Multi-Agent Reinforcement Learning for Maritime Operational Technology Cyber Security

Alec Wilson¹, Ryan Menzies¹, David Foster², Marco Casassa Mont¹, Neela Morarji¹, Esin Turkbeyler¹, Lisa Gralewski¹

CAMLIS 2023 | 20th October 2023

(BMT¹, ADSP²)



Overview

- Context Setting
- IPMSRL
- IPPO vs MAPPO
- Hyperparameters
- Reward Shaping
- Impact of Partial Observability





Context Setting: Maritime, Vessels and OT

- Vessels are complex systems-of-systems inclusive of Information Technology (IT) and Operational Technology (OT) infrastructures.
- OT systems are vulnerable to cyber-attacks as traditional IT cyber security controls may either not be available or may not be able to prevent attacks.
- OT cyber defensive actions are less mature than for Enterprise IT.
- Cyber security skills and SMEs might not be readily available during vessels' missions and operational activities.







Context Setting: IPMS

- Integrated Platform Management System (IPMS) representation consists of:
 - An abstraction of a bridge (a set of HMIs).
 - A Chilled Water Plant system.
 - A representation of a ships Propulsion system.
- While the scenario is a high-level abstraction of a real scenario, its design is grounded in reality and exhibits several features which are intended to reflect real challenges when developing agents capable of autonomous cyber responses.





IPMSRL Environment

• IPMSRL – network-based environment where nodes represent the different components within an IPMS.

Abbreviations:

- The nodes are sub-divided into infectable nodes (e.g. RTUs) and critical nodes (e.g. CWPs). :
 - Infectable nodes are nodes in the network that the attacker can spread through and have 12 infection levels based on the MITRE ATT&CK framework.
 - Critical nodes are the nodes in the network that represent the critical infrastructure.

Key												
Intrusion detection alert (red glow)												
not infected	1 1	2	3	4	5	6	7	8	9	10	11	12







IPMSRL Attacker

• An attacker's virality can be configured on a sliding scale from fully targeted to fully viral:

- **Fully targeted** Attackers will always seek to move directly towards critical infrastructure.
- **Fully viral** Attackers will move randomly to any adjacent node.
- An attacker's behaviour is also informed by the following parameters:
 - Lateral Movement Probability The probability that a lateral movement is successful.
 - Infection Progress Probability The probability that the infection on any given infected node will progress

to a later stage in the MITRE ATT&CK framework.







IPMSRL Attacker Visualisation

• The IPMS quickly becomes overrun, and the propulsion system is taken offline, resulting in a mission failure.









IPMSRL Defender

- Defenders have a restricted view and initially can only see alerts from nodes.
- Defenders collect infection progress information for each infectable node they interact with. This knowledge cannot be shared and is static in nature.
- The actions available to a defender are:
 - Contain Prevents the infection moving laterally from the node;
 - **Eradicate** Removing an infection from the node;
 - **Recover** Puts the node back into operational mode;
 - Wait This is a null action that does not result in any change to the environment.





Trained Demo - Walkthrough

 Infection level
 MITRE ATTRCK.

 not
 1
 2
 3
 4
 5
 6
 7
 8
 9
 10
 11
 12

 infected
 3
 4
 5
 6
 7
 8
 9
 10
 11
 12





HMI = Human Machine Interface LAN = Local Area Network LOP = Local Operator Panel PCS = Propulsion Control System RTU = Remote Terminal Unit



IPPO vs MAPPO

- We tested Independent PPO (IPPO independent critics) against multiagent PPO (MAPPO – single centralised critic).
- MAPPO outperformed IPPO, with all hyperparameters kept constant, showing the benefit of a centralised critic in this instance.
- A centralised critic allows all agents to value the current environment in the same way, leading to faster collaborative efforts.
- Without the centralised critic, each agent must learn a suitable value function independently which results in a slower training process.







Default vs Tuned Hyperparameters

Tuning hyperparameters was found to be highly important - tuned parameters (blue) vs default PPO parameters (orange)

We tuned 11 hyperparameters in total:

- 3 general RL parameters (train batch size, learning rate, gamma (discount factor).
- 8 PPO parameters (lambda (GAE), KL coefficient, VF clip parameter, SGD minibatch size, num SGD iterations, VF loss coeff, entropy coeff and clip parameter (epsilon).



Default vs Tuned Experiment





Reward Shaping

- We found that 'shaping' the reward function had an impact on the agent finding optimal policies.
- If the agent was only rewarded on the state of the environment (state reward, orange), there was no incentive to complete the episode quickly, so it was inefficient (~10 timesteps).
- By providing a small negative reward for action taking (balanced reward, blue), the agent was able to find a more efficient policy (~4 timesteps).

State Reward vs Balanced Reward







Impact of Partial Observability

- We experimented with making the environment partially observable by adjusting the alert success probability.
- We found that after 1m training steps, an agent with only 75% observability could still almost perfectly solve the environment, but that performance dramatically decreased when observability was reduced to 50% and 25%.







Thank You.

Questions?

