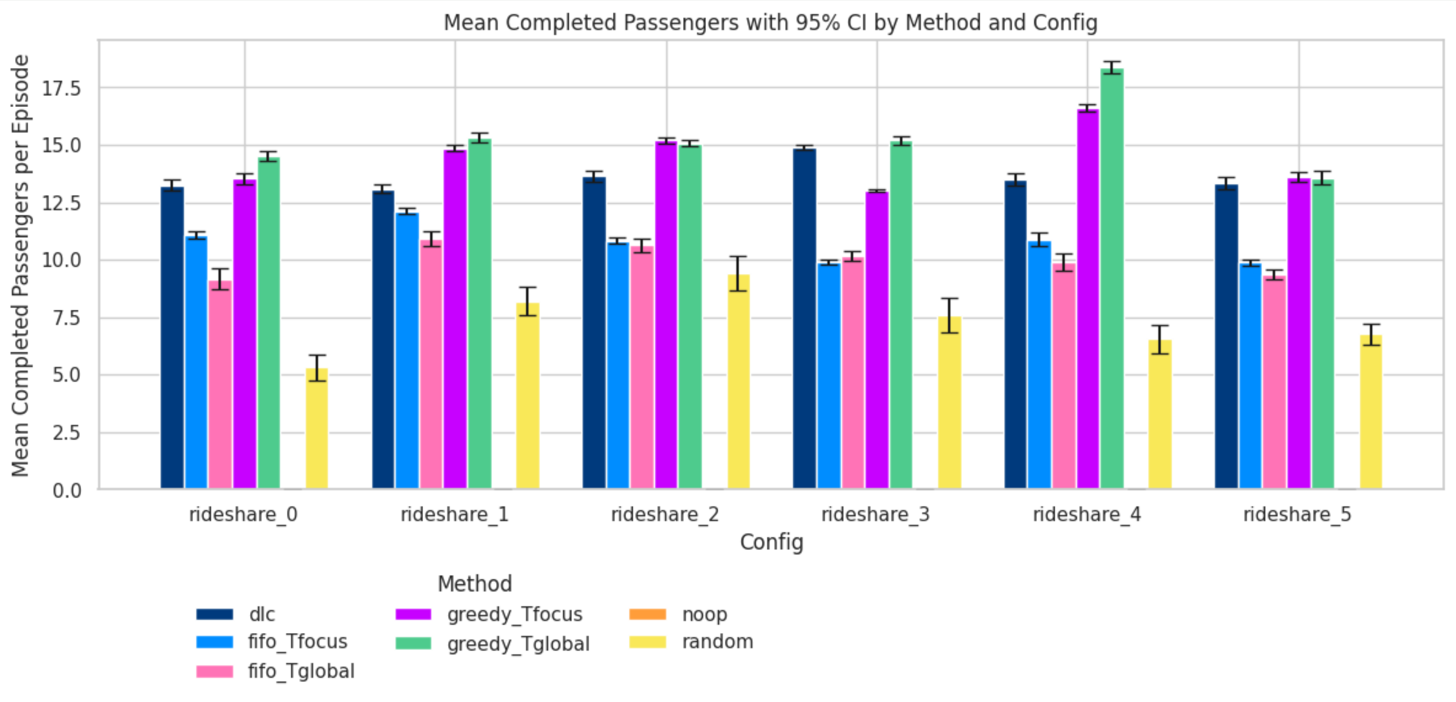
Competition results - Reward

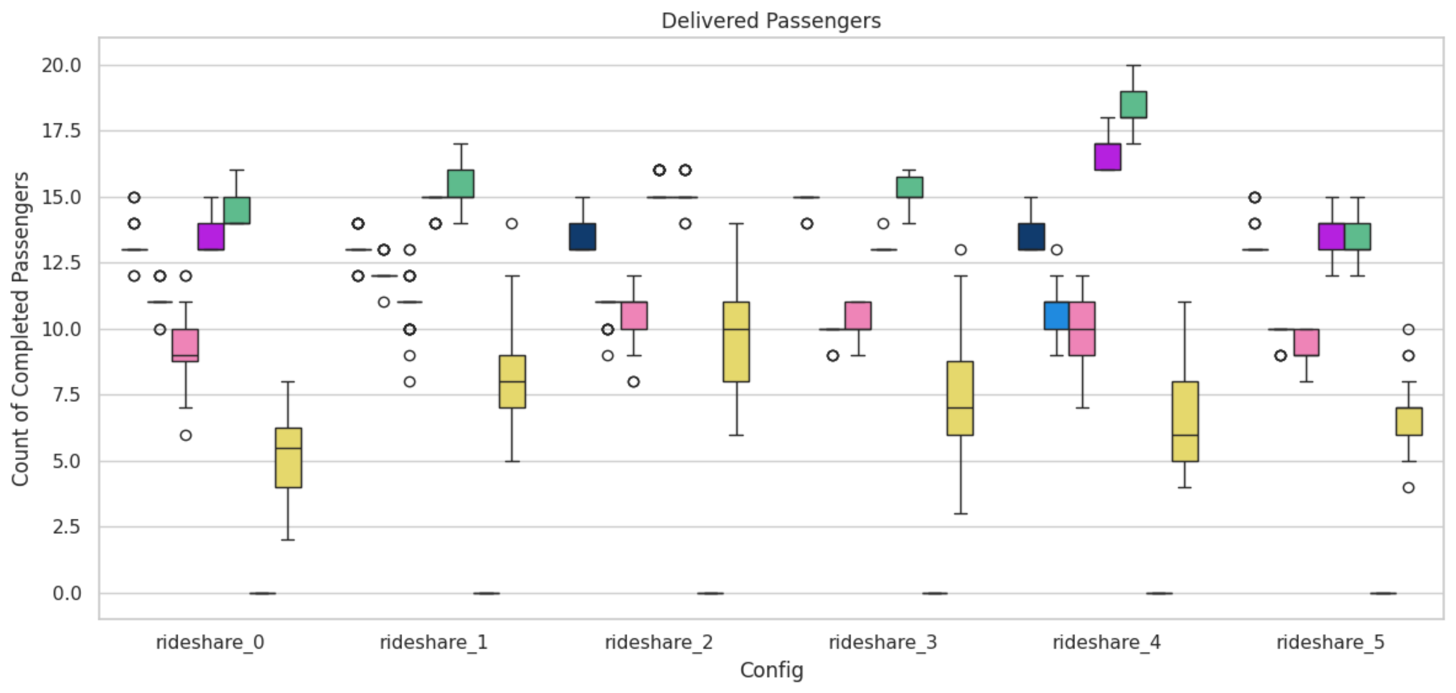




Rideshare

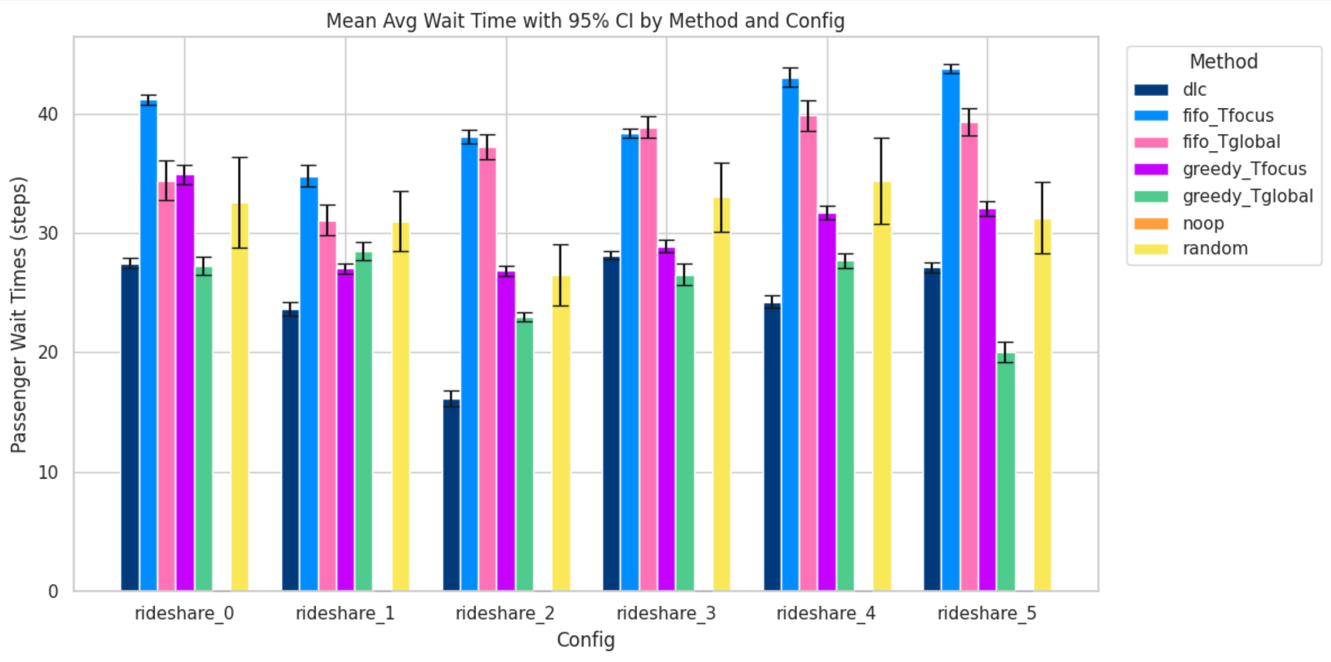
Competition results - Reward

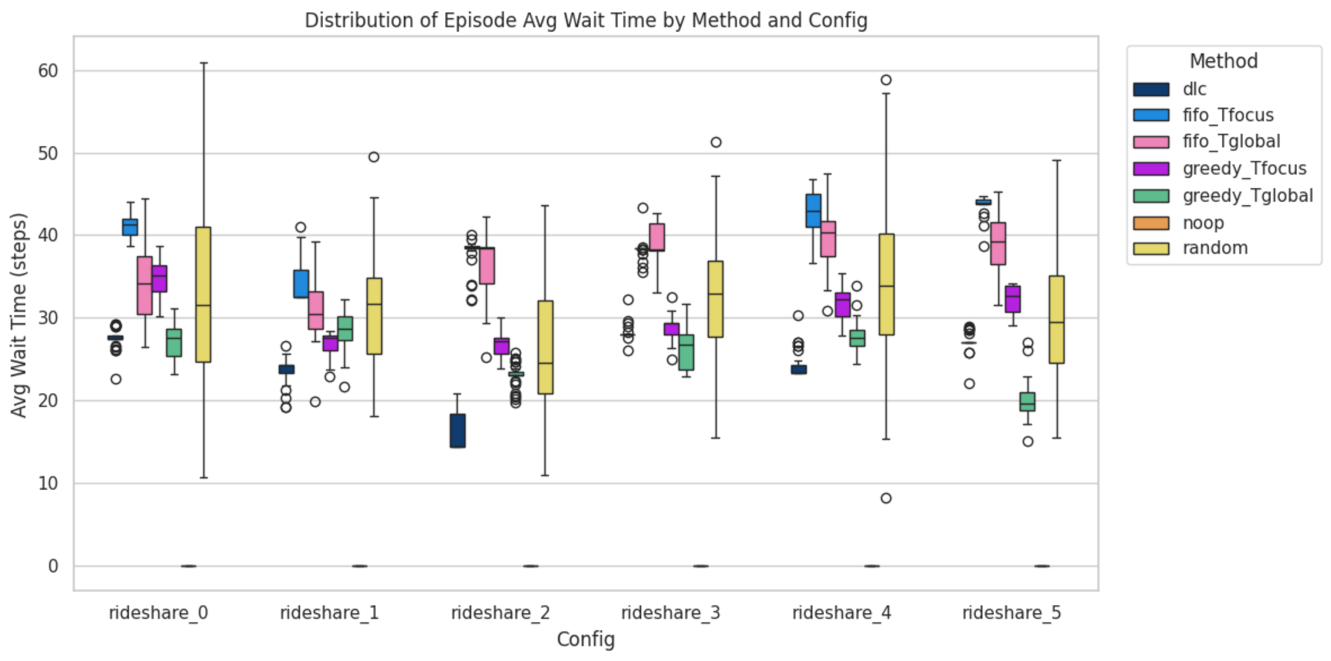




Rideshare

Competition results – Completed tasks

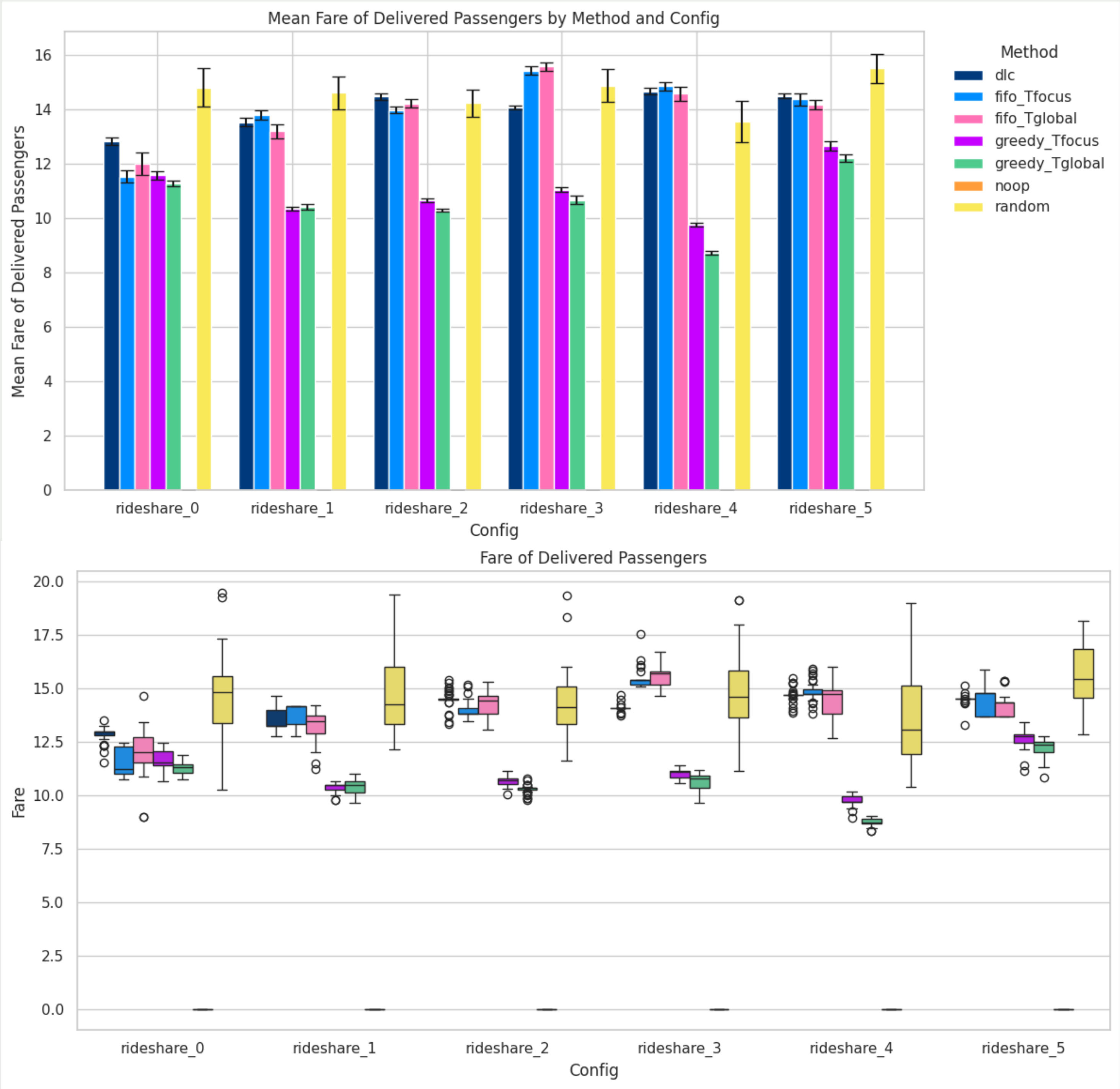




Ridesharing

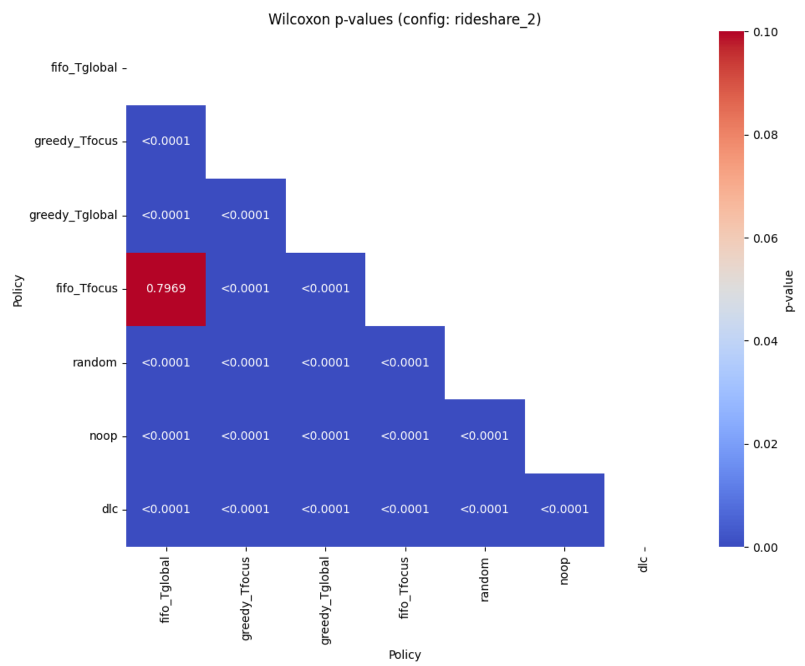
Competition results

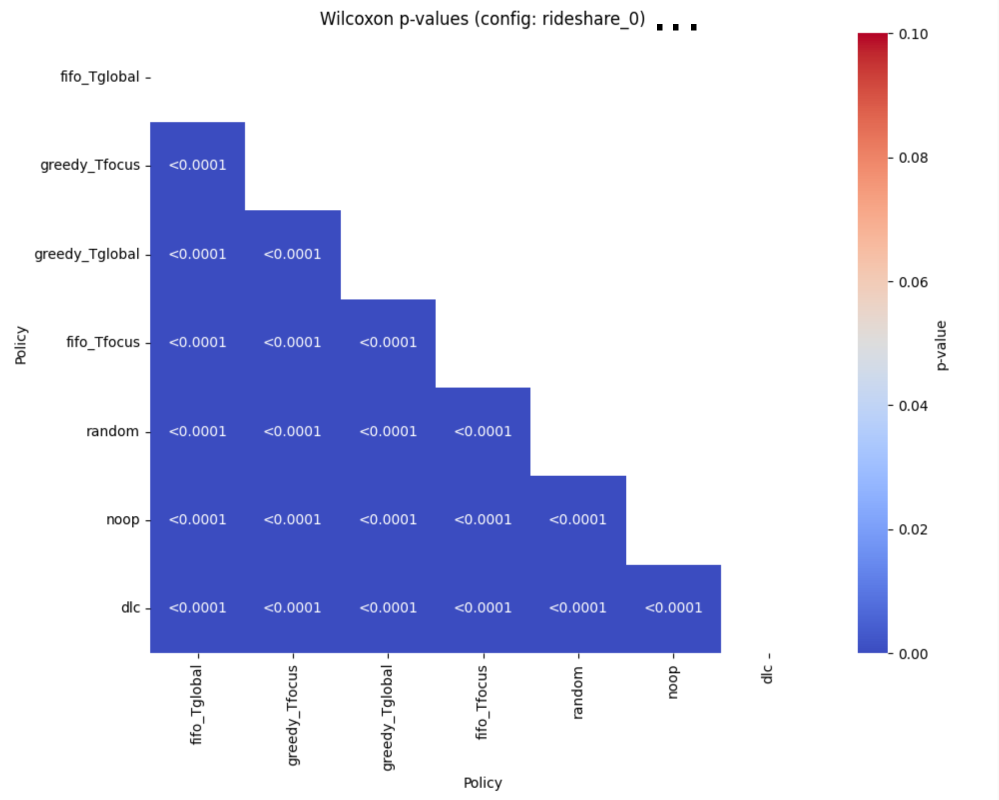
– Time before riding



Ridesharing

Competition results – Value of Completed Tasks





...

Rideshare

Wilcoxon test for statistical significance

DISCUSSION ON CHANGES AND IMPROVEMENT

Next Competition

Frame Openness

- **Rideshare:**
  Drivers may switch between different vehicles exchanging **capacity** and **move cost.**
- **Cyber Security:**
  Attackers may have distinct aims, preferring to attack different kinds of nodes.

Head-to-Head policy comparisons

- **Cyber Security:**
  Participants will submit attacker and defender policies then compete in a round robin tournament.

CONCLUDING REMARKS

Moving Forward …

Expect to organize the 3rd Annual MOASEI Competition at AAMAS'2027

- With similar deadlines
- With more complex configurations
- Open to discussions and ideas from this year's teams to improve the competition

Expanding on research in OASYS

- Developing domains and benchmarks
- Promoting new methods for OASYS
- Conducting comparative studies
- Co-authoring papers

Acknowledgments

This research was supported by a collaborative NSF Grant #IIS-2312657 (to P.D.), #IIS-2312658 (to L.K.S.), and #IIS-2312659 (to A.E.). Additionally, this work was completed utilizing the Holland Computing Center of the University of Nebraska, which receives support from the UNL Office of Research and Economic Development, and the Nebraska Research Initiative.

Congratulations & Thank You!!

DLC | Birmingham University, England, United Kingdom | Ziyue Chu

Hope that you will participate again next year!

Please also help us encourage others to participate

Contact Info

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https://oasys-mas.github.io/moasei.html

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Survey

- https://go.unl.edu/moasei2026survey

ADJOURNED

OASYS

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Oberlin College

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