SoSECIE Webinar

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2023 System of Systems Engineering Collaborators
Information Exchange (SoSECIE)

We will start at 11AM Eastern Time

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NDIA System of Systems SE Committee

- **Mission**
  - To provide a forum where government, industry, and academia can share lessons learned, promote best practices, address issues, and advocate systems engineering for Systems of Systems (SoS)
  - To identify successful strategies for applying systems engineering principles to systems engineering of SoS
- **Operating Practices**
  - Face to face and virtual SoS Committee meetings are held in conjunction with NDIA SE Division meetings that occur in February, April, June, and August

NDIA SE Division SoS Committee Industry Chairs:
Mr. Rick Poel, Boeing
Ms. Jennie Horne, Raytheon
OSD Liaison:
Dr. Judith Dahmann, MITRE

Simple Rules of Engagement

- **I have muted all participant lines for this introduction and the briefing.**
- **If you need to contact me during the briefing, send me an e-mail at sosecie@mitre.org.**
- **Download the presentation so you can follow along on your own**
- **We will hold all questions until the end:**
  - **I will start with questions submitted online via the CHAT window in Teams.**
  - **I will then take questions via telephone; State your name, organization, and question clearly.**
- **If a question requires more discussion, the speaker(s) contact info is in the brief.**

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2022 System of Systems Engineering Collaborators Information Exchange Webinars

Sponsored by MITRE and NDIA SE Division

November 29, 2022

What Systems Engineers Should Know about Emergence

Jakob Axelsson

https://www.mitre.org/capabilities/systems-engineering/collaborations/system-of-systems-engineering-collaborators

Ramakrishnan Raman & Anitha Murugesan

Honeywell | AEROSPACE

Framework for Complex SoS Emergent Behavior Evolution Using Deep Reinforcement Learning

Presentation Outline

Introduction → **Proposed Framework** → **Conclusion**

Introduction
- MOEs/MOPs
- Complex SoS
- Emergent Behavior
- MOE Relationships
- Machine Learning

Proposed Framework
- Overview
- Reinforcement learning
- Power Grid SoS Case Study
- Experimental Setup
- Scenario Simulations
- Strengths & Limitations

Conclusion
- Future Work
- Conclusions

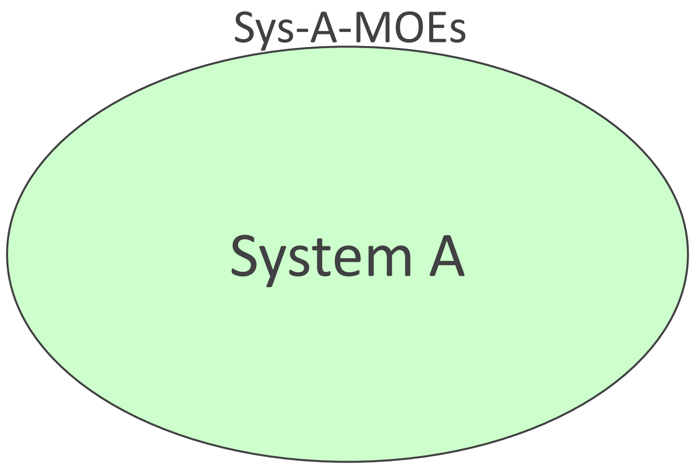
Introduction Section

Introduction → Proposed Framework → Conclusion

- MOEs/MOPs
- Complex SoS
- Emergent Behavior
- MOE Relationships
- Machine Learning

Measures of Effectiveness - MOEs

- Operational measures of success that are closely related to the achievement of the objective of the system of interest
- Related to the achievement of the mission or operational objective being evaluated
  - In the intended operational environment
  - Under a specified set of conditions
- Manifest at the boundary of the system
- Examples
  - Response time to a user action
  - Time to Alert
  - Availability of the system

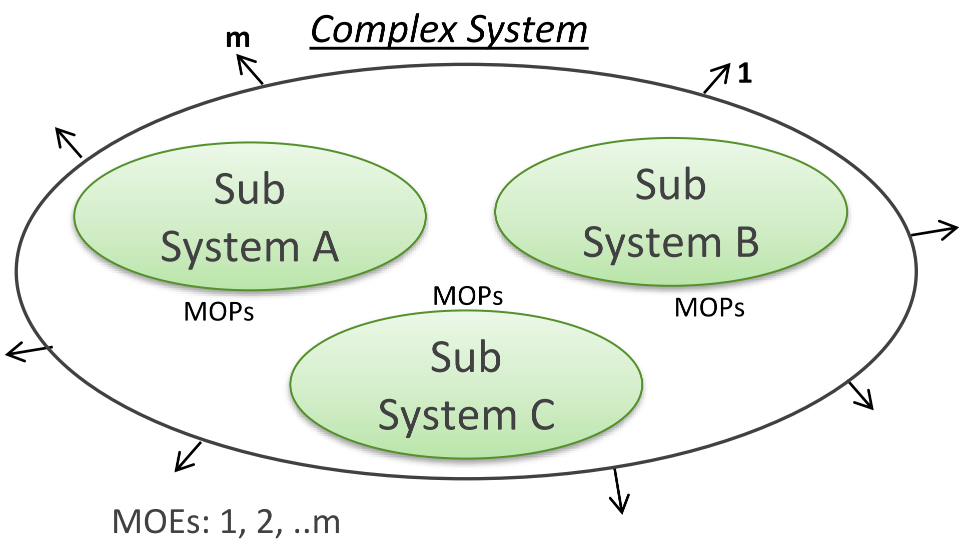


Each system is associated with a desired set of MOEs.

Measures of Performance - MOPs

- MOPs: measures that characterize physical or functional attributes relating to the system operation, measured or estimated under specified test and/or operational environmental conditions

- MOPs define the key performance characteristics the system should have when fielded and operated in its intended operating environment, to achieve the desired MOEs of the system



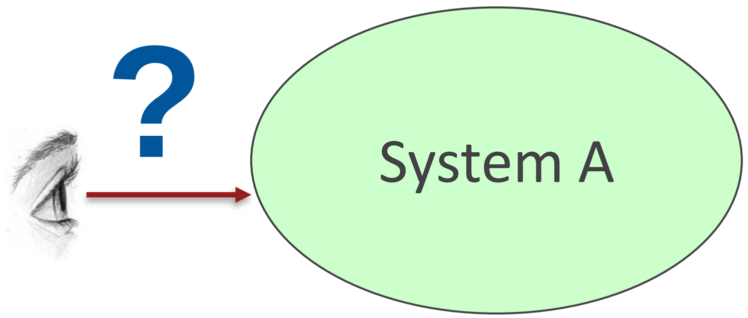
MOPs are dependent on the specific solution

Complex Systems

Complexity: Degree of difficulty in accurately predicting the future behavior

Complexity is determined by the system being observed, the capabilities of the observer, and the behavior that the observer is attempting to predict

The perspective of complexity used in this work is with respect to the degree of difficulty in accurately <u>understanding</u> the <u>behavior</u> and adapting to the same

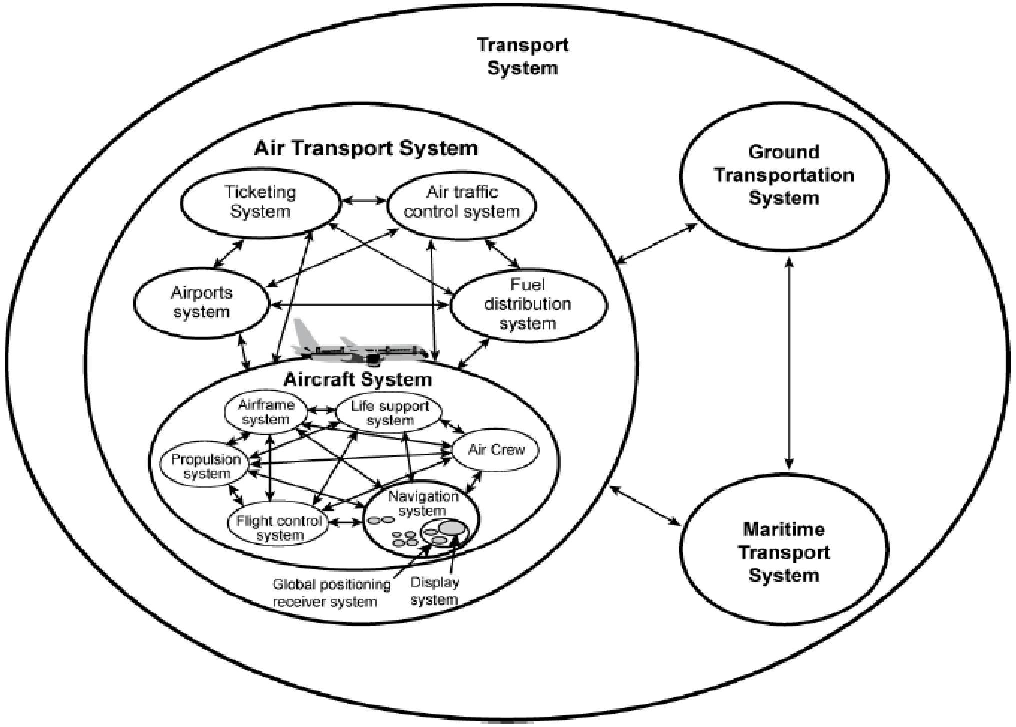


- Multiplex of relationships/ forces/ interactions between subsystems & constituent systems
- Difficulties in establishing cause-and-effect chain
- Characteristics: Emergence, hierarchical organization, numerosity….

System-of-Systems

System-of-Systems are systems-of-interest whose system elements are themselves systems - they typically entail large-scale inter-disciplinary problems involving multiple, heterogeneous and distributed systems

Each system has an independent purpose and viability, in addition to the SoS by itself having an independent purpose and viability



Source: INCOSE SE Handbook

Emergent Behavior

Emergence refers to the ability of a system to produce a highly-structured collective behavior over time, from the interaction of individual subsystems

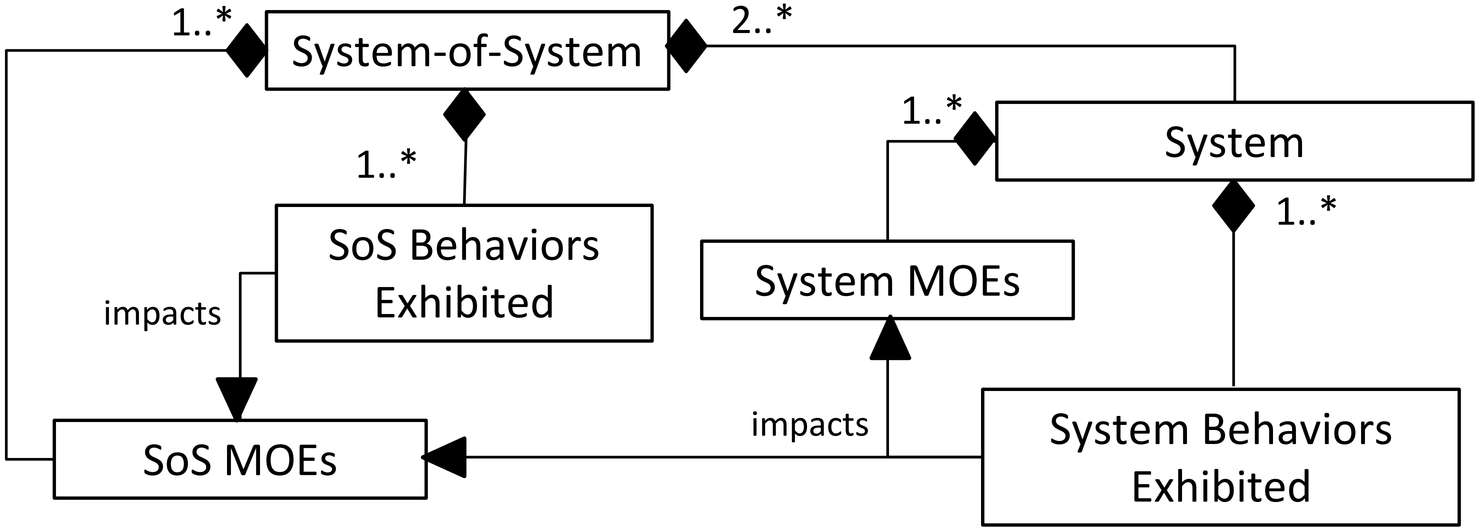
For a system, emergent behavior refers to all that arises from the set of interactions among its subsystems and components

For system-of-system, emergent behavior refers to all that arises from the set of interactions among its constituent systems

(howitworksdaily.com)

Complex systems are expressed by the emergence of global properties. It is difficult, if not impossible, to anticipate emergence just from a complete knowledge of component or subsystem behaviors

MOE Relationships



The MOEs of the system are impacted by the behaviors exhibited by the system.

Similarly, the MOEs of the SoS are impacted by the behaviors exhibited at SoS level.

Further, the behaviors exhibited at constituent system level also impacts the SoS MOEs.

MOE Relationship Matrix

A means to analyze the MOE relationships between the constituent systems and SoS

Relative importance of each SoS MOE

System Of System - MoEs	SoS MoE Weight	MOEs of constituent Systems: SysA-MoE-1	SysA-MoE-2	SysA-MoE-3	SysB-MoE-1	SysB-MoE-2	SysC-MoE-1	SysC-MoE-2	SysD-MoE-1	SysD-MoE-2
SoS-MoE-1	9	9	9	7					1	
SoS-MoE-2	7			5	7	7	7		1	
SoS-MoE-3	5	7	9	5					7	
SoS-MoE-4	1	9	9	7				7	5	5
	Raw score	125	135	130	49	49	49	7	56	5
	Relative Weight	21%	22%	21%	8%	8%	8%	1%	9%	1%
	Rank	3	1	2	5	5	5	8	4	9

System A is a key player in the SoS

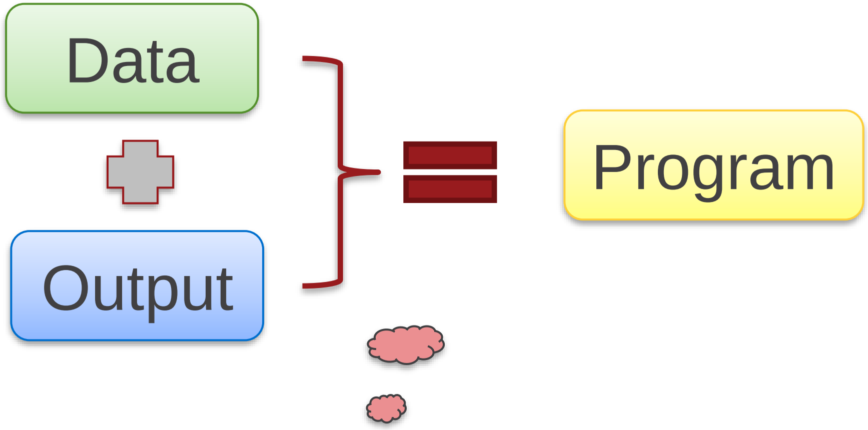
Relative impact of each System MOE on each SoS MOE

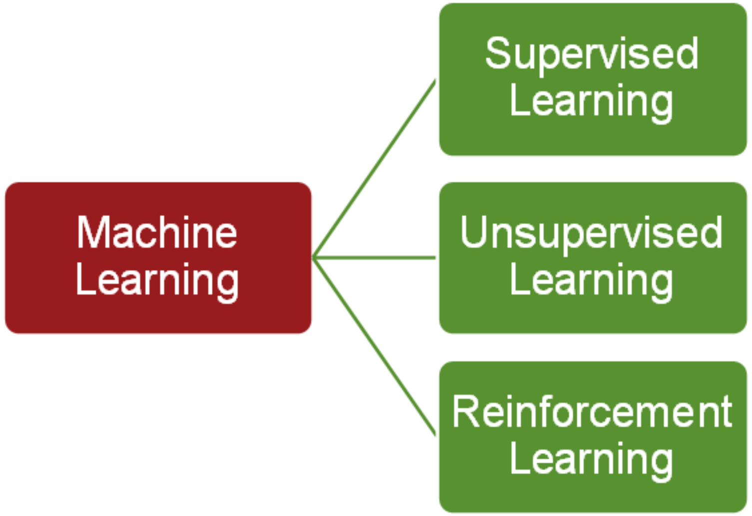
SoS Evolution will impact the relationships

Machine Learning

“Machine learning can be broadly defined as computational methods using experience to improve performance or to make accurate predictions”

“Machine Learning represents the field of study that allows computer programs to learn without being explicitly programmed”



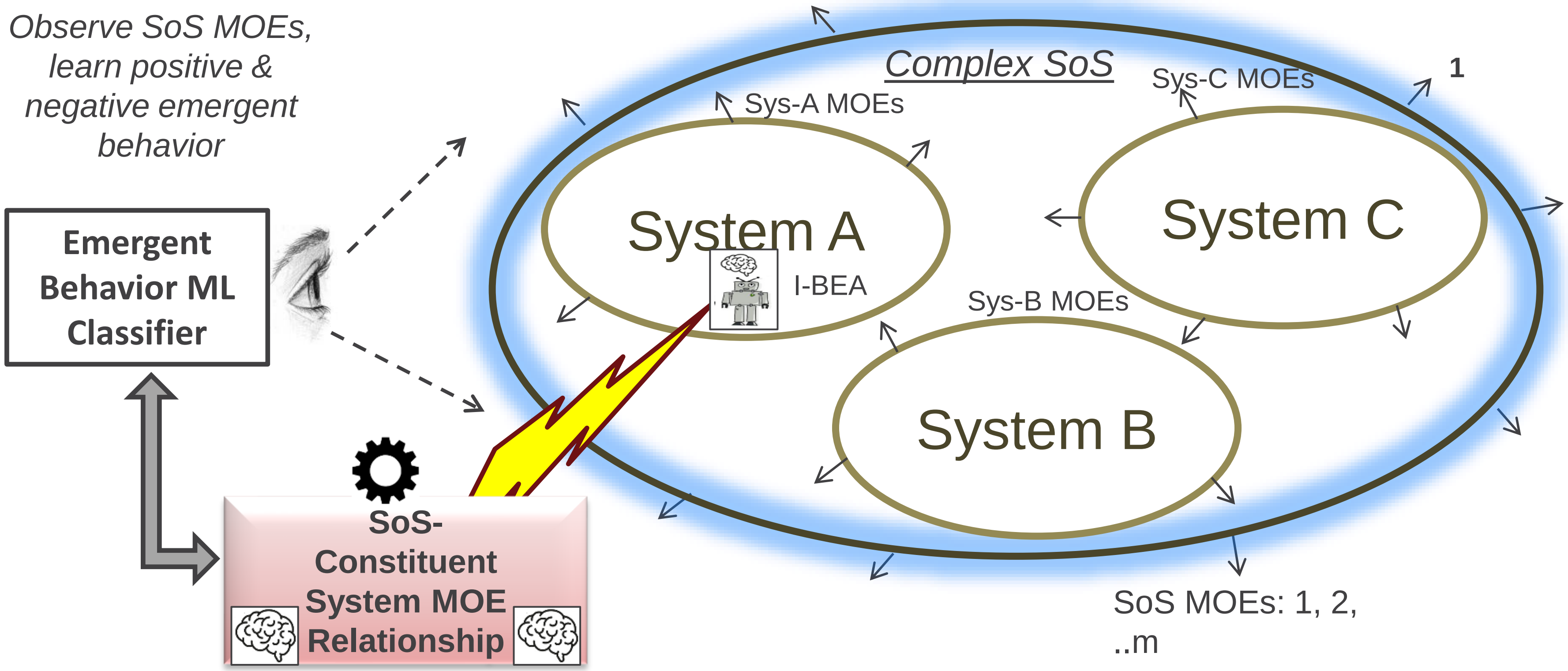


Proposed Framework

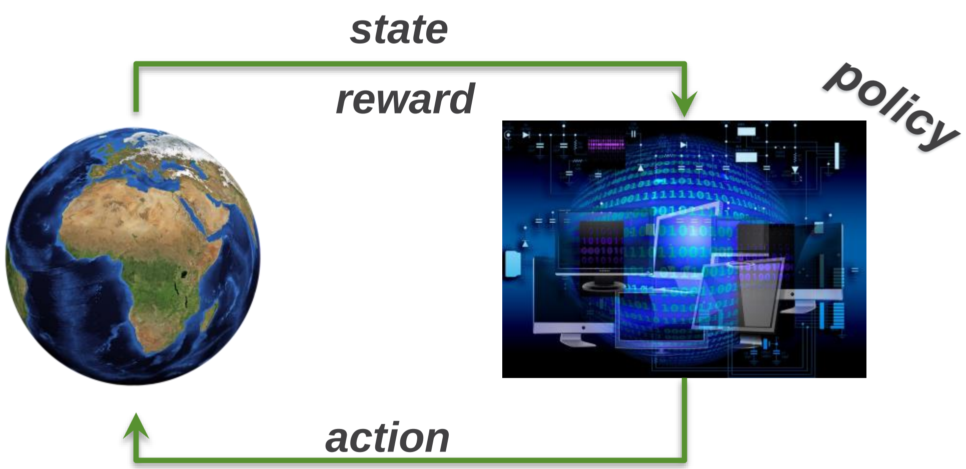
Introduction → **Proposed Framework** → Conclusion

- Overview
- Reinforcement learning
- Power Grid SoS Case Study
- Experimental Setup
- Scenario Simulations
- Strengths & Limitations

Approach Overview



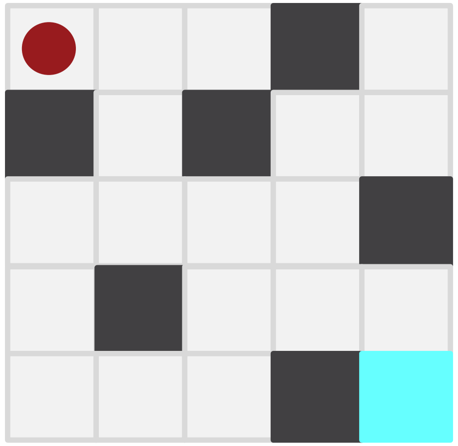
Reinforcement Learning (RL)



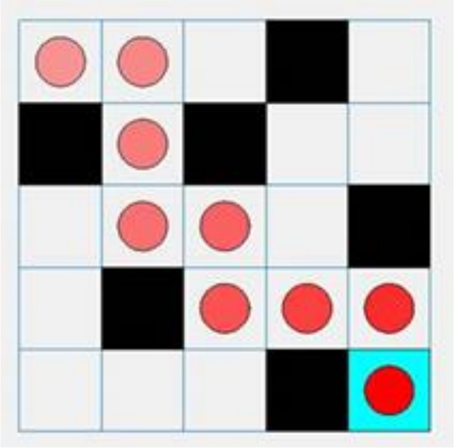
"….Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal. The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them…" - Richard S. Sutton and Andrew G. Barto

- Reinforcement learning is a type of machine learning approach that allows agents to automatically learn optimal control strategies by iteratively interacting with its environment
- An RL agent performs an *action;* in response it receives the description of the environment –*state* – and feedback indicating the impact of the action on the environment– *reward*
- Using this feedback, the agent optimizes its *policy* for choosing its next action to receive higher reward

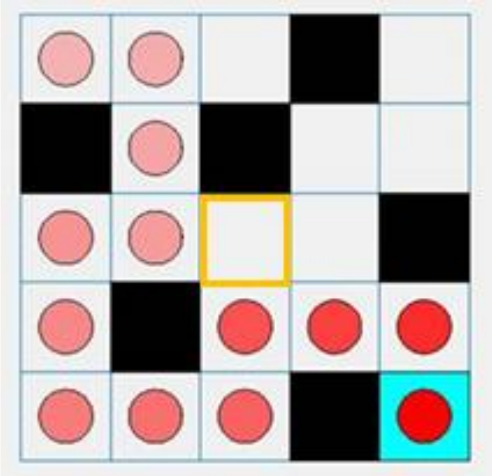
ILLUSTRATIVE GRID WORLD EXAMPLE



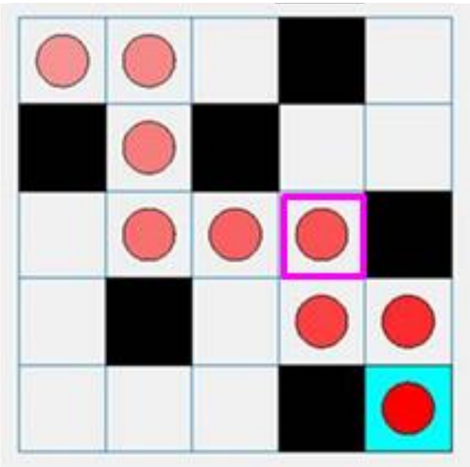
System MOEs only



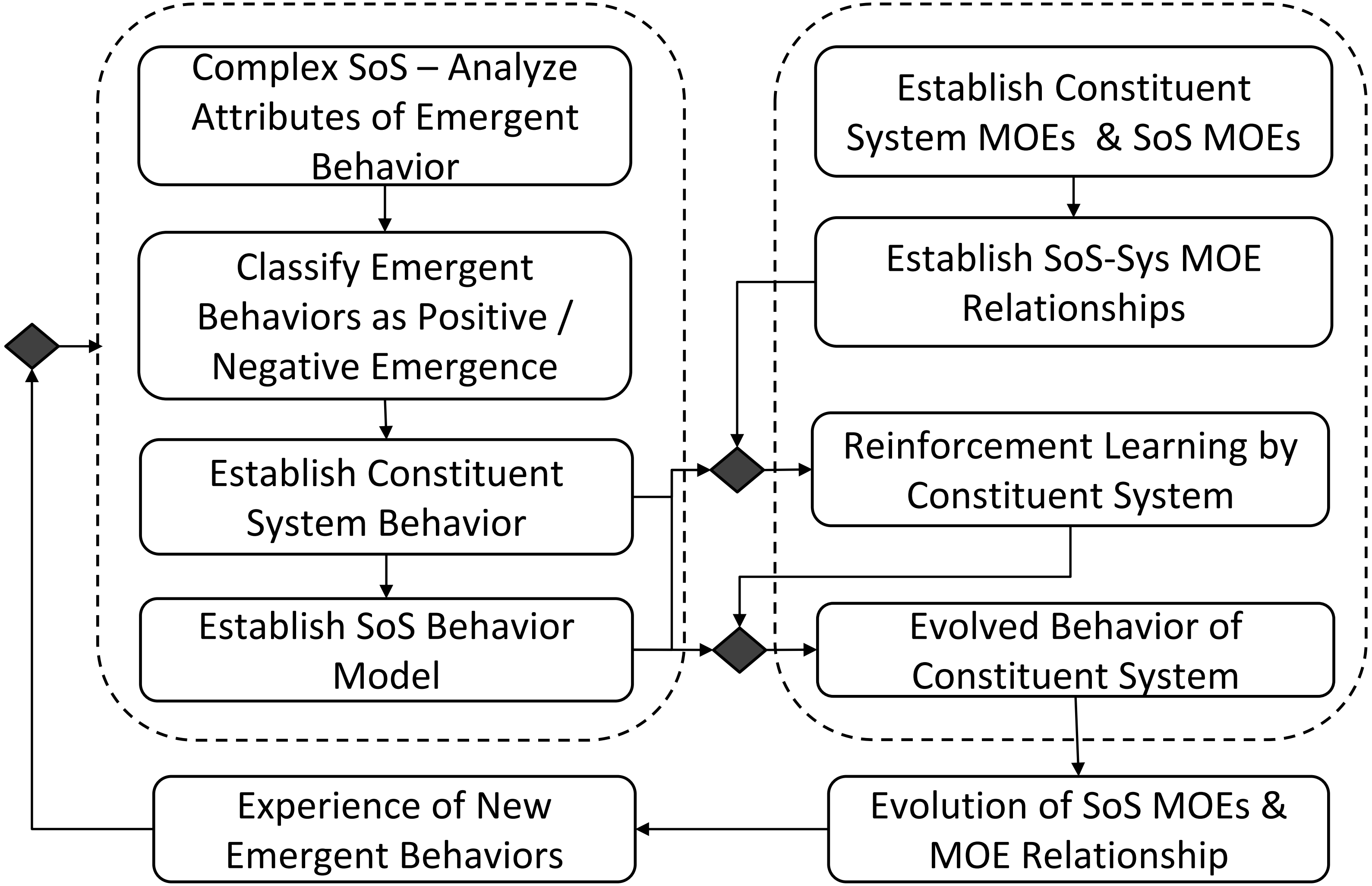
System+SoS MOEs
Low SoS MOEs for [3,3]



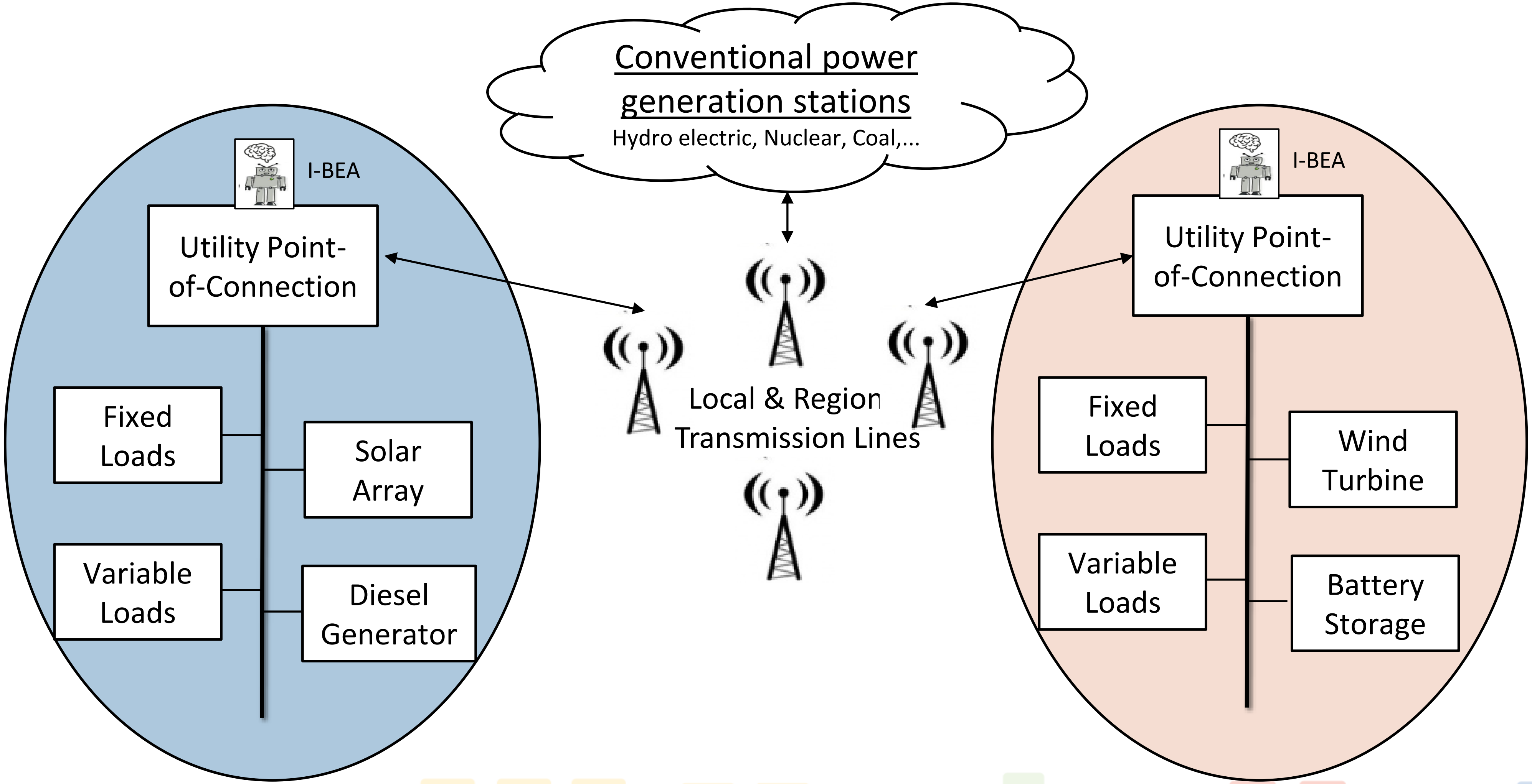
System+SoS MOEs
High SoS MOEs for [3,4]



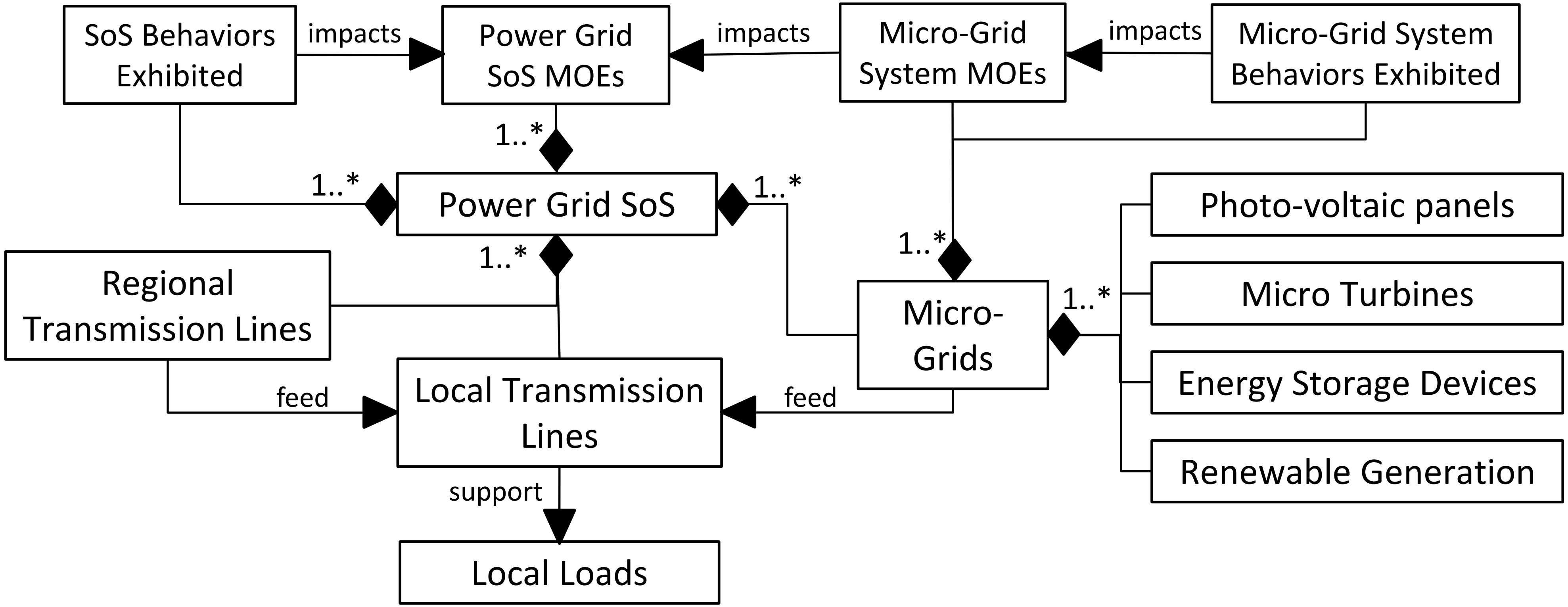
Proposed Framework



Power Grid SoS – Constituent Systems

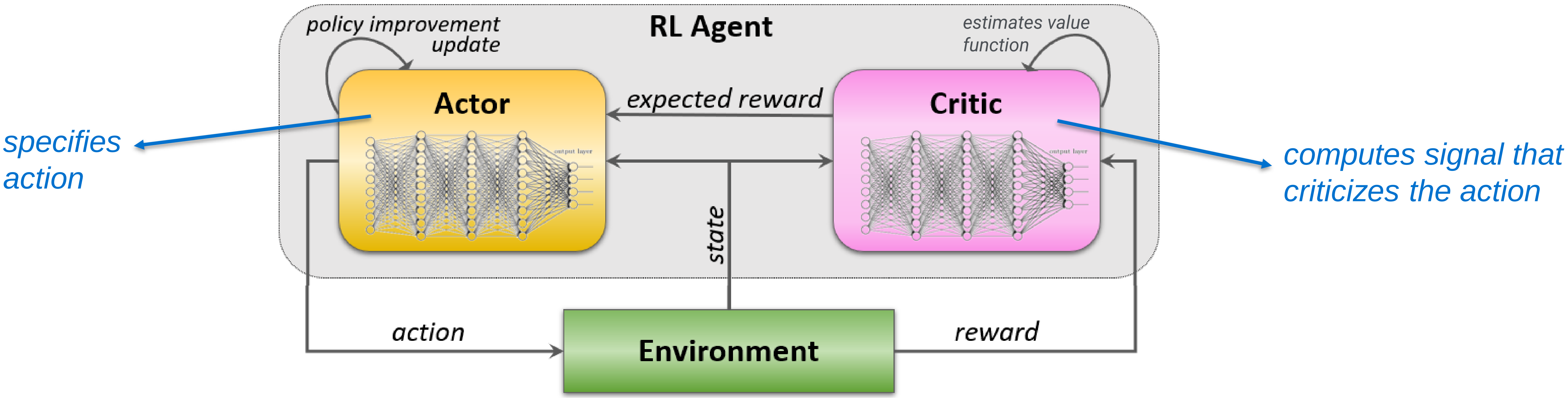


Power Grid SoS

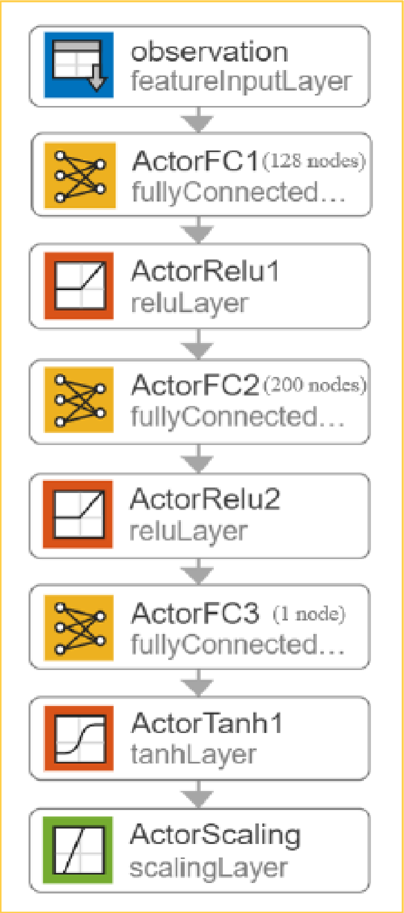


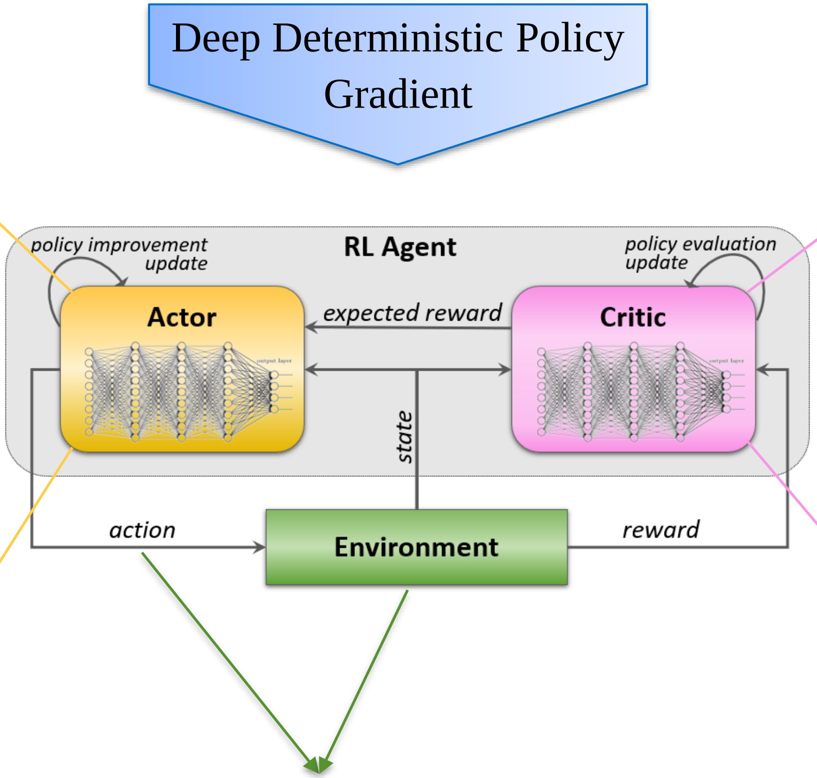
Deep RL

- RL involving artificial neural networks is called Deep RL
- Deep Deterministic Policy Gradient (DDPG) - gradient update rule to learn deterministic policy
  - Actor-Critic Approach that simultaneously learn a policy and value function

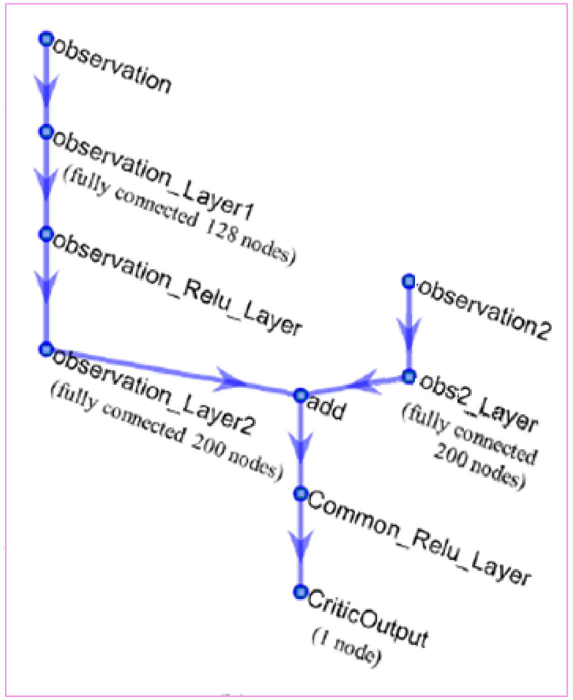


Experimental Setup





$\{x \mid x \in \mathbb{R} \text{ and } 0 \leq x \leq 1\}$



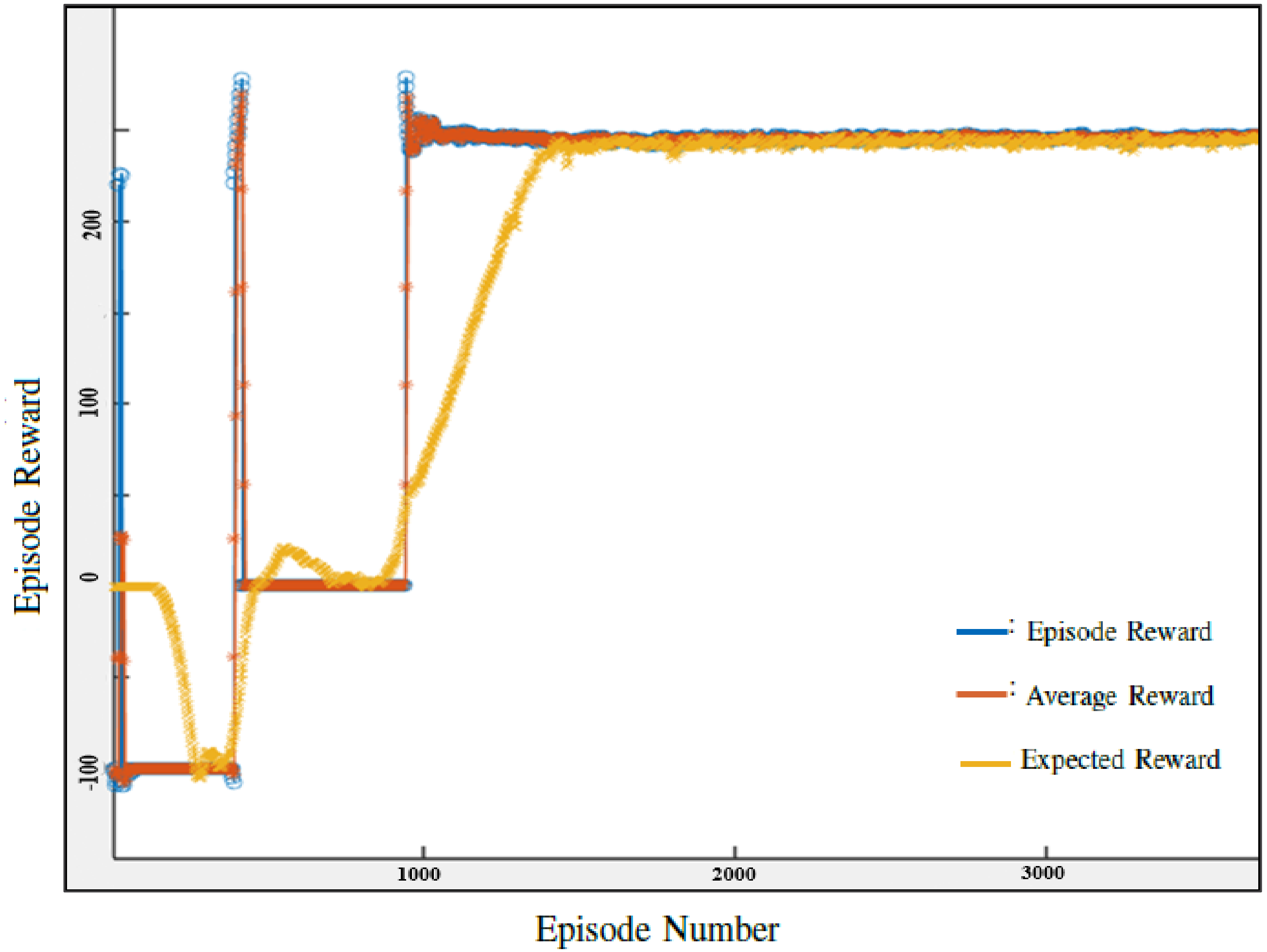
MATLAB RL Toolbox was used for simulation experiments

Scenario Simulation

- New Constituent System in SoS
  - Desired Range per SSMR
- SoS Emergent Behavior Evolution
  - Step Up Rewards
  - Step Down Rewards

Scenario 1: New Constituent System Introduced in SoS

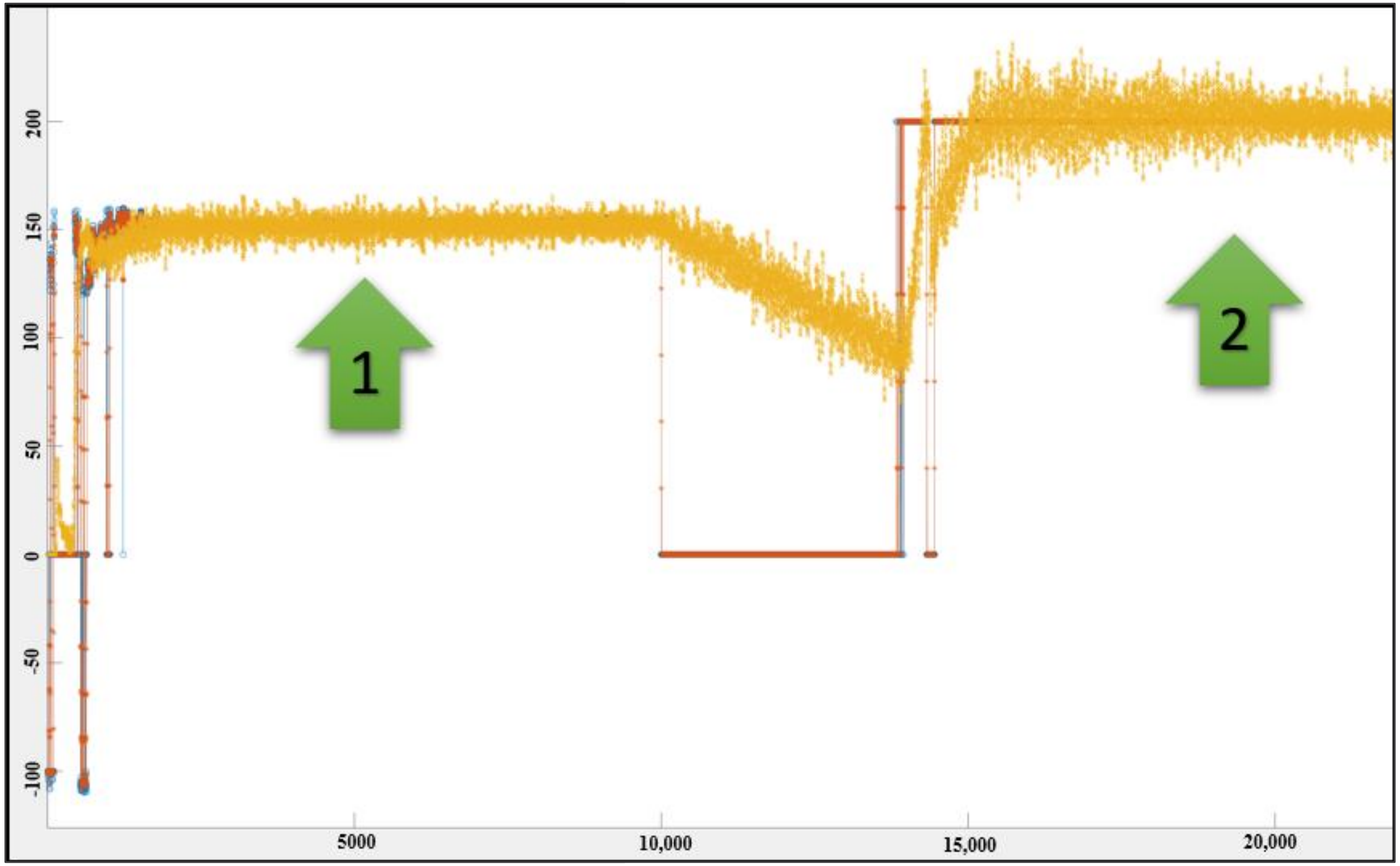
#	Behavior	Action Value	Reward
1	Desired	0.1 to 0.4	200+
	Undesired	< 0.1	-100



Scenario 2: SoS Emergent Behavior Evolution

Step Up Rewards

#	Behavior	Action Value	Reward
1	Desired	0.2 to 0.6	150+
1	Undesired	< 0.1	-100
2	Desired	0.59 to 0.9	**200**
2	Undesired	< 0.3	-100

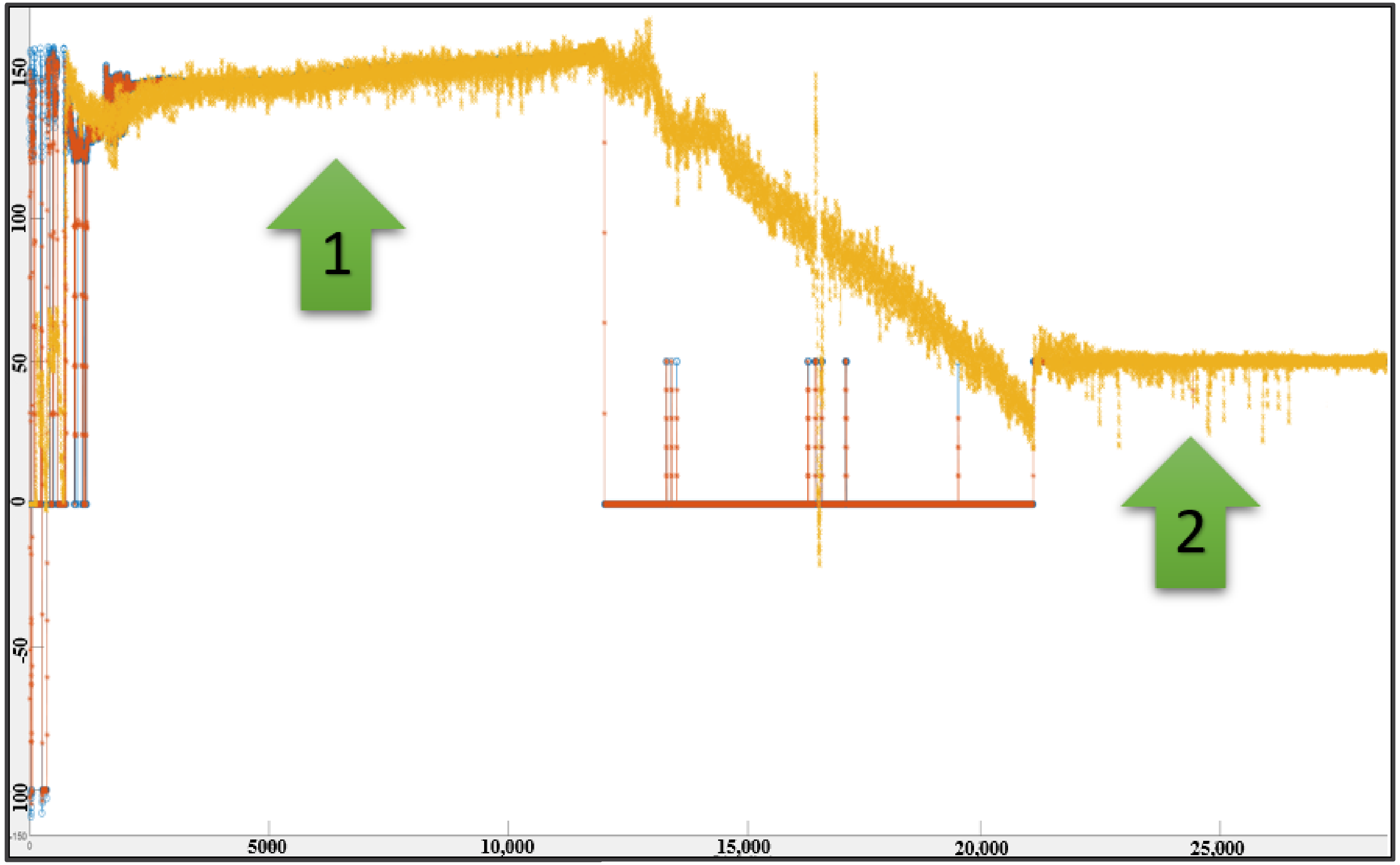


Legend: *X-Axis*: Episode Number *Y-Axis*: Episode Reward —: Episode Reward —: Average Reward —: Expected Reward

Scenario 2: SoS Emergent Behavior Evolution

Step Down Rewards

#	Behavior	Action Value	Reward
1	Desired	0.2 to 0.6	150+
1	Undesired	< 0.1	-100
2	Desired	0.59 to 0.9	**50**
2	Undesired	< 0.3	-100



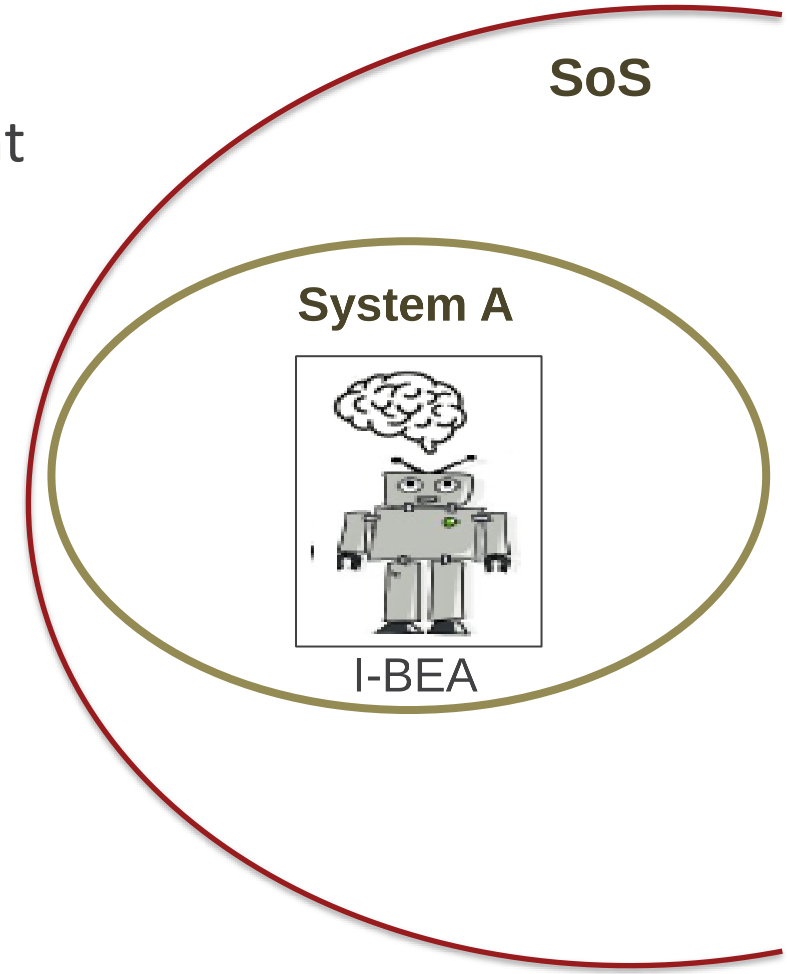
Legend: *X-Axis*: Episode Number *Y-Axis*: Episode Reward : Episode Reward : Average Reward : Expected Reward

Strengths & Limitations

- The I-BEA can be considered as a "plug-in" component agent across the various heterogenous constituent systems (micro grids) that provides adaptable intelligence in tandem with the evolution at the Power grid SoS

- I-BEAs are able to learn faster and adapt to the new evolution if the new range either overlaps or is moderately different from that learnt prior

- However, for drastic evolution at SoS level, the I-BEAs are not able learn within a reasonable number of training episodes



Conclusions

Introduction

Proposed Framework

Conclusion

- Future Work
- Conclusions

Conclusion & Future Work

- In this session, we presented a novel framework that leverages deep RL to inculcate adaptable intelligence in constituent systems in tandem with the evolution of emergent behavior at SoS level.
- The framework incorporates an I-BEA in each constituent system of the SoS and leverages SoS-constituent System MOE Relationships to learn to maximize the SoS and system level MOEs by enabling positive emergent behavior.
- The framework was illustrated through a case study of Power Grid SoS, that comprises multiple constituent system micro grids.
- In future, we plan to:
  1. Analyze the operational performance and scalability of I-BEA on real-time scenarios
  2. Compare-Contrast studies among various RL algorithms
  3. Integrate our approach with Deep Neural Network based SSMR for rewards
  4. Extend our approach to online RL learning approaches

Using Reinforcement Learning to Enable Individual Systems to Dynamically Adapt within System-of-Systems

1. Murugesan, A. and Raman, R. 2021, April. Reinforcement Learning for Emergent Behavior Evolution in Complex System-of-Systems. In *ICONS 2021, The Sixteenth International Conference on Systems* (pp. 5-10).

2. Raman, R. and Murugesan, A., 2022, April. Reinforcement Learning based System-of-Systems Approach for UAV Swarms Behavioral Evolution. In *2022 IEEE International Systems Conference (SysCon)* (pp. 1-8). IEEE.

3. Raman, R. and Murugesan, A., 2022, Jul. Framework for Complex SoS Emergent Behavior Evolution Using Deep Reinforcement Learning. *INCOSE International Symposium*, 32: 809-823.

Thank You