Leverage AI to Learn, Optimize, and Wargame (LAILOW) for Strategic Laydown and Dispersal (SLD) of the Operating Forces of the U.S. Navy

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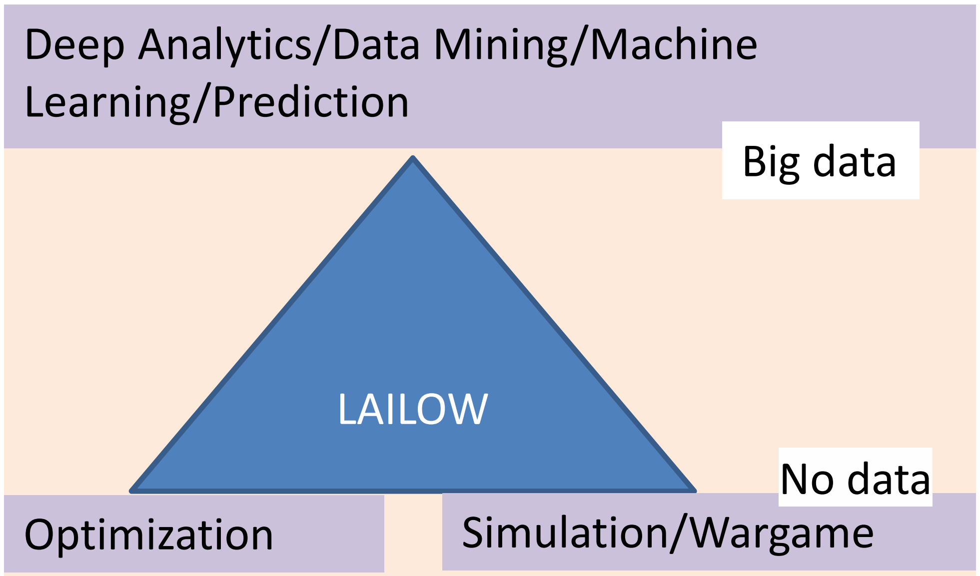
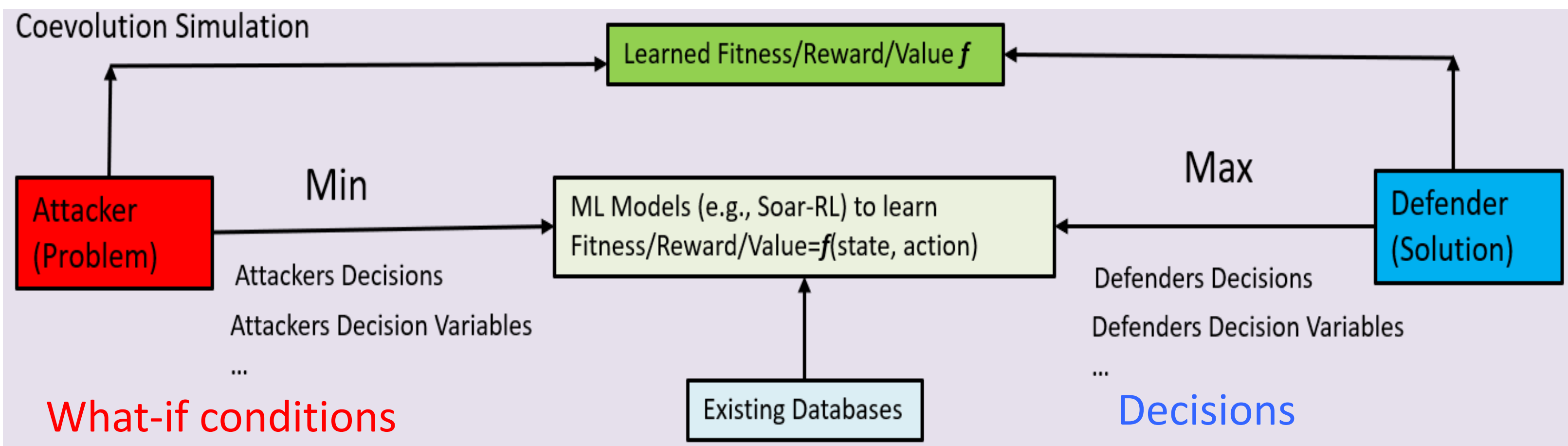
Background and Research Questions

- Background
  - The laydown and dispersal of U.S. Naval forces requires manual processing
  - The current process takes one full year to develop
  - Not responsive to changes in the operating environment or strategic guidance
- Research Questions
  - How to standardize, digitize the process, and capture better data for decision making?
  - Requirements and Objectives [Source: A memo from RDML T.R. Williams, former Director for Plans, Policy, and Integration (N5)]
    - **Descriptive Phase**
      - How can we take the current standalone SLD database to a cloud based and shareable website?
    - **Predictive Phase**
      - How are we making decisions?
      - What happens if I make a different decision?
      - How do we develop an “Excursion” Modeling Tool – A decision support tool that uses existing authoritative data and models SLD excursions to assist in rapid decision making with increased accuracy?
    - **Prescriptive Phase**
      - Are we making the right decisions?
      - How shall we utilize deep analytics including AI?
      - How do we evaluate an SLD plan?
      - How do we create an optimized plan by including global and theater posture and force generation (Fg) and force development (Fd) into the calculations?

Method: Leverage Artificial Intelligence to Learn, Optimize, and Wargame (LAILOW) for Decision Making Enterprises

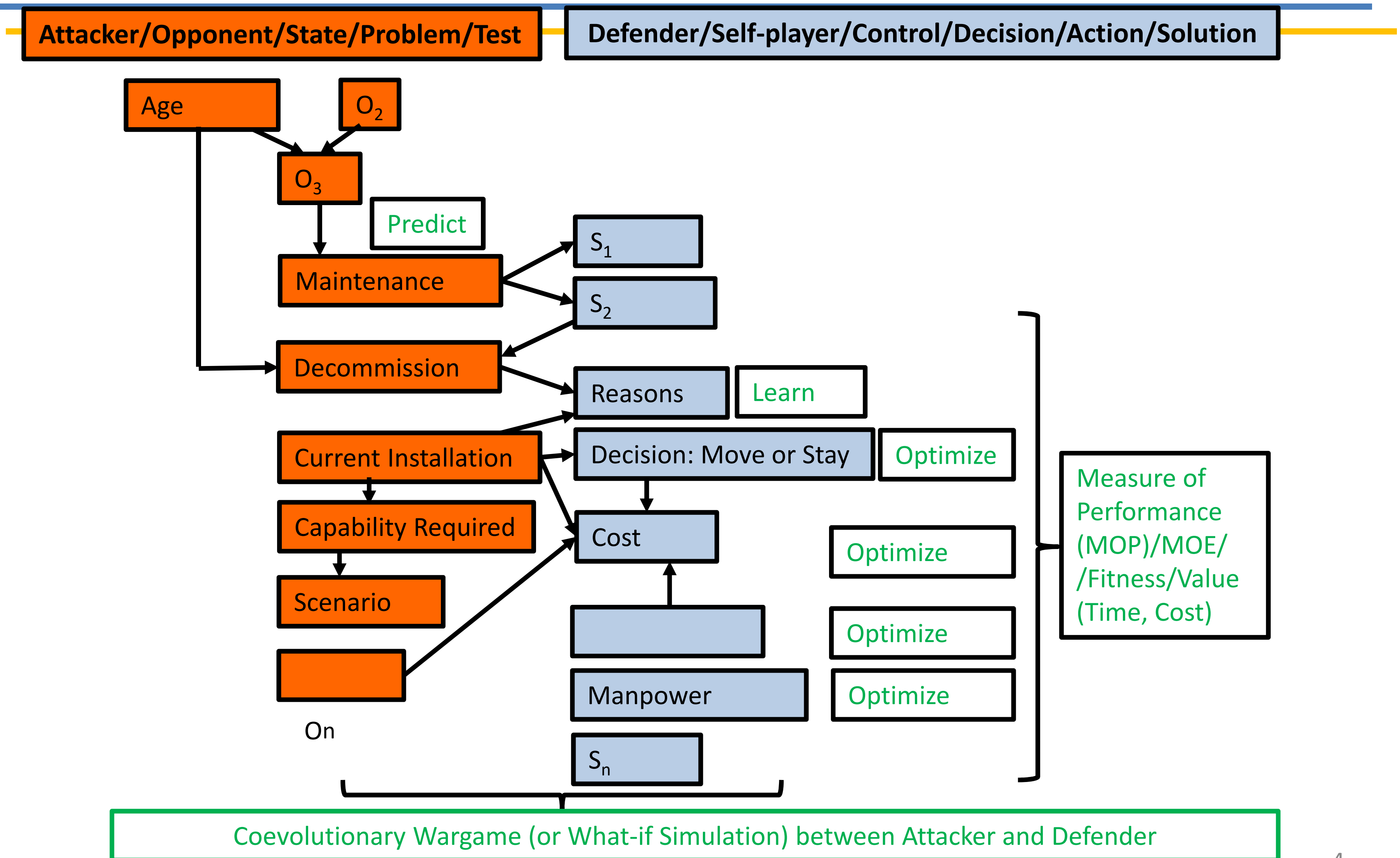


- Logistics
- Cyber
- Mission planning
- SLD



DISTRIBUTION STATEMENT A, APPROPRIATE FOR PUBLIC RELEASE

Use Case - Force Strategic Laydown and Dispersal (SLD): Standardize and digitize the current SLD decision making process, make an electronic SLD model, and reduce manual workload for the current method, parsing variables into Attacker and Defender



DISTRIBUTION STATEMENT A, APPROPRIATE FOR PUBLIC RELEASE

Using Mock Data: Can LAILOW Improve Decisions to Reduce Cost?

Variables marked with (O): Opponent - Attacker

Variables marked with (S): Self-player - Defender

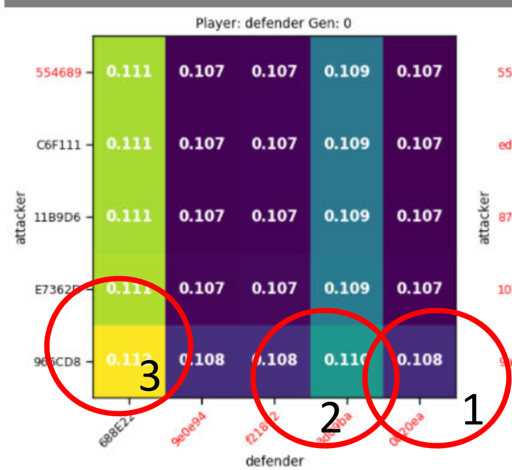
DecisionCostLow=1 if (billets + DistanceCost)<1492

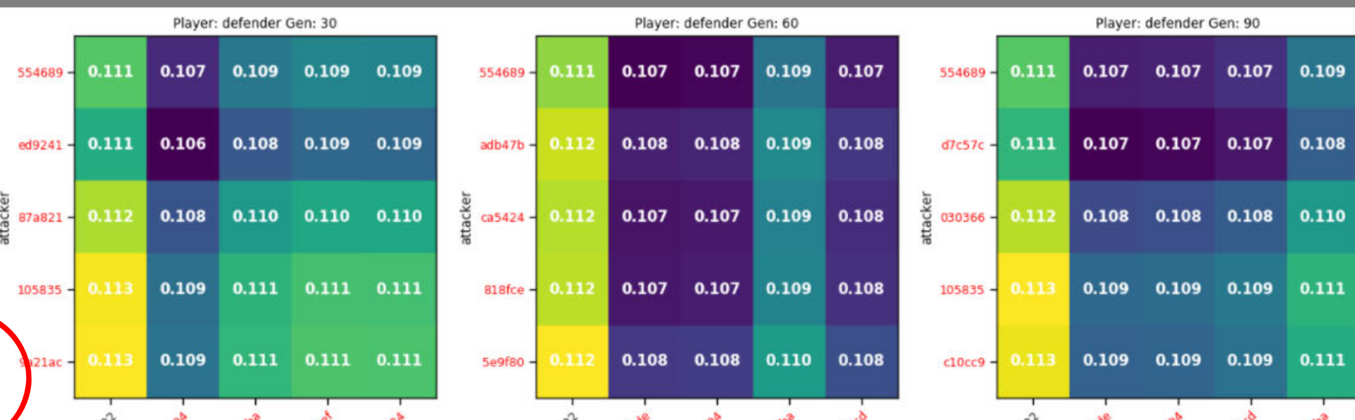
Name_I	(O)Hull	(O)CurrentInstallationGeolocation	(O)Reason	(S)Decision	(S)NextInstallationGeolocation	(O)Billets_I	(O)DistanceCost_	(O)Age_N	TotalCost_I	DecisionCostLow
Newfane	AS-17	YokosukaJA	OCONUM_PACOM	STAY	n/a	149	0	5	149	1
Nyack	AS-18	MaineUS	COMM	MOVE	SigonellaIT	338	7000	1	7338	0
Nanny	AS-19	SaseboJA	OCONUS_PACOM	STAY	n/a	420	0	5	420	1
Goldspur	AS-27	YokosukaJA	MAINT	MOVE	HawaiiUS	149	1000	11	1149	1
Hampus	AS-28	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Godfrey	AS-29	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Acheson	AS-37	YokosukaJA	DECOMM	MOVE	NorfolkUS	149	7000	30	7149	0
Admiral	AS-38	MaineUS	COMM	MOVE	BahrainBH	338	0	1	338	1
Abram	AS-39	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Sharp	AS-47	YokosukaJA	OCONUM_PACOM	STAY	n/a	149	0	5	149	1
Shockley	AS-48	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Secor	AS-49	SaseboJA	OCONUS_PACOM	STAY	n/a	420	0	5	420	1
Tetofski	AS-57	YokosukaJA	OCONUM_PACOM	STAY	n/a	149	0	10	149	1
Thompson	AS-58	MaineUS	BUILDING	STAY	n/a	338	0	0	338	1
Telstar	AS-59	SaseboJA	OCONUS_PACOM	STAY	n/a	420	0	10	420	1
Water	AS-67	YokosukaJA	OCONUM_PACOM	STAY	n/a	149	0	15	149	1
Webster	AS-68	MaineUS	BUILDING	STAY	n/a	338	0	0	338	1
Victory	AS-69	SaseboJA	OCONUS_PACOM	STAY	n/a	420	0	15	420	1
Fuji	DDG-112	SaseboJA	OCONUS_PACOMSenario	MOVE	YokosukaJA	490	1000	11	1490	1
Jonathan	DDG-113	GuamUS	OCONUS_PACOMScenario	MOVE	BarkingSandsUS	491	7000	11	7491	0
Lodi	DDG-114	YokosukaJA	OCONUM_PACOMScenario	MOVE	SaseboJA	492	1000	11	1492	1
Hokuto	DDG-115	GuantanomoBayCU	OCONUS_EUCOMScenario	MOVE	SoudaBayGR	493	7000	11	7493	0
Cameo	DDG-116	NorfolkUS	COMM	MOVE	SigonellaIT	494	7000	1	7494	0
Baldwin	DDG-117	BahrainBH	OCONUS_AFRICOMScenario	MOVE	GuantanomoBay	495	7000	11	7495	0
Suncrisp	DDG-119	KanedaAB	OCONUS_PACOMScenario	MOVE	YokosukaJA	490	1000	11	1490	1
Ultra Gold	DDG-120	GuamUS	OCONUS_PACOMSenario	MOVE	ChinhaeKR	491	1000	11	1491	1
Wild Chrisp	DDG-121	YokosukaJA	OCONUM_PACOMScenario	MOVE	RotaES	492	7000	11	7492	0
Rome	DDG-122	GuantanomoBayCU	OCONUS_PACOMSenario	MOVE	KanedaAB	493	7000	11	7493	0
Yorky	DDG-123	ChinhaeKR	OCONUS_EUCOMScenario	MOVE	SigonellaIT	494	7000	11	7494	0
Earlisilver	DDG-124	RotaES					7000	11	7495	0
Adzamovka	DDG-19	BahrainBH					0	5	1080	1

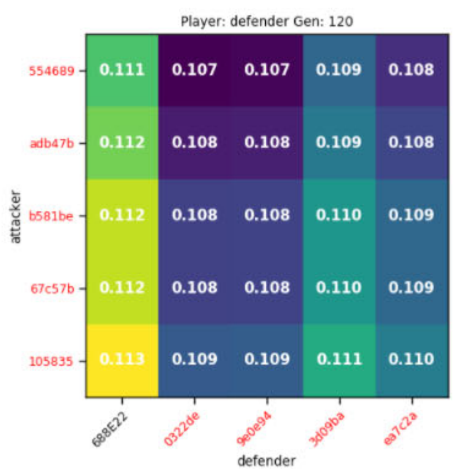
Results and Drill-Down

Results

Machine Learning | Coevolutionary Wargame: Attacker | Coevolutionary Wargame: Defender | Coevolutionary Wargame Optimization: Heatmaps and Drill-Down







1

Sequence	Variable	Variable Name	Mean	Soar-RL_1_1	Soar-RL_0_1	Soar-RL_1_0	Soar-RL_0_0		Defender's Reward
0	F0	(O)Age_bt_02_08	0.467889908	0.000605917	0.000137289	-1.90E-06	1.27E-06	1	
9	F9	(O)CurrentInstallationGeolocation_KanedaAB	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	1	
41	F41	(O)Hull_DDG-119	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	1	
128	F128	(O)Reason_OCONUM_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1	
138	F138	(S)Decision_MOVE	0.256880734	-0.000195164	0.00093837	1.27E-06	-1.90E-06	1	
155	F155	(S)NextInstallationGeolocation_YokosukaJA	0.018348624	2.40E-05	0.000719252	0	-6.33E-07	1	0.108
1	F1	(O)Age_bt_08_14	0.266055046	0.000143931	0.000599276	0	-6.33E-07	0	

2

Sequence	Variable	Variable Name	Mean	Soar-RL_1_1	Soar-RL_0_1	Soar-RL_1_0	Soar-RL_0_0		Defender's Reward
2	F2	(O)Age_lt_02	0.091743119	-5.75E-05	0.000800722	5.93E-11	-6.33E-07	1	
10	F10	(O)CurrentInstallationGeolocation_MaineUS	0.055045872	-4.09E-06	0.000747293	5.93E-11	-6.33E-07	1	
41	F41	(O)Hull_DDG-119	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	1	
123	F123	(O)Reason_COMM	0.073394495	-8.14E-05	0.000824637	5.93E-11	-6.33E-07	1	
128	F128	(O)Reason_OCONUM_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1	
138	F138	(S)Decision_MOVE	0.256880734	-0.000195164	0.00093837	1.27E-06	-1.90E-06	1	0.110
142	F142	(S)NextInstallationGeolocation_ChinhaeKR	0.027522936	1.05E-05	0.000732682	0	-6.33E-07	1	

3

Sequence	Variable	Variable Name	Mean	Soar-RL_1_1	Soar-RL_0_1	Soar-RL_1_0	Soar-RL_0_0		Defender's Reward
0	F0	(O)Age_bt_02_08	0.467889908	0.000605917	0.000137289	-1.90E-06	1.27E-06	1	
6	F6	(O)CurrentInstallationGeolocation_GuamUS	0.073394495	7.00E-05	0.000673199	0	-6.33E-07	1	
41	F41	(O)Hull_DDG-119	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	1	
128	F128	(O)Reason_OCONUM_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1	
138	F138	(S)Decision_MOVE	0.256880734	-0.000195164	0.00093837	1.27E-06	-1.90E-06	1	
142	F142	(S)NextInstallationGeolocation_ChinhaeKR	0.027522936	1.05E-05	0.000732682	0	-6.33E-07	1	0.113

1 is original decision, yet 2, 3 may be better than 1

Soar-RL Generated Rules

Feature variable and value (e.g., age of a ship)

```
sp {classification-rl*likelihood-f_107-v_1-c_1
    (state <s> ^name base ^features <f*1> ^operator <op> +)
    (<f*1> ^f107 1)
    (<op> ^classification 1 ^name classify)
    -->
    (<s> ^operator <op> = 8.195202978366032e-007)
}
```

Decision class (e.g., move or not)

Preference or reward (e.g., be included in the recommendation), learned from data

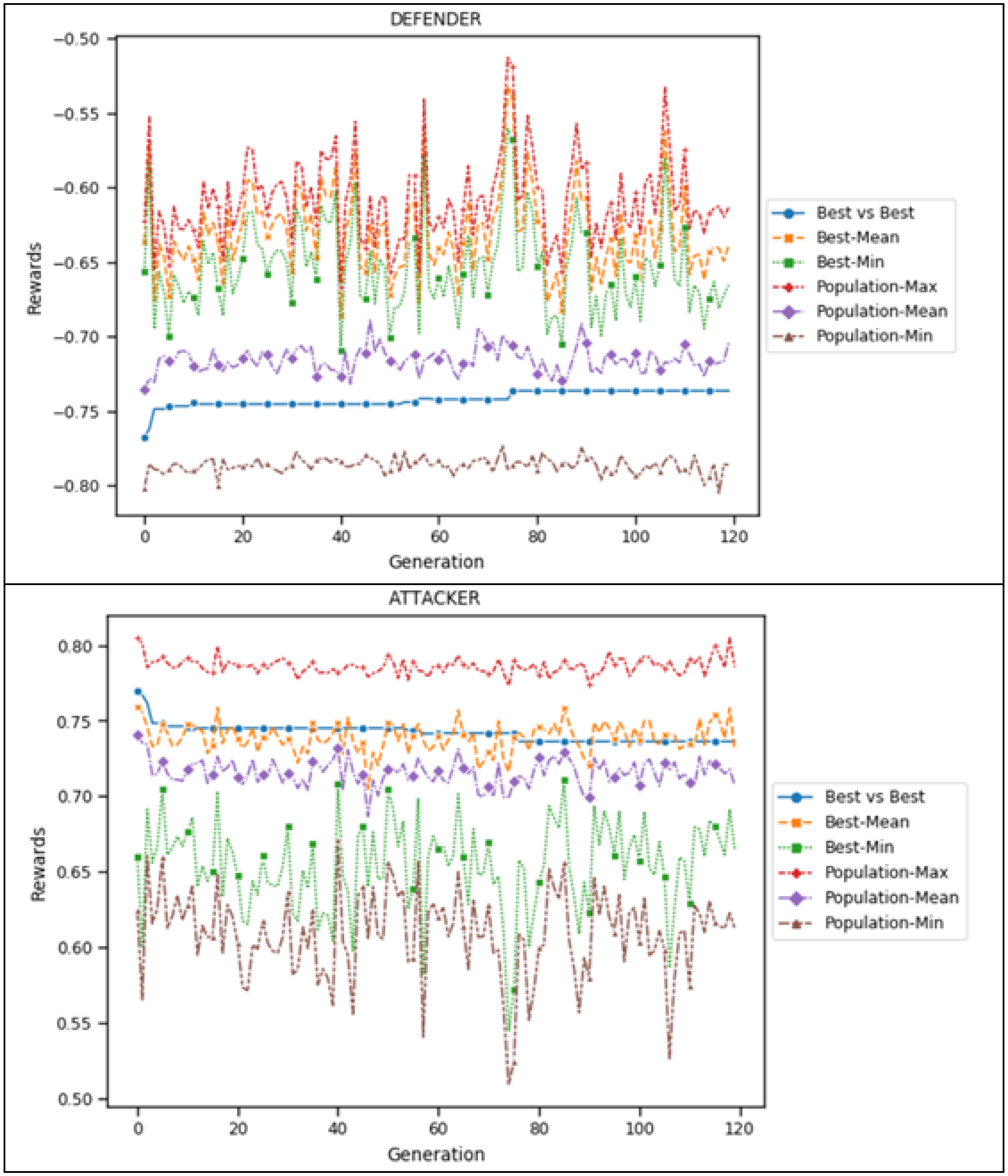
on-policy learning.

$$Q(s_{t+1}, a_{t+1}) = Q(s_t, a_t) + \alpha[r_{t+1} + \gamma \max_{a \in A} Q(s_{t+1}, a) - Q(s_t, a_t)] \quad (1)$$

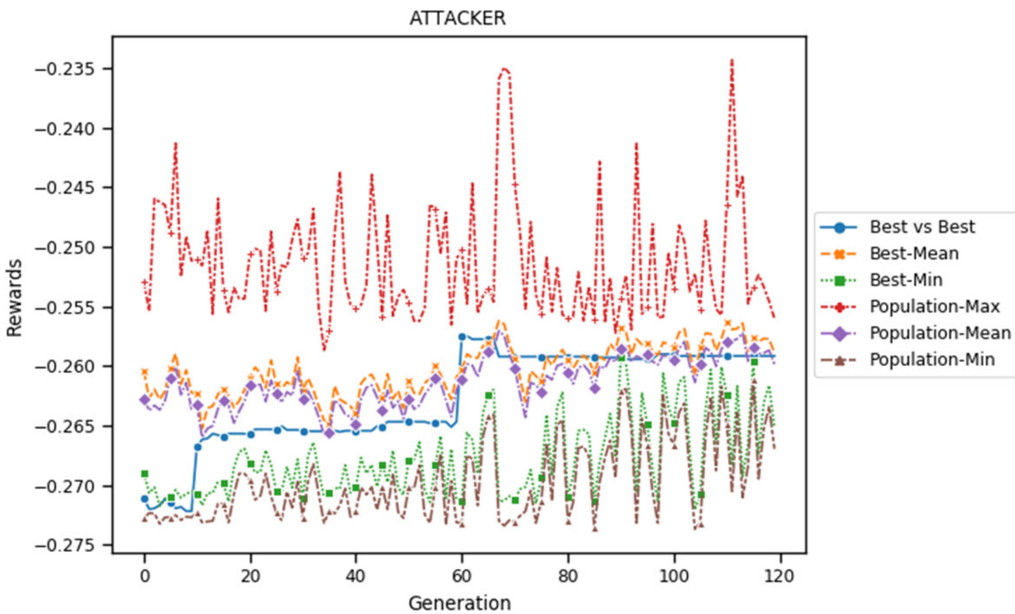
Since we only consider an on-policy setting or SARSA, $Q(s_{t+1}, a) = 0$ and let

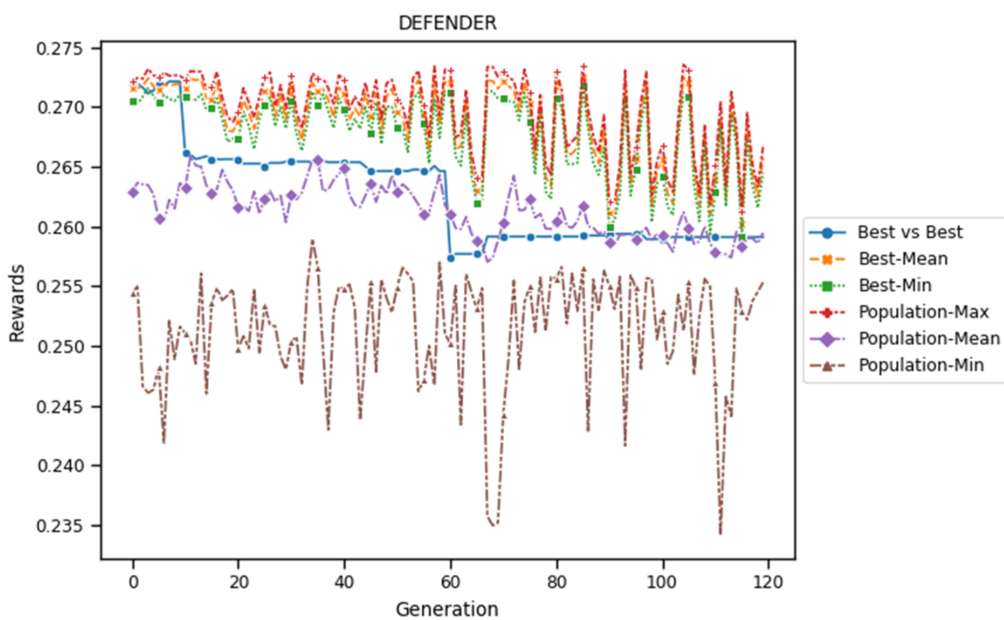
$$\delta_t = \alpha(r_{t+1} - Q(s_t, a_t)) \quad (2)$$

$r_{t+1} = 1$ for a positive reward or -1 for a negative reward.



- Resilient system





- Discovered vulnerabilities

Use Data Mining Patterns for Solution Constraints

attacker e96130 's LLA associations (normalized):

"F30-F81": 9.837075639985133e-05,
"F30-F88": 8.580090952105031e-05,
"F30-F99": 0.00010159685209578353,
"F100-F30": 3.094642214121056e-05,
"F105-F30": 3.158368044106617e-05,
"F107-F30": 0.00011363110974448826,
"F113-F30": 0.00011363110974448826,
"F81-F88": 7.427807744164287e-05,
"F81-F99": 8.795266728432887e-05,
"F100-F81": 2.679040062835970 3e-05,
"F105-F81": 2.734207684730964e-05,
"F107-F81": 9.837075639985133e-05,
"F113-F81": 9.837075639985133e-05,
"F88-F99": 7.667088558254023e-05,
"F100-F88": 2.880345817087563e-05,
"F105-F88": 2.941578713352343e-05,
"F107-F88": 8.580090952105031e-05,
"F113-F88": 8.580090952105031e-05,

- Constraints
  - Lexical link analysis
  - Length of solutions

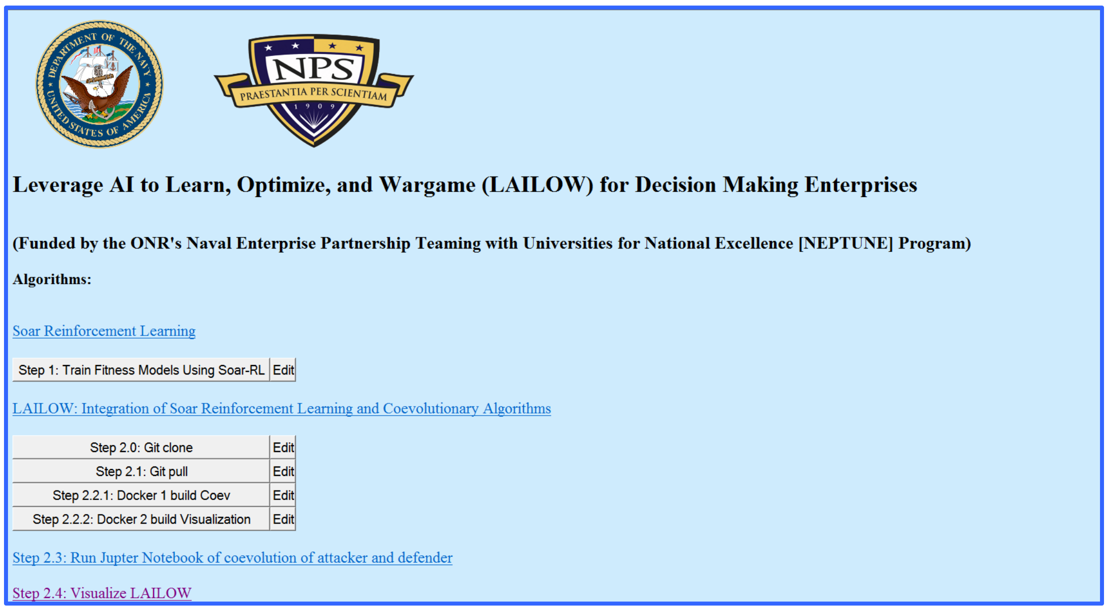
If a ship's age > 20 years
Then it is likely to be decommissioned

Discussions and Observations

- In the training process, since most of the ships do not move, we had extremely unbalanced samples for Soar-RL
  - The model tends to give better rules for the ships that do not move.
  - However, we need justification for the ships that do need to move.
- Soar-RL is explainable however, accuracy seems worse than large-scale neural networks such as BERT
- There are MANY unstructured documents (e.g., excursions from fleet commanders and human decision justification materials) that are not correctly represented in the process
  - GPT (fine-tuned) might help to drill-down cases

Technology Transfer

- NPS will provide a minimum level user interface to link the algorithms together so the sponsors can run the system themselves
- Need help from summer students or post docs!



Conclusions, Recommendation, and Disclaimer

- Conclusions
  - – Demonstrated LAILOW using a mock data set towards the objectives (2022)
  - – Validating using SIPR level real data (2023)
    - Use Recursion data and models related to Fg and Fd
    - Modelling
      - – Cost
      - – Risk
- Recommendation
  - – Develop a minimum viable product (MVP): Integrate all components including a cloud database, deep analytics, and web-site sharing and display (FY 2024)