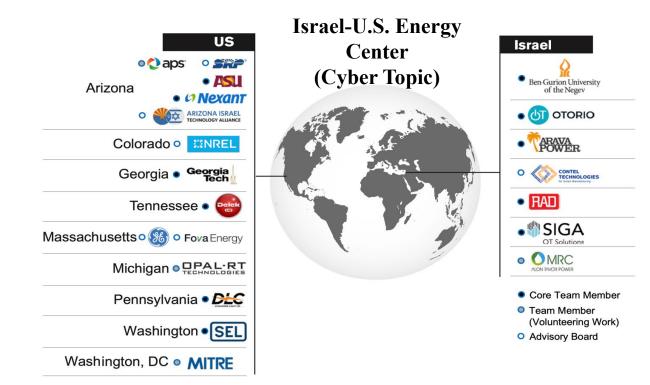
Comprehensive Cybersecurity Technology for Critical Power Infrastructure AI-Based Centralized Defense and Edge Resilience



Prepared for **Itai Ganzer** and **Ofer Goldhirsh** Israel Innovation Authority **Avi Shavit** and **Eynan Lichterman** Israel Ministry of Energy

> Mohammadamin Moradi on behalf of Ying-Cheng Lai Arizona State University 8/25/2022

Task 16: Reinforcement Learning Control for Cyber Physical Systems

Preference Based Resource Allocation in CPS Using DRL

Preferences:

• Preferences and priorities play a key role in the real-world decision-making problems

Examples:

- In Chess, an AI player wants to win. It also prefers to win without losing its **queen**. Moreover, it prefers losing the **rooks** rather than losing the **knights**.
- In cybersecurity of power grids, the government wants to keep transmission lines safe; however, if a blackout happens due to attacks, it prefers blackouts in less populated/significant areas.







Preferences in a Power Grid

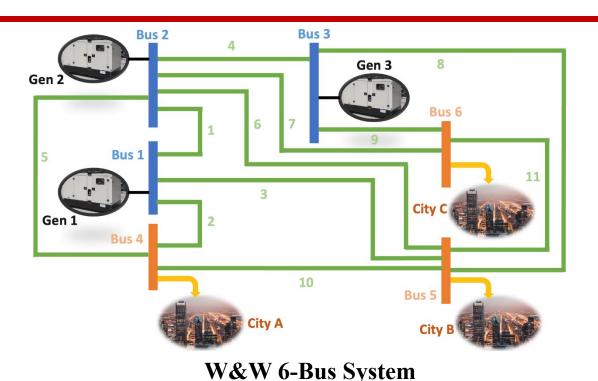
• Attacker attacks generators. Defender defends them.

Attacker's Preferences (P):

- *PA*: The more generators being attacked the better.
- *PB*: If attacking all generators is possible, attacking Gen 3 in the end is preferred.
- *PC*: Attacking Gen 1 first is preferred to attacking other generators first.

From **defender's Point of View**, preferences can be the complement of the above (P°) .

- *PA*°: The less generators being attacked the better.
- *PB*°: If defending all generators is not possible, Gen 3 going down first or second is preferred.
- *PC*°: Gen 1 not going down first is preferred to other generators going down first.





Preference Transformed into Mathematical Formula

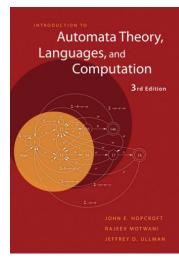


Attacker's Preferences (P):

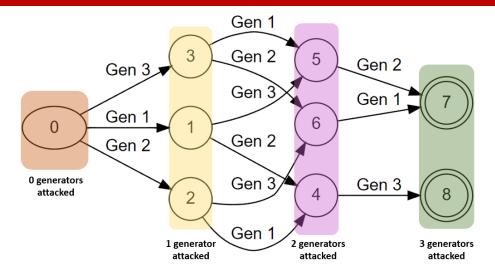
- *PA*: The more generators being attacked the better.
- *PB*: If attacking all generators is possible, attacking Gen 3 in the end is preferred.
- *PC*: Attacking Gen 1 first is preferred to attacking other generators first.

Using Automata Theory:

- $\phi_1 \coloneqq \{8\} \ge \{7\} \ge \{4,5,6\} \ge \{1,2,3\} \ge \{0\}$
- $\phi_2 \coloneqq \{1\} \ge \{2,3\}$



- Value of Preference Satisfaction:
- V_{PS} is closely related to the probability of occurring of that preference.
- V_{PS} for a preference formula X₀ ≤ X₁... ≤ X_n is defined as P(X_i) if there exists some i such that P(X_i) ≥ P(X_{i-1}) while for all k ≥ i the P(X_k) < P(X_{k-1}) holds and is zero if otherwise.
- Policy π₁ satisfies the preference by %50 while policy π₂ satisfies the preference by %80

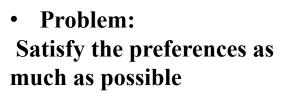


Deterministic Finite Automaton

Automaton state set	P_{π_1}	P_{π_2}
{8}	0.05	0.8
$\{7\}$	0.15	0.05
$\{4, 5, 6\}$	0.5	0
$\{1, 2, 3\}$	0.1	0.05
{0}	0.2	0.1

 $\phi_1 \coloneqq \{8\} \ge \{7\} \ge \{4,5,6\} \ge \{1,2,3\} \ge \{0\}$

Optimization Problem Formulation

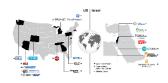


• Formulate the problem as a Mixed Integer Program (MIP)

Constraints are constructed from the

- definition of V_{PS} ,
- the MDP equations(power grid simulated through DCSIMSEP) and the
- automaton made from preferences

MIP problem: $\max_{B,y,V_{PS}} V_{PS}$		
$subject \ to \ Eqs. \ 2, \ 3, \ 4, \ 5, \ 6, \ 7, \ 8$		
Constraints: $0 \le V_{PS} \le B$	(2)	
$B-1 \le V_{PS} - y(T, P') \le 0$	(3)	
$B(1+\epsilon) + 1 \le y(T, P') - y(T, P) \le B(1+\epsilon) - \epsilon$	(4)	
$B \ is \ a \ binary$	(5)	y^{i}
$all \ y \ are \ non-negative,$	(6)	0
$\sum_{a \in A} y(0, (\tilde{s}, s), a) = d(\tilde{s}, s)$	(7)	y3
$\sum_{a \in A} y(t, (\tilde{s}', s'), a) =$		
$\sum_{a \in A} \sum_{(\tilde{s},s) \in \tilde{S} \times S} \Delta((\tilde{s}',s') (\tilde{s},s), a) y(t-1,(\tilde{s},s), a).$	(8)	



$B_{,y,VPS}$
s.t.: y1 + y2 = 0.9
y3 + y4 = 0.05
y5 + y6 = 0.05
y7 + y8 = 0
y9 + y10 - 0.05y1 - 0.05y2 - 0.05y6 - 0.05y3 = 0
y11 + y12 - 0.8y1 - 0.1y2 - 0.95y3 = 0
y13 + y14 - 0.1y1 - 0.8y2 - 0.95y6 = 0
y15 + y16 - 0.05y1 - 0.05y2 - y4 - y5 - y7 - y8 = 0
y17 + y18 - 0.05y9 - 0.05y10 - 0.05y14 - 0.05y11 = 0
y19 + y20 - 0.8y9 - 0.1y10 - 0.95y11 = 0
y21 + y22 - 0.1y9 - 0.8y10 - 0.95y14 = 0
y23 + y24 - 0.05y9 - 0.05y10 - y12 - y13 - y15 - y16 = 0
y25 + y26 - 0.05y17 - 0.05y18 - 0.05y22 - 0.05y19 = 0
y27 + y28 - 0.8y17 - 0.1y18 - 0.95y19 = 0
y29 + y30 - 0.1y17 - 0.8y18 - 0.95y22 = 0
y31 + y32 - 0.05y17 - 0.05y18 - y20 - y21 - y23 - y24 = 0
$-V_{PS} + y27 + y28 + B \le 1$
$V_{PS}-y27-y28 \leq 0$
$y27 + y28 - y29 - y30 - (1+\epsilon)B \le -\epsilon$
$-y27 - y28 + y29 + y30 + (1+\epsilon)B \le 1$
$-V_{PS} \le 0$
$V_{PS} - B \le 0$
$-y_i \le 0$ $i = 1,, 32$
$B \in \{0,1\}$

min $-V_{PS}$

Resource Allocation



• Constraints are constructed from the definition of V_{PS} , the MDP equations(the power grid simulated through DCSIMSEP) and the automaton made from preferences

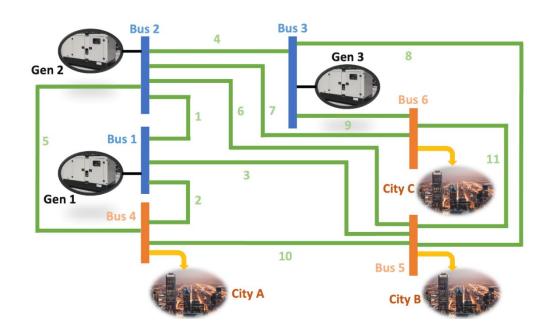
Resource Allocation:

- Defender has limited resources (funding, soldiers, etc.)
- The probability of attack success depends on allocated resources

$$p(i) = \frac{1}{1+h(i)}$$

• Different resource allocation changes MDP equations

New Resource Allocation New MDP equations New Constraints New MIP



MIP problem: $\max_{B,y,V_{PS}} V_{PS}$ subject to Eqs. 2, 3, 4, 5, 6, 7, 8

Deep RL in Preference Based Resource Allocation



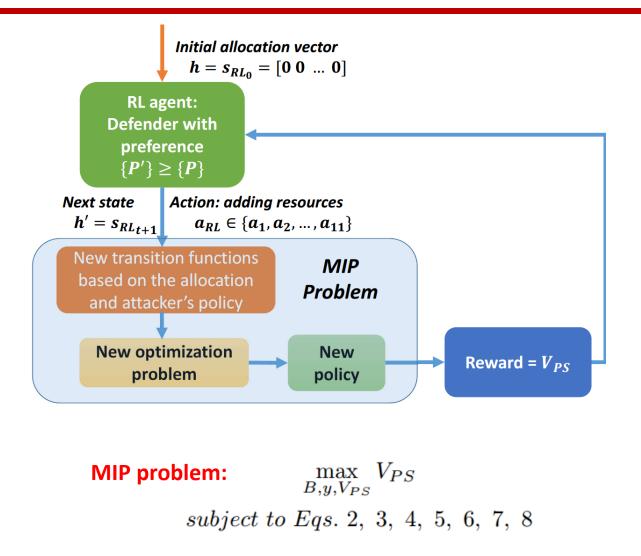
 New Resource
 New MDP
 New
 New

 Allocation
 equations
 New
 MIP

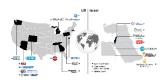
• Problem:

Optimally allocate resources to defend transmission lines such that the allocation satisfies the preferences as much as possible

- Use Deep Reinforcement Learning (DRL) to learn the optimal resource allocation
- At each time step, a new MIP will be constructed and solved



Results



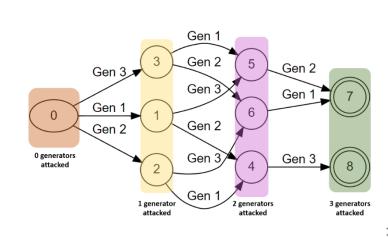
• Problem:

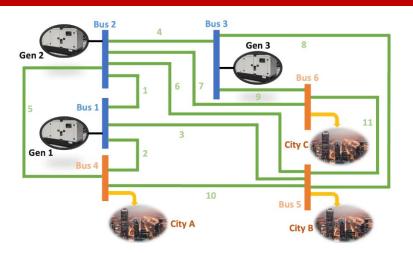
Optimally allocate resources to defend transmission lines and satisfy the preferences as much as possible

- Power Grid: W&W 6-Bus System
- DRL method: DQN
- Preferences considered:
- $\#1: \{6\} \le \{0, 1, 2, 3, 4, 5\}$
- $#2: \{5, 6, 7, 8\} \le \{0, 1, 2, 3, 4, 5\}$
- $#3: \{4, 5, 6, 7, 8\} \le \{0, 1, 2, 3\}$

Simulation tool:

DC load flow simulator of cascading (separation) in power systems (DCSIMSEP)





Resources (H)	Pref.#	Allocation Vector (h)	V_{PS}
H=0	1	h = [0,0,0,0,0,0,0,0,0,0,0]	0.3192
H=0	2	h = [0,0,0,0,0,0,0,0,0,0,0]	0.3192
H=0	3	h = [0,0,0,0,0,0,0,0,0,0,0]	0
H=1	2	h = [0,0,0,0,1,0,0,0,0,0,0]	1
H=2	2	h = [0,0,0,0,1,0,0,0,0,1,0]	1
H=3	2	h = [0,0,0,1,1,1,0,0,0,0,0]	1
H=4	1	h = [0, 0, 0, 2, 1, 1, 0, 0, 0, 0, 0]	1
H=7	3	h = [0, 0, 0, 0, 3, 0, 2, 2, 0, 0, 0]	0.5941
H=10	3	h = [0,0,1,0,4,0,2,3,0,0,0]	0.6057
H=20	3	h = [0,0,0,0,10,0,1,9,0,0,0]	0.6475



Defending smart electrical power grids against cyberattacks with deep Q-learning

Mohammadamin Moradi,¹ Yang Weng,¹ and Ying-Cheng Lai^{1, 2, *} ¹School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ 85287, USA ²Department of Physics, Arizona State University, Tempe, Arizona 85287, USA

(Dated: July 19, 2022)

A key to ensuring the security of smart electrical power grids is to devise and deploy effective defense strategies against cyberattacks. To achieve this goal, an essential task is to simulate and understand the dynamical interplay between the attacker and defender, for which stochastic game theory and reinforcement learning stand out as a powerful mathematical/computational framework. Existing works were based on conventional Q-learning to find the critical sections of a power grid to choose an effective defense strategy, but the methodology was applicable to small systems only. Additional issues with Q-learning are the difficulty to consider the timings of cascading failures

Preference based resource allocation in cyber-security defense of power grids using reinforcement learning

Mohammadamin Moradi,¹ Yang Weng,¹ and Ying-Cheng Lai^{1, 2, *}

 ¹School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ 85287, USA
 ²Department of Physics, Arizona State University, Tempe, Arizona 85287, USA (Dated: August 10, 2022)

Abstract. Preferences and priorities play a key role in the real world decision making problems. Moreover, limited human/financial resources in cyber-security applications highlight the significance of an optimal resource allocation. When combined, a preference based optimal resource allocation problem proves itself worthy in the decision making field. In this paper, we propose reinforcement learning based framework to solve the mentioned problem. Our solution, uses Automata theory Status: Submitted to PRX Energy

Status: Draft version ready



Basic Research:

- Larger power grids or more complex preferences cause the number of constraints to grow exponentially
- Large number of constraints renders the MIP to be infeasible by conventional solvers
- Find a way to deal with large number of constraints

Commercialization:

• Work with Nexant to implement the principle and methodologies of reinforcement learning control of cyber physical systems into the existing industrial Operational Technology and Industrial Control Systems management software tools.

