MOASEI

LEEN-KIAT SOH, UNIVERSITY OF NEBRASKA
ADAM ECK, OBERLIN COLLEGE
PRASHANT DOSHI, UNIVERSITY OF GEORGIA

Participating via Zoom

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

Agenda

2:00 PM: Introduction and Welcome (Organizers and Finalists)

2:20 PM: Team Presentations (15 minutes each)

3:20 PM: Competition Results

3:45 PM: Coffee Break

4:30 PM: Discussions on Improvement/Revision

5:30 PM: Concluding Remarks

5:45 PM: Adjourned

INTRODUCTION & WELCOME

Team Members

PIs

- **Prashant Doshi** University of Georgia
- **Adam Eck** Oberlin College
- **Leen-Kiat Soh** University of Nebraska

Students

- **Daniel Redder** University of Georgia
- **Ceferino Patino IV** University of Nebraska
- **Tyler Billings** University of Nebraska
- **Alireza Saleh Abadi** University of Nebraska

Openness in Environment

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

Open Agent Systems (OASYS)

We call these multiagent systems **open agent systems**

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

Agent Openness

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

This could include

- agents temporarily disengaging from the environment before returning (e.g., autonomous ride-sharing cars recharging when low on energy)
- new groups of agents joining over time (e.g., new attackers appearing globally in a cybersecurity defense application)
- existing agents leaving permanently (e.g., firefighting robots becoming damaged and needing to leave the operations to recover valuable hardware)

Task Openness

Task openness, where the set of tasks that agents aim to accomplish change over time

This could include

- new tasks appearing that are novel compared to existing tasks (e.g., transporting ride-sharing passengers for unique events)
- popular existing tasks disappearing forever
- a gradual shift in the requirements of tasks over time so that tasks gradually become different from their initial context

Type Openness

Type openness, where the types (e.g., capabilities) of agents change over time.

This could include

- agents learning new skills and gaining new responsibilities (e.g., promotions of office workers)
- robots losing abilities over time (e.g., modeling damage to robots engaged in the field)
- agents changing preferences or priorities over time

Why Investigating OASYS?

Modeling

Openness in MAS makes *modeling* challenging

An agent has to simultaneously answer several questions:

- how to measure the level or amount of openness,
- how to reason about existing agents (or tasks) that leave and the new agents (or tasks) that arrive, and their associated properties or capabilities,
- Ultimately how to represent the unknown including the bounds of what is possible and what is not possible?

Why Investigating OASYS?

Planning

Openness in MAS makes *planning* challenging

Maintaining the required information about changes to the system increases

- size of the problem representation being considered by the agent
- amount of uncertainty the agent faces, requiring more deliberations to ascertain accurately the expected rewards

Together, these pose significant challenges to the *computational scalability* of planning algorithms

Why Investigating OASYS?

Reinforcement Learning

Openness in MAS makes *reinforcement learning* challenging

Learning from the rewards is made more difficult due to increase in

- uncertainty about the causes behind changes in the outcomes
- amount of training experience to learn stable, optimal behavior rules (or policies)

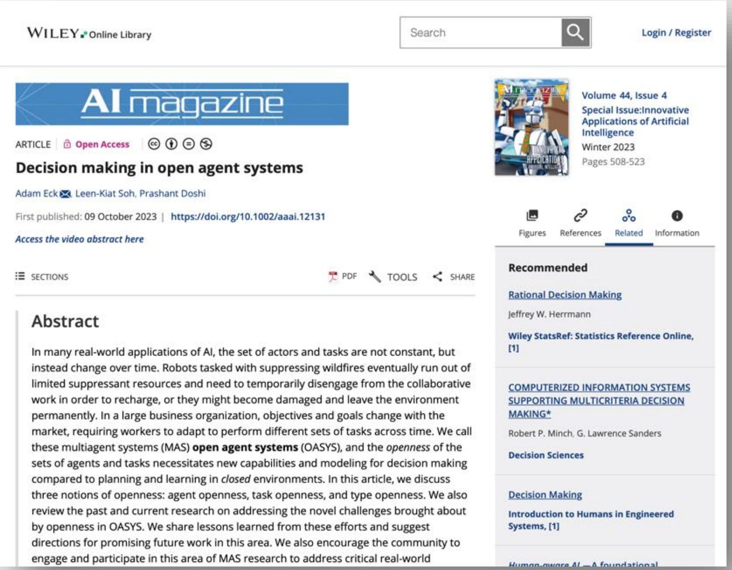
Why Investigating OASYS?

Reinforcement Learning 2

Most importantly, the **tradeoff of balancing exploration and exploitation** is complicated in critical ways by openness

- In an open environment, it might be difficult to simulate all of the causes of openness, *necessitating online learning*
- Furthermore, *previously optimal policies may be rendered largely useless* if other agents and their actions have left the environment while new agents and their actions are now impacting the environment
- *Understanding where in the policy space* does an agent need to explore more versus what knowledge it can still exploit is an open problem

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

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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

Volume 44, Issue 4
Special Issue:Innovative Applications of Artificial Intelligence
Winter 2023
Pages 508-523

Figures References Related Information

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COMPUTERIZED INFORMATION SYSTEMS SUPPORTING MULTICRITERIA DECISION MAKING*
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Decision Sciences

Decision Making
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Eck, A., Soh, L.-K., & Doshi, P. 2023. Decision Making in Open Multiagent Systems. AI Magazine. 44(4), 508-523. [link]

Kakarlapudi, A., Anil, G., Eck, A., Doshi, P., & Soh, L.-K. 2022. Decision-Theoretic Planning with Communication in Open Multiagent Systems. Proceedings of the 2022 Conference on Uncertainty in Artificial Intelligence (UAI'22), Eindhoven, Netherlands, August 1-5, 2022 [link][Open Review with Appendices] [Code]

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Chandrasekaran, M., Eck, A., Doshi, P., & Soh, L.-K. 2016. Individual Planning in Open and Typed Agent Systems. Proceedings of the 2016 Conference on Uncertainty in Artificial Intelligence (UAI'16), New York City, NY, June 25-29, 2016. [link]

TEAM PRESENTATIONS

Hossein Savari;Ali Jahani; Afsaneh Habibi

Teams

11 teams registered

4 teams submitted solutions

Markov Mayhem

- University of Utah, Utah, USA
- Varun Raveendra, Yanxi Lin, Seongil Heo

University of Tehran

- University of Tehran, Tehran, Iran
- Hossein Savari, Ali Jahani, Afsaneh Habibi

BitStudent

- Beijing University of Technology, Beijing, China
- Yu Zou, Tianjiao Yi, Yinuo Zhao, Yuxiang Song, Chi Harold Liu

Zana-Cyber

- Carleton University, Ottawa, Canada
- Thomas Kunz, Azad Jalalian

TEAM PRESENTATIONS

MARKOV MAYHEM

TEAM PRESENTATIONS

UNIVERSITY OF TEHRAN

TEAM PRESENTATIONS
BIT STUDENT

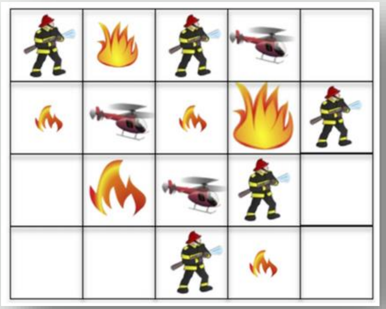
TEAM PRESENTATIONS
ZANA-CYBER

COMPETITION RESULTS

COMPETITION RESULTS

EVALUATION METHODOLOGY

Methodology - Wildfire



Evaluation Metrics

- rewards

Simulation Setup

- 256 evaluation runs / configuration

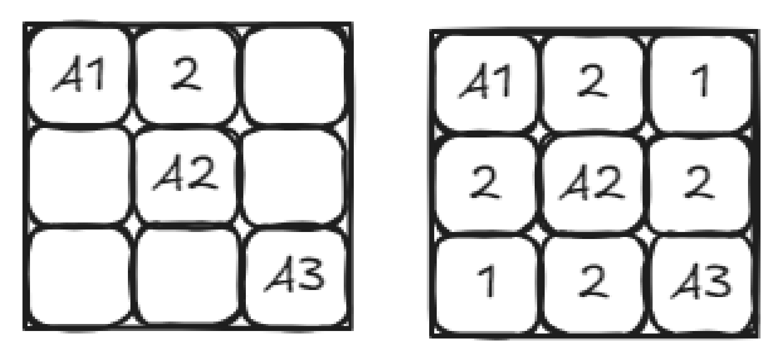
Baselines Compared

- 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

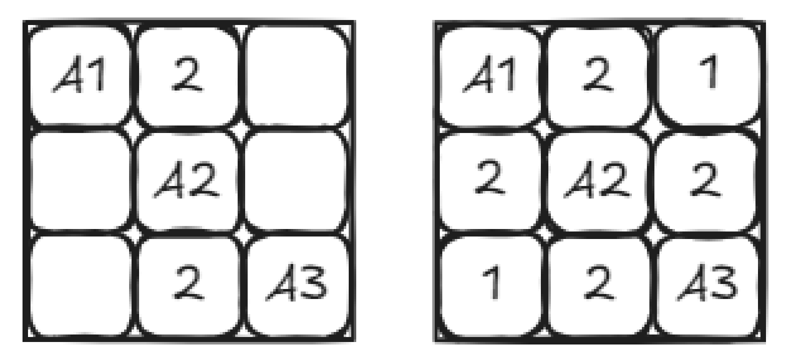
Evaluation Procedure

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

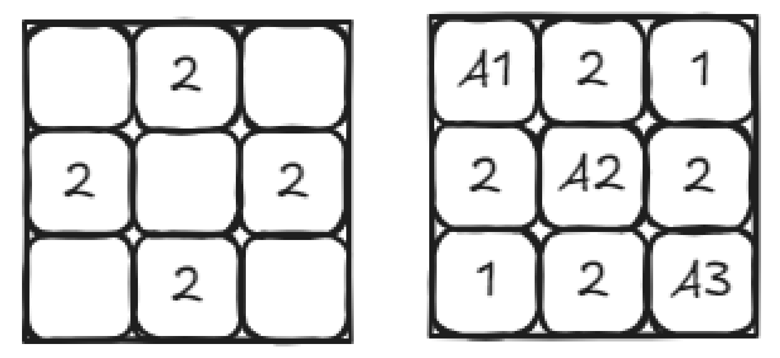
Wildfire



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

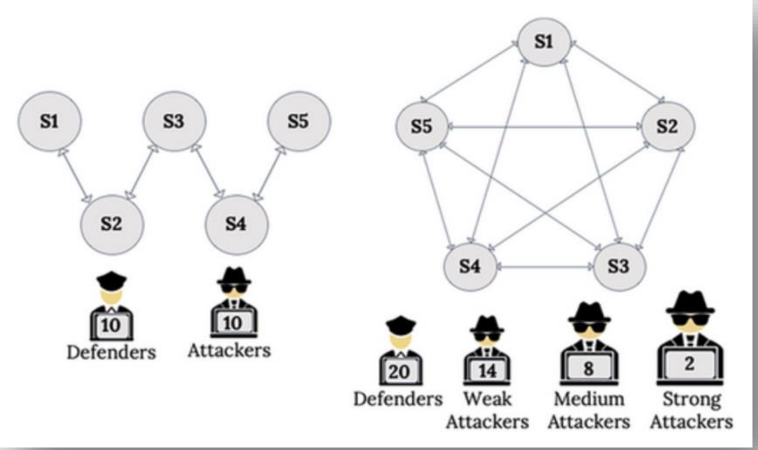


WS2
- base spread rate: 0.5
- random ignition probability: 0.25
- two initial fires, all agent present



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

Methodology - Cybersecurity



Evaluation Metrics

- rewards

Simulation Setup

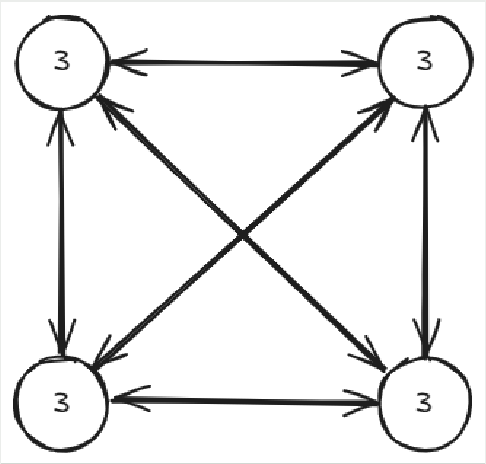
- 256 evaluation runs / configuration

Baselines Compared

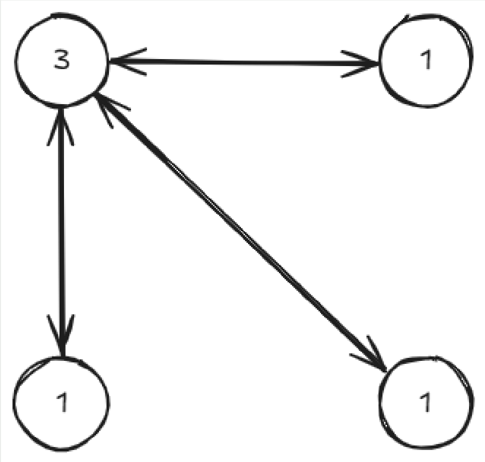
- noop – agents take no actions
- random – agents take random actions
- exploited – agents patch the node which is most exploited for 3 consecutive steps, then retarget
- patched – agents patch the node which is closest to completely patched for 3 consecutive steps, then retarget

Evaluation Procedure

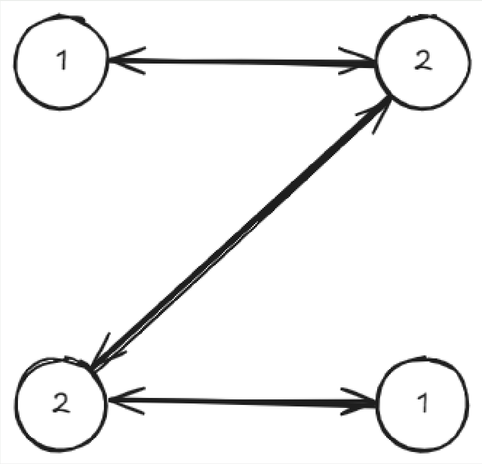
1. Each team's solution tested on same 256-seed set per configuration
2. Collected average and variance across 256 total trials
3. Visualizations generated after all evaluations for post-hoc analysis



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



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

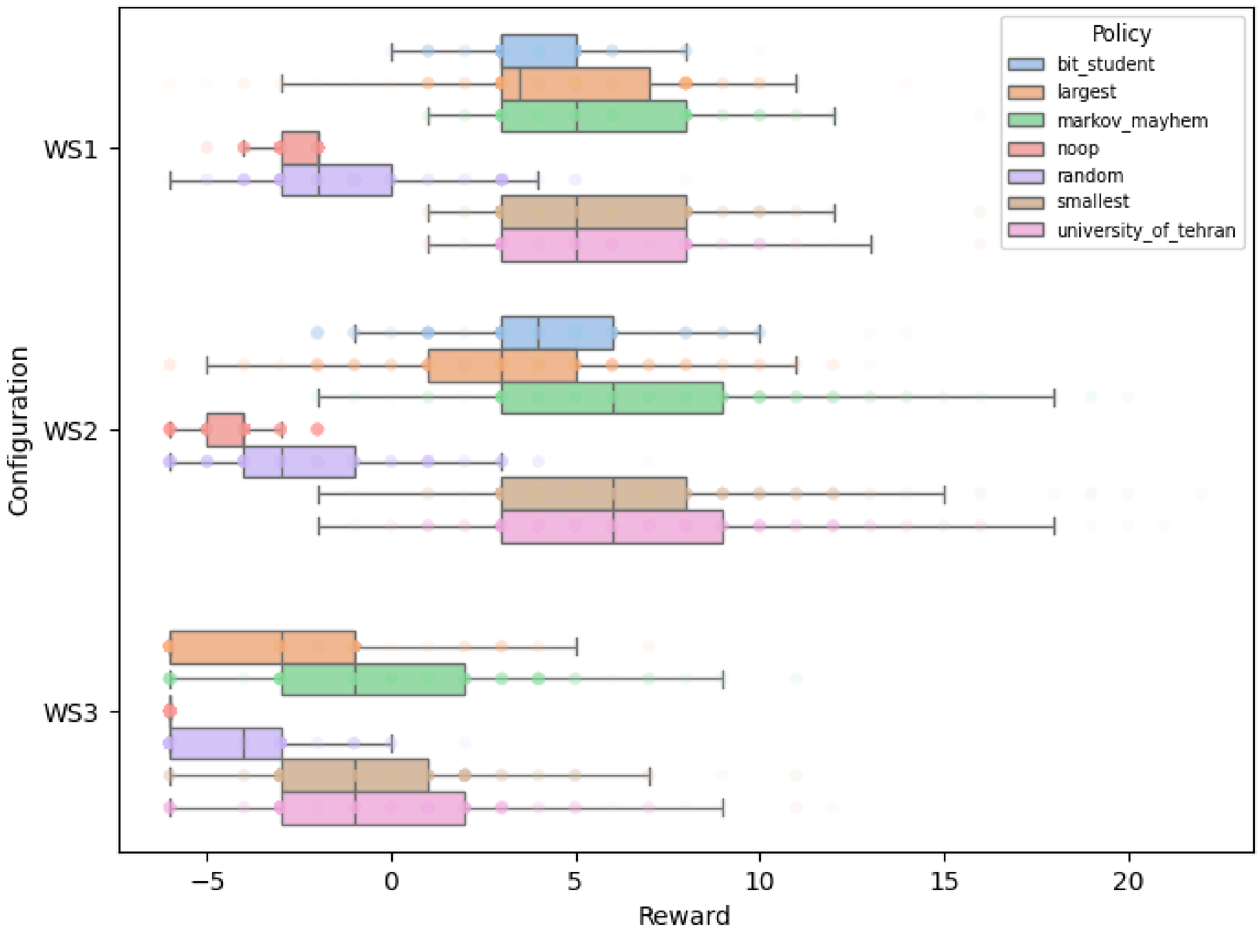


CS3
- persist probability: 0.5
- return probability: 0.25
- linear network

Cybersecurity

COMPETITION RESULTS

PERFORMANCES & PLACINGS

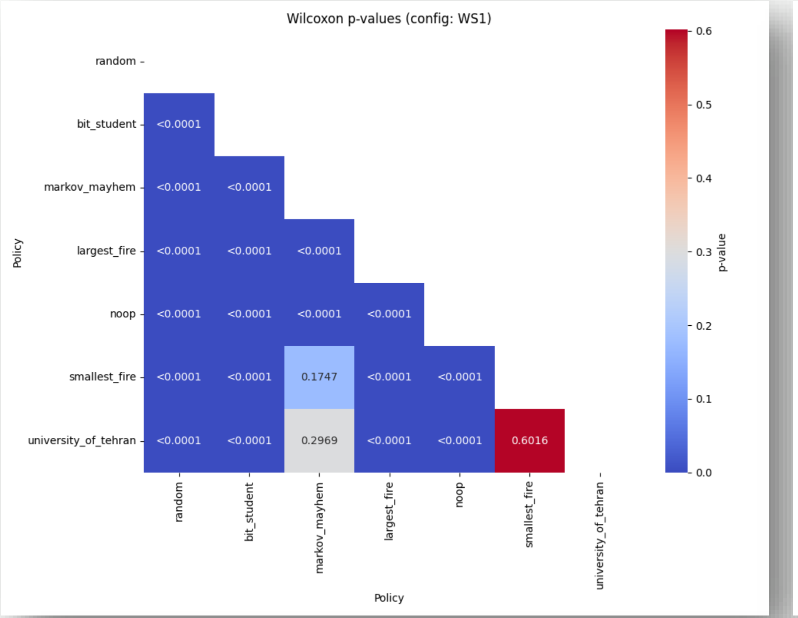

Policy
bit_student
largest
markov_mayhem
noop
random
smallest
university_of_tehran
WS1
WS2
WS3
Configuration
−5
0
5
10
15
20
Reward

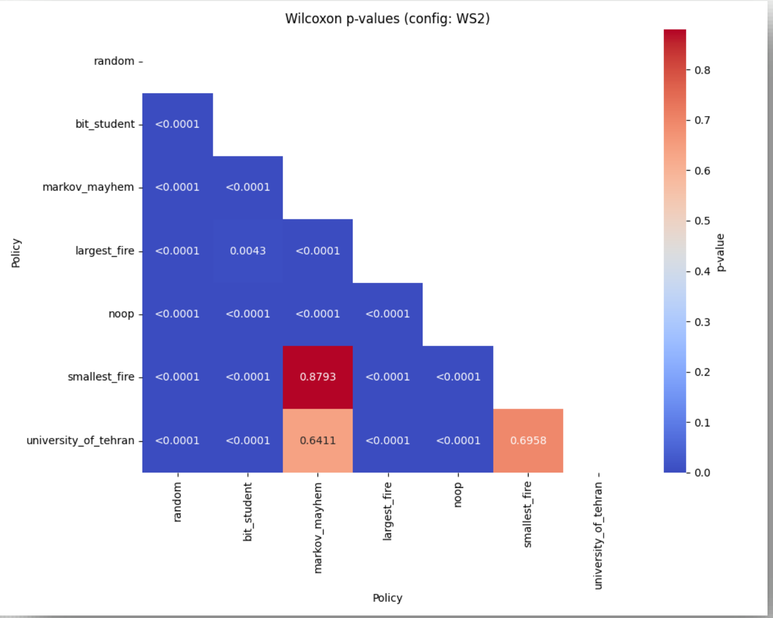
Wildfire

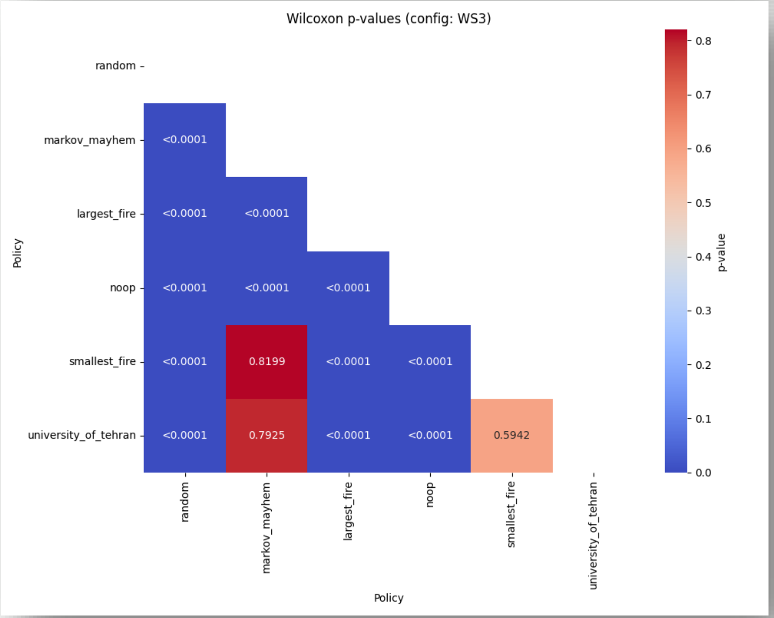
Wildfire

Rewards

Policy	WS1	WS2	WS3	Total
noop	-2.54 ± 0.05	-4.20 ± 0.08	-6.00 ± 0.00	-12.73 ± 0.12
random	-1.23 ± 0.15	-2.38 ± 0.17	-4.27 ± 0.12	-7.88 ± 0.44
smallest	5.23 ± 0.16	6.46 ± 0.23	-0.34 ± 0.18	11.35 ± 0.57
largest	4.52 ± 0.18	3.26 ± 0.22	-2.80 ± 0.17	4.98 ± 0.57
bit_student	3.75 ± 0.09	3.97 ± 0.18	crash	7.71 ± 0.27
markov_mayhem	5.18 ± 0.16	6.48 ± 0.23	**-0.30 ± 0.22**	11.36 ± 0.61
university_of_tehran	**5.27 ± 0.16**	**6.53 ± 0.25**	-0.39 ± 0.21	**11.41 ± 0.63**



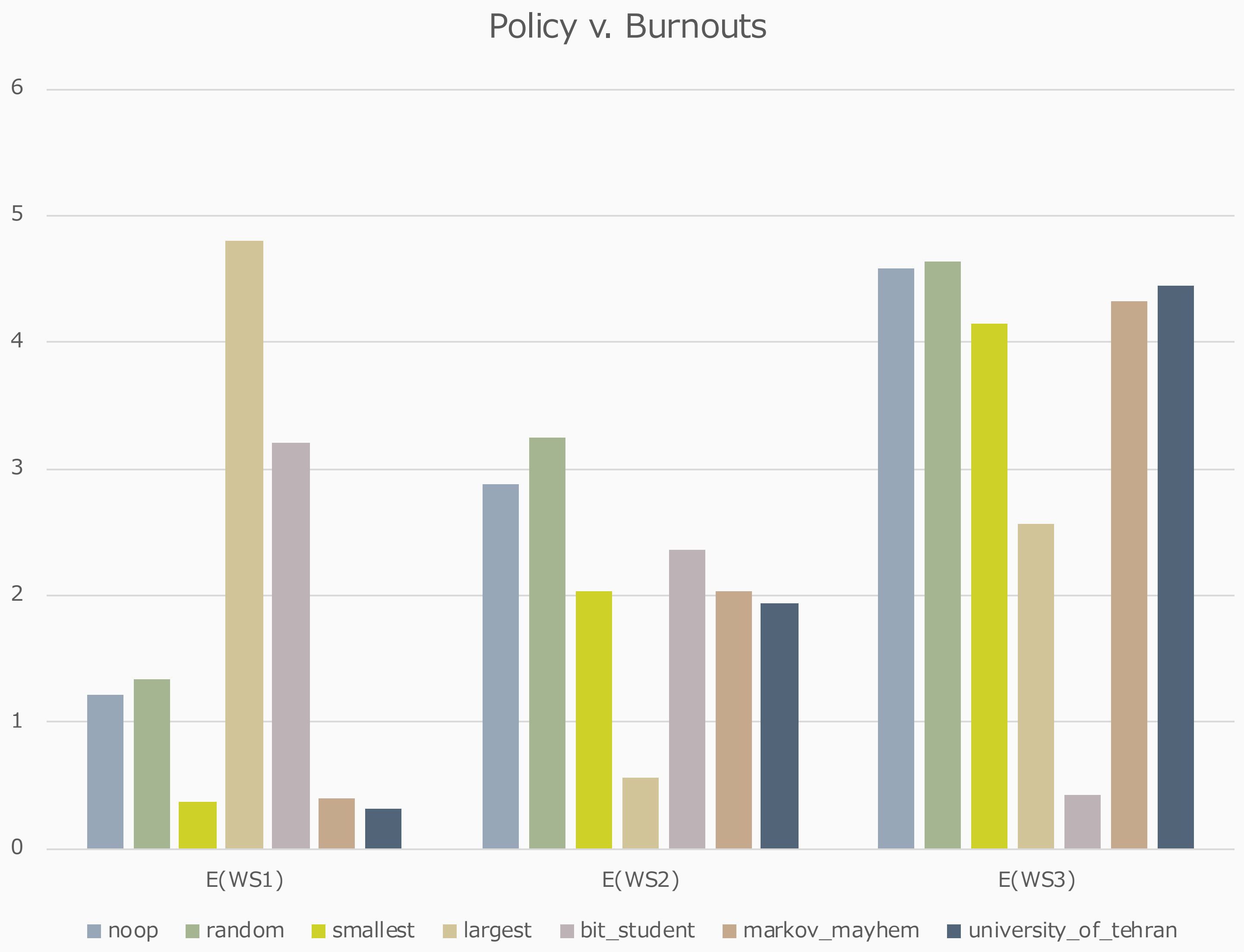




No statistically significant differences between the University of Tehran and Markov Mayhem

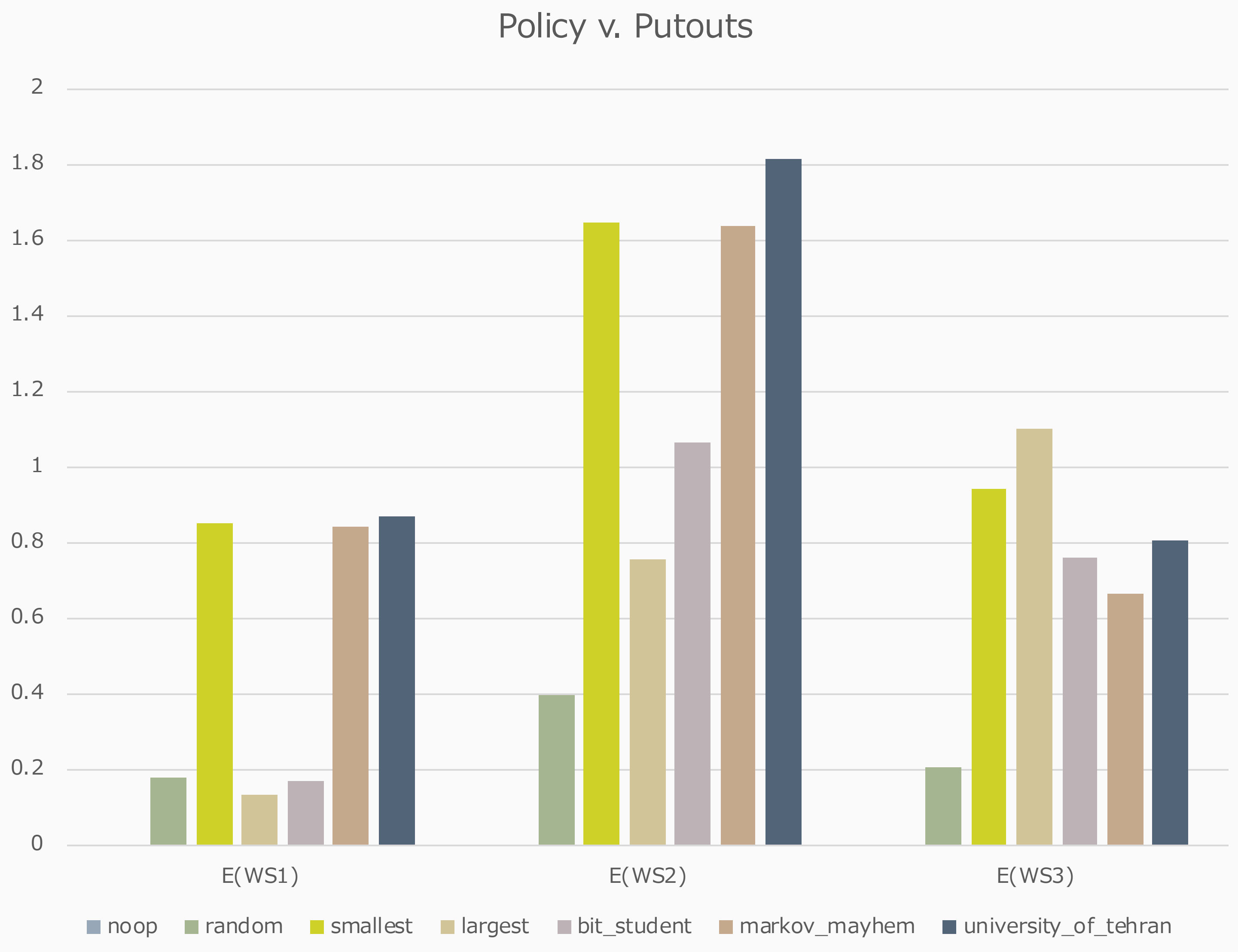
Wildfire

Wilcoxon test for statistical significance



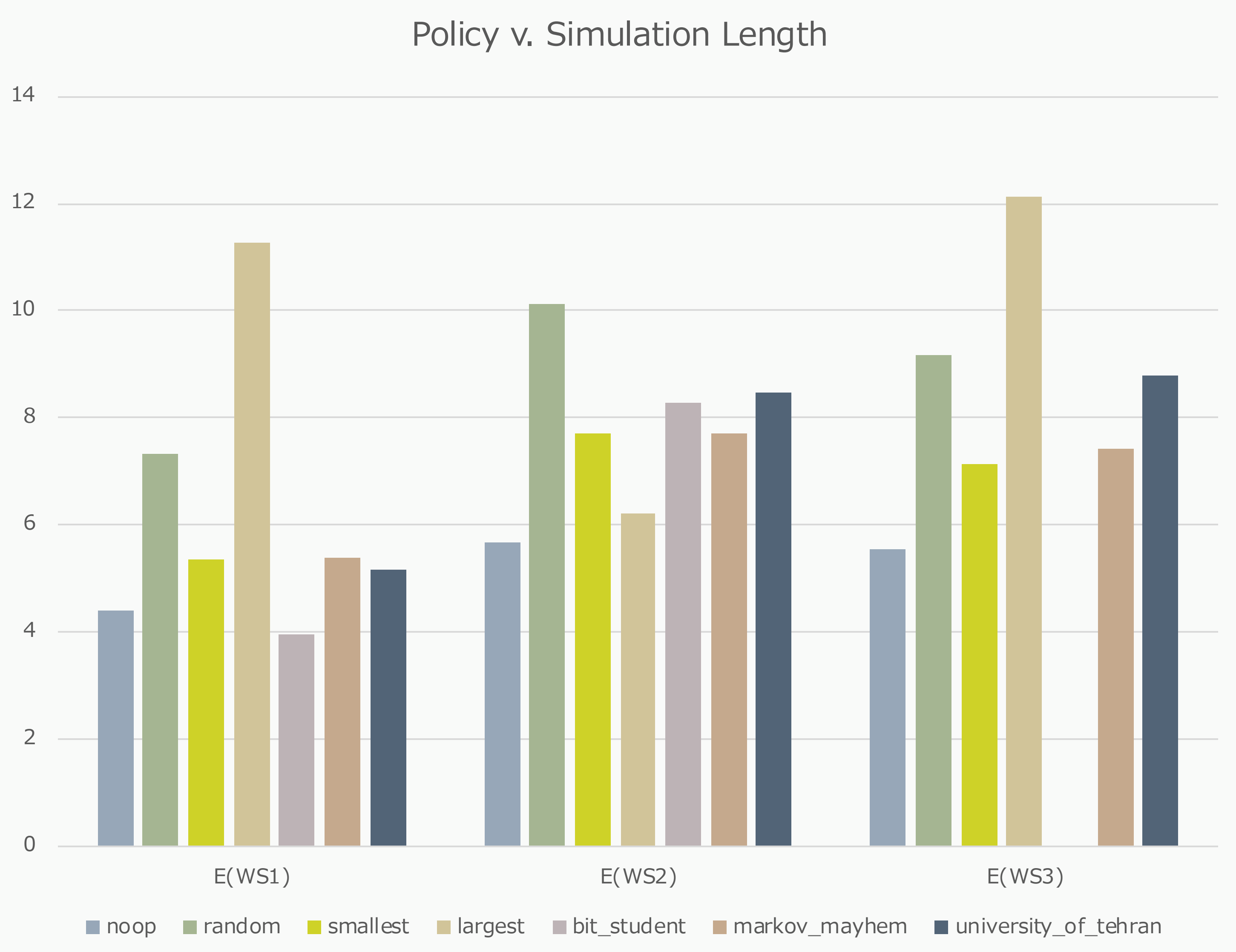
Wildfire

Burnouts



Wildfire

Putouts



Wildfire

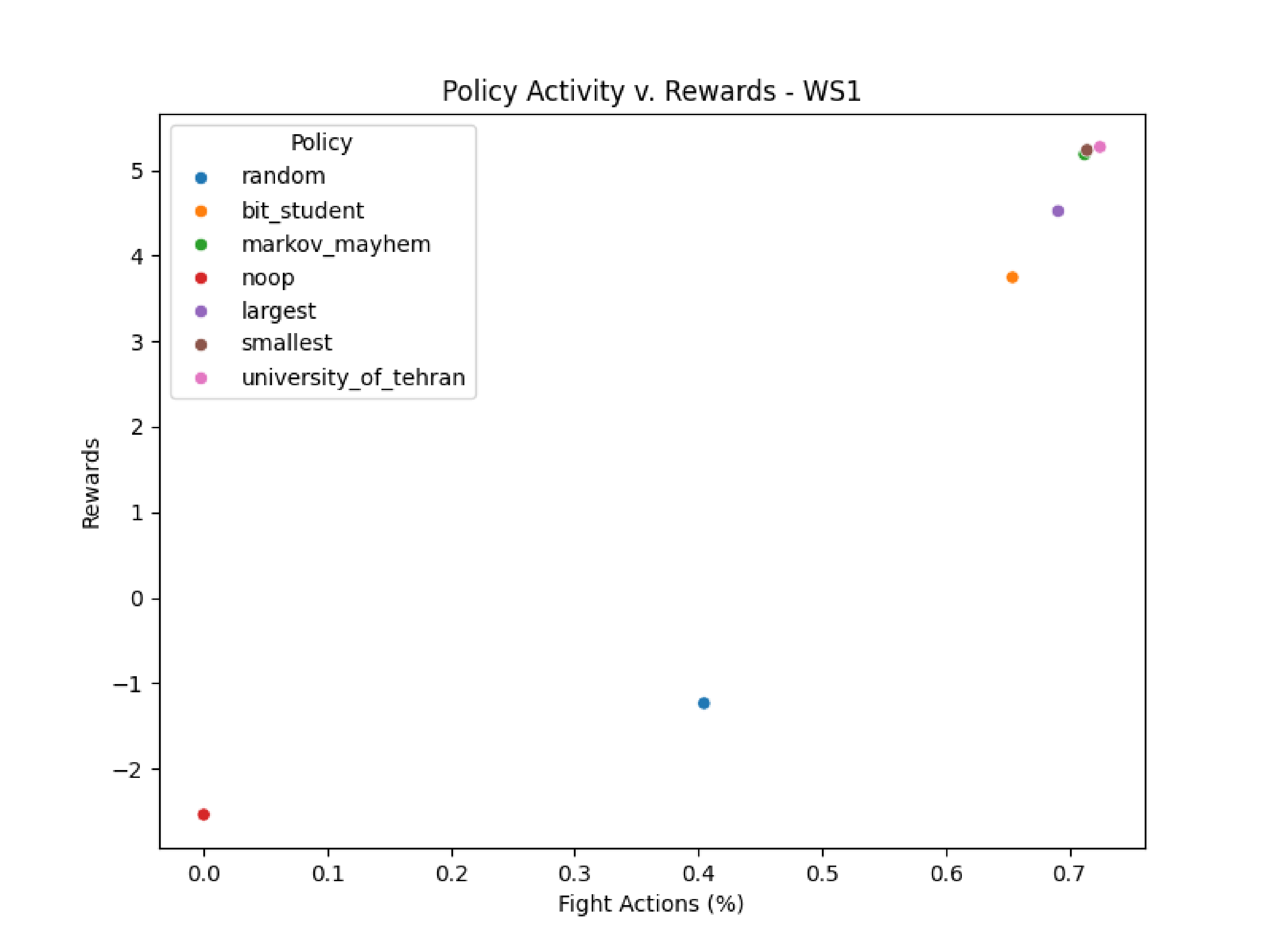
Simulation Length

Wildfire

Policy Action Preferences

Policy v. Fights	WS1	WS2	WS3	Average
noop	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%
random	40.46% ± 0.01%	40.31% ± 0.01%	25.91% ± 0.01%	35.56% ± 0.02%
smallest	71.44% ± 0.01%	72.01% ± 0.01%	45.68% ± 0.01%	63.05% ± 0.03%
largest	48.63% ± 0.01%	69.10% ± 0.01%	65.98% ± 0.01%	61.24% ± 0.02%
bit_student	36.63% ± 0.02%	62.82% ± 0.01%	65.41% ± 0.01%	54.95% ± 0.04%
markov_mayhem	71.24% ± 0.01%	72.21% ± 0.01%	47.20% ± 0.01%	63.55% ± 0.03%
university_of_tehran	72.48% ± 0.01%	69.39% ± 0.01%	47.16% ± 0.01%	63.01% ± 0.03%

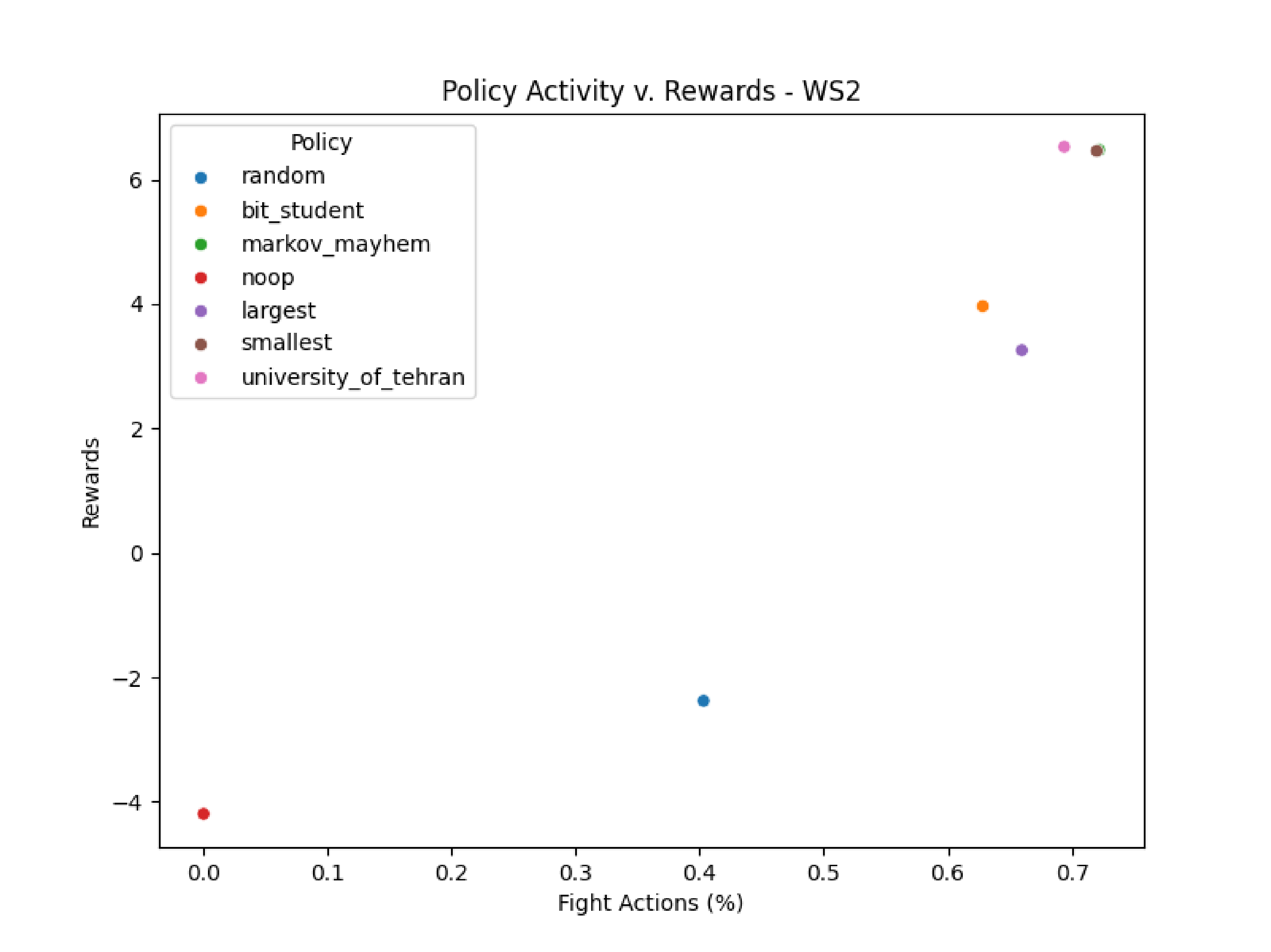
Policy v. Noop	WS1	WS2	WS3	Average
noop	100.00% ± 0.00%	100.00% ± 0.00%	100.00% ± 0.00%	100.00% ± 0.00%
random	59.54% ± 0.01%	59.69% ± 0.01%	74.09% ± 0.01%	64.44% ± 0.02%
smallest	28.56% ± 0.01%	27.99% ± 0.01%	54.32% ± 0.01%	36.95% ± 0.03%
largest	51.37% ± 0.01%	30.90% ± 0.01%	34.02% ± 0.01%	38.76% ± 0.02%
bit_student	63.37% ± 0.02%	37.18% ± 0.01%	34.59% ± 0.01%	45.05% ± 0.04%
markov_mayhem	28.76% ± 0.01%	27.79% ± 0.01%	52.80% ± 0.01%	36.45% ± 0.03%
university_of_tehran	27.52% ± 0.01%	30.61% ± 0.01%	52.84% ± 0.01%	36.99% ± 0.03%



Wildfire

Policy Action Preferences v. Rewards

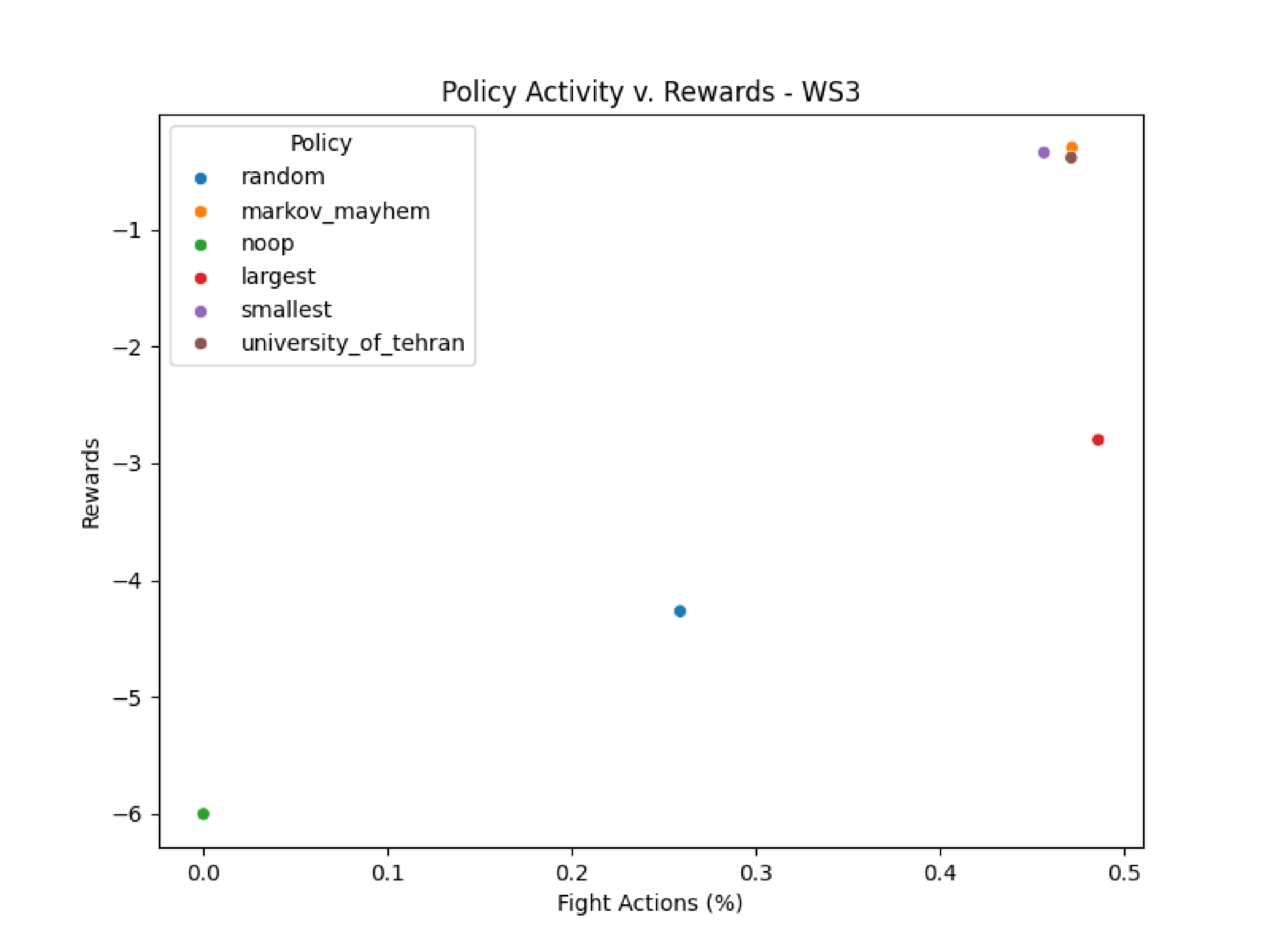
WS1



Wildfire

Policy Action Preferences v. Rewards

WS2



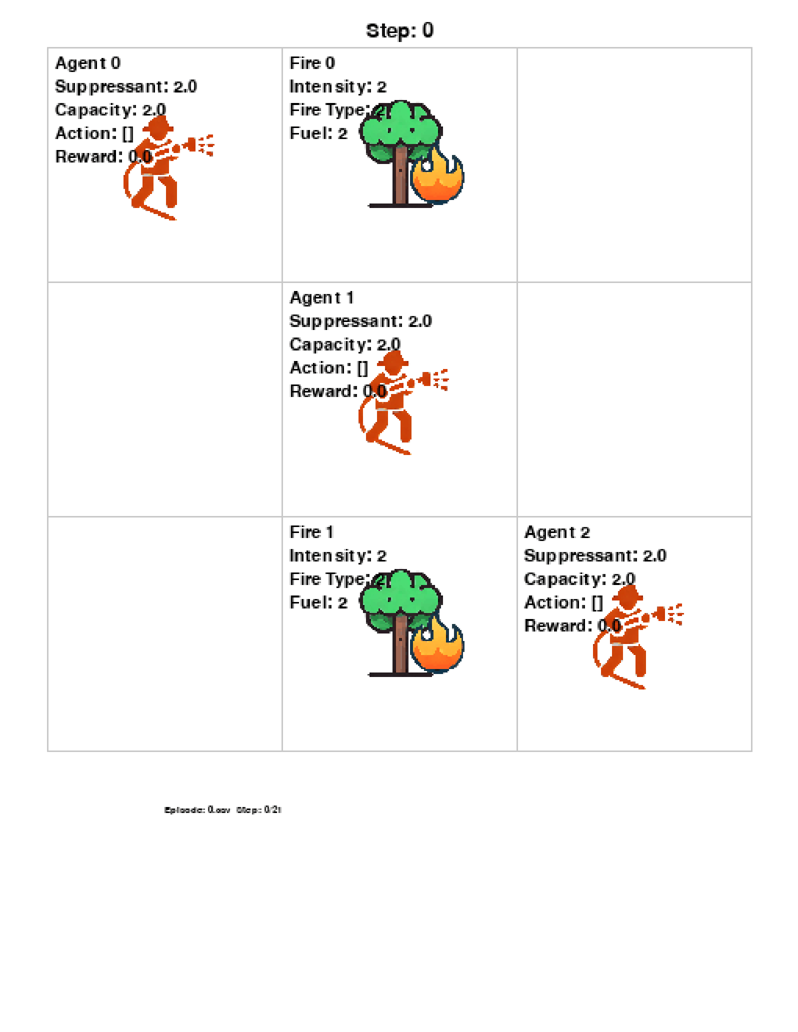
Wildfire

Policy Action Preferences v. Rewards

WS3

BIT Student

Configuration: WS2

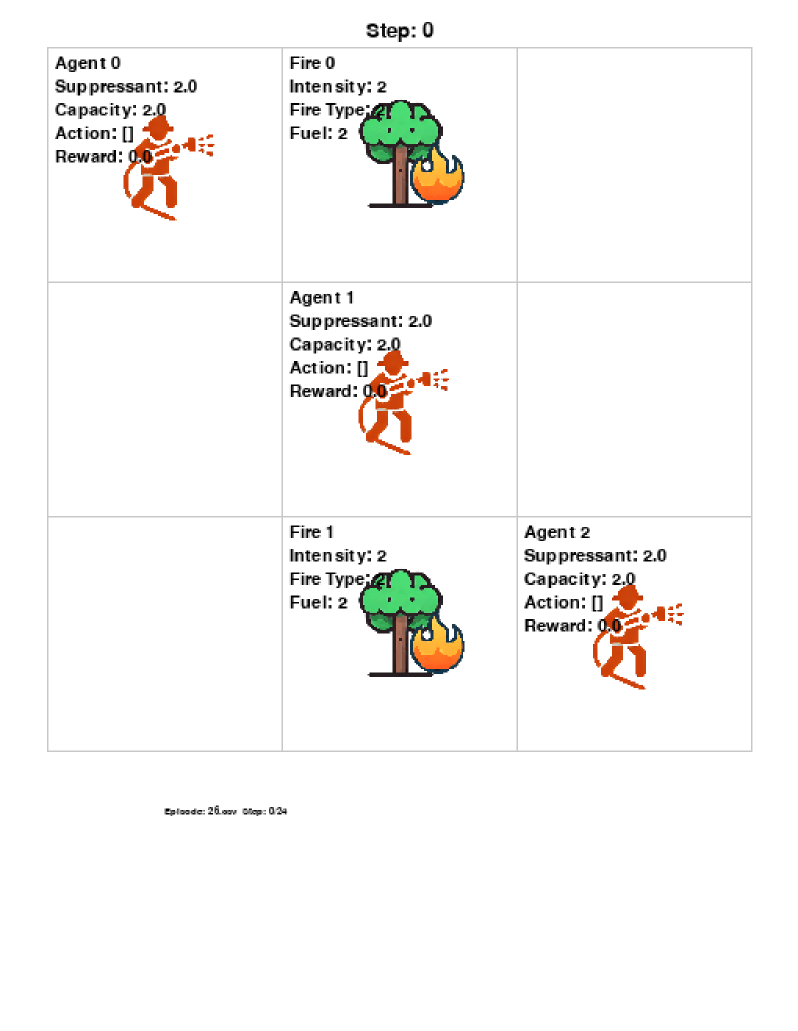


Wildfire

Animations of Renderings

Markov Mayhem

Configuration: WS2

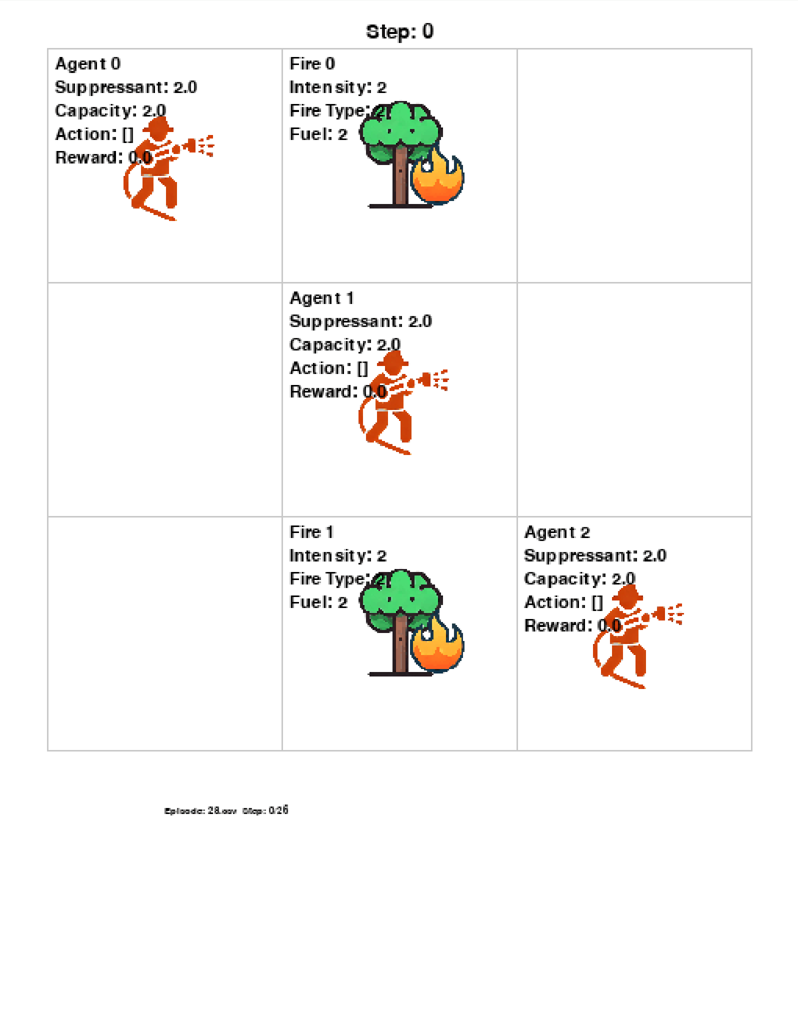


Wildfire

Animations of Renderings

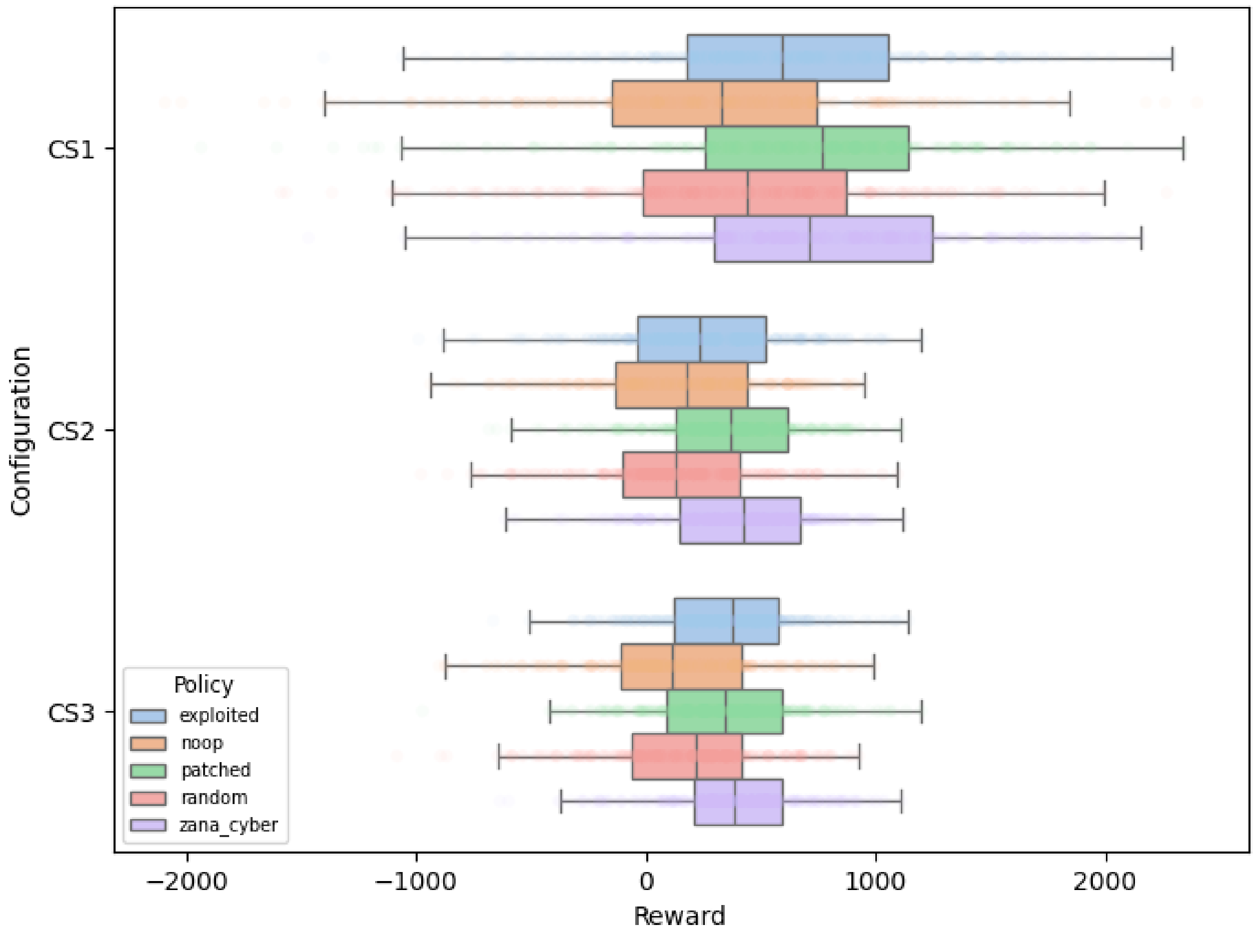
University of Tehran

Configuration: WS2



Wildfire

Animations of Renderings

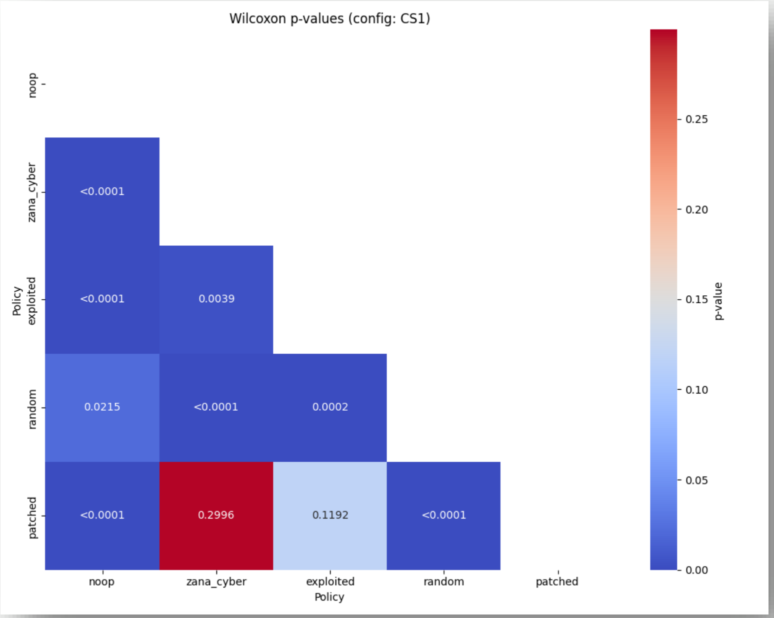


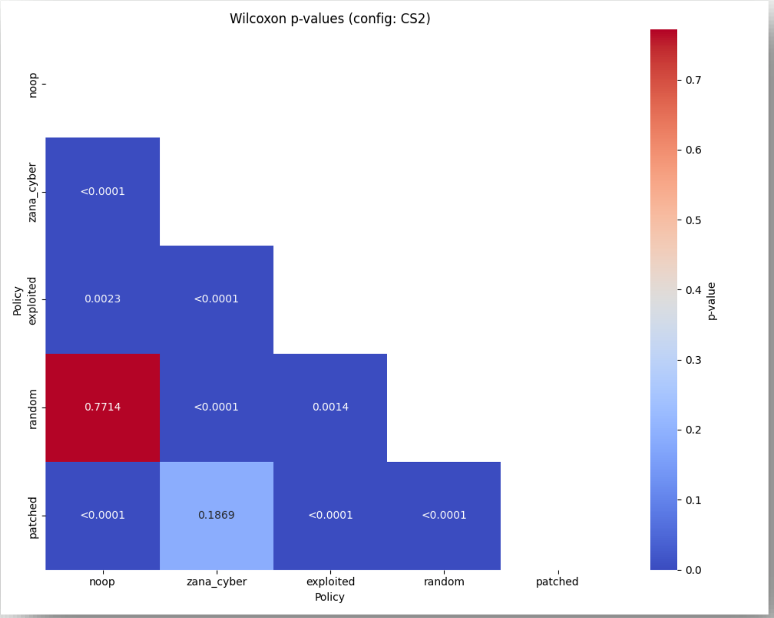
Cybersecurity

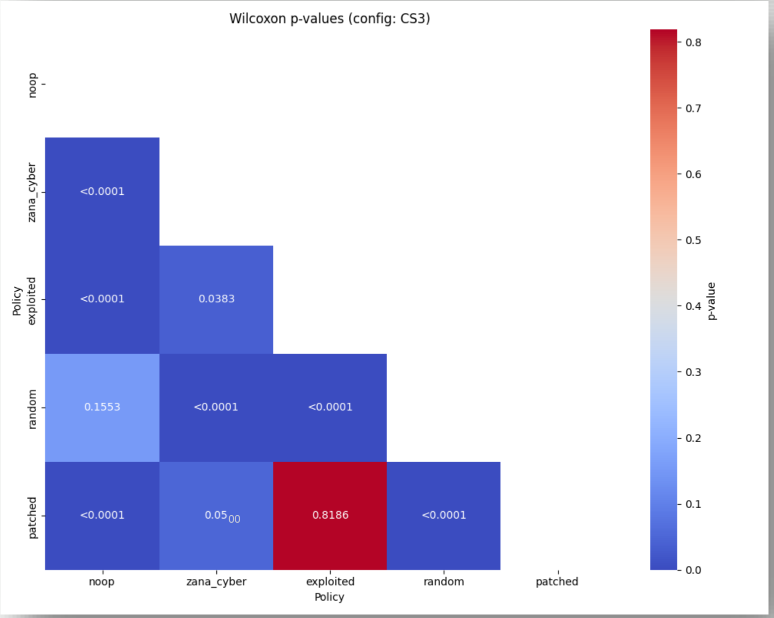
Cybersecurity

Rewards

Policy	CS1	CS2	CS3	Total
noop	282.56 ± 47.15	154.30 ± 25.18	131.41 ± 24.36	568.27 ± 96.69
random	406.83 ± 43.52	144.64 ± 24.51	168.70 ± 22.91	720.16 ± 90.94
patched	680.41 ± 45.16	353.91 ± 21.49	340.04 ± 21.30	1374.36 ± 87.95
exploited	605.30 ± 40.87	241.08 ± 24.79	347.99 ± 20.10	1194.37 ± 85.75
zana_cyber	**743.65 ± 42.58**	**386.37 ± 22.39**	**386.34 ± 20.14**	**1516.36 ± 85.11**







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

Cybersecurity

Wilcoxon test for statistical significance

Cybersecurity

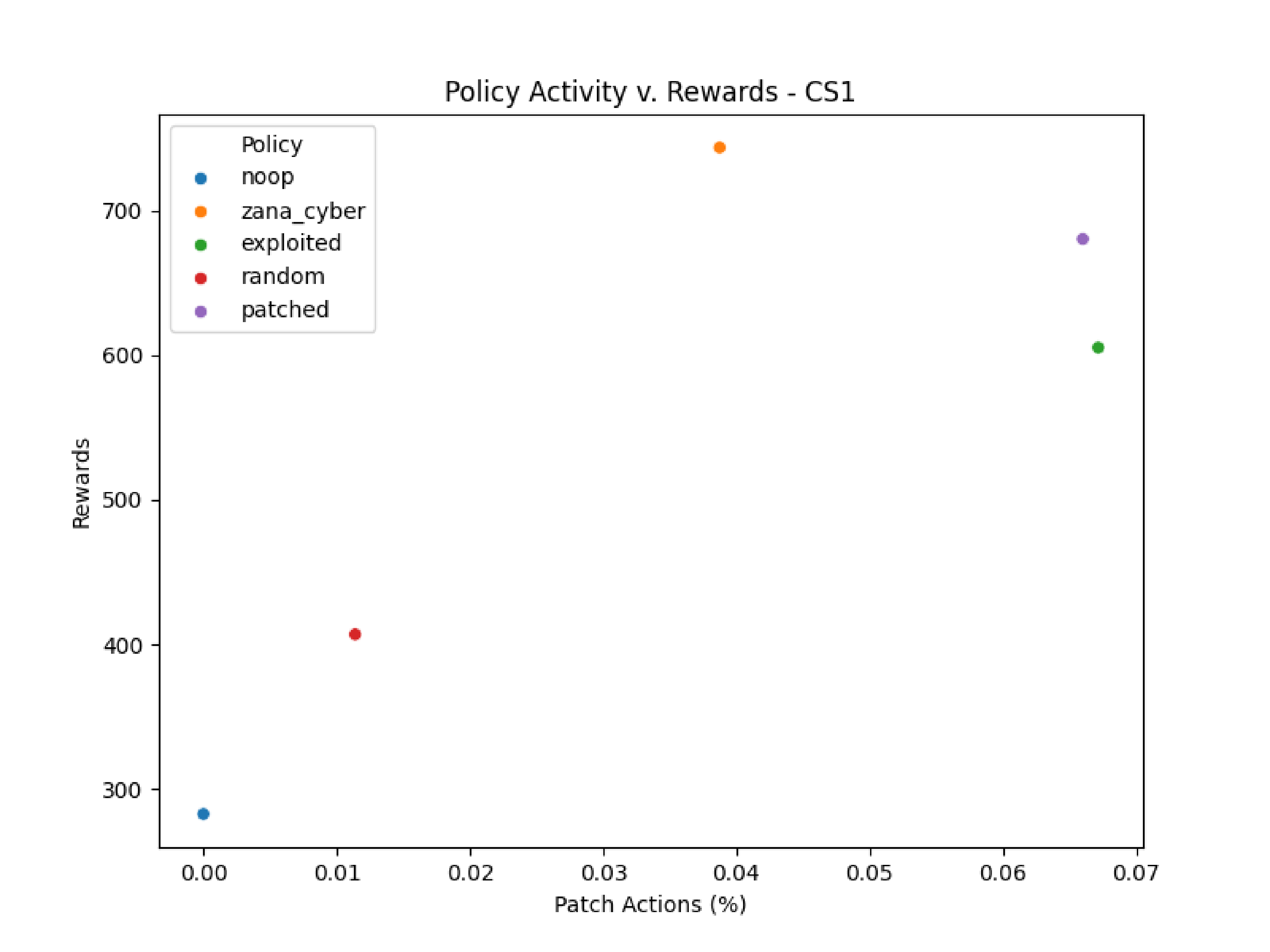
Policy Action Preferences

Policy v. Move	CS1	CS2	CS3	Average
noop	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%
random	24.47% ± 0.00%	24.57% ± 0.00%	24.61% ± 0.00%	24.55% ± 0.00%
patched	22.22% ± 0.00%	22.24% ± 0.00%	22.08% ± 0.00%	22.18% ± 0.00%
exploited	22.12% ± 0.00%	22.04% ± 0.00%	21.91% ± 0.00%	22.02% ± 0.00%
zana_cyber	19.89% ± 0.00%	19.77% ± 0.00%	19.71% ± 0.00%	19.79% ± 0.00%

Policy v. Noop	CS1	CS2	CS3	Average
noop	100.00% ± 0.00%	100.00% ± 0.00%	100.00% ± 0.00%	100.00% ± 0.00%
random	71.46% ± 0.00%	71.29% ± 0.00%	71.34% ± 0.00%	71.36% ± 0.00%
patched	68.36% ± 0.00%	68.39% ± 0.00%	68.45% ± 0.00%	68.40% ± 0.00%
exploited	68.47% ± 0.00%	68.42% ± 0.00%	68.53% ± 0.00%	68.47% ± 0.00%
zana_cyber	68.44% ± 0.00%	68.48% ± 0.00%	68.57% ± 0.00%	68.49% ± 0.00%

Policy v. Monitor	CS1	CS2	CS3	Average
noop	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%
random	1.14% ± 0.00%	1.14% ± 0.00%	1.11% ± 0.00%	1.13% ± 0.00%
patched	6.60% ± 0.00%	6.56% ± 0.00%	6.64% ± 0.00%	6.60% ± 0.00%
exploited	6.59% ± 0.00%	6.70% ± 0.00%	6.72% ± 0.00%	6.67% ± 0.00%
zana_cyber	3.87% ± 0.00%	3.84% ± 0.00%	3.88% ± 0.00%	3.86% ± 0.00%

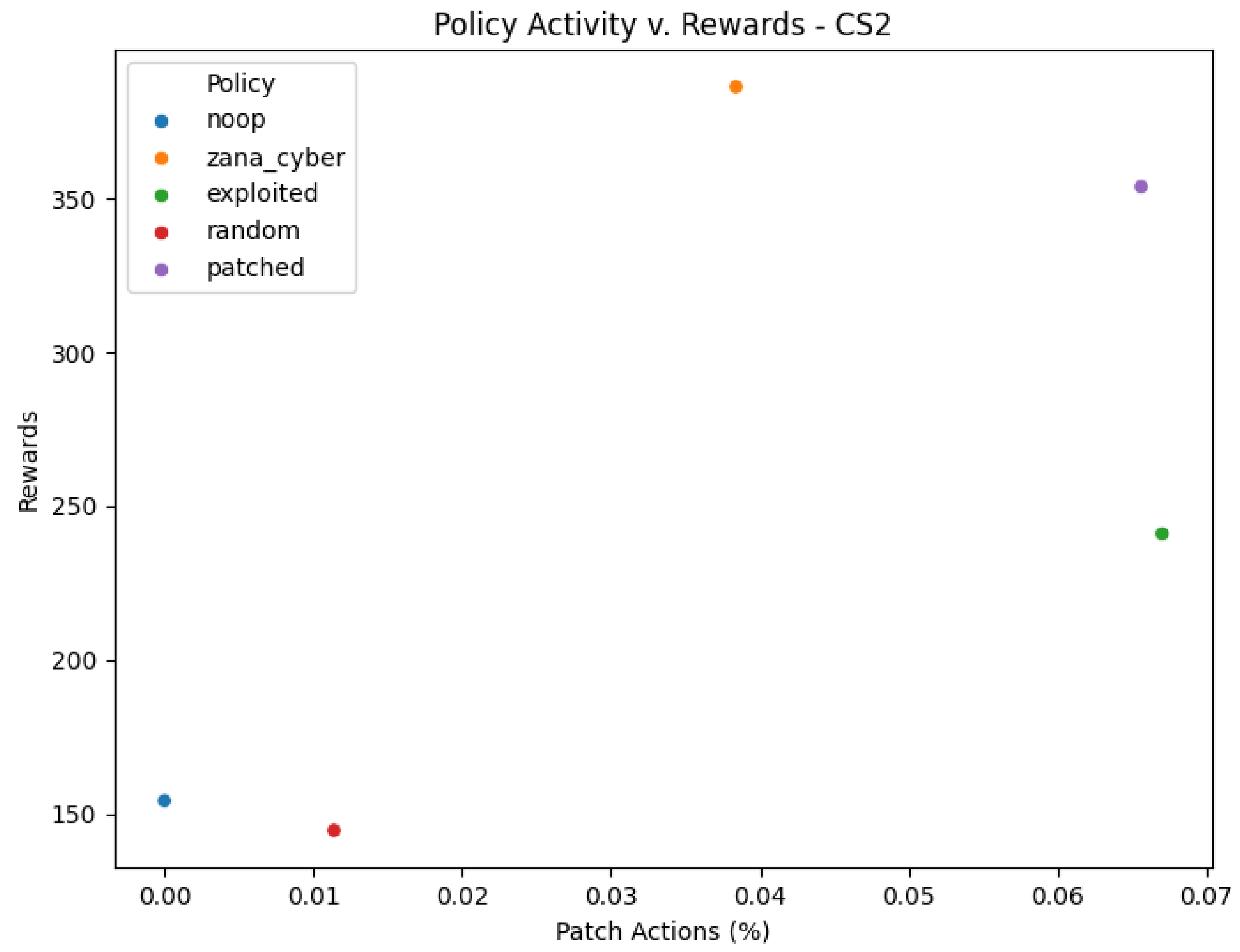
Policy v. Patch	CS1	CS2	CS3	Average
noop	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%	0.00% ± 0.00%
random	2.94% ± 0.00%	3.01% ± 0.00%	2.95% ± 0.00%	2.96% ± 0.00%
patched	2.82% ± 0.00%	2.81% ± 0.00%	2.82% ± 0.00%	2.82% ± 0.00%
exploited	2.82% ± 0.00%	2.84% ± 0.00%	2.85% ± 0.00%	2.84% ± 0.00%
zana_cyber	7.80% ± 0.00%	7.91% ± 0.00%	7.85% ± 0.00%	7.85% ± 0.00%



Cybersecurity

Policy Action Preferences v. Rewards

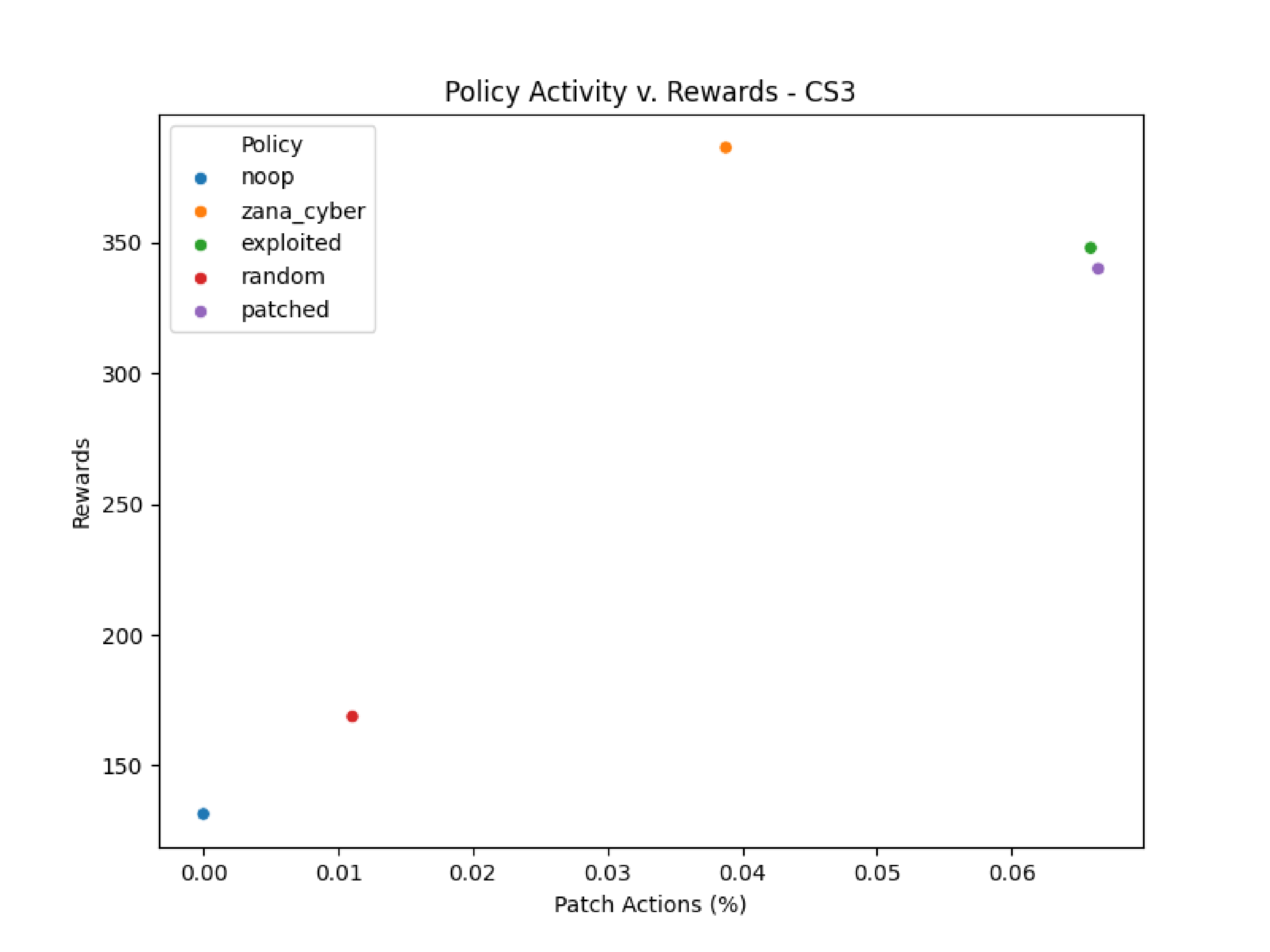
CS1



Cybersecurity

Policy Action Preferences v. Rewards

CS2



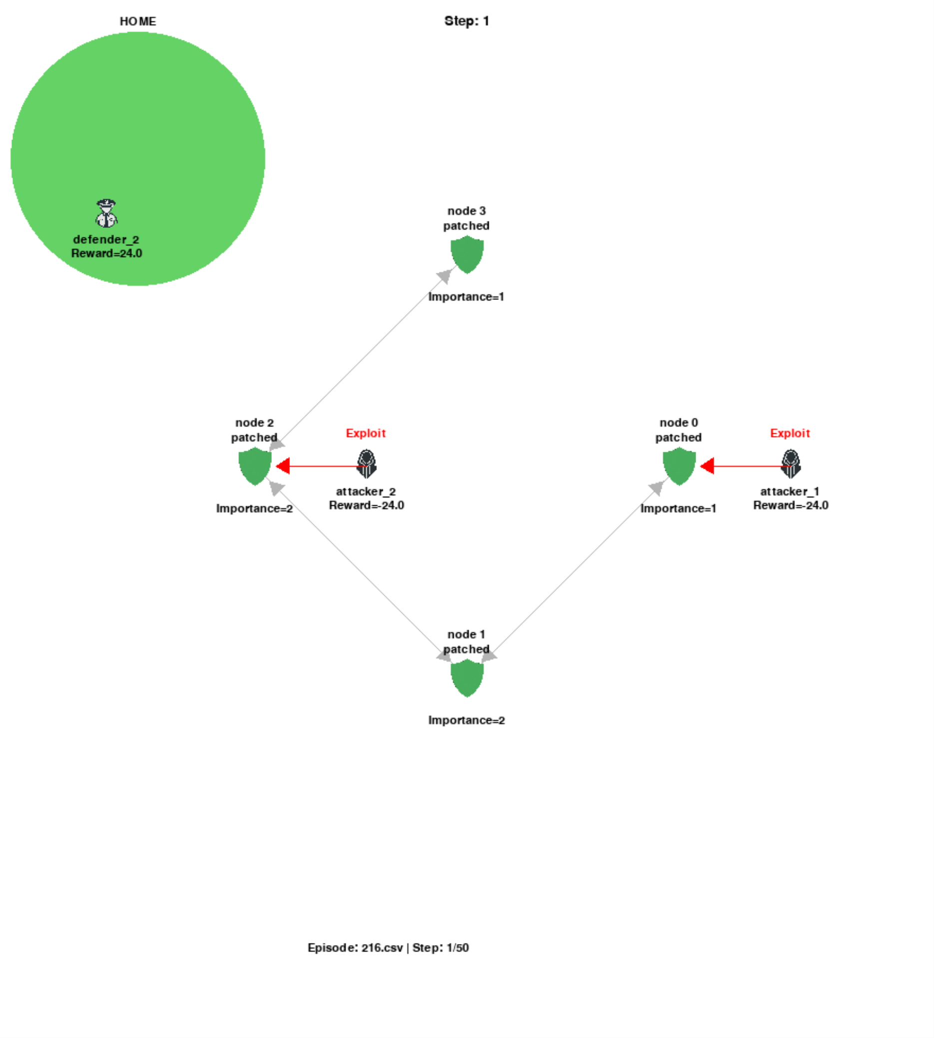
Cybersecurity

Policy Action Preferences v. Rewards

CS3

Zana Cyber

Configuration CS3

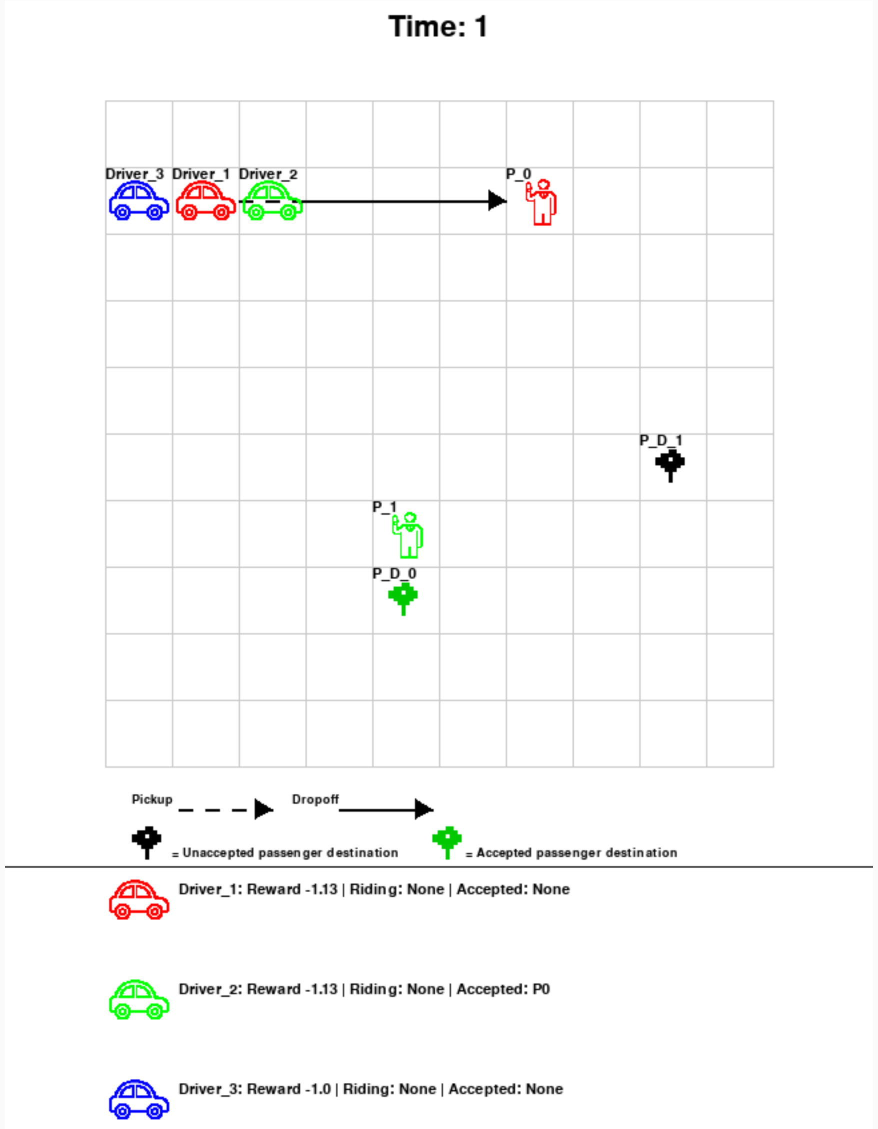


Cybersecurity

Animations of Renderings

Rideshare

Animations of Renderings



MOHITO

Configuration DR3

Placings

Wildfire Track

Winner: University of Tehran
University of Tehran, Tehran, Iran
Hossein Savari, Ali Jahani, Afsaneh Habibi

Winner: Markov Mayhem
University of Utah, Utah, USA
Varun Ravendra, Yanxi Lin, Seongil Heo

Honorable Mention: BitStudent
Beijing University of Technology, Beijing, China
Yu Zou, Tianjiao Yi, Yinuo Zhao, Yuxiang Song, Chi Harold Liu

Cybersecurity Track

Winner: Zana-Cyber
Carleton University, Ottawa, Canada
Thomas Kunz, Azad Jalalian

COFFEE BREAK

COMING UP NEXT: DISCUSSIONS ON IMPROVEMENT/REFINEMENT OF MOASEI

DISCUSSIONS ON IMPROVEMENT/REFINEMENT

Contributing to shared notes

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

Increase in Environment Size

WILDFIRE

Larger grid sizes, exacerbating the number of tasks which can appear and disappear. More agents and tasks requiring greater cooperation and planning.

CYBERSECURITY

Greater number of subnetwork nodes and agents, increasing the complexity of possible interactions.

Smarter Attacker Heuristics for Cybersecurity

Smarter attacker heuristics may be used, which make full use of the observations to maximize their attack surface.

Incorporation of Type Openness in Wildfire

Agent abilities and skills can be added, removed, or modified, increasing the difficulty and environmental complexity of task and agent openness.

Manifestation:

Agents can damage their equipment over time, and have capabilities slowly degrade. Agents might also receive different equipment on return to the environment.

Rideshare

Domain:

Passengers periodically appear around the map with a random initial location, destination, and fare. Agents must travel to the passenger’s location and deliver them to their destination.

Key Components:

- Competitive Domain: Direct competition against other submissions, encouraging submissions which can take advantage of natural Nash equilibria.

CONCLUDING REMARKS

Summary of Approaches

Teams	Approaches	Domains
Zana-Cyber (Winner)	Prioritizes tasks using a weighted scoring function, focusing on the most critical tasks.	Cybersecurity
University of Tehran (Winner)	Processes a spatial grid that represents the environment, while using historical data to prioritize actions based on urgency.	Wildfire
Markov Mayhem (Winner)	Leverages GNNs to handle openness by modifying observations into flexible graph-structured data.	Wildfire
Bit Student (Honorable Mention)	Uses an iterative process with multiple-sampling from LLM models to continuously improve upon a baseline policy.	Wildfire

Moving Forward …

Organizing the 2nd Annual MOASEI Competition at AAMAS'2026

- 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
- Conducting comparative studies
- Co-authoring papers

Acknowledgments

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Congratulations & Thank You!!

Zana-Cyber | Carleton University, Ottawa, Canada | Thomas Kunz, Azad Jalalian

Markov Mayhem | University of Utah, Utah, USA | Varun Raveendra, Yanxi Lin, Seongil Heo

University of Tehran | University of Tehran, Tehran, Iran | Hossein Savari, Ali Jahani, Afsaneh Habibi

BitStudent | Beijing University of Technology, Beijing, China | Yu Zou, Tianjiao Yi, Yinuo Zhao, Yuxiang Song, Chi Harold Liu

Hope that you will participate again next year!

Please also help us encourage others to participate

Contact Info

https://oasys-mas.github.io

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

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Survey

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

ADJOURNED

OASYS

University of Nebraska – Lincoln

Oberlin College

University of Georgia - Athens