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Honeywell | AEROSPACE

Framework for Complex SoS Emergent Behavior Evolution Using Deep Reinforcement Learning

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Presentation Outline

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

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

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

Conclusion
- Future Work
- Conclusions

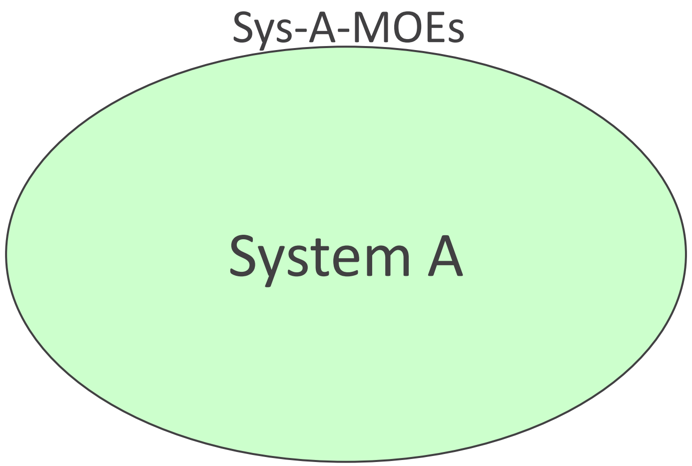
Introduction Section

Introduction → Proposed Framework → Conclusion

- MOEs/MOPs
- Complex SoS
- Emergent Behavior
- MOE Relationships
- Reinforcement 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

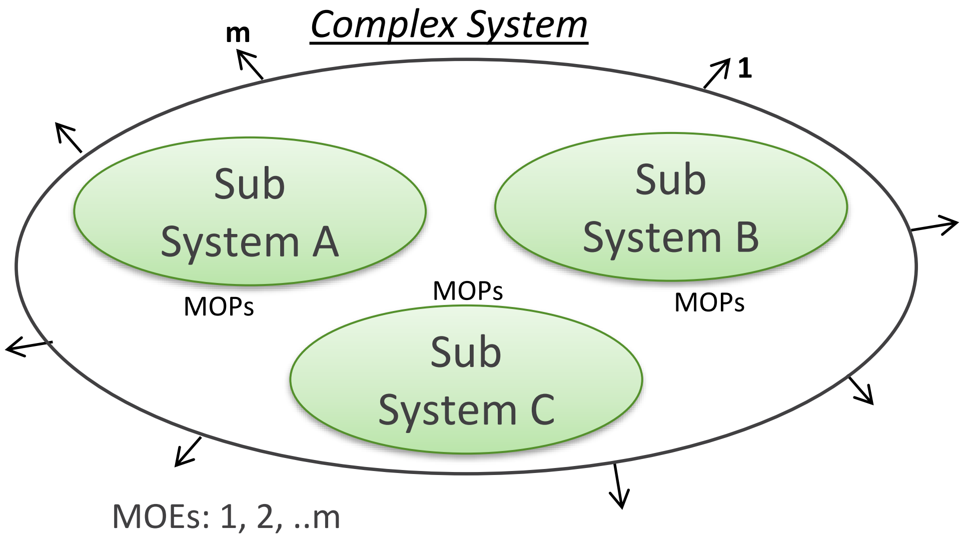


Each system is associated with a desired set of MOEs.

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



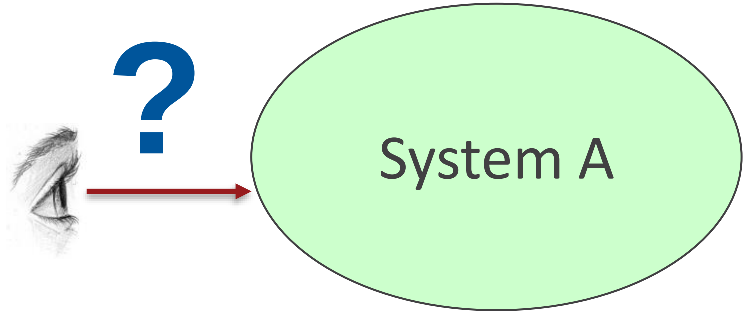
MOPs are dependent on the specific solution

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>predicting</u> the future <u>behavior</u>

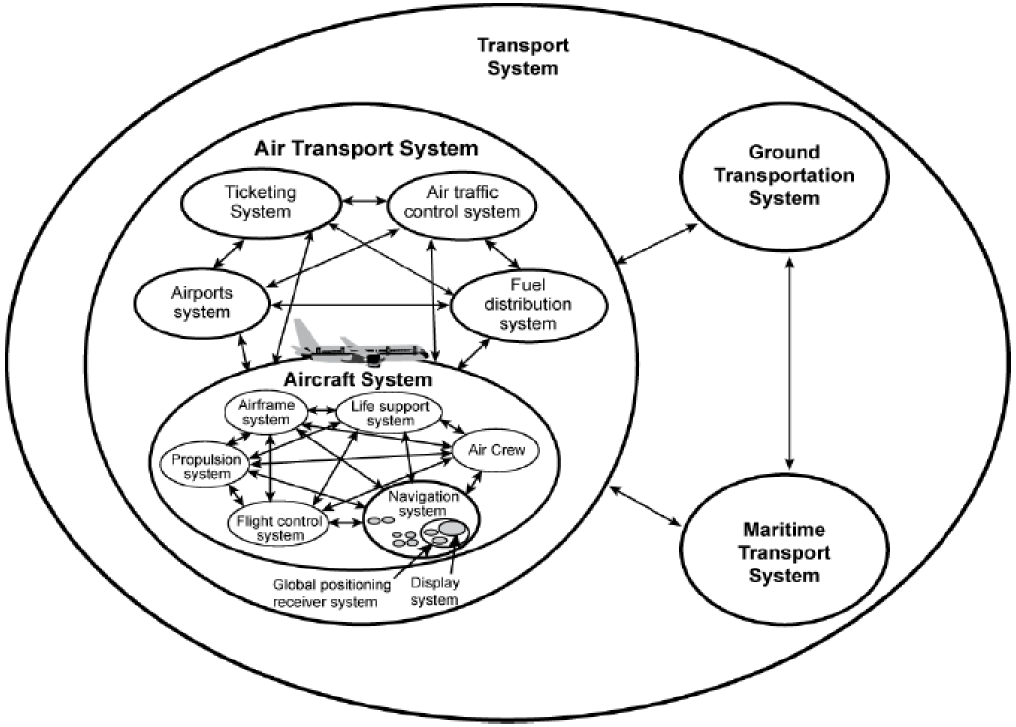


- Multiplex of relationships/ forces/ interactions between subsystems & constituent systems
- Difficulties in establishing cause-and-effect chain
- Characteristics: Emergence, hierarchical organization, numerosity….

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

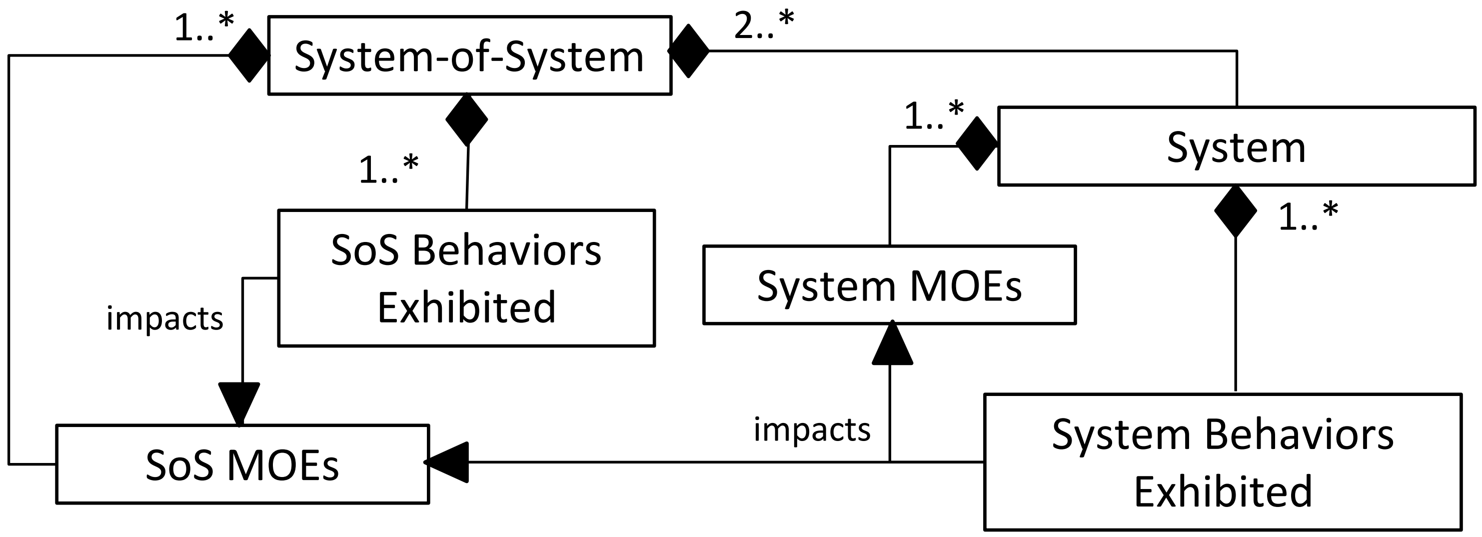
For a system, emergent behavior refers to all that arises from the set of interactions among its subsystems and components

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

System Of System - MoEs	SoS MoE Weight	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
Relative importance of each SoS MOE		MOEs of constituent Systems								
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

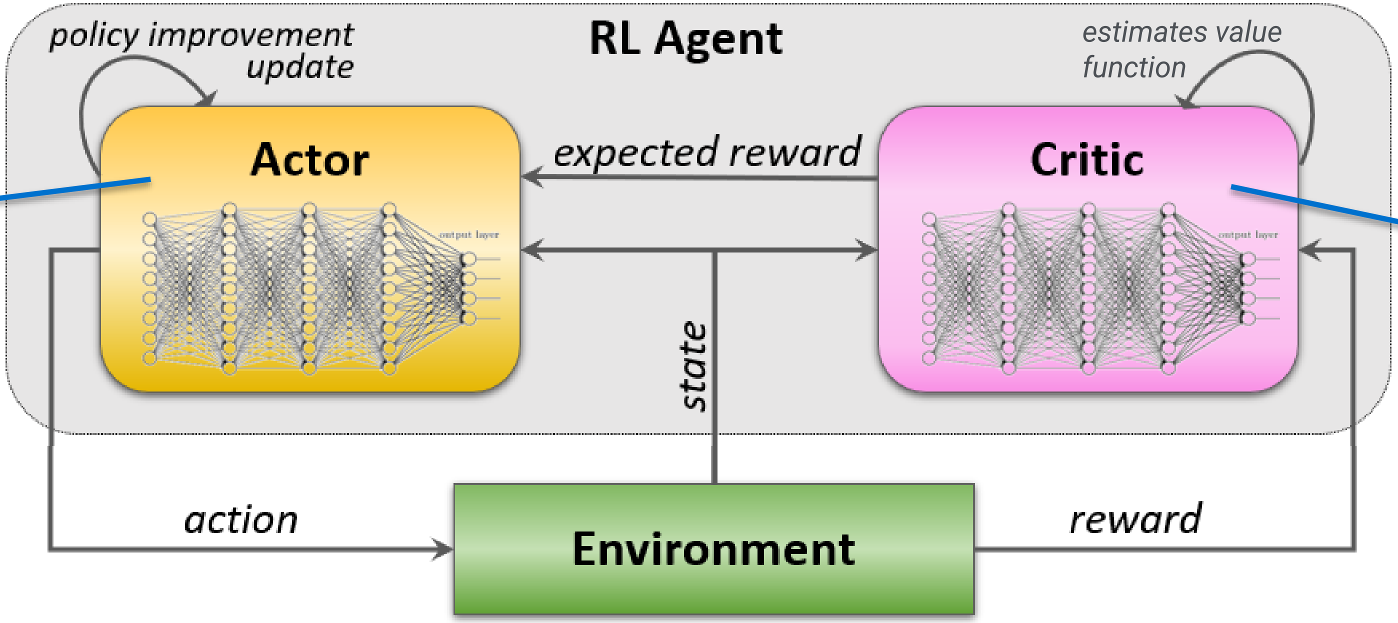
Relative impact of each System MOE on each SoS MOE

SoS Evolution will impact the relationships

Reinforcement Learning (RL)

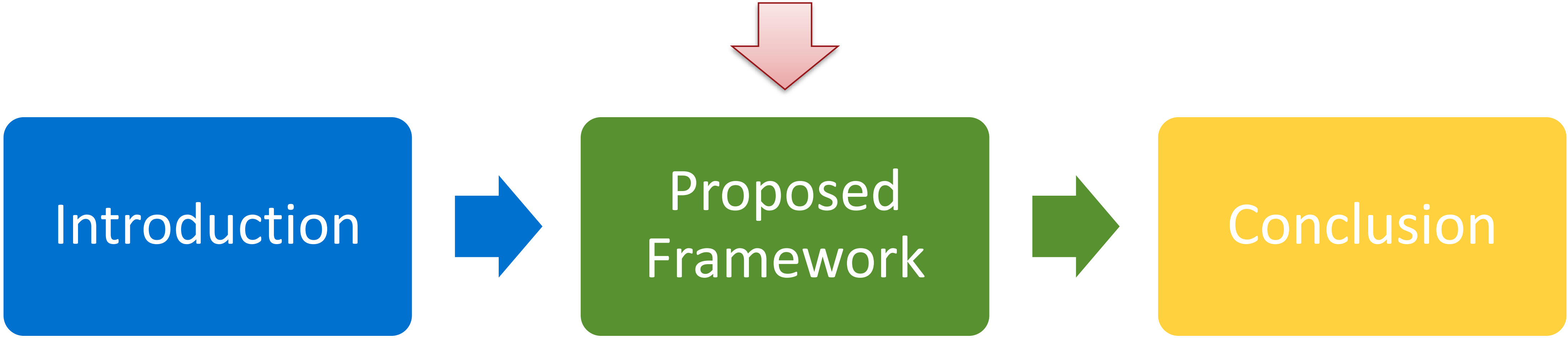
- Agent learns by iteratively performing actions on its environment and receiving rewards
- RL involving artificial neural networks is called Deep RL
- Deep Deterministic Policy Gradient (DDPG) - gradient update rule to learn deterministic policy
  - Actor-Critic Approach that simultaneously learn a policy and value function

specifies action



computes signal that criticizes the action

Proposed Framework



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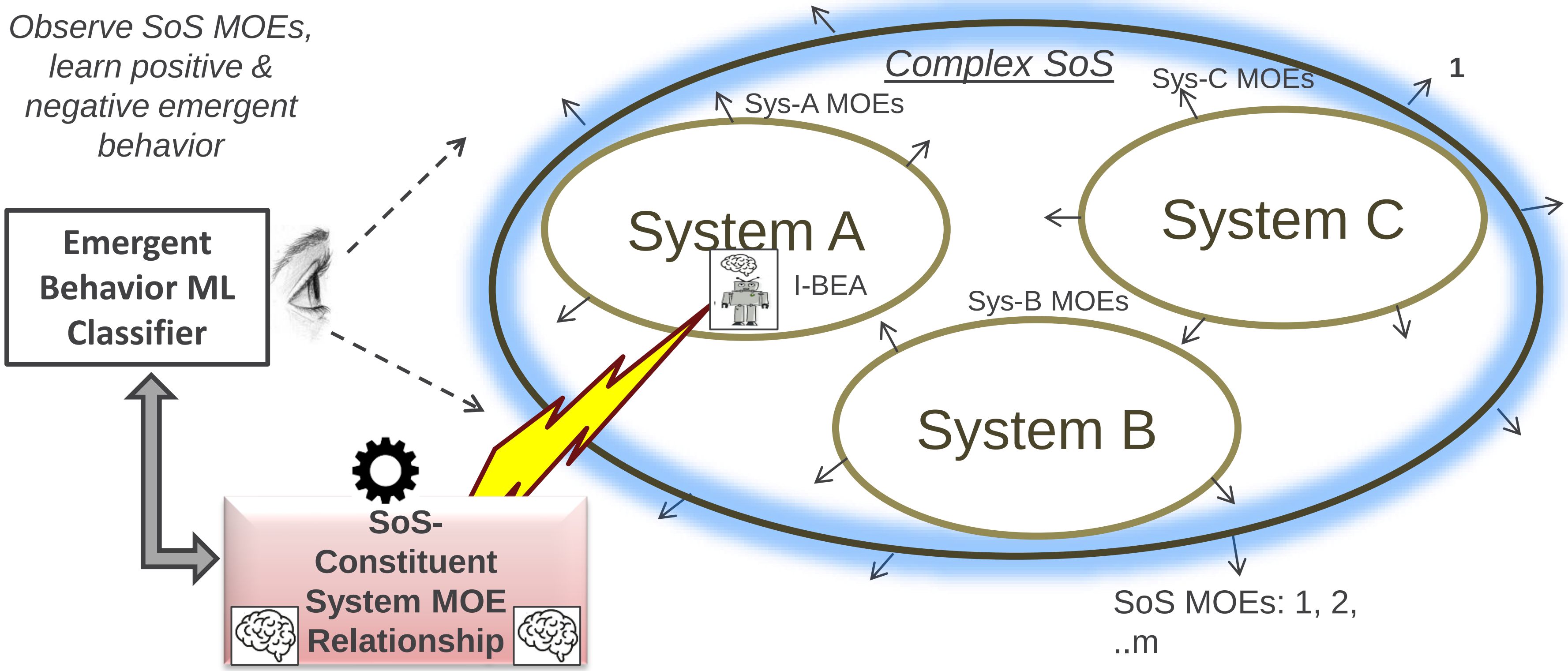
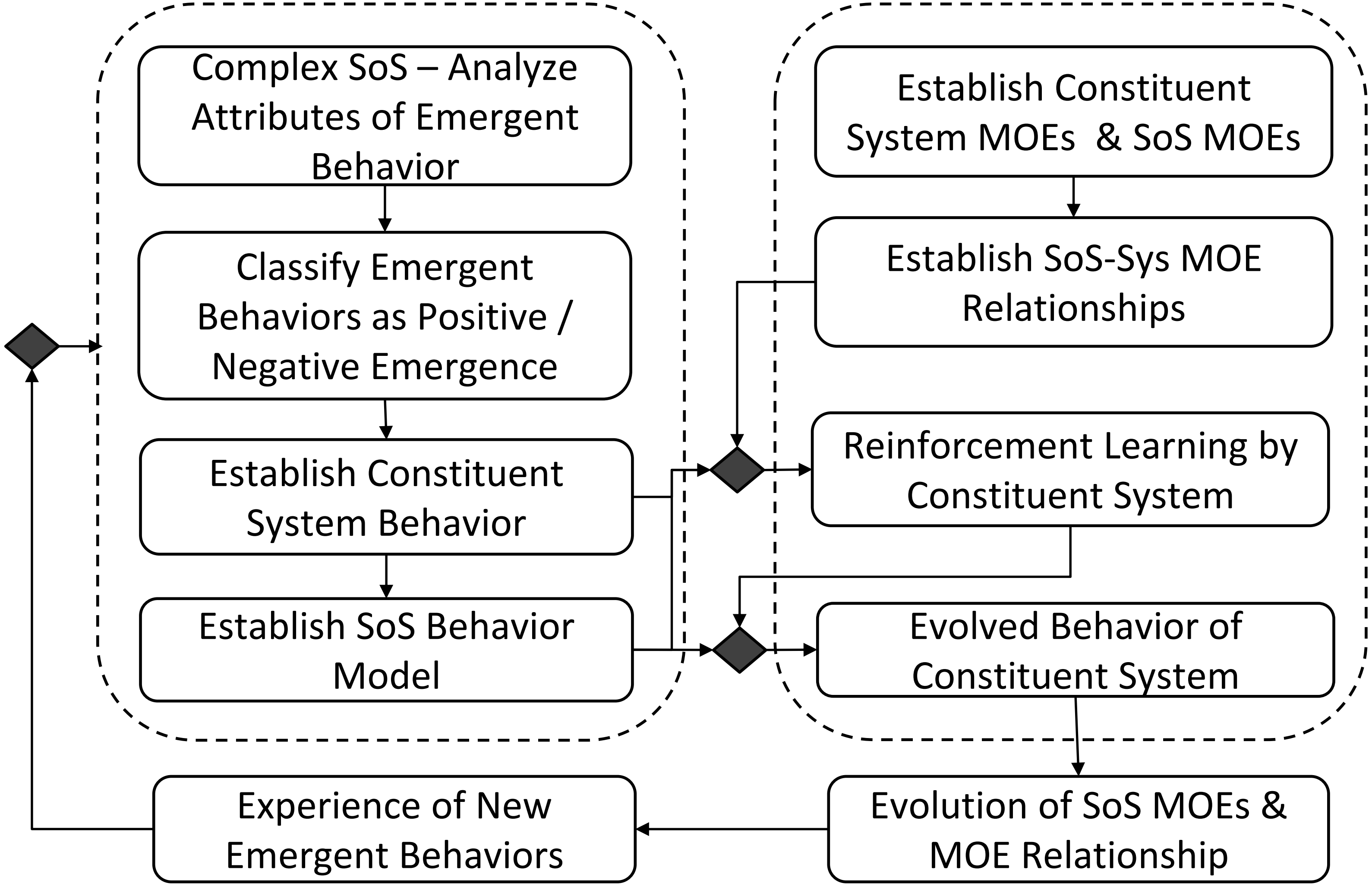
- Strengths & Limitations

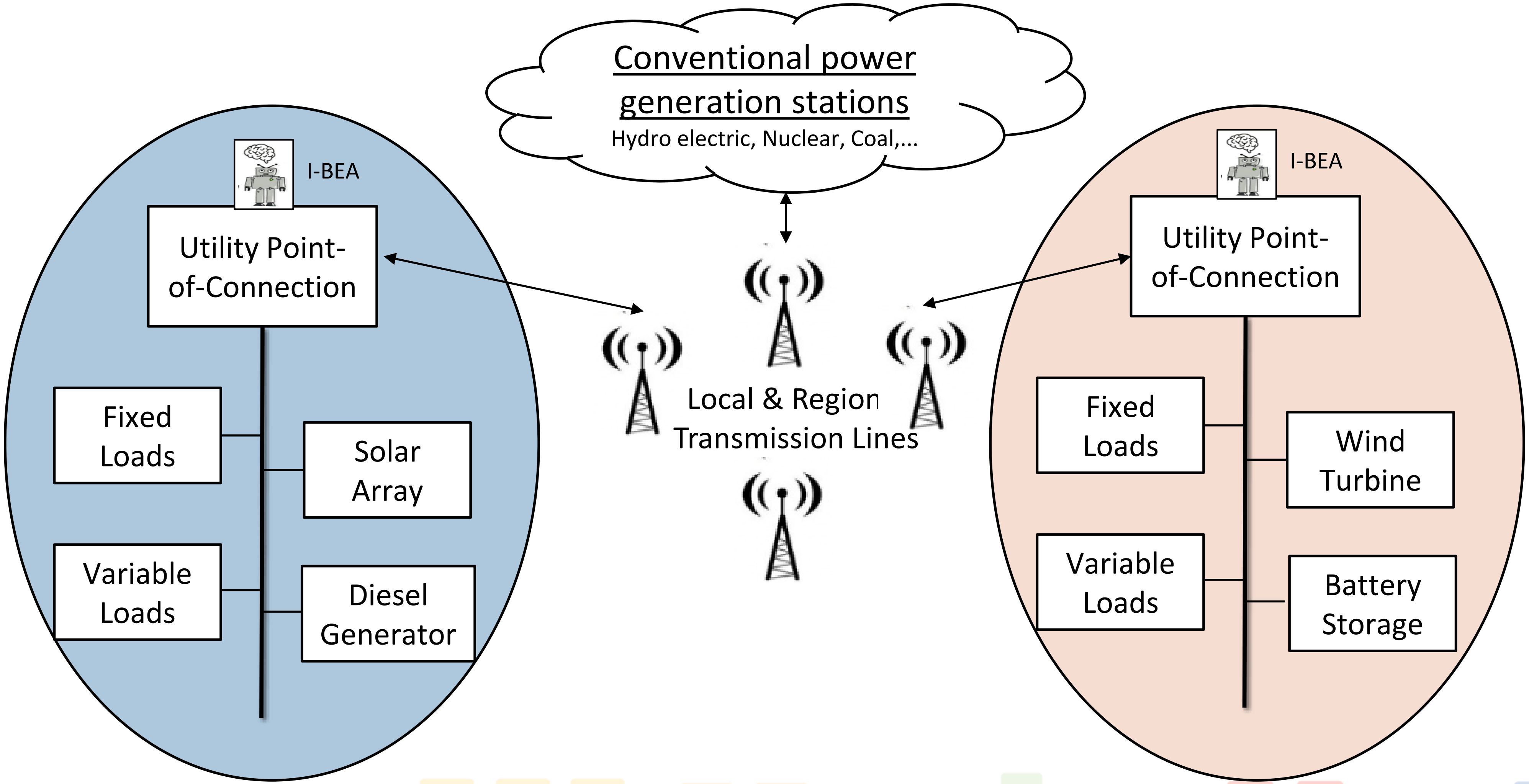
Proposed Framework



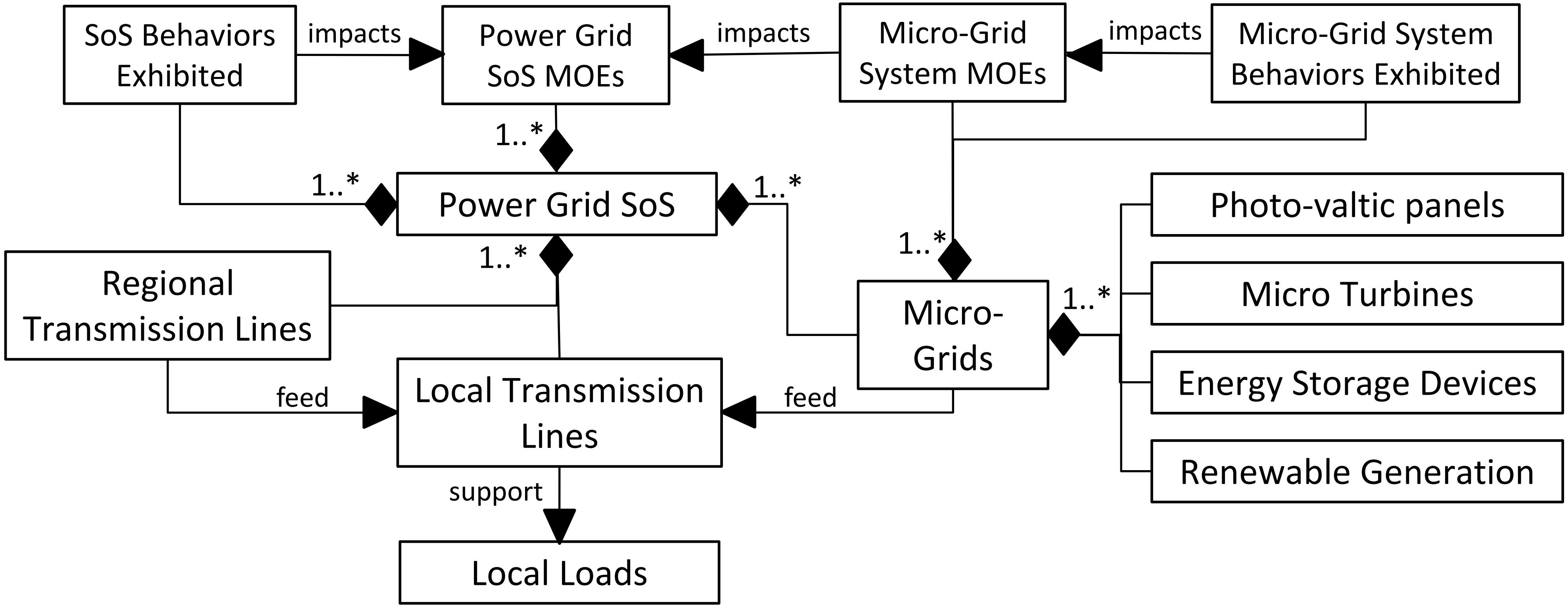
Proposed Framework



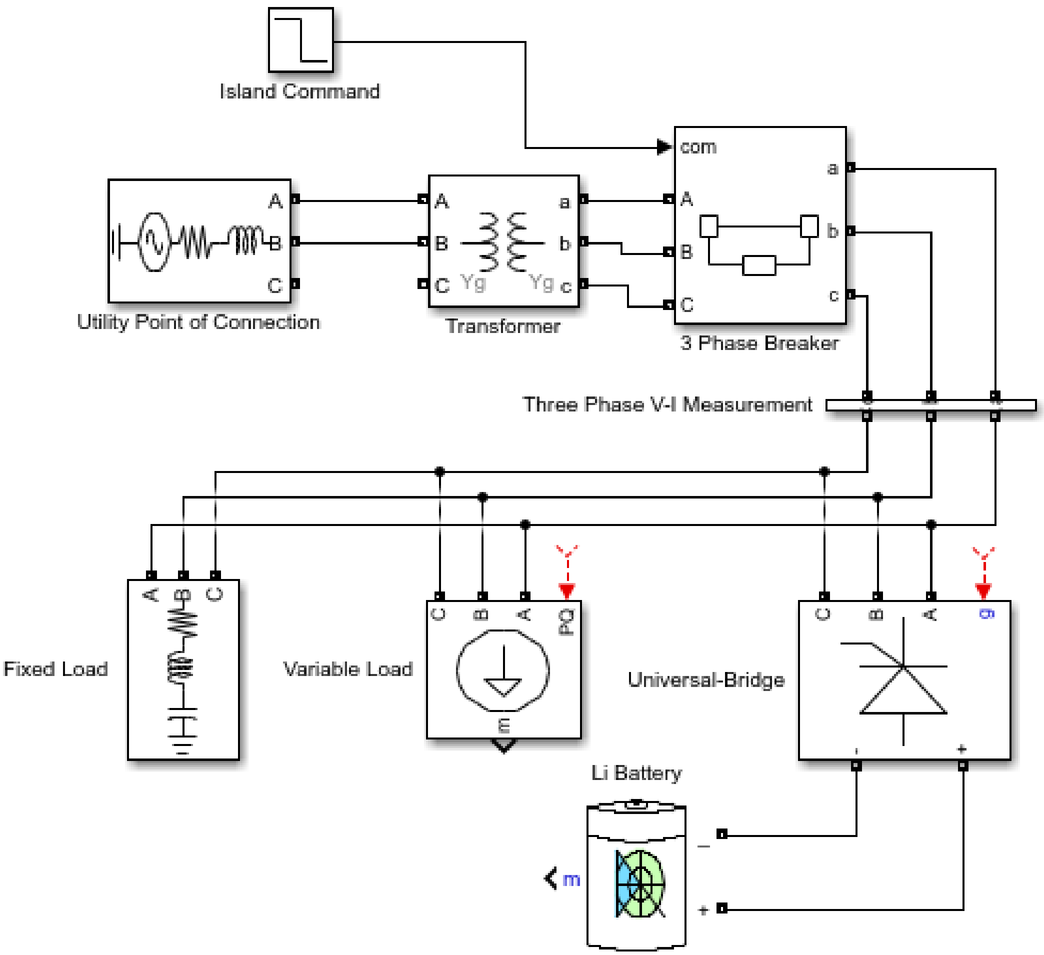
Power Grid SoS – Constituent Systems



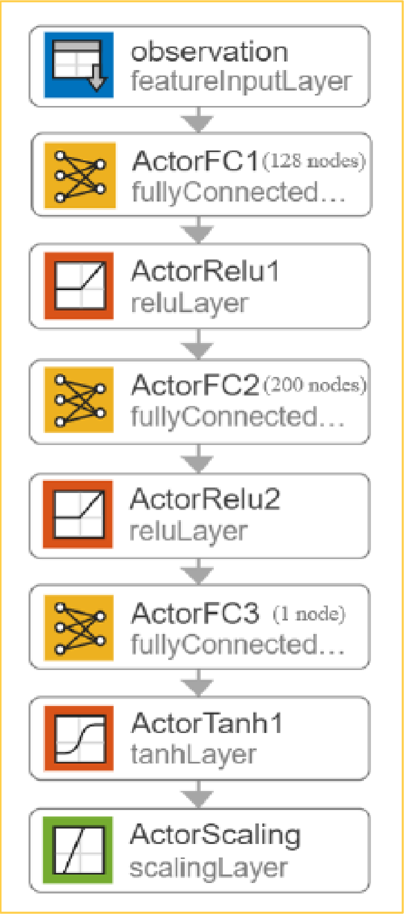
Power Grid SoS

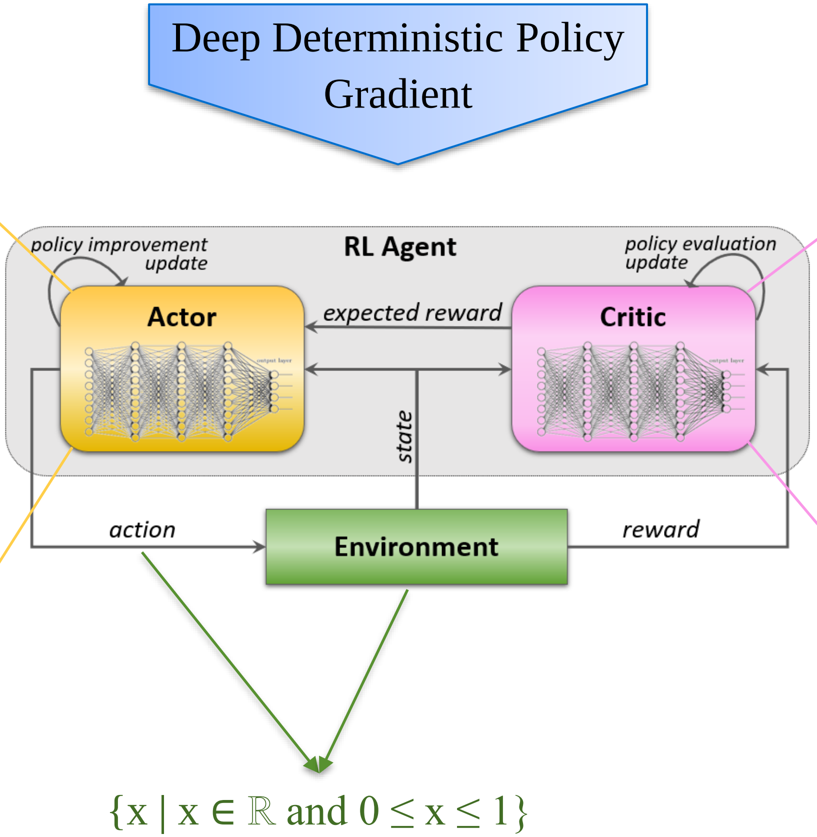


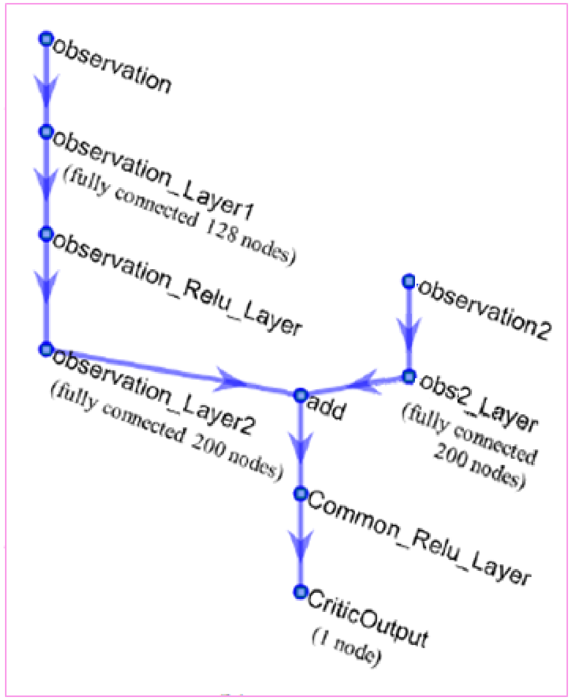
Microgrid Simulink Model



Experimental Setup







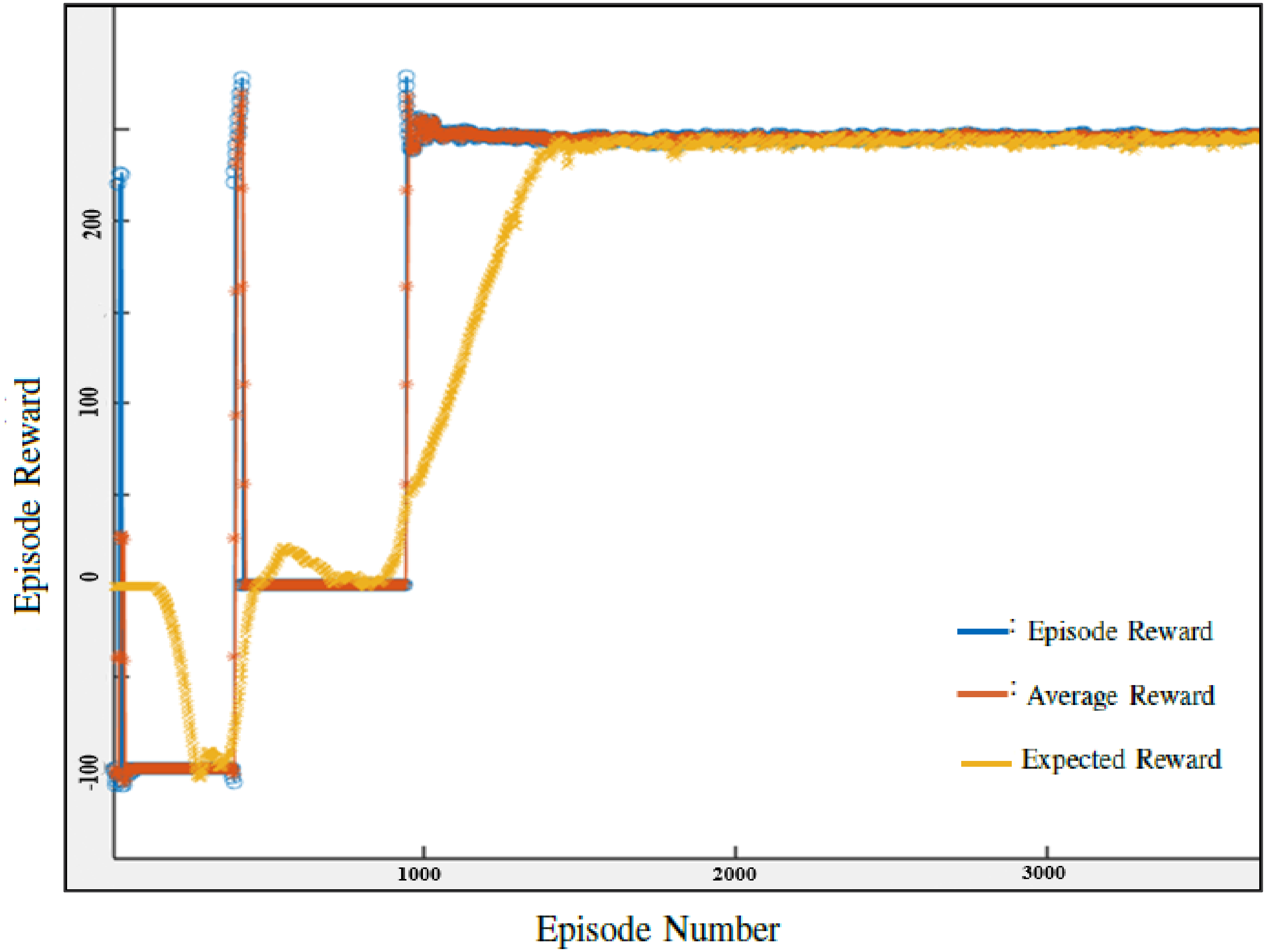
MATLAB RL Toolbox was used for simulation experiments

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

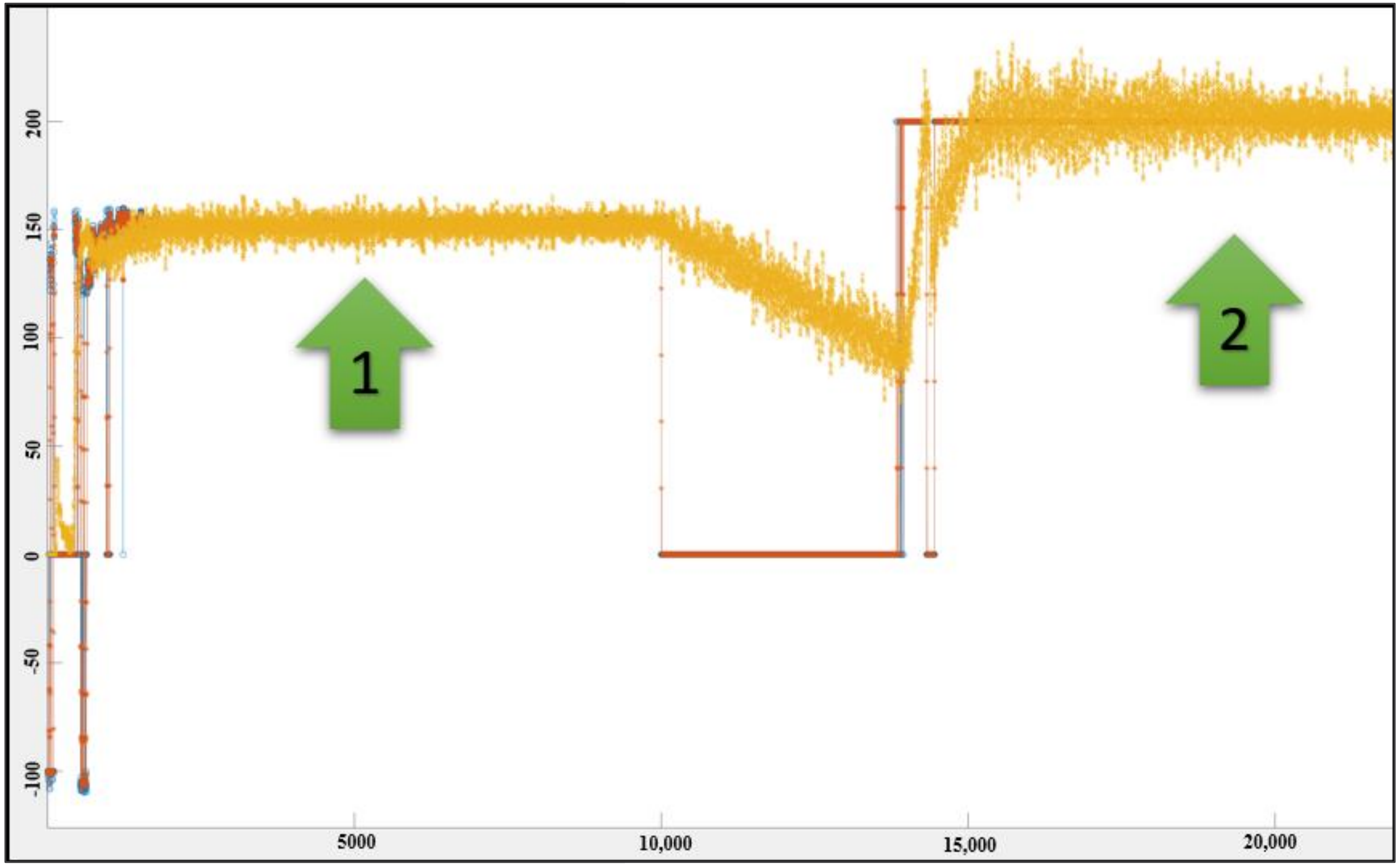
#	Behavior	Action Value	Reward
1	Desired	0.1 to 0.4	200+
	Undesired	< 0.1	-100



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

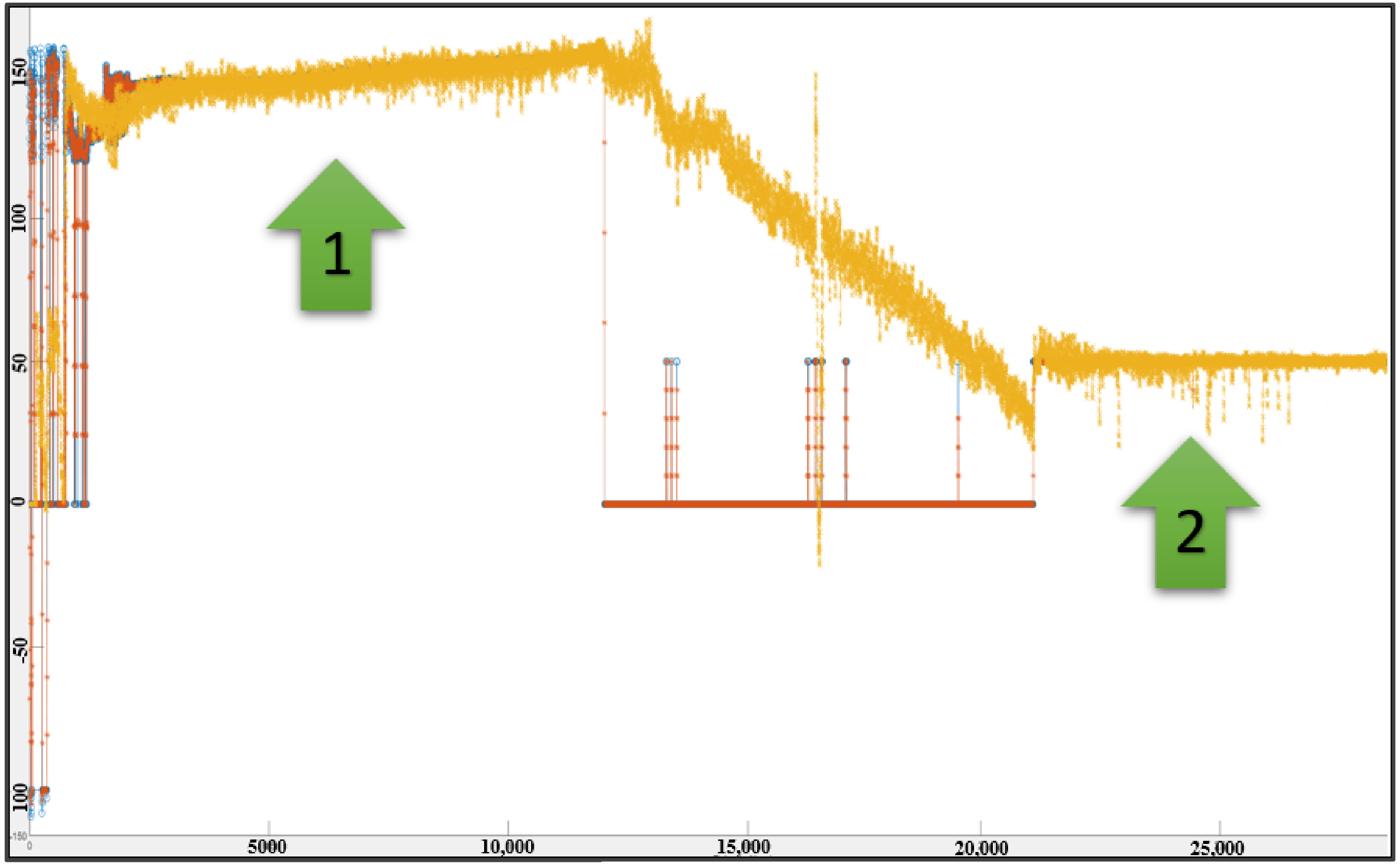


Legend: *X-Axis*: Episode Number *Y-Axis*: Episode Reward —: Episode Reward —: Average Reward —: Expected Reward

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



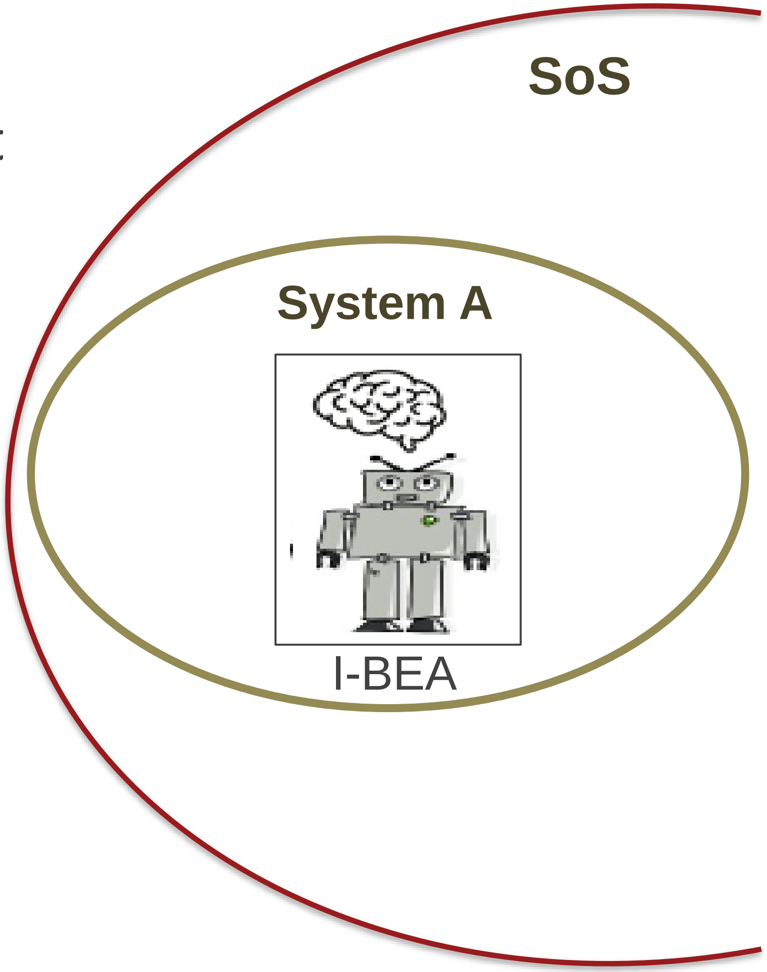
Legend: *X-Axis*: Episode Number *Y-Axis*: Episode Reward : Episode Reward : Average Reward : Expected Reward

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

- Future Work
- Conclusions

Conclusion

- In this paper, 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. Experiment results pertaining to two specific evolution scenarios were discussed –
  - scenario wherein a new constituent system introduced in the SoS needs to learn towards meeting both the system MOEs and SoS MOEs,
  - scenario wherein an existing constituent system needs to adapt its behavior towards addressing the behavioral evolution at SoS level
- In future, we plan to explore the performance of I-BEA with different RL algorithms in more complex SoS scenarios

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