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

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LEVERAGE AI TO LEARN, OPTIMIZE, AND WARGAME (LAILOW) FOR STRATEGIC LAYDOWN AND DISPERSAL (SLD) OF THE OPERATING FORCES OF THE U.S. NAVY

by

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The Secretary of the Navy disperses Navy forces in a deliberate manner to support DoD guidance, policy and budget. The current strategic laydown and dispersal (SLD) process is labor intensive, time intensive, and less capable of becoming agile for considering competing alternative plans. SLD could benefit from the implementation of artificial intelligence. We introduced a relatively new methodology to address these questions which was recently derived from an earlier Office of Naval Research funded project that combined deep analytics of machine learning, optimization, and wargames. This methodology is entitled LAILOW which encompasses Leverage AI to Learn, Optimize, and Wargame (LAILOW). We began by collecting data then employed data mining, machine learning, and predictive algorithms to perform artificial intelligent analysis to learn about and understand the data. This data included historical, phased force deployment data among others to learn patterns of what decisions were made and how they were executed. We then developed a stand-alone set of pseudo data that mimicked the actual, classified data so that experimental excursions cold be performed safely. We also limited our data to include ships. Our efforts produced a first-ever, relative, and optimal, score derived from a wargame like scenario for every available ship that might be moved. The score for each ship increases as fewer resources are required to fulfill an SLD plan requirement to move that ship to a new homeport. This not only produced a mathematically optimal response, but also enabled the immediate comparison between competing or alternate ship movement scenarios that might be chosen instead.

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ABSTRACT

The Secretary of the Navy disperses Navy forces in a deliberate manner to support DoD guidance, policy, and budget. The current strategic laydown and dispersal (SLD) process is labor intensive, time intensive, and less capable of becoming agile for considering competing alternative plans. SLD could benefit from the implementation of artificial intelligence. We introduced a relatively new methodology to address these questions which was recently derived from an earlier Office of Naval Research funded project that combined deep analytics of machine learning, optimization, and wargames. This methodology is entitled LAILOW which encompasses Leverage AI to Learn, Optimize, and Wargame (LAILOW). We began by collecting data then employed data mining, machine learning, and predictive algorithms to perform artificial intelligent analysis to learn about and understand the data. This data included historical, phased force deployment data among others to learn patterns of what decisions were made and how they were executed. We then developed a stand-alone set of pseudo data that mimicked the actual, classified data so that experimental excursions cold be performed safely. We also limited our data to include ships. Our efforts produced a first-ever, relative, and optimal, score derived from a wargame like scenario for every available ship that might be moved. The score for each ship increases as fewer resources are required to fulfill an SLD plan requirement to move that ship to a new homeport. This not only produced a mathematically optimal response, but also enabled the immediate comparison between competing or alternate ship movement scenarios that might be chosen instead. In consideration of future efforts, we envision a more integrated, coherent, and large-scale, deep analytics effort leveraging methods that link to existing data sources to more easily enable the direct comparisons of potential scenarios of platform movement considered through the SLD process. The resulting product could the facilitate decision makers' ability to learn, document, and track the reasons for complex decision making of each SLD process and identify potential improvements and efficiencies.

I. INTRODUCTION

The SECNAV disperses Navy forces in a deliberate manner to support DoD guidance, policy and budget. The current SLD process is labor intensive, takes too long, and needs AI. The research questions are:

- How does the Navy weight competing demands for naval forces between the CCMDs to determine an optimal dispersal of operating forces?
- How does the Navy optimize force laydown to maximize force development (Fd) and force generation (Fg) efficiency?

We propose LAILOW to address these questions. LAILOW was derived from the ONR funded project and focuses on deep analytics of machine learning, optimization, and wargame and consists of the following steps.

Learn: When there are data, data mining, machine learning, and predictive algorithms are used to analyze data. Historical Phased Force Deployment Data (TPFDDs) and SLD Report Cards data among others, one can learn patterns of what decisions were made and how they are executed with in the past.

Optimize: Patterns from learn are used to optimize future SLD plans. A SLD plan may include how many homeports, home bases, hubs, and shore posture locations (Fd) and staffs (Fg). The optimization can be overwhelming. LAILOW uses integrated Soar reinforcement learning (Soar-RL) and coevolutionary algorithms. Soar-RL maps a total SLD plan to individual ones used in excursion modeling and what if analysis.

Wargame: There might be no or rare data for new warfighting requirements and capabilities. This motivates wargame simulations. A SLD plan can include state variables or problems (e.g., future global and theater posture, threat characteristics), which is only observed, sensed, and cannot be changed. Control variables are solutions (e.g., a SLD plan). LAILOW sets up a wargame between state and control variables. Problems and solutions coevolve based on evolutionary principles of selection, mutation, and crossover.

The tasks include scoping data and demonstrating the LAILOW framework to address the research questions and challenges of the SLD process. Since the data for the project are in the secret level, some of the meta data models (e.g., detailed actual variables used in the SLD decision making) are also is in the secret level, we documented the methodology in a mock data set in this report. The following deliverables

1) Since the data for the project is in the secret level, we discussed an alternative of developing a mock data set with the topic sponsors and obtained historical databases at the NPS SBTL lab. We studied the databases using our lexical link analysis (LLA). The demonstration of LLA was screenshot and analyzed in a power point presentation (Report 1), which was sent to the sponsor via SIPR. We briefed the sponsors in person based on Report 1.

2) This report focuses on the methodology and an unclassified mock data on which we were able to run and demonstrate LAILOW. We screenshot the mock demo and analyzed it in the power point slides (Appendix A: SLD_report_2_version2.pptx). We briefed the results to the topic sponsors in person. The deliverables also included the presentation to the sixth Naval applications of machine learning conference, virtual, 22-24 March 2022 (Appendix B: NAYZ153-NAML-2022-oral-red-agent-NPS-template-no-audio.pptx) and a paper proposal submitted to the 20th Annual Acquisition Research Symposium, May, 2023, Monterey (Appendix C: ARP2023-945-SLD.pdf), and final presentation to the sponsor (Appendix D: Appendix D - SLD - Final Presentation).

A. BACKGROUND

The laydown and dispersal of U.S. Naval forces requires manual manipulation of data via weekly Working Groups, which is manpower intensive, and only presents one option to CNO and SECNAV for consideration. The current SLD process takes one full year to develop and is not responsive to changes in the operating environment or strategic guidance. For example, there is no mechanism to leverage existing data resources to monitor plan execution and track progress toward completion. The SLD plan needs more than just simple process revision - it requires wholesale re-imagining to be an Information Age decision support tool. The 10 years of projected force laydown optimization problem can be overwhelming.

More specifically, based on a memo from RDML T.R. Williams, Director for Plans, Policy, and Integration (N5) for Deputy Chief of Naval Operations for operations, plans, and strategy (N3/N5) [1], N52 is teaming with industry and academia to modernize the SLD process, the challenges are described in the following phases.

a. Descriptive Phase

What decisions were made? This phase is focused on developing a new database utilizing modern data analytics to display information in shareable website. The current SLD database exists on a standalone computer with a single user's access in the Pentagon requiring manual update. This phase's end state is a cloud based SLD database accessible to the SLD working group that offers permission controls and features improved analysis and display functions. Estimated time to completion: 6-12 months.

b. Predictive Phase

How are we making decisions? What happens if I make a different decision? This phase's end state is an Excursion Modeling Tool. The goal is to develop a decision support tool that uses existing authoritative data and model SLD excursions to assist decision making rapidly and more accurately. Estimated time to completion: 18-36 months

c. Prescriptive Phase

Are we making the right decisions? This phase's end state will utilize an artificial intelligence (AI) algorithm to take the SLD calculations and other inputs to evaluate the SLD plan and create an optimized plan by including global and theater posture and TPFDDs into the calculations. Estimated time to completion: 36-60 months.

N52's goal is to radically update the SLD process with a cloud based SLD database, utilize big data analytics and AI to aid decision making, and reduce manpower requirements to focus on the strategic basis and integration of the SLD Plan for improved efficiency and better-informed decision making.

B. APPROACHES

A LAILOW framework can be set up as a multi-segment wargame played by a self-player and the opponent as shown in Figure 1. The self-player is the SLD enterprise. The opponent is the environment including competing demands or adversaries. In the past, the LAILOW framework is developed and applied to the maintenance and supply enterprise for a major USMC equipment. When the equipment has a problem or a trouble ticket is opened, it has to go through a long chain process to be fixed. The objective is to minimize the customer waiting time and improve the overall readiness of the equipment. When applying LAILOW, we first divided the processes into state variables and decision variables as follows:

- State variables: These variables and data can be sensed, observed, and estimated, however, cannot be decided or changed by the self-player. They are the input variables, or problems that the self-player must consider. They are also called *tests* or *attacks* for the SLD enterprise.
- Decision variables: These variables are needed to solve the problem using optimization algorithms. In LAILOW, the optimization of the decision variables is achieved by the integration of Soar reinforcement learning (Soar-RL) and coevolutionary search and optimization algorithms [2][3].

Both opponent (tests) and self-player (solutions) evolve and compete like a wargame. LAILOW is like a Monte Carlo simulation but guided by machine learning and AI with optimization algorithms. In the wargame, the opponent generates large-scale what-if tests to challenge the self-player to come up with better solutions, e.g., SLD configurations to answer the questions such as "what happens if I choose a different decision?" in a systematic simulation.

Machine learning (ML) algorithms are used to model the fitness or utility functions for both players.

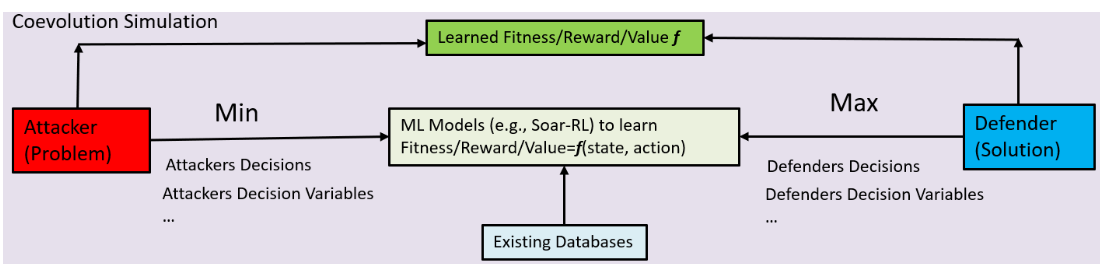

Figure 1. LAILOW viewed in a Coevolutionary wargame simulation

Although the USMC example is more than specific and the SLD optimization has a larger scope, the LAILOW method can still apply in a similar fashion. Each "learn, optimize, wargame" cycle dynamically iterates in each stage and across all the value areas with the analytic components and algorithms detailed as follows.

Component 1 - Learn: When data exists, we employ data mining, machine learning, and predictive algorithms to analyze the data.

The self-player first uses its multiple business intelligence, data mining, and machine learning algorithms to learn patterns and rules from big data. Historical Phased Force Deployment Data (TPFDDs) and SLD Report Cards data, among others, reveal the patterns and constraints for the plans and decisions made and executed within the past, which can be relevant for the future.

The "learn" component also applies to supervised ML algorithms such as classification, regression, and predictive algorithms. For example, the data mining tool Orange [4] includes a wide range of state-of-the-art supervised ML algorithms from the sciki-learn python such as logistic regression, decision trees, naïve Bayes, random forest, k-nearest neighbors, neural networks. TensorFlow deep learning [5] is also in this category where the input data need to be pre-processed as images. Supervised ML algorithms can be used to learn the state variables and assessment measures in the function areas for potential SLD and excursion plans such as speed, quality, and fitness of deployment and execution, balance of competing demands and constraints (e.g., avoidance of unacceptable reduction of capability), along with Fd and Fg measures.

In LAILOW, we use Soar reinforcement learning (Soar-RL) to learn two fitness functions separately for the self-player and opponent. The coevolution simulation can potentially generate more problems to challenge the SLD enterprise and require novel and innovative solutions are not observed in the historical databases.

The Soar-RL carries the following advantages for the military applications:

- In reinforcement learning, an agent takes an action and generates a new state based on its current state and on the expected value it estimates from its internal model [6]. It also learns from the reward data from the environment by modifying its internal models. Soar-RL can scalably integrate a rule-based AI system with many other capabilities, including short- and long-term memory [7].
- Soar-RL can include existing knowledge (e.g., rules of engagements of SLD) and also modify and discover new rules from data.

- Soar-RL learns in an online, real-time, incremental fashion and thus does not require batch processing of (potentially big) data.
- Soar-RL provides the advantage of explainable AI [8].
- Soar-RL is linked to a causal learning [3] since it fits the pillars of causal learning (e.g., associations, intervention, and counterfactuals) [9][10] by generating the desired effect data using intervention (i.e., responding to the right actions or causes), associations, and counterfactuals [11].

The "learn" component can also apply unsupervised learning algorithms. The self-player performs unsupervised machine learning algorithms such as k-means, principle component analysis (PCA), and lexical link analysis (LLA) [12][13] for discovering anomalies association, sequential patterns, and transition patterns of subsystems and processes. One might discover benefits and risks caused by the cascade effects and dependence of subprocesses. The self-player can also use the association and sequential patterns to improve prediction, optimization, and allow anomaly detection.

Component 2 - Optimize: Based on the patterns learned from Component 1, the self-player optimizes the measures of effectiveness (MOEs) or the measures of performances (MOPs), defined by decision makers, by searching through all possible courses of actions or combinations of configurations. MOEs and MOPs can be the assessment measures defined for SLD process such as force development (Fd) and force generation (Fg) efficiency. Patterns from "learn" are used to optimize future SLD plans. An SLD plan may include how many homeports, home bases, hubs, and shore posture locations (Fd) and staffs (Fg). The optimization can be overwhelming. LAILOW uses integrated Soar Soar-RL and coevolutionary algorithms. Soar-RL maps a total SLD plan to individual ones used in excursion modeling and *what-if* analysis.

Component 3 - Wargame: There might be no or rare data for a new SLD. This motivates wargame simulations. An SLD plan can include state variables or problems (e.g., future global and theater posture, threat characteristics), which is only observed, sensed, and cannot be changed. Control variables are solutions (e.g., an SLD plan). LAILOW sets up a wargame between state and control variables. Problems and solutions coevolve based on evolutionary principles of selection, mutation, and crossover.

LAILOW has been used in wargames in DMO and EABO [8], discover vulnerability and resilience for the logistics operations for Navy ships and Marine's maintenance and supply chain [5], and over-the-horizon strike mission planning [19][20][21][22].

The number of state and decision variables for a SLD plan and excursion models can be extremely large. Coevolutionary algorithms can simulate dynamic configurations of future warfighting requirements, threats, and global environment and future capabilities, and other competing factors in a wargame simulation. As shown earlier in Figure 2, competitive coevolutionary algorithms are used to solve minmax-problems like those encountered by generative adversarial networks (GANs) [23][24]. Adversarial engagements of players can be computationally modeled. Competitive coevolutionary algorithms take a population-based (parallel) approach to iterative adversarial engagement and can explore a different behavioral space. The use case tests (adversarial attacker population) are actively or passively thwarting the effectiveness of the problem solution (defender). The coevolutionary algorithms are used to identify successful, novel, as well as the most effective means of solutions (defenses) against various tests (attacks). In this competitive game, the test (attacker) and solution (defender) strategies can lead to an arms race between the adversaries, both adapting or evolving while pursuing conflicting objectives.

A basic coevolutionary algorithm evolves two populations with a tournament selection and for variation uses crossover and mutation. One population comprises tests (attacks) and the other solutions (defenses). In each generation, engagements are formed by pairing attack and defense. The populations are evolved in alternating steps: first the test population is selected, varied, updated and evaluated against the solutions, and then the solution's population is selected, varied, updated, and evaluated against the tests. Each test--solution pair is dispatched to the engagement component and the result is used as a part of the fitness for each of them. Fitness is calculated overall from an adversary's engagements.

II. DATA SETS AND RESULTS

We began by customizing LAILOW to the SLD process in a high level as shown in Figure 2. This involved defining self-player variables and opponent variables in the SLD process. Self-player variables are also called defender, control, decision, action, or solution variables. The opponent variables are also called attacker, state, problem, or test variables. Opponent variables include profile variables for a ship such as age, maintenance status, decommission schedule, current installation location, capability and scenarios required at the current installation location, these variables are considered pre-determined and known information for a ship and cannot be easily changed for decision makers (defenders) at the time of the SLD process. Attacker variables are the state variables for the defenders to handle.   Decision variables include move (to what location) or stay, cost, manpower, and are also known as defender variables. Both the defenders and attackers evolve and coevolve, and both are guided by their own fitness functions that reflect the self-player and opponent's competing objectives.

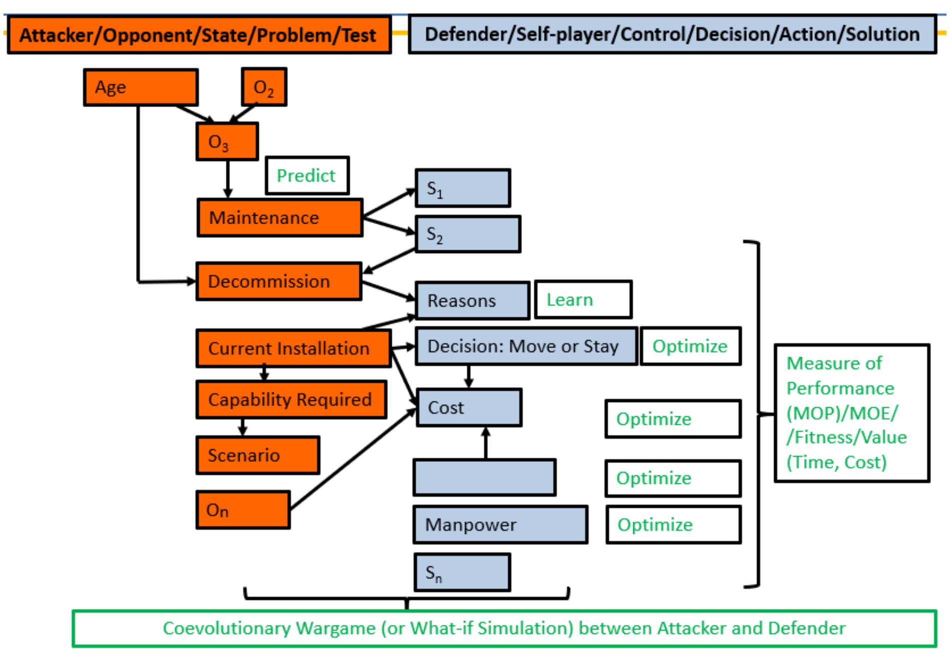

Figure 2. The LAILOW is tailored to the SLD process in a high level to reflect the what-if decision process used by decision makers in the process

We next we worked with the sponsor, designed and developed an unclassified mock data set as shown in Figure 3 to reflect the understanding of the SLD process in Figure 2.

Variables start with (O): Opponent - Attacker

Variables start 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_I	(O)Age_N	TotalCost_I	DecisionCostLow
Witos	DDG-275	RotaES	OCONUS_PACOMScenario	MOVE	GuamUS	895	7000	15	7895	0
Bismarck	DDG-25	SigonellaIT	COMM	MOVE	MaineUS	692	7000	1	7692	0
Banks	DDG-24	SoudaBayGR	DECOMM	MOVE	NorfolkUS	591	7000	30	7591	0
Banks	DDG-24	SoudaBayGR	DECOMM	MOVE	NorfolkUS	591	7000	30	7591	0
Banks	DDG-24	SoudaBayGR	MAINT	MOVE	SanDiegoUS	591	7000	11	7591	0
Windsor	DDG-245	SoudaBayGR	OCONUS_EUCOM	MOVE	ChinhaeKR	591	7000	15	7591	0
Baldwin	DDG-117	BahrainBH	OCONUS_AFRICOMScenario	MOVE	GuantanomoBay	495	7000	11	7495	0
Earlisilver	DDG-124	RotaES	OCONUS_CENTCOMScenario	MOVE	BahrainBH	495	7000	11	7495	0
Cameo	DDG-116	NorfolkUS	COMM	MOVE	SigonellaIT	494	7000	1	7494	0
Yorky	DDG-123	ChinhaeKR	OCONUS_EUCOMScenario	MOVE	SigonellaIT	494	7000	11	7494	0
Hokuto	DDG-115	GuantanomoBayCU	OCONUS_EUCOMScenario	MOVE	SoudaBayGR	493	7000	11	7493	0
Rome	DDG-122	GuantanomoBayCU	OCONUS_PACOMScenario	MOVE	KanedaAB	493	7000	11	7493	0
Wild Chrisp	DDG-121	YokosukaJA	OCONUS_PACOMScenario	MOVE	RotaES	492	7000	11	7492	0
Jonathan	DDG-113	GuamUS	OCONUS_PACOMScenario	MOVE	BarkingSandsUS	491	7000	11	7491	0
Avajlilja	DDG-23	NorfolkUS	COMM	STAY	n/a	490	7000	1	7490	0
Godfrey	AS-29	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Abram	AS-39	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Nyack	AS-18	MaineUS	COMM	MOVE	SigonellaIT	338	7000	1	7338	0
Hampus	AS-28	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Shockley	AS-48	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Apollo	DDG-22	NorfolkUS	COMM	MOVE	GuantanomoBayCU	286	7000	1	7286	0
Acheson	AS-37	YokosukaJA	DECOMM	MOVE	NorfolkUS	149	7000	30	7149	0
Lodi	DDG-114	YokosukaJA	OCONUS_PACOMScenario	MOVE	SaseboJA	492	1000	11	1492	1
Ultra Gold	DDG-120	GuamUS	OCONUS_PACOMScenario	MOVE	ChinhaeKR	491	1000	11	1491	1
Fuji	DDG-112	SaseboJA	OCONUS_PACOMScenario	MOVE	YokosukaJA	490	1000	11	1490	1
Suncrisp	DDG-119	KanedaAB	OCONUS_PACOMScenario	MOVE	YokosukaJA	490	1000	11	1490	1
Metzger	DDG-311	SaseboJA	OCONUS_PACOMScenario	MOVE	ChinhaeKR	205	1000	2	1205	1
Goldspur	AS-27	YokosukaJA	MAINT	MOVE	HawaiiUS	149	1000	11	1149	1
Adzamovka	DDG-19	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Herma	DDG-191	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	2	1080	1
Orin	DDG-192	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Shoesmith	DDG-193	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Tinmoth	DDG-194	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	10	1080	1
Wedge	DDG-195	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	15	1080	1

Figure 3. An unclassified data set designed and developed to reflect the understanding in Figure 2.

Finally, we input the mock data and demonstrated the LAILOW software, e.g., build a machine learning, optimization, and simulation model using detail historical profiles and known information about each Navy asset illustrated using the mock data set. Figure 4 shows LAILOW solutions as heatmaps (solutions). For each iteration (i.e., generation in the coevolution algorithm), e.g., circled as 1, 2, and 3, a potential SLD plan against an environmental test (Attacker) is produced. The heat color shows the fitness for the solution. Clicking on the heatmap cell shows the detail of the corresponding solution configuration.

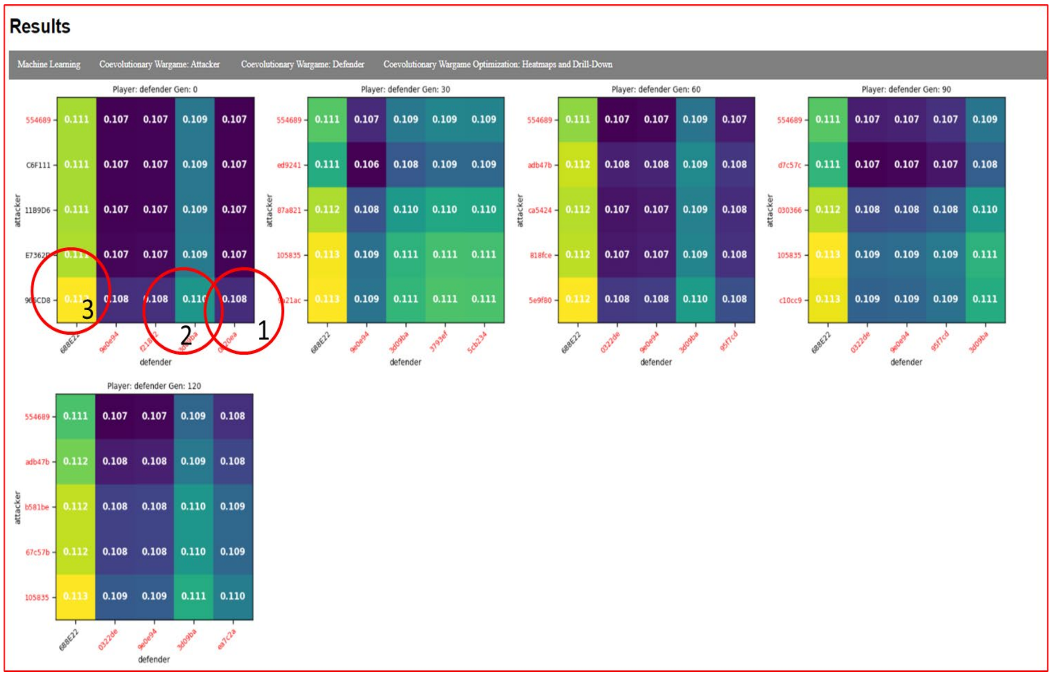

Figure 4. LAILOW solutions as heatmaps (solutions)

Lastly, we analyzed drill-down details of the LAILOW simulation in Figure 4. As shown in Figure 5. The LAILOW software illustrates that better decision configurations (6) than ones in the historical databases (4 and 5) can be discovered using the LAILOW software.

4

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_OCONUS_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1			
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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			0.108772543

5

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			
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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			0.107222755

6

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_OCONUS_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1			
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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			0.108861738

4 is the original in the database, 6 is better than 4 and 5 (in terms of lower cost)

Figure 5. Better decision configurations (6) than ones in the historical databases (4 and 5) can be discovered using the LAILOW software. This shows the potential to discover alternative SLD plans for Naval assets.

III. FINDINGS AND CONCLUSIONS

Our efforts produced a first-ever, relative, and optimal, score derived from a wargame like scenario for every available ship that might be moved. The score for each ship increases as fewer resources are required to fulfill an SLD plan requirement to move that ship to a new homeport. This not only produced a mathematically optimal response, but also enabled the immediate comparison between competing or alternate ship movement scenarios that might be chosen instead.

Our original understanding of how the Navy scores these potential ship movements was improved through our exploration of this topic. The Navy considers variables such as available maintenance, pier space, required schools as well as the distance between the ship's present location and its potential new homeport. Additionally, each ship overseas must return to the continental United States within ten tears and each one fulfills tactical and strategic requirements that are also considered. There are also unseen political preferences that can also outweigh numerically based resource requirements.

IV. RECOMMENDATIONS AND FUTURE WORK

We anticipate our findings to guide the way forward toward further exploration and digitalization in this area through our suggested methodology. This would likely save time and energy of the decision makers and offer otherwise undiscovered potential alternative solutions to future SLD plans.

More can be accomplished to consider how machine learning and artificial intelligence methodologies might improve the SLD process to optimize force laydown to maximize force development and force generation efficiency. Having shown the LAILOW potential to solve a smaller problem using artificial data, the recommendation for the next steps is to an electronic model of the strategic laydown and dispersal (SLD) process into a minimum variable product (MVP) that can assist future SLD development and justify potential movement scenarios and their decisions consistently.

Two potential research questions guiding this future research could be:

1) How can a proof of concept, electronic model, be developed to help decision makers standardize the SLD process?

2) How can SLD scenario development and scenario comparisons be more readily made in terms of risk and cost?

Based on the sponsors' feedback, the Plan for Phase II can be summarized as follows. We plan to:

- Apply Phase I research results to real SLD databases and unstructured data, mainly, apply the LAILOW models to evaluate the fitness of an SLD plan considering the details of the current state of each Naval asset and each Naval organization and its involvement in the decision making (i.e., reason codes).
- Apply and evaluate coevolutionary algorithms to determine if they can generate SLD alternatives that allow the decisions and environmental conditions (opponent) to evolve in a coherent fashion, explore many possible solutions for many what-if requirements, and maximize the total value of the SLD plan. The SLD plan usually contains large input data, states, and potential decisions with large numbers of attributes and relations. When considering environmental conditions, configurations of successful SLD plans can be rare and may be only discovered using novel

mechanisms and powerful computation. Coevolutionary algorithms can help by scaling up to the requisite complexity.

- Integrate the database and models using the Microsoft Power BI environment and tools. It will be advantageous to make the resulted electronic model available for decision makers by using COTS available software solutions such as Microsoft Power BI since NPS has established a CRADA with Microsoft and SLD's real database has been placed into a Microsoft Access Database. This path is interesting in terms of technical transfer to the operational domains, and because Power BI is also very flexible to integrate external analytic algorithms.

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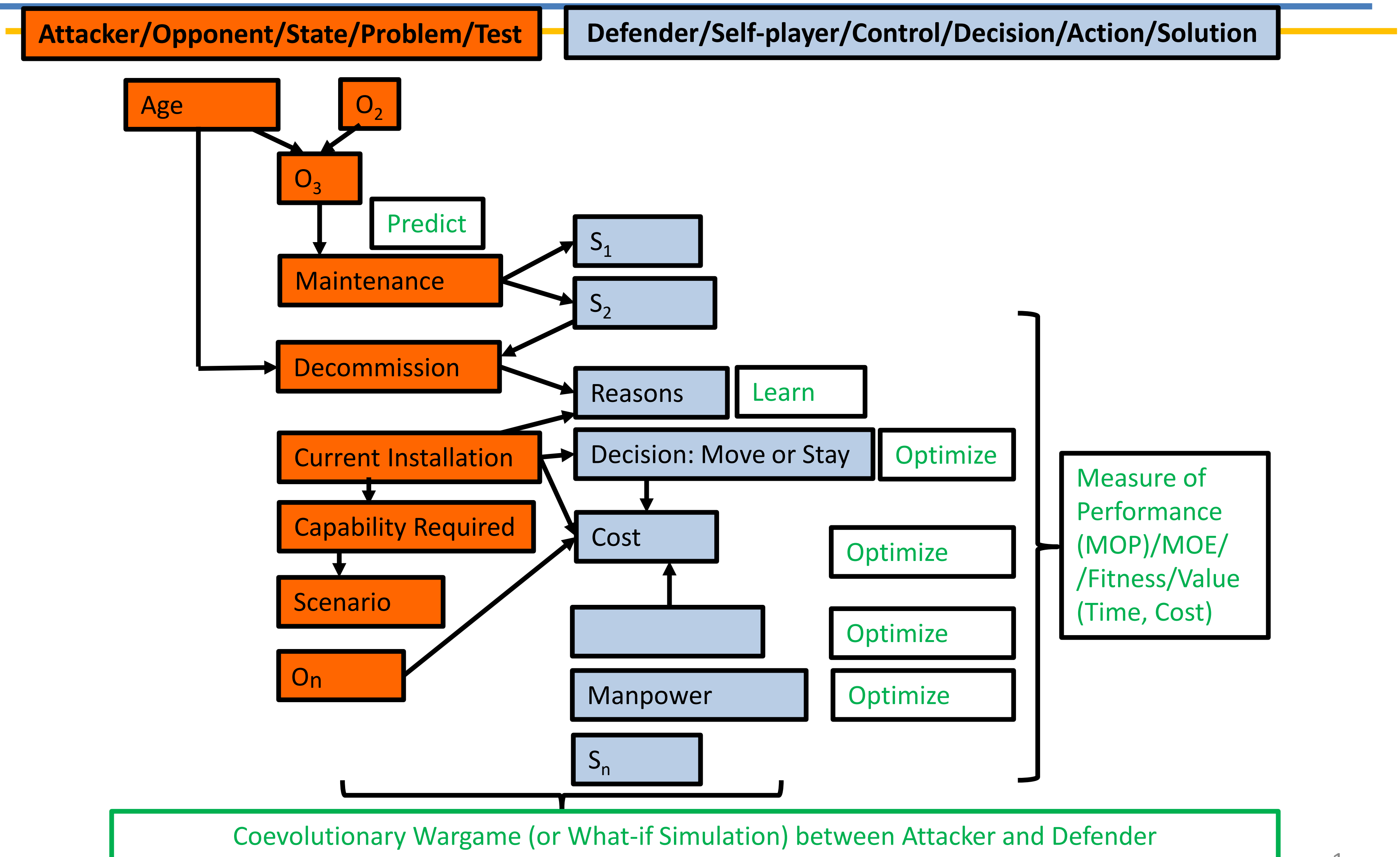
Appendix A

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, search for alternatives that reduce cost



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

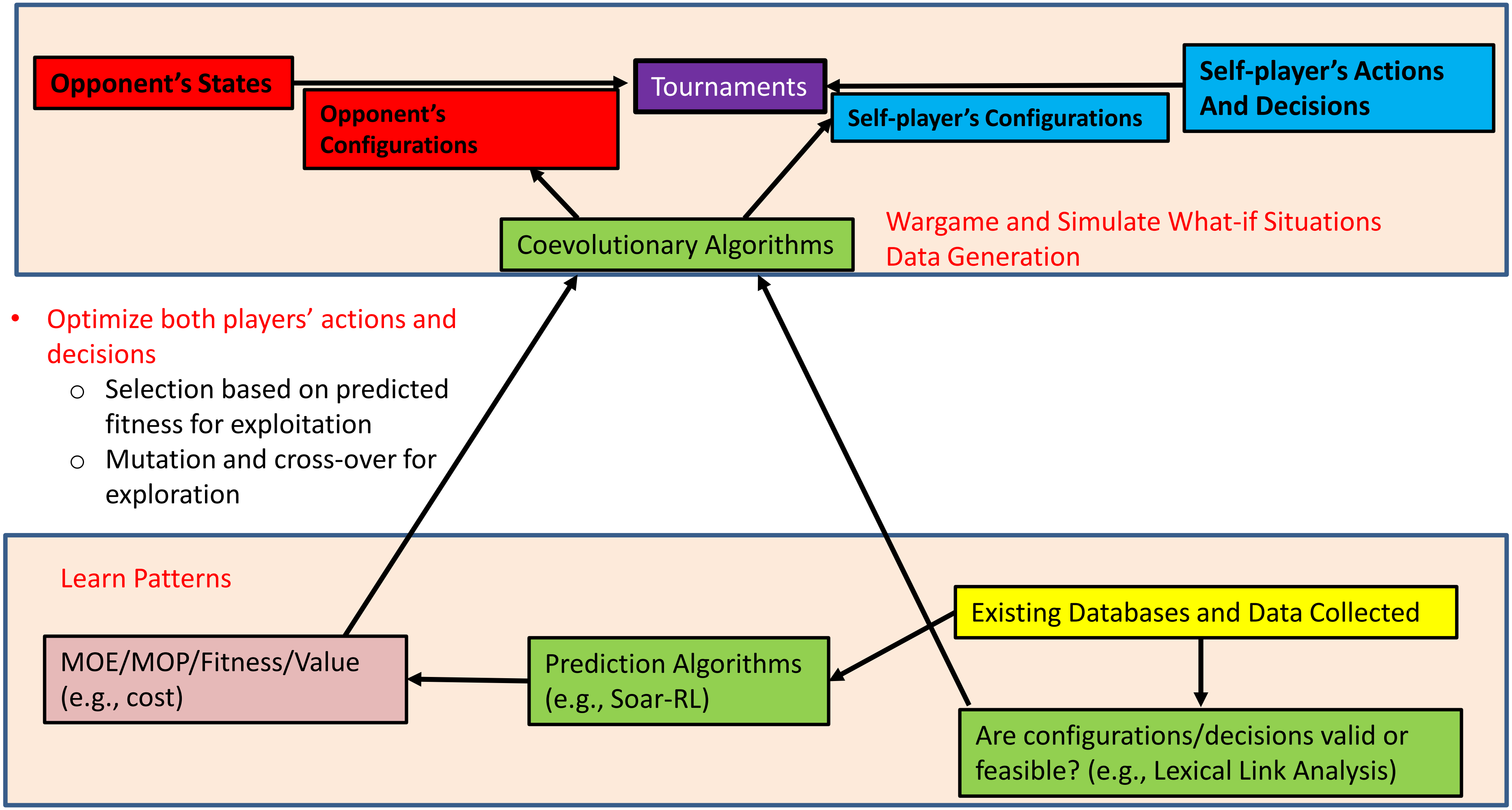
Variables start with (O): Opponent - Attacker

Variables start 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_I	(O)Age_N	TotalCost_I	DecisionCostLow
Witos	DDG-275	RotaES	OCONUS_PACOMScenario	MOVE	GuamUS	895	7000	15	7895	0
Bismarck	DDG-25	SigonellaIT	COMM	MOVE	MaineUS	692	7000	1	7692	0
Banks	DDG-24	SoudaBayGR	DECOMM	MOVE	NorfolkUS	591	7000	30	7591	0
Banks	DDG-24	SoudaBayGR	DECOMM	MOVE	NorfolkUS	591	7000	30	7591	0
Banks	DDG-24	SoudaBayGR	MAINT	MOVE	SanDiegoUS	591	7000	11	7591	0
Windsor	DDG-245	SoudaBayGR	OCONUS_EUCOM	MOVE	ChinhaeKR	591	7000	15	7591	0
Baldwin	DDG-117	BahrainBH	OCONUS_AFRICOMScenario	MOVE	GuantanomoBay	495	7000	11	7495	0
Earlisilver	DDG-124	RotaES	OCONUS_CENTCOMScenario	MOVE	BahrainBH	495	7000	11	7495	0
Cameo	DDG-116	NorfolkUS	COMM	MOVE	SigonellaIT	494	7000	1	7494	0
Yorky	DDG-123	ChinhaeKR	OCONUS_EUCOMScenario	MOVE	SigonellaIT	494	7000	11	7494	0
Hokuto	DDG-115	GuantanomoBayCU	OCONUS_EUCOMScenario	MOVE	SoudaBayGR	493	7000	11	7493	0
Rome	DDG-122	GuantanomoBayCU	OCONUS_PACOMScenario	MOVE	KanedaAB	493	7000	11	7493	0
Wild Chrisp	DDG-121	YokosukaJA	OCONUS_PACOMScenario	MOVE	RotaES	492	7000	11	7492	0
Jonathan	DDG-113	GuamUS	OCONUS_PACOMScenario	MOVE	BarkingSandsUS	491	7000	11	7491	0
Avajlilja	DDG-23	NorfolkUS	COMM	STAY	n/a	490	7000	1	7490	0
Godfrey	AS-29	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Abram	AS-39	SaseboJA	DECOMM	MOVE	NorfolkUS	420	7000	30	7420	0
Nyack	AS-18	MaineUS	COMM	MOVE	SigonellaIT	338	7000	1	7338	0
Hampus	AS-28	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Shockley	AS-48	MaineUS	COMM	MOVE	GuamUS	338	7000	1	7338	0
Apollo	DDG-22	NorfolkUS	COMM	MOVE	GuantanomoBayCU	286	7000	1	7286	0
Acheson	AS-37	YokosukaJA	DECOMM	MOVE	NorfolkUS	149	7000	30	7149	0
Lodi	DDG-114	YokosukaJA	OCONUS_PACOMScenario	MOVE	SaseboJA	492	1000	11	1492	1
Ultra Gold	DDG-120	GuamUS	OCONUS_PACOMScenario	MOVE	ChinhaeKR	491	1000	11	1491	1
Fuji	DDG-112	SaseboJA	OCONUS_PACOMScenario	MOVE	YokosukaJA	490	1000	11	1490	1
Suncrisp	DDG-119	KanedaAB	OCONUS_PACOMScenario	MOVE	YokosukaJA	490	1000	11	1490	1
Metzger	DDG-311	SaseboJA	OCONUS_PACOMScenario	MOVE	ChinhaeKR	205	1000	2	1205	1
Goldspur	AS-27	YokosukaJA	MAINT	MOVE	HawaiiUS	149	1000	11	1149	1
Adzamovka	DDG-19	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Herma	DDG-191	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	2	1080	1
Orin	DDG-192	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Shoesmith	DDG-193	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1
Tinmoth	DDG-194	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	10	1080	1

LAILOW

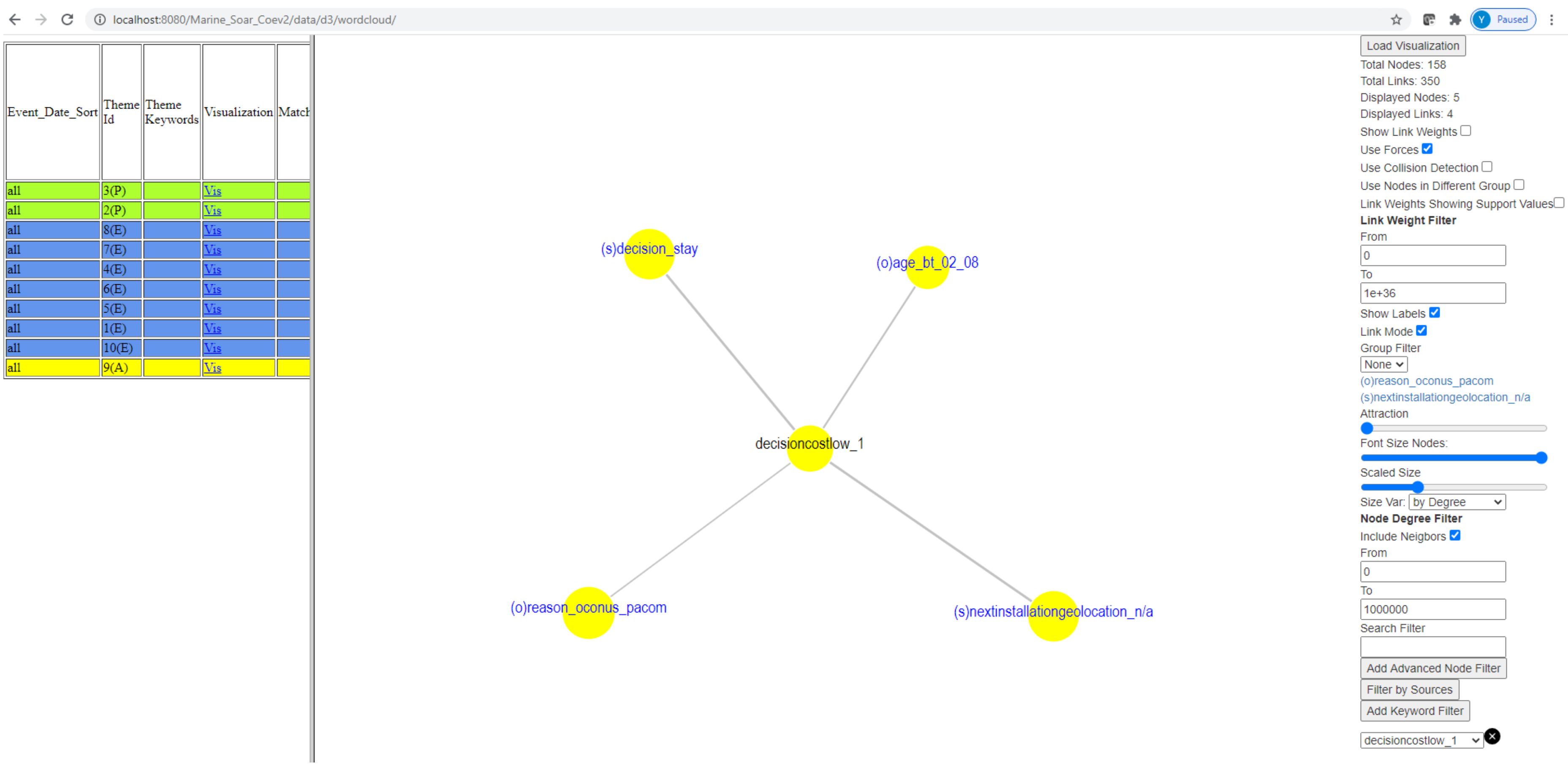


- Optimize both players' actions and decisions
  - Selection based on predicted fitness for exploitation
  - Mutation and cross-over for exploration

Soar-RL Model from Mining Mock Data

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			
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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			0.107222755
0	F0	(O)Age_bt_02_08	0.467889908	0.000605917	0.000137289	-1.90E-06	1.27E-06	0			
1	F1	(O)Age_bt_08_14	0.266055046	0.000143931	0.000599276	0	-6.33E-07	0			
3	F3	(O)Age_mt_14	0.174311927	5.09E-05	0.000692333	1.27E-06	-1.90E-06	0			
4	F4	(O)CurrentInstallationGeolocation_BahrainBH	0.119266055	0.000129984	0.000613223	0	-6.33E-07	0			
5	F5	(O)CurrentInstallationGeolocation_ChinhaeKR	0.055045872	4.62E-05	0.00069698	0	-6.33E-07	0			
6	F6	(O)CurrentInstallationGeolocation_GuamUS	0.073394495	7.00E-05	0.000673199	0	-6.33E-07	0			
7	F7	(O)CurrentInstallationGeolocation_GuantanomoBayCU	0.064220183	3.30E-05	0.000710208	0	-6.33E-07	0			
8	F8	(O)CurrentInstallationGeolocation_HawaiiUS	0.055045872	7.14E-05	0.000671795	0	-6.33E-07	0			
9	F9	(O)CurrentInstallationGeolocation_KanedaAB	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	0			
11	F11	(O)CurrentInstallationGeolocation_NorfolkUS	0.137614679	0.000103051	0.000640155	0	-6.33E-07	0			
12	F12	(O)CurrentInstallationGeolocation_RotaES	0.055045872	2.09E-05	0.000722283	0	-6.33E-07	0			
13	F13	(O)CurrentInstallationGeolocation_SaseboJA	0.119266055	0.000104423	0.000638783	6.01E-11	-6.33E-07	0			
14	F14	(O)CurrentInstallationGeolocation_SigonellaIT	0.055045872	4.62E-05	0.000696965	0	-6.33E-07	0			
15	F15	(O)CurrentInstallationGeolocation_SoudaBayGR	0.073394495	-5.75E-06	0.00074896	0	-6.33E-07	0			
16	F16	(O)CurrentInstallationGeolocation_YokosukaJA	0.128440367	0.000115801	0.000627406	-6.33E-07	1.19E-10	0			

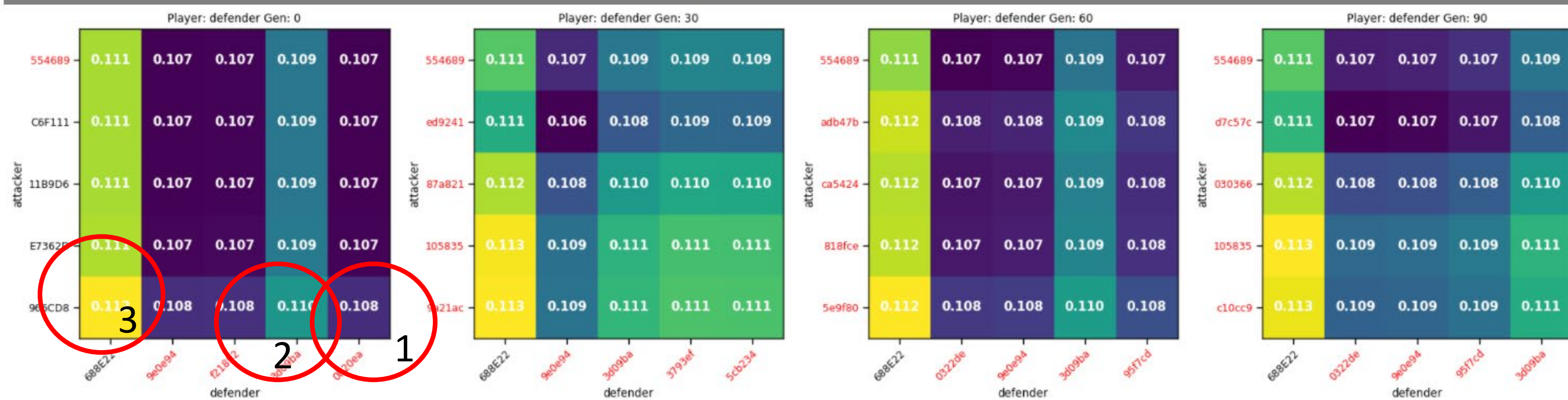
LLA Model from Mining Mock Data

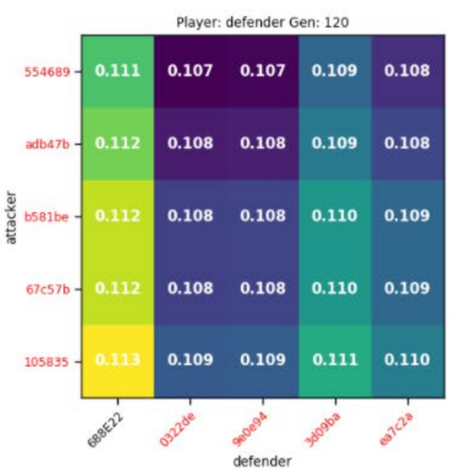


Soar-RL and LLA Models are both used in LAILOW: Results Drill-Down

Results

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





Defender and Attacker Variables Coevolve

1

defender 0b20ea 's fitness:0.06616802096603218
defender 0b20ea 's configuration:
(S)Decision_MOVE[F138]
(S)NextInstallationGeolocation_BarkingSandsUS[F141]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender 0b20ea 's Soar-RL reward:0.1077434372120195

defender 0b20ea 's LLA associations (normalized):
"F1-F138": 0.001986103554630653,
"F136-F138": 0.0021546821809134086,
"F136-F141": 0.004307174421466967,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

Variables

2

defender f21892 's fitness:0.06511564037651324
defender f21892 's configuration:
(S)Decision_MOVE[F138]
(S)NextInstallationGeolocation_ChinhaeKR[F142]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender f21892 's Soar-RL reward:0.10779116827353517

Higher reward solution

defender f21892 's LLA associations (normalized):
"F138-F142": 0.0021546821809134086,
"F1-F138": 0.001986103554630653,
"F136-F138": 0.0021546821809134086,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

3

defender 688e22 's fitness:0.06779949767605575
defender 688e22 's configuration:
(S)Decision_STAY[F139]
(S)NextInstallationGeolocation_n/a[F156]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender 688e22 's Soar-RL reward:0.11192405506897778

defender 688e22 's LLA associations (normalized):
"F139-F156": 0.00753029572009989,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

Other Possible Configurations:

4

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_OCONUS_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1		
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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		0.108772543

5

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		
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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		0.107222755

6

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_OCONUS_PACOMScenario	0.018348624	-1.36E-06	0.000744571	0	-6.33E-07	1		
138	F138	(S)Decision_MOVE	0.256880734	-0.00019516	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		0.108861738

4 is the original in the database, 6 is better than 4 and 5 (in terms of lower cost)

Conclusion and Future Work

- Showed how to apply for LAILOW to search for alternatives that reduce cost
- Phase II of 2023
  - Install LAILOW in STBL and test on real Data
  - MVP tool to be used in the real SLD process

Appendix B

Simulating a Complex Enterprise Using an Asymmetrical Wargame Simulation with Soar Reinforcement Learning, Coevolutionary Algorithms, and Lexical Link Analysis

Researcher:
Naval Postgraduate School: Dr. Ying Zhao (yzhao@nps.edu),

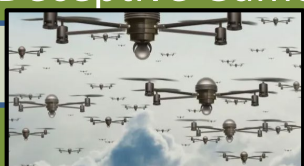
Collaborators: The Air Force AI Accelerator at MIT, MIT CSAIL

Presentation to
The Sixth Annual Workshop on Naval Applications of Machine Learning
Virtual, 22-24 March 2022

Warfighters Need Automation Tools and Trusted AI Used in Different Levels of Applications: Strategic, Operational, and Tactical

AI as Weapons

Cyber Honey Pots, Virtual Swarms, Deceptive Games

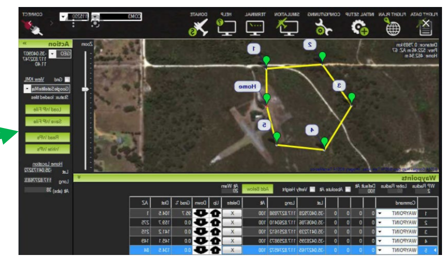


Weapon Systems

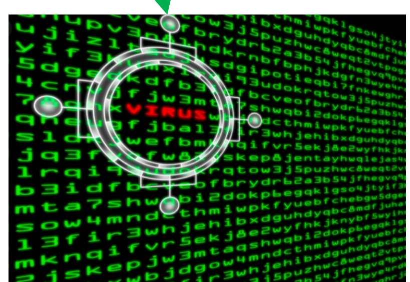
Robot Fighters

Help Warfighters

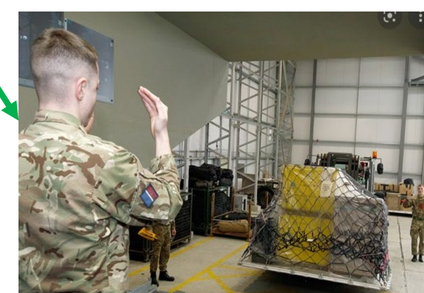
Tactical Action Officer (TAO)



Over-the-horizon Strike Mission Planner



Cyber Warriors



Combat Logistics Officer (CLO)

Leverage Artificial Intelligence to Learn, Optimize, and Wargame (LAILOW) for Complex Enterprises

Requirements

Operation concepts
- Distributed Maritime Operations (DMO)
- Expeditionary Advanced Base Operations (EABO)

- Capability
- Manpower
- Logistics & Supply
  - Equipment, …,

Deep Analytics/Data Mining/Machine Learning/Prediction

Data Sources
USMC
- Master Data Repository (MDR)
- Global Combat Support System-Marine Corps (GCSS-MC)

NAVWARSYSCOM
Navy ERP
Digital Twin

Big data

LAILOW

No data

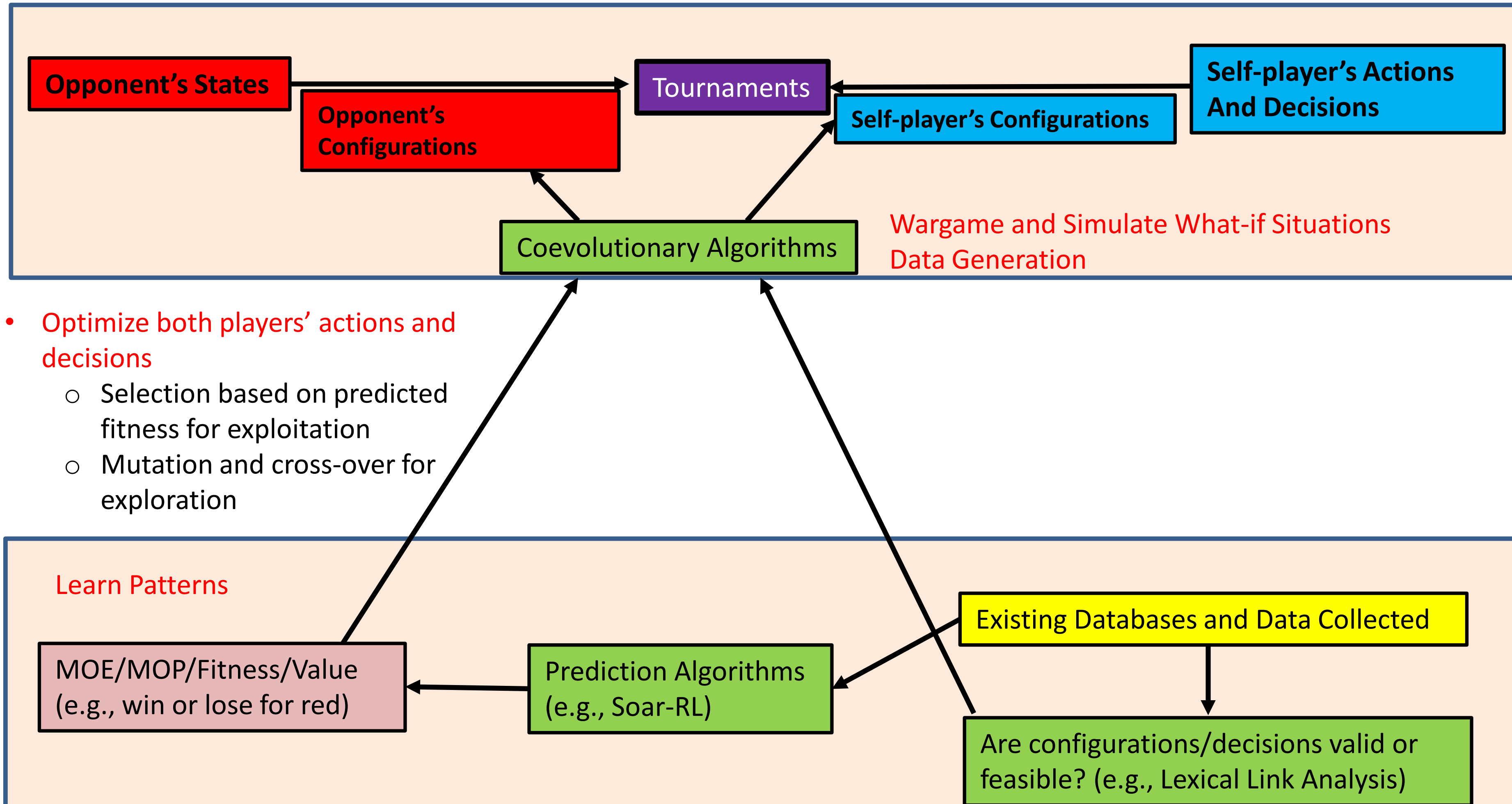
Optimization

Simulation/Wargame

Analytics

Big data feed from a long chain of readiness components
- Deployment
- Demand, CASREPs
- Maintenance
- Supply
- Requisition
- Transportation
- Finance processes
- Activities
- Decisions

LAILOW



- Optimize both players' actions and decisions
  - Selection based on predicted fitness for exploitation
  - Mutation and cross-over for exploration

DISTRIBUTION STATEMENT A, APPROPRIATE FOR PUBLIC RELEASE

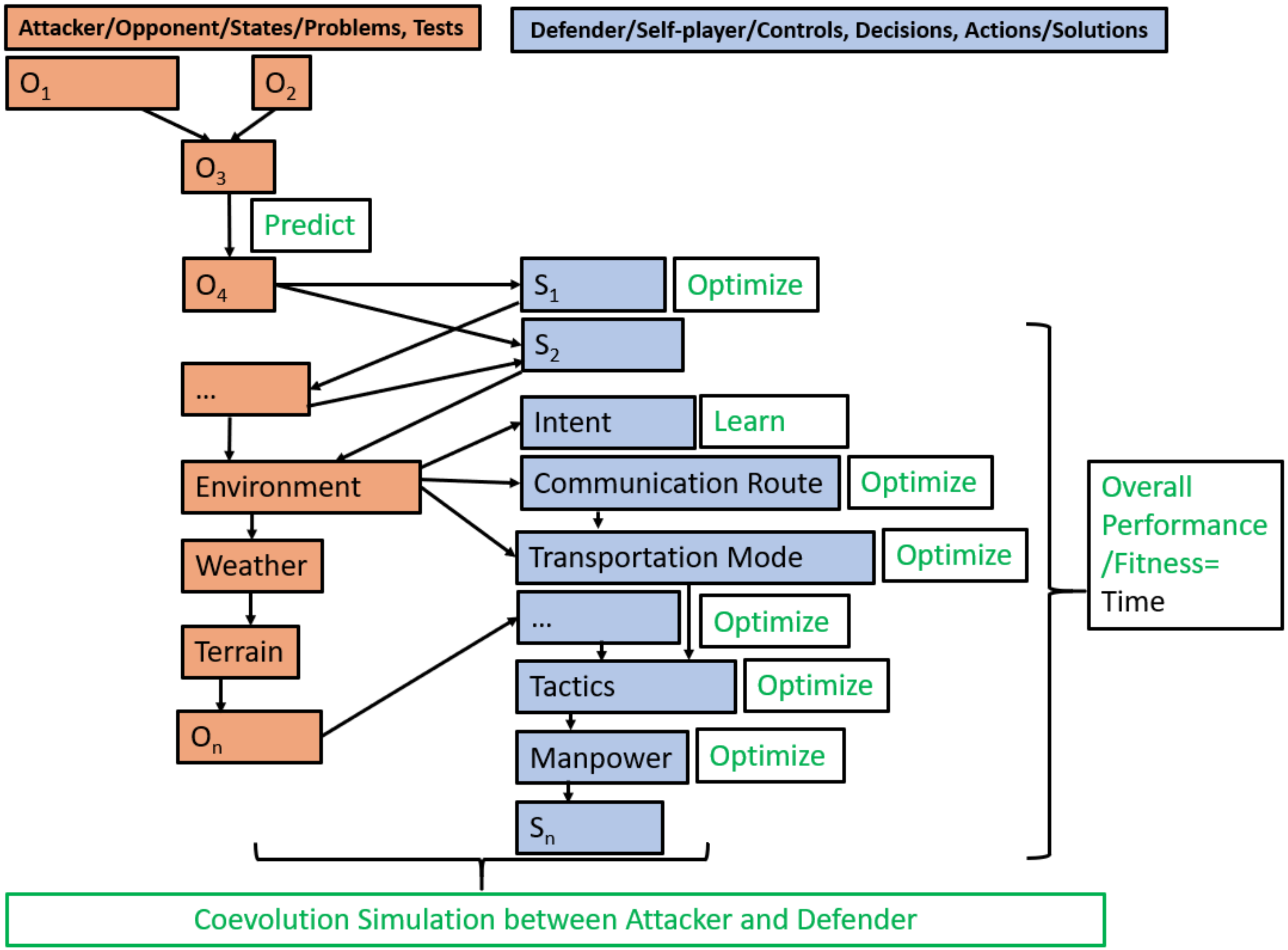
Background and Objective: Opponent Artificial General Intelligence (AGI) Agent

- Opponent AGI Agent for Cross-Domain Applications
  - Sets of AI/ML models and simulation models,
    - consistent
    - explainable, no black boxes
    - test theories for a range of users in a wide range of applications such
      - campaign/mission planning
      - future warfighting concepts designing and simulation,
      - warfighter training, etc., allow different questions to be asked easily
  - Do not need re-program heavily towards plug-and-play
  - Artificial General intelligence (AGI), just plug in business, process, and data models, fully generating data based on patterns and law of physics and engineering
- Related to the cutting edges of AI models
  - GANS, GPT3 of AI, AGI
  - Belief, LAILOW models, visualizing uncertainty, control theory models, meta-learning, active learning

Opponent agent

- Case 1: Environmental (neutral)
- Case 2: Strategic complementary factors
- Case 3: Strategic competitive factors

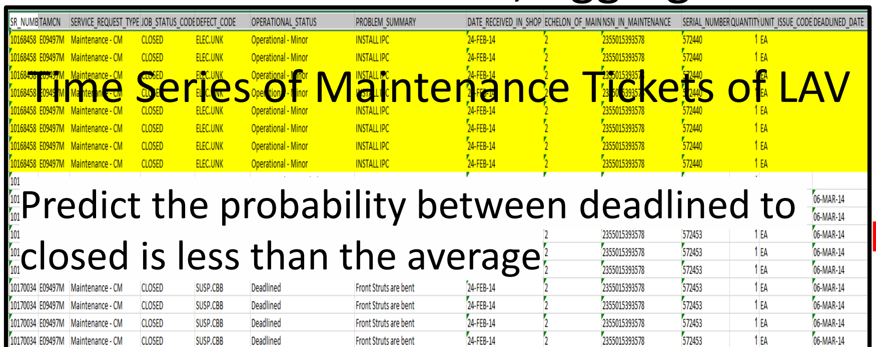
LAILOW for a Process – Plug-and-Play

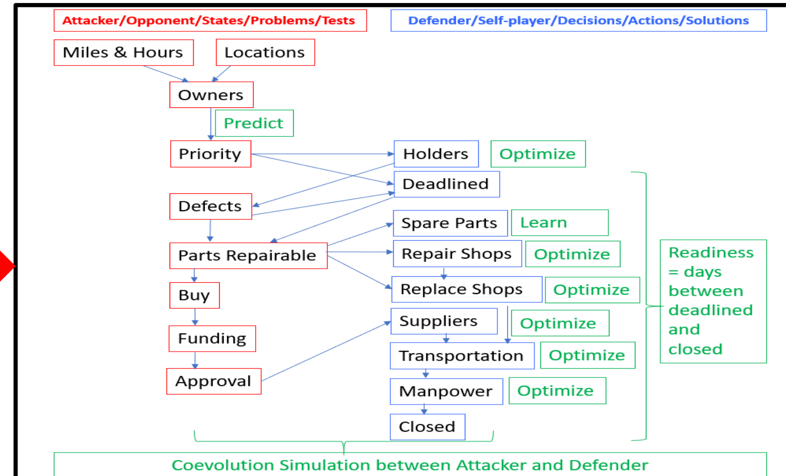


DISTRIBUTION STATEMENT A, APPROPRIATE FOR PUBLIC RELEASE

Use Case: Marine Maintenance and Supply System

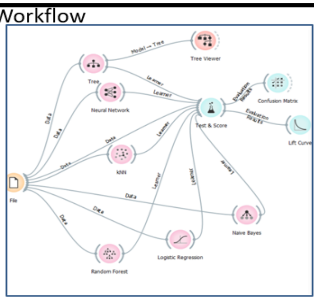
- Land Armored Vehicle (LAV) (1/2013 to 1/2020), E0949 GCSS-MC Maintenance Data, Aggregated





Predictive Models

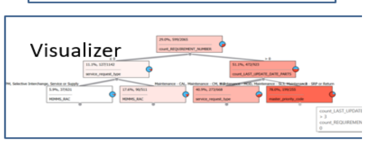
Workflow

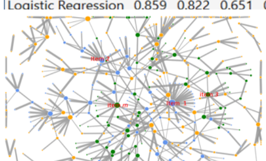


Method	AUC	CA	F1	Precision	Recall
kNN	0.679	0.716	0.421	0.516	0.356
Tree	0.683	0.760	0.554	0.600	0.514
Random Forest	0.849	0.815	0.658	0.711	0.613
Neural Network	0.848	0.802	0.634	0.683	0.593
Naive Bayes	0.828	0.713	0.618	0.503	0.800
Logistic Regression	0.859	0.822	0.651	0.756	0.573

Added Soar-RL Outside Orange

Performance



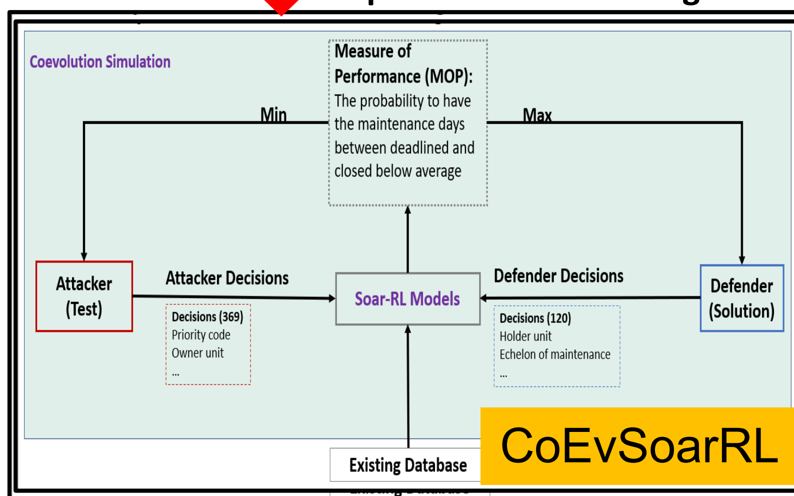


Probability of Failure/Demand

Lexical Link Analysis: Cluster items and compute centrality of items

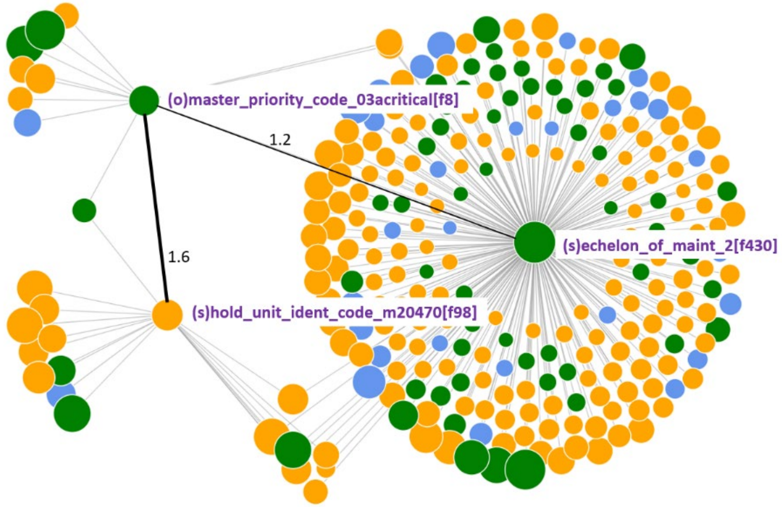
Individual item predictive models

Optimization and Wargame



CoEvSoarRL

Context-dependent Models



- Handle constraints by modifying fitness function
  - Length
  - Associations from Lexical Link Analysis

- **Discover** new approach to handle old problem
- **Perform what if analysis** by generating new problems and solutions based on length and historical association patterns

LAILOW Use Cases (2022)

- Cognitive and agile radio, sponsored by ONR NEPTUNE (code 33). LAILOW is used to learn and optimize high radio frequency for communicate and replace traditional automatic link establishment (ALE).
- Leverage AI to Learn, Optimize, and Wargame (LAILOW) for Strategic Laydown and Dispersal (SLD) of the Operating Forces of the U.S. Navy (funded by N3/N5): this is to standardize and digitize the current SLD decision making process, make an electronic SLD model, and reduce manual workload for the current method.
- Leverage AI to Learn, Optimize, and Wargame (LAILOW) for a Complex Enterprise: Application to the Sustainment in a Contested Environment: Navy Battle Damage Assessment and Repair (BDAR) (funded by N4): this is to reconstruct an actual wargame and simulate more.
- Threat and Capability Coevolutionary Wargame (TCCW) Applied to Advanced Persistent Threats (funded by OUSD(R&E as part of Cyber Agreements for Resilient Machines through Augmented AI (CARMA-AI) Project), use LAILOW to learn cyber decoy and detection models
- Structured and Unstructured Data Sciences and Business Intelligence for Analyzing Requirements Post Mortem, N8 - Integration of Capabilities & Resources, LAILOW will be used to perform distributed what-if analysis and simulation.

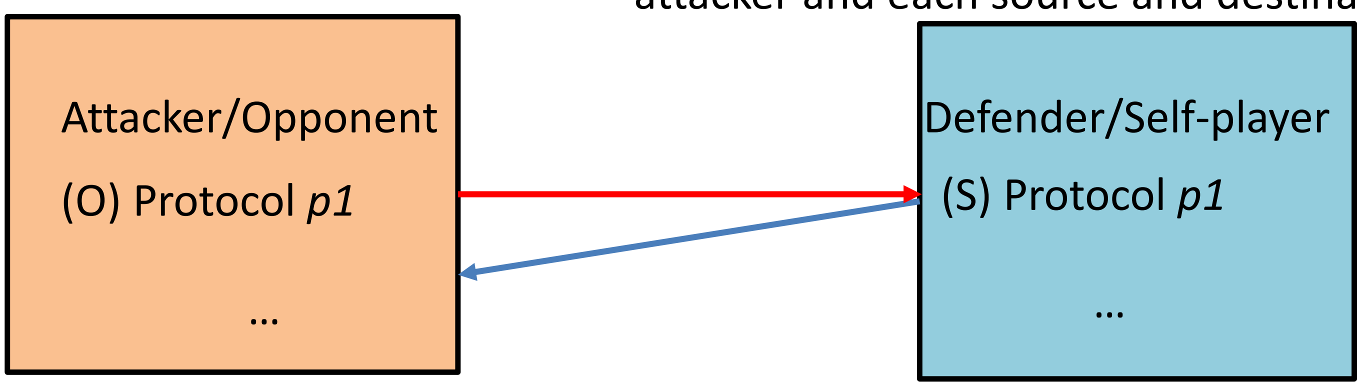
Use Case: Threat and Capability Coevolutionary Wargame (TCCW) Applied to Advanced Persistent Threats, funded by OUSD(R&E) as part of Cyber Agreements for Resilient Machines through Augmented AI (CARMA-AI) Project

Objective: What are the characteristics of effective decoys? How can ML/AI methods inform configuration of more effective decoys?

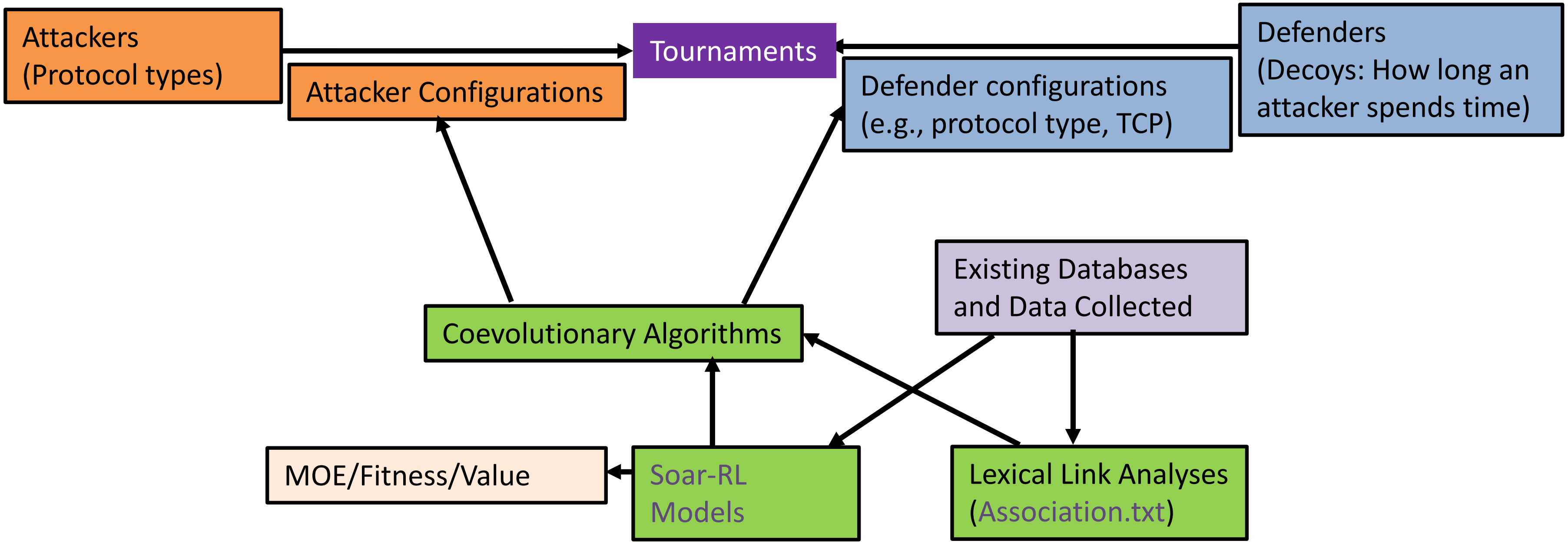
Initial Data: Network traffic generated during cyber deception experimentation with human attackers and decoy systems

Attacker ID	Source IP	Destination IP	Packet Count	Protocol	Timestamps
…	…	…	…	…	…

Transformation → "**Tournament**:" number of protocols source to destination and destination to source for each attacker and each source and destination

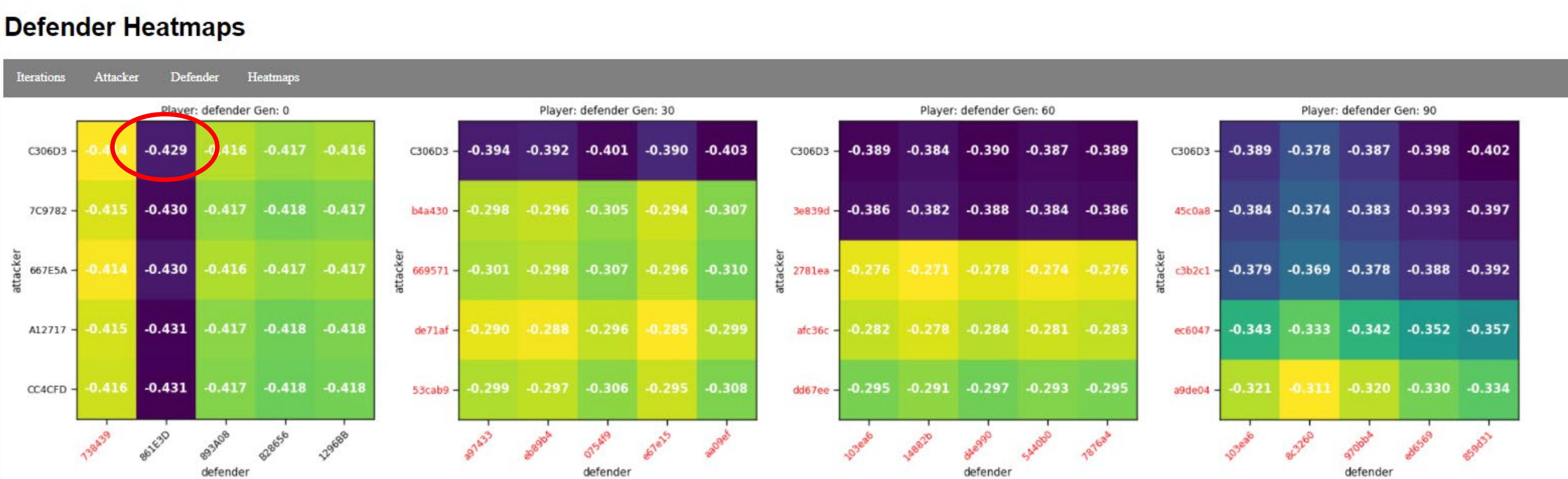


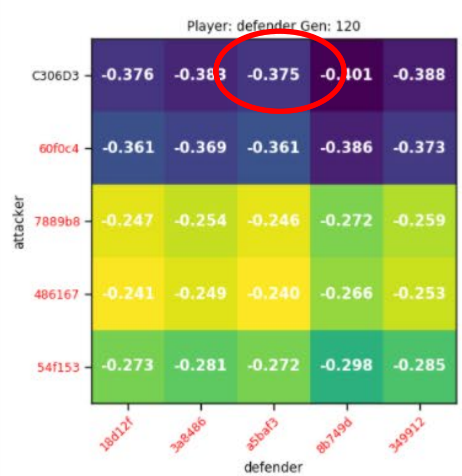
LAILOW Setting Up



- MOE for defender = Success of using decoy for cyber defense: Probabilities of holding an attacker's attention longer than shorter (e.g., than x timestamps = the average time plus one standard deviation)

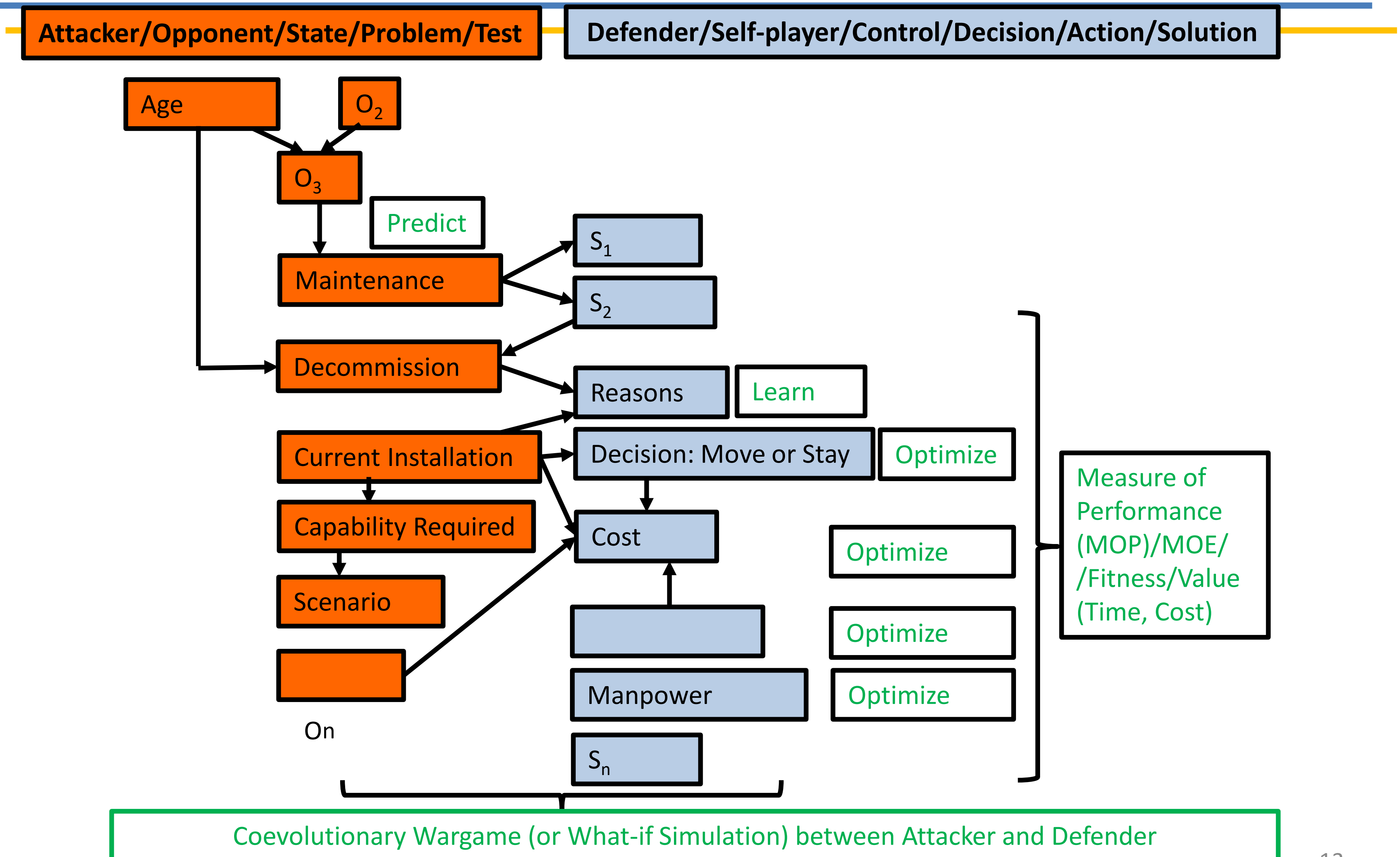
Defender and Attacker’s Coevolution





- Uppercase BLACK configurations are from the existing databases
- Lowercase red configurations are new and synthetic
- Drill down

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



Acknowledgements and Disclaimer

Authors would like to thank

- the Naval Postgraduate School (NPS)'s Naval Research Program (NRP) for supporting the research
- the Office of Naval Research (ONR)'s Naval Enterprise Partnership Teaming with Universities for National Excellence (NEPTUNE 2.0) program
- the OUSD(R&E), NIWC Pacific

Appendix C

Proposal Details

20th Annual Acquisition Research Symposium

ID: P23-0018
Created On: November 10 2022
Title: Leverage AI to Learn, Optimize, and Wargame (LAILOW) for Strategic Laydown and Dispersal (SLD) of the Operating Forces of the U.S. Navy
Type: Paper/Presentation
Status: Received
Keywords: artificial intelligence,machine learning,optimization,strategic laydown and dispersal,SLD,data mining

Paper/Panel Paper

Name of Presenter Ying Zhao, Douglas J. MacKinnon

Presenter Organization Naval Postgraduate School

Presenter Email Address yzhao@nps.edu,djmackin@nps.edu

Presenter Phone Number 408-218-8484

Abstract The Secretary of the Navy disperses Navy forces in a deliberate manner to support DoD guidance, policy and budget. The current strategic laydown and dispersal (SLD) process is labor intensive, time intensive, and less capable of becoming agile for considering competing alternative plans. SLD could benefit from the implementation of artificial intelligence.

We introduced a relatively new methodology to address these questions which was recently derived from an earlier Office of Naval Research funded project that combined deep analytics of machine learning, optimization, and wargames. This methodology is entitled LAILOW which encompasses Leverage AI to Learn, Optimize, and Wargame (LAILOW). We began here by collecting data then employed data mining, machine learning, and predictive algorithms to perform artificial intelligent analysis to learn about and understand the data. This data included historical, phased force deployment data among others to learn patterns of what decisions were made and how they were executed. We then developed a stand-alone set of pseudo data that mimicked the actual, classified data so that experimental excursions cold be performed safely. We also limited our data to include ships. Our efforts produced a first-ever, relative, and optimal, score derived from a wargame like scenario for every available ship that might be moved. The score for each ship increases as fewer resources are required to fulfill an SLD plan requirement to move that ship to a new homeport. This not only produced a mathematically optimal response, but also enabled the immediate comparison between competing or alternate ship movement scenarios that might be chosen instead.

Research Issue The research issues are as follows:

1. How Navy weighs competing demands for naval forces to determine an optimal dispersal of operating forces?
2. How does the Navy optimize force laydown to maximize force development and force generation efficiency?

Research Results Statement Our efforts produced a first-ever, relative, and optimal, score derived from a wargame like scenario for every available ship that might be moved. The score for each ship increases as fewer resources are required to fulfill an SLD plan requirement to move that ship to a new homeport. This not only produced a mathematically optimal response, but also enabled the immediate comparison between competing or alternate ship movement scenarios that might be chosen instead.

Our original understanding of how the Navy scores these potential ship movements was improved through our exploration of this topic. The Navy considers variables such as available maintenance, pier space, required schools as well as the distance between the ship's present location and its potential new homeport. Additionally, each ship overseas must return to the continental United States within ten tears and each one fulfills tactical and strategic requirements that are also considered. There are also unseen political preferences that can also outweigh numerically based resource requirements.

In summary, we demonstrated the feasibility of the methodologies of leveraging AI to learn, optimize, and wargame (LAILOW), including predictive algorithms that learn.

We anticipate our findings to guide the way forward toward further exploration in this area through our suggested methodology. This would likely save time and energy of the decision makers and offer otherwise undiscovered potential alternative solutions to future SLD plans. In consideration of future efforts, we envision a more integrated, coherent, and large-scale, deep analytics effort leveraging methods that link to existing data sources to more easily enable the direct comparisons of potential scenarios of platform movement considered through the SLD process. The resulting product could the facilitate decision makers' ability to learn, document, and track the reasons for complex decision making of each SLD process and identify potential improvements and efficiencies.

No Files have been uploaded

Authors

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Ying Zhao	Research Associate Professor	Naval Postgraduate School	408-218-8484	yzhao@nps.edu	Yes	Yes

Biographies

Douglas MacKinnon
None Given

Riqui Schwamm
None Given

Ying Zhao
None Given

Appendix D

NAVAL
POSTGRADUATE
SCHOOL

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

NRP Project ID: NPS-22-N117-A

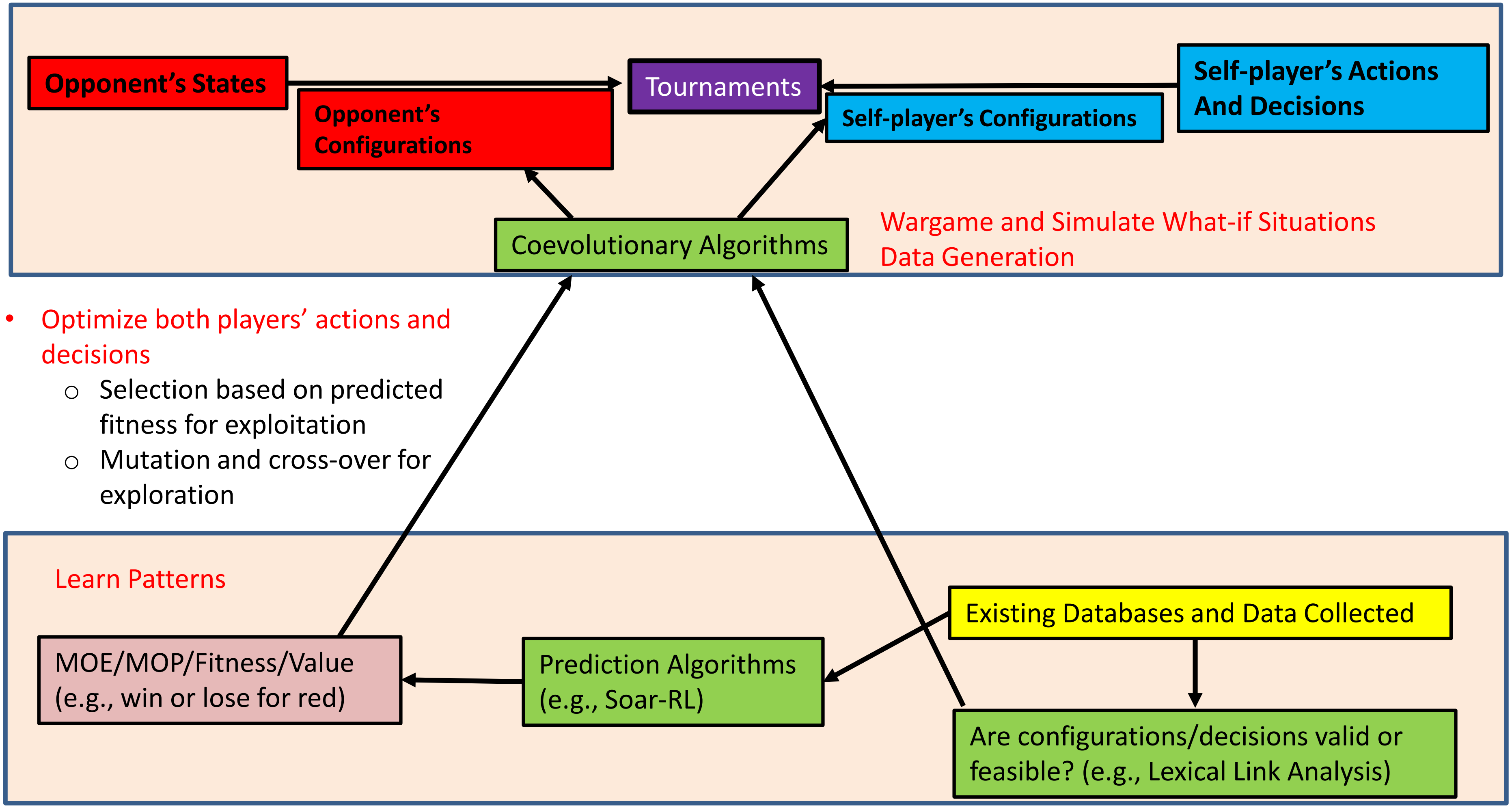
09 Sep 2022

Doug MacKinnon, Ph.D.
Associate Research Professor
NPS, IS Department

State of the Project FY22

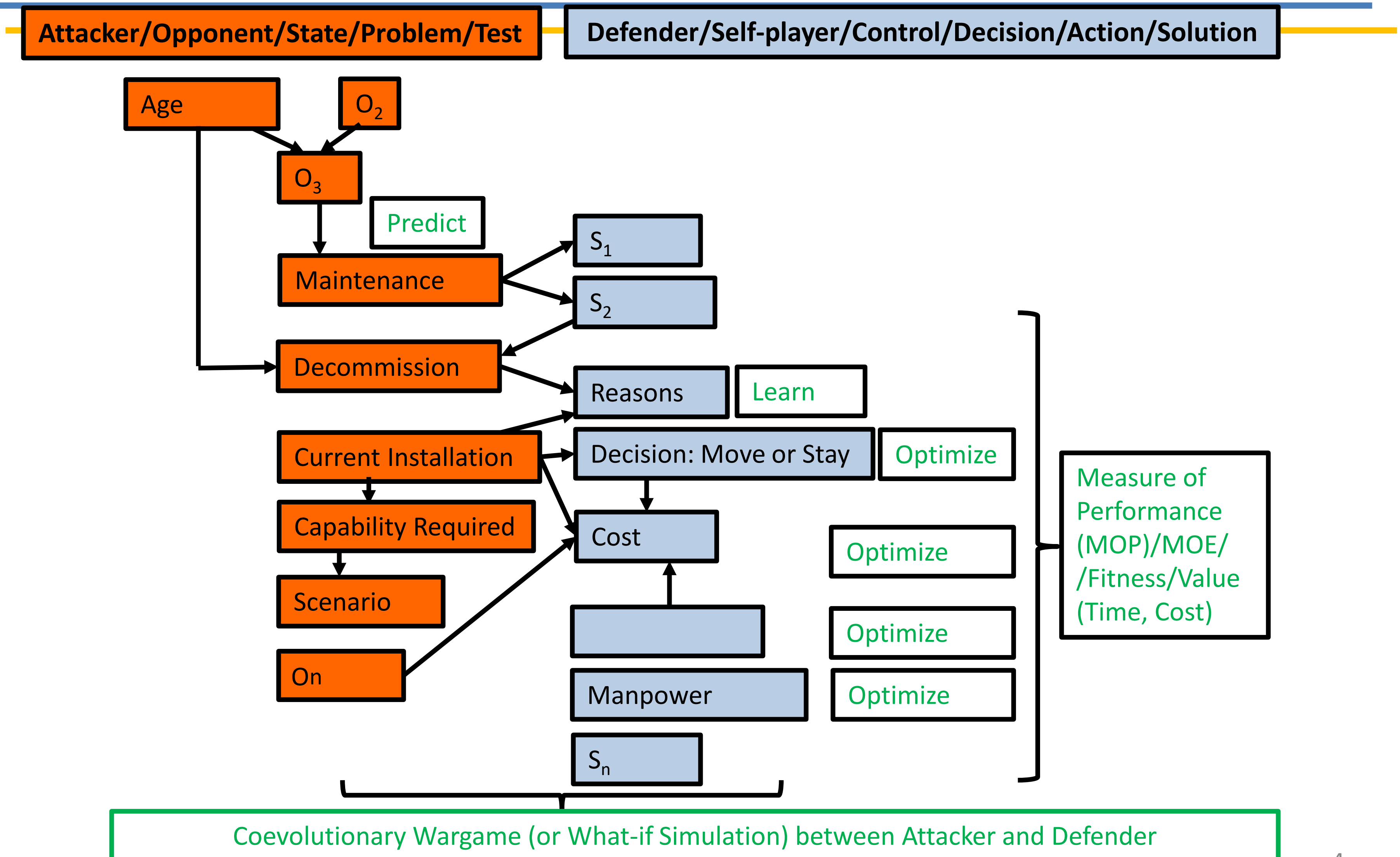
- Collected data and built a pseudo data set of surface ships
- Applied LAILOW to search and analyze the data to determine optimal move decisions - and offered alternatives.
- Much improved over manual method

Learn, Optimize, and Wargame (LAILOW) (Generically)



- Optimize both players' actions and decisions
  - Selection based on predicted fitness for exploitation
  - Mutation and cross-over for exploration

Use Case - Force Strategic Laydown and Dispersal (SLD): Standardize and digitize the current SLD decision making process, made an electronic SLD model, reducing manual workload for the current method, searched for alternatives that reduce cost – and found competing alternatives.



DISTRIBUTION STATEMENT A, APPROPRIATE FOR PUBLIC RELEASE

Soar-RL Model from Mining Mock Data

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	0.108142
1	F1	(O)Age_bt_08_14	0.266055046	0.000143931	0.000599276	0	-6.33E-07	0	
2	F2	(O)Age_lt_02	0.091743119	-5.75E-05	0.000800722	5.93E-11	-6.33E-07	0	
3	F3	(O)Age_mt_14	0.174311927	5.09E-05	0.000692333	1.27E-06	-1.90E-06	0	
4	F4	(O)CurrentInstallationGeolocation_BahrainBH	0.119266055	0.000129984	0.000613223	0	-6.33E-07	0	
5	F5	(O)CurrentInstallationGeolocation_ChinhaeKR	0.055045872	4.62E-05	0.00069698	0	-6.33E-07	0	
7	F7	(O)CurrentInstallationGeolocation_GuantanomoBayCU	0.064220183	3.30E-05	0.000710208	0	-6.33E-07	0	
8	F8	(O)CurrentInstallationGeolocation_HawaiiUS	0.055045872	7.14E-05	0.000671795	0	-6.33E-07	0	
9	F9	(O)CurrentInstallationGeolocation_KanedaAB	0.009174312	1.20E-05	0.000731227	0	-6.33E-07	0	
10	F10	(O)CurrentInstallationGeolocation_MaineUS	0.055045872	-4.09E-06	0.000747293	5.93E-11	-6.33E-07	0	
11	F11	(O)CurrentInstallationGeolocation_NorfolkUS	0.137614679	0.000103051	0.000640155	0	-6.33E-07	0	
12	F12	(O)CurrentInstallationGeolocation_RotaES	0.055045872	2.09E-05	0.000722283	0	-6.33E-07	0	
13	F13	(O)CurrentInstallationGeolocation_SaseboJA	0.119266055	0.000104423	0.000638783	6.01E-11	-6.33E-07	0	
14	F14	(O)CurrentInstallationGeolocation_SigonellaIT	0.055045872	4.62E-05	0.000696965	0	-6.33E-07	0	
15	F15	(O)CurrentInstallationGeolocation_SoudaBayGR	0.073394495	-5.75E-06	0.00074896	0	-6.33E-07	0	
16	F16	(O)CurrentInstallationGeolocation_YokosukaJA	0.128440367	0.000115801	0.000627406	-6.33E-07	1.19E-10	0	
17	F17	(O)Hull_AS-17	0.009174312	1.13E-05	0.00073189	-6.33E-07	1.82E-10	0	
18	F18	(O)Hull_AS-18	0.009174312						
19	F19	(O)Hull_AS-19	0.009174312						
20	F20	(O)Hull_AS-27	0.009174312						
21	F21	(O)Hull_AS-28	0.009174312						
22	F22	(O)Hull_AS-29	0.009174312						
23	F23	(O)Hull_AS-37	0.009174312						
24	F24	(O)Hull_AS-38	0.009174312						
25	F25	(O)Hull_AS-39	0.009174312						
26	F26	(O)Hull_AS-47	0.009174312						
27	F27	(O)Hull_AS-48	0.009174312						
28	F28	(O)Hull_AS-49	0.009174312	1.13E-05	0.000731891	-6.33E-07	1.78E-10	0	

For Soar-RL (Reinforcement Learning), we use numeric preferences to represent a state-operator value function. Rewards can be modified by internal knowledge as they arise.

Mock Data: Can LAILOW Improve Decisions to Reduce Cost?

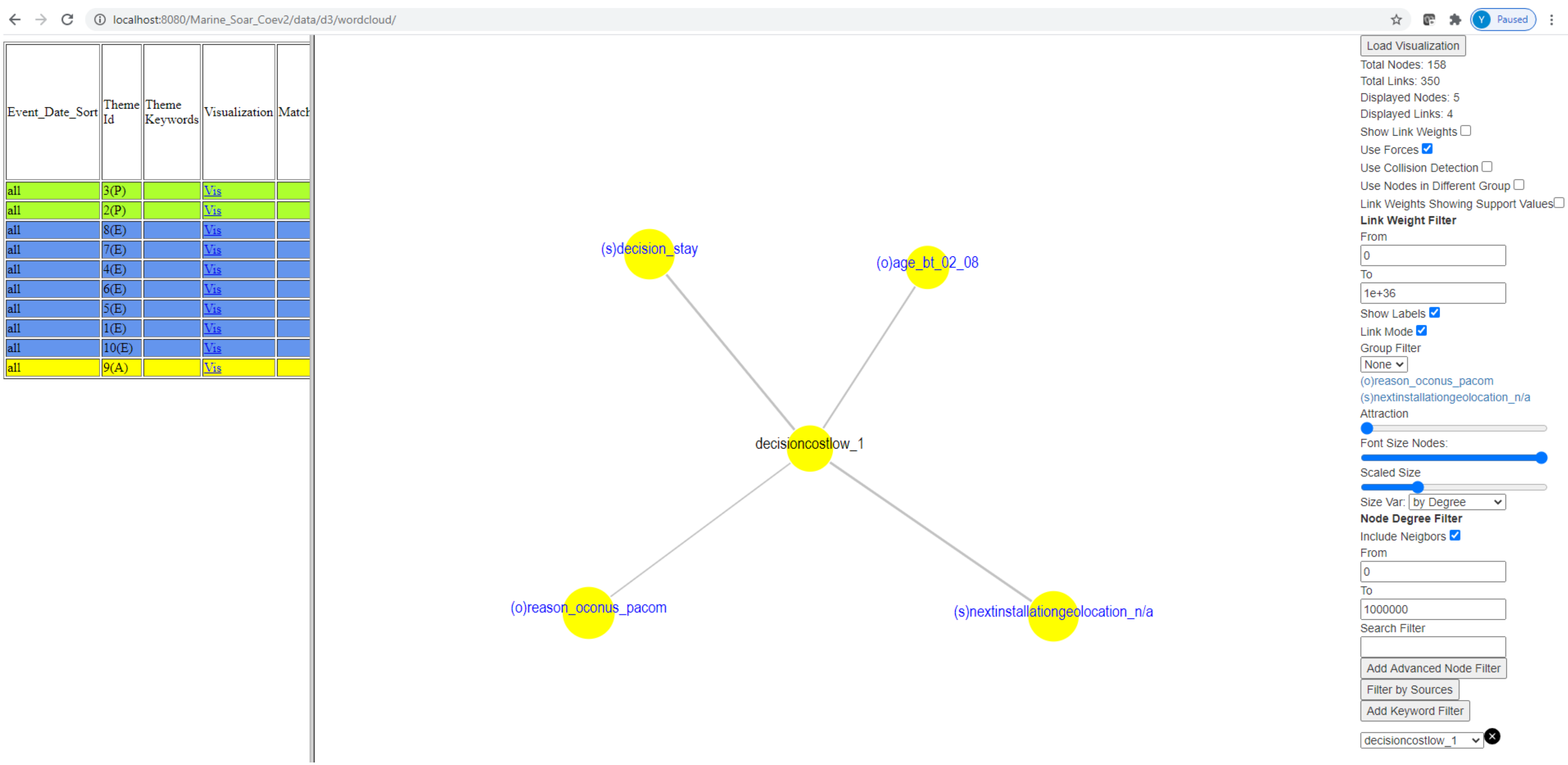
Variables marked with (O): Opponent - Attacker

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	OCONUS_CENTCOMScenario	MOVE	BahrainBH	495	7000	11	7495	0
Adzamovka	DDG-19	BahrainBH	OCONUS_CENTCOM	STAY	n/a	1080	0	5	1080	1

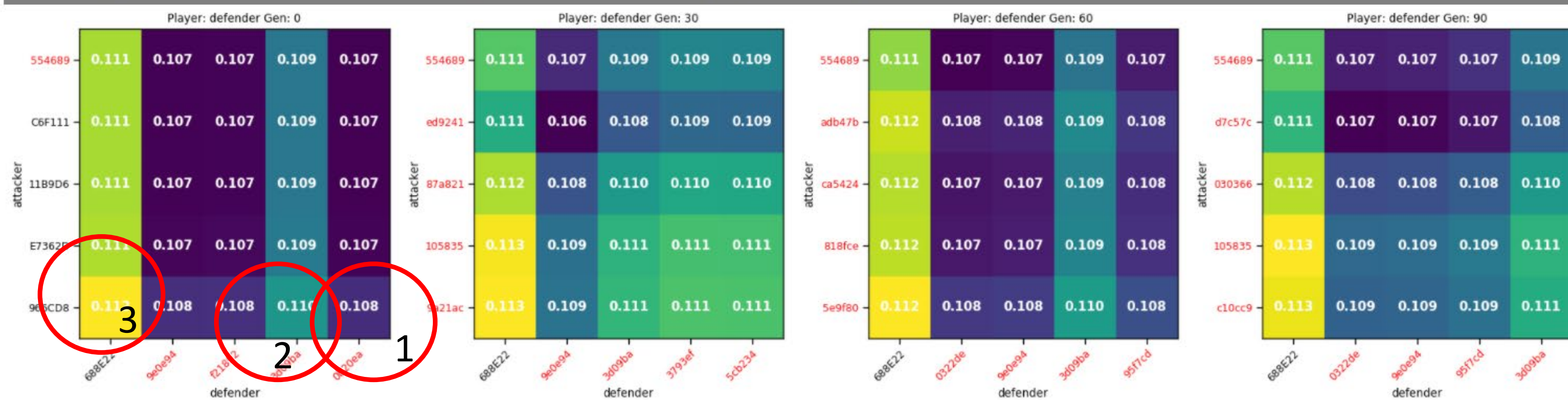
LLA Model from Mining Mock Data

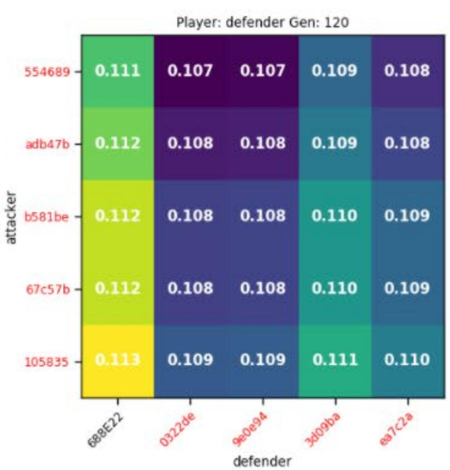


Soar-RL and LLA Models are both used in LAILOW: Results Drill-Down

Results

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





Defender and Attacker Variables Coevolve
(see following slides)

1

defender 0b20ea 's fitness:0.06616802096603218
defender 0b20ea 's configuration:
(S)Decision_MOVE[F138]
(S)NextInstallationGeolocation_BarkingSandsUS[F141]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender 0b20ea 's Soar-RL reward:0.1077434372120195

defender 0b20ea 's LLA associations (normalized):
"F1-F138": 0.001986103554630653,
"F136-F138": 0.0021546821809134086,
"F136-F141": 0.004307174421466967,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

2

defender f21892 's fitness:0.06511564037651324
defender f21892 's configuration:
(S)Decision_MOVE[F138]
(S)NextInstallationGeolocation_ChinhaeKR[F142]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender f21892 's Soar-RL reward:0.10779116827353517

Higher reward solution

defender f21892 's LLA associations (normalized):
"F138-F142": 0.0021546821809134086,
"F1-F138": 0.001986103554630653,
"F136-F138": 0.0021546821809134086,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

3

defender 688e22 's fitness:0.06779949767605575
defender 688e22 's configuration:
(S)Decision_STAY[F139]
(S)NextInstallationGeolocation_n/a[F156]

attacker 966cd8 's configuration:
(O)Age_bt_08_14[F1]
(O)CurrentInstallationGeolocation_KanedaAB[F9]
(O)Hull_DDG-119[F41]
(O)Reason_OCONUS_PACOMScenario[F136]

defender 688e22 's Soar-RL reward:0.11192405506897778

defender 688e22 's LLA associations (normalized):
"F139-F156": 0.00753029572009989,
"F41-F9": 0.00753029572009989,
"F136-F9": 0.004307174421466967,
"F136-F41": 0.004307174421466967

Alternatives

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		4	
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			0.108015
1	F1	(O)Age_bt_08_14	0.266055046	0.000143931	0.000599276	0	-6.33E-07	0			

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		5	
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			
142	F142	(S)NextInstallationGeolocation_ChinhaeKR	0.027522936	1.05E-05	0.000732682	0	-6.33E-07	1			0.106476

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		6	
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			0.108142

4 is originally chosen, yet 6 may be better than 2

FY23 Goal

- Having shown our mathematical ability to solve a smaller problem using artificial data, we seek to
  - Continue our research to develop an electronic model of the Strategic Laydown and Dispersal (SLD) into a minimum variable product (MVP)
  - Assist future SLD development
  - Justify SLD potential movement scenarios and their decisions consistently
- Next Steps
  - Install LAILOW in NPS SCIF and test on real data
  - Develop a tool that can be used in the real SLD process
  - Perhaps leverage Microsoft Power BI (Business Intelligence)
    - COTS analytic and depiction tool