Deep Reinforcement Learning for Combat System-of-Systems Architectural Path Selection

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Author’s Bio Info

Zhemei Fang received her Ph.D. degree from the School of Aeronautics and Astronautics Engineering at Purdue University in 2017. She is currently an Assistant Professor in the School of Artificial Intelligence and Automation in Huazhong University of Science and Technology in Wuhan, China.

Her primary research interests center on developing theories and methods for system-of-systems architecture design and evolution. The methods include but are not limited to model-based systems engineering, discrete event simulation, approximate dynamic programming, and reinforcement learning.

Outline

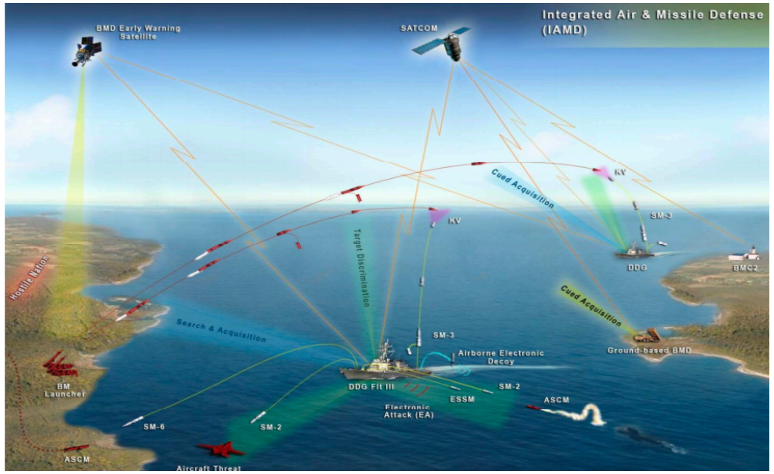
1 Motivation & Research Objective

2 Proposed Approach

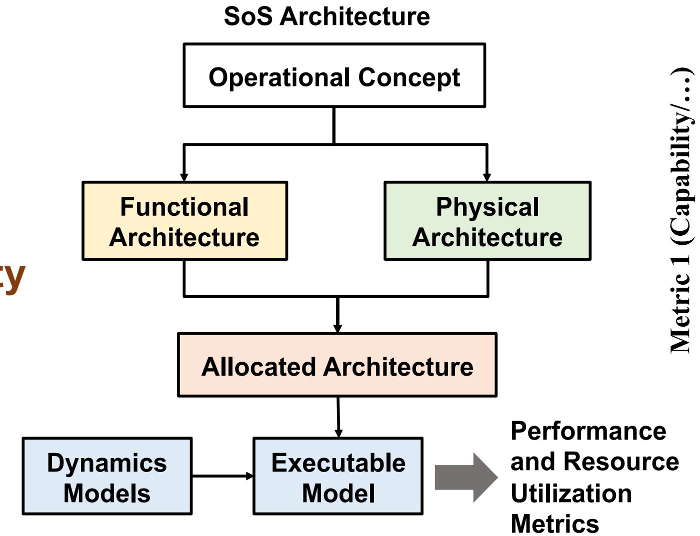
3 Illustrative Study

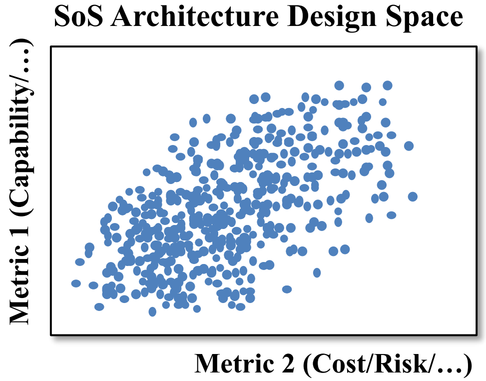
4 Conclusion & Future Work

Motivation & Research Objective



Complexity





Architecture Selection

Difficulties

Interdependency | **Evolution + Uncertainty**

Research Objective: Develop a learning-based framework for managing interdependency-incorporated System-of-Systems (SoS) architecture path selection

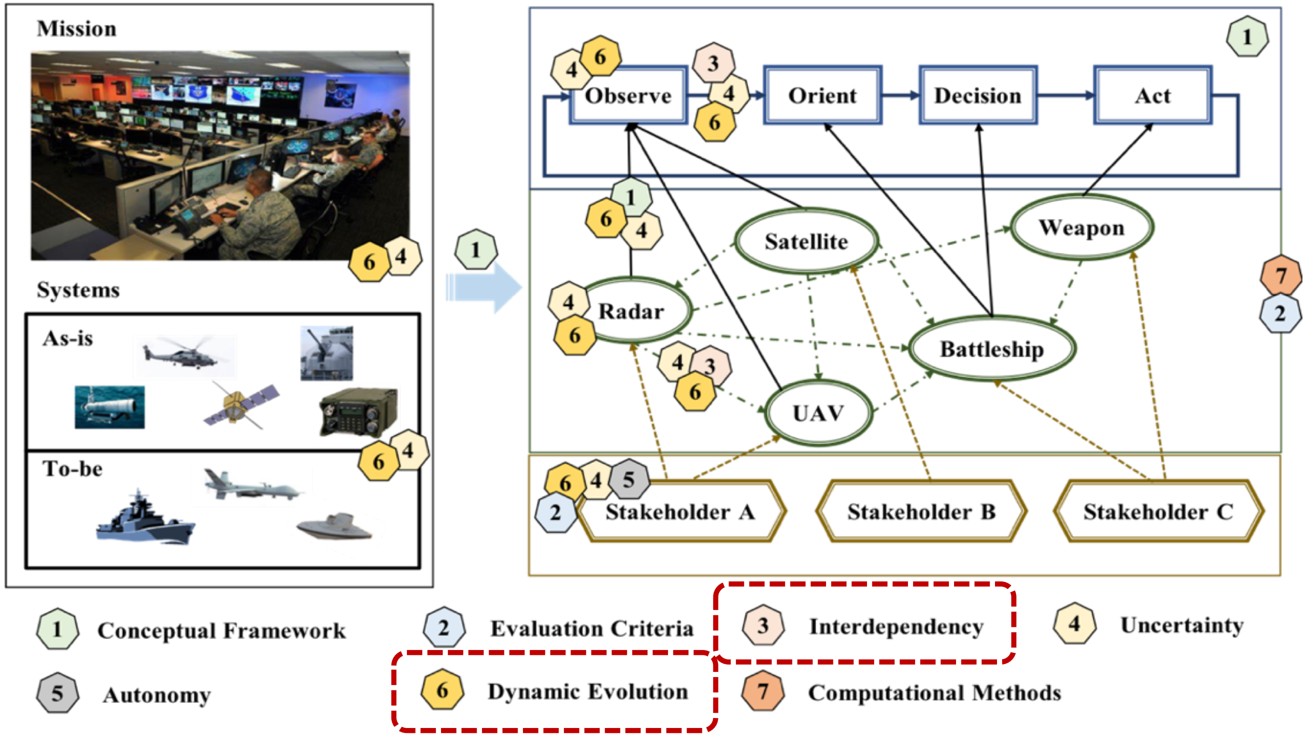
Related Work

SoS Architecture Selection

Simulation-based Methods
- Agent-based simulation
- Petri net based simulation
- Parametric models

Trade-off Space Exploration
- Multi-attribute tradespace exploration (MATE)

Optimization-based Methods
- Mathematical optimization: Evolutionary algorithms
- Modern portfolio theory



Related Work

Impact of Interdependency

Simulation-based Methods
- Message passing between different agents
- Token flows between places and transitions
- Dependency parameters; Conditional probability

Optimization-based Methods
- Synergy value
- Compatibility/prerequisite constraints
- Co-variance

Architectural Path Selection

Dynamic Strategic Planning based Methods
- Real options analysis
- Epoch-era analysis
- Time-expanded decision network

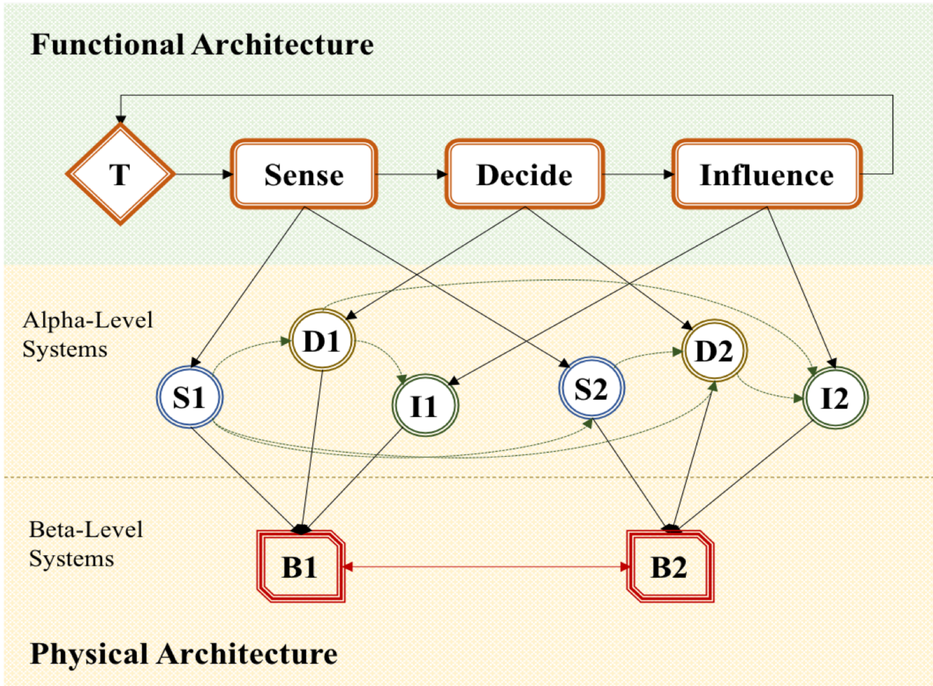
Algorithm based Methods
- Evolutionary algorithms
- **Approximate dynamic programming (previous work)**

Issues:
- **Interdependency in the optimal architecture selection problems has not been well captured**
- **Inadequate support for multi-stage architecture development**

Weighted sum of capability → inadequate
Linear value function approximation → inadequate

SoS Architectural Path Selection Problem

Representation of SoS Architecture



Functional Architecture

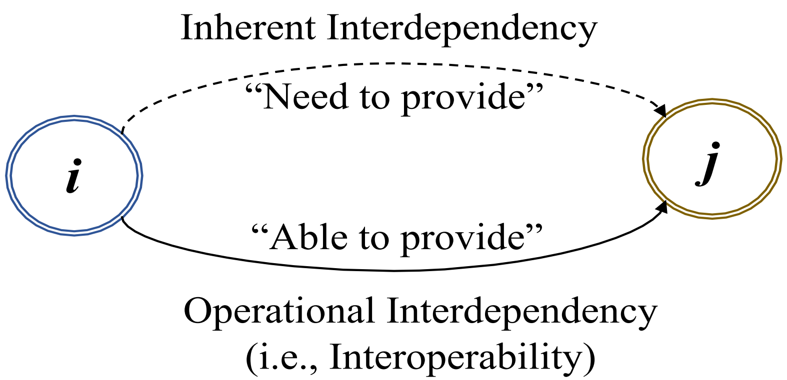
- Adopts "Information Age Combat Model (IACM)" proposed by Jeffrey Cares
- IACM includes elements: Target (T), Sensor (S), Decider (D), Influencer (I)

Physical Architecture

- Alpha-level systems: sensor entities, Command and Control (C2) entities, and firing entities
- Beta-level systems: integrated platform including sensor, C2, and firing entities

SoS Architectural Path Selection Problem

Impact of Interdependency



$$cap_j = \xi_{ij} \cdot \delta_{ij} \cdot cap_i + \left(1 - \xi_{ij}\right) \cdot SC_j$$

Inherent Interdependency

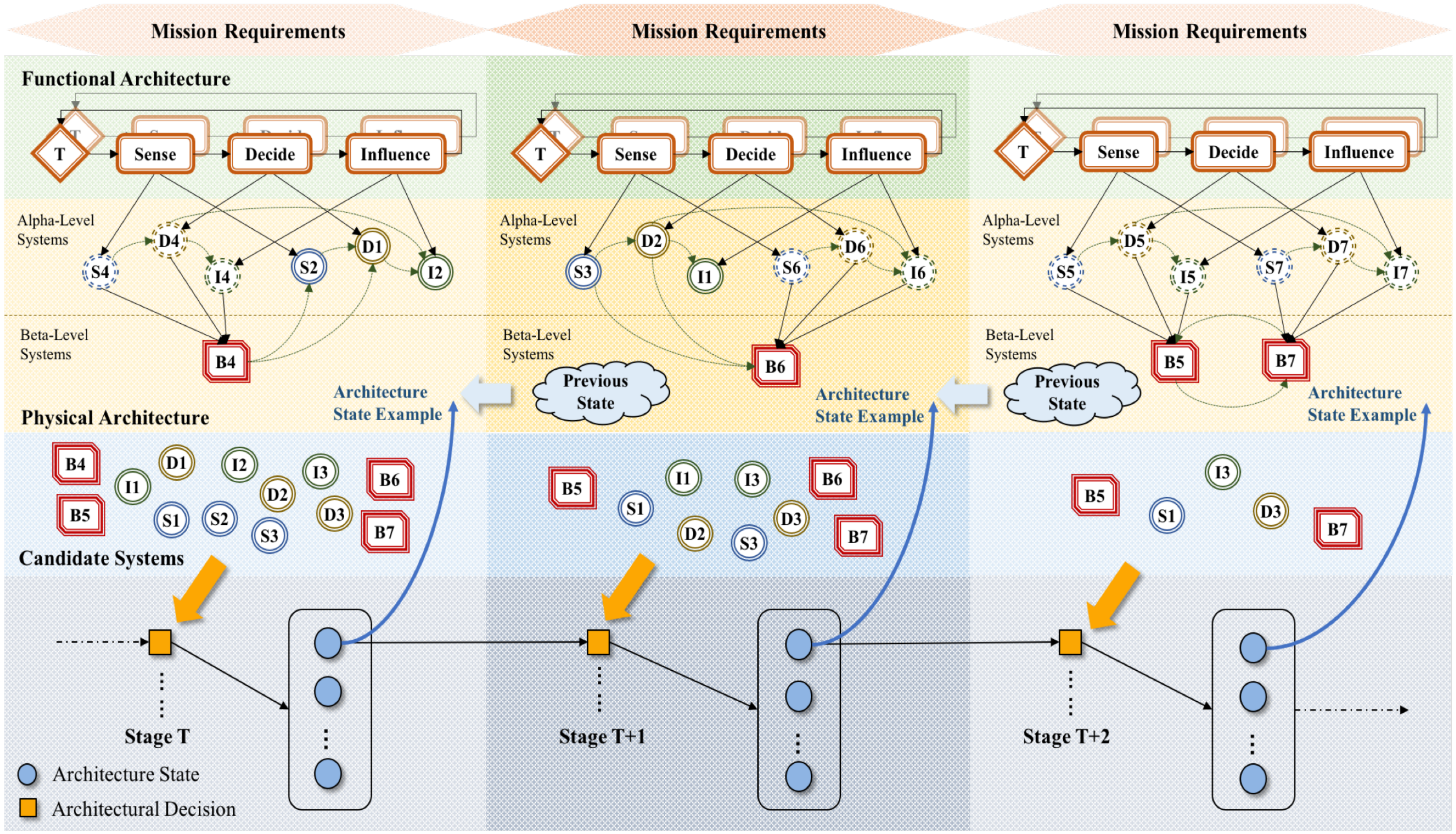
- Inherent functional need that centers on required information exchange between two nodes
- ξ_{ij}: degree of dependency
  - $\xi_{ij} = 0$: node j can work well without any support of node i
  - $\xi_{ij} = 1$: node j cannot work at a;; without information from node i

Operational Interdependency

- Functional capability of conducting satisfactory information exchange between two nodes
- δ_{ij}: interoperability level
  - $\delta_{ij} = 1$: full interoperability
  - $\delta_{ij} = 0$: zero interoperability

SoS Architectural Path Selection Problem

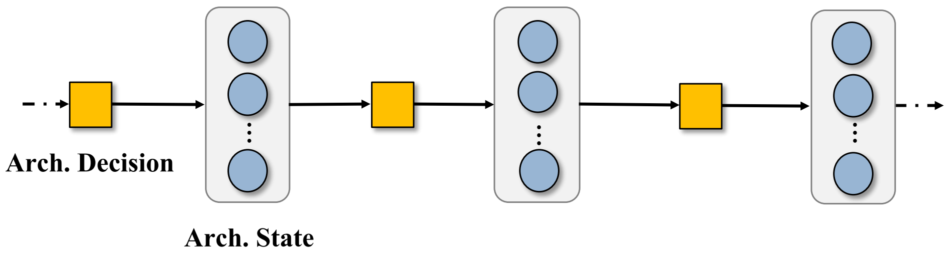
SoS Architectural Path Selection



Path Selection Process

- Sequential allocation of candidate systems to functional architecture
- Objective: Maximize combat mission capability
- Assumption
  - Candidate systems are given
  - Functional architectures are given and fixed

Mathematical Formulation



Markovian Property Satisfaction

- An SoS architecture state (analogous to MDP state) contains full information of the architectural history
- An architecture state depends only on the architecture state of the previous decision stage

MDP tuple

$$M = < S, A, P, R, \gamma >$$

Bellman Equation

$$Q_t(S_t, X_t) = \mathrm{E}\left[cap_{kt}^{I} + \gamma \max_{X_{t+1}} Q_{t+1}(S_{t+1}, X_{t+1})\right] \Leftarrow \max_{\{x_{it}^{S}, x_{jt}^{D}, x_{kt}^{I}\}} \sum_{t=1}^{T} cap_{kt}^{I}$$

State variables

$$S_t = \{R_t, SC_t, \xi_t, \delta_t, cost_t, CapReq_t, BG_t\}$$

Decision variables

$$X_t = \{x_{it}^{S}, x_{jt}^{D}, x_{kt}^{I}\}$$

Reward function refers to the operational capability of node Influence cap_{kt}^{I} that indicates the threat neutralization capability at each decision stage.

Reward function

$$cap_{kt}^{I} = \xi_{jkt} \cdot \delta_{jkt} \cdot (\xi_{ijt} \cdot \delta_{ijt} \cdot SC_{it}^{S} \cdot x_{it}^{S} + (1 - \xi_{ijt}) \cdot SC_{jt}^{D} \cdot x_{jt}^{D}) + (1 - \xi_{jkt}) \cdot SC_{kt}^{I} \cdot x_{kt}^{I}$$

MDP: Markov Decision Process

Mathematical Formulation

Same for D and I

Transition function

$$SC_{i,t+\tau}^{S} = \min\left(SC_{i,t}^{S} + x_{i,t}^{S} \cdot \sum_{m=t}^{t+\tau-1} \widehat{dev}_{i,t}^{S}, SCU_{i}^{S}\right), \tau \in [1, T-t]$$

$$BG_{t+1} = BG_{t} - \left(\sum_{i \in N_t^S} cost_{it}^{S} \cdot x_{it}^{S} + \sum_{j \in N_t^D} cost_{jt}^{D} \cdot x_{jt}^{D} + \sum_{k \in N_t^I} cost_{kt}^{I} \cdot x_{kt}^{I}\right) + BG_{t+1}^{new}$$

Architecture Constraints

Developmental budget constraint

$$\sum_{i \in N_t^S} cost_{it}^{S} \cdot x_{it}^{S} + \sum_{j \in N_t^D} cost_{jt}^{D} \cdot x_{jt}^{D} + \sum_{k \in N_t^I} cost_{kt}^{I} \cdot x_{kt}^{I} \leq BG_t$$

Intermediate capability demand

$$\sum_{t} cap_{kt}^{I} \geq CapReq_t$$

Must-selection constraint

$$\sum_{i \in N_t^S} x_{it}^{S} = 1 \qquad \sum_{j \in N_t^D} x_{jt}^{D} = 1 \qquad \sum_{k \in N_t^I} x_{kt}^{I} = 1$$

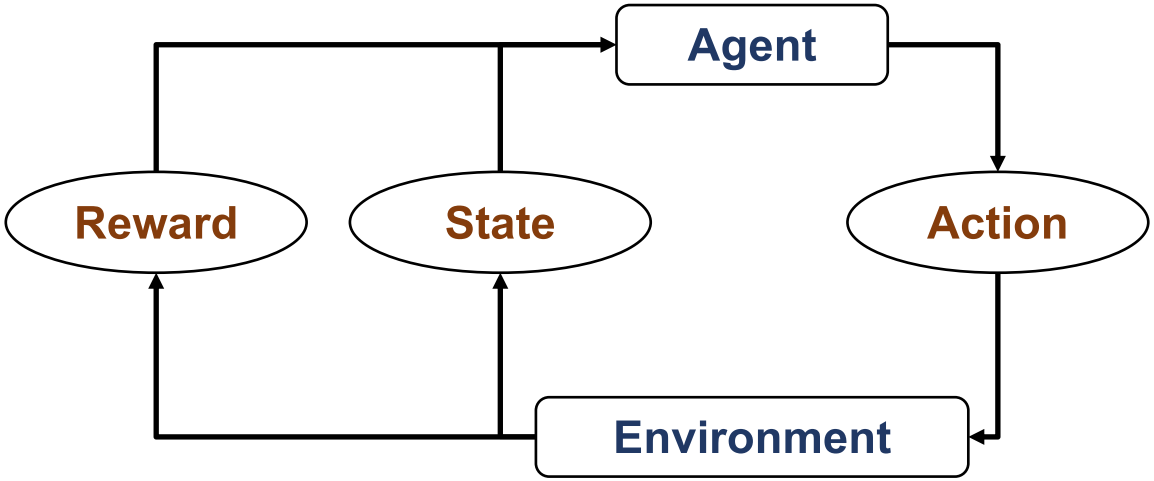
Beta-level system selection constraint

$$\left(x_{it}^{S,beta} \cdot x_{jt}^{D,beta}\right) + \left(1 - x_{it}^{S,beta}\right) \cdot \left(1 - x_{jt}^{D,beta}\right) \geq 1$$

$$\left(x_{it}^{S,beta} \cdot x_{kt}^{I,beta}\right) + \left(1 - x_{it}^{S,beta}\right) \cdot \left(1 - x_{kt}^{I,beta}\right) \geq 1$$

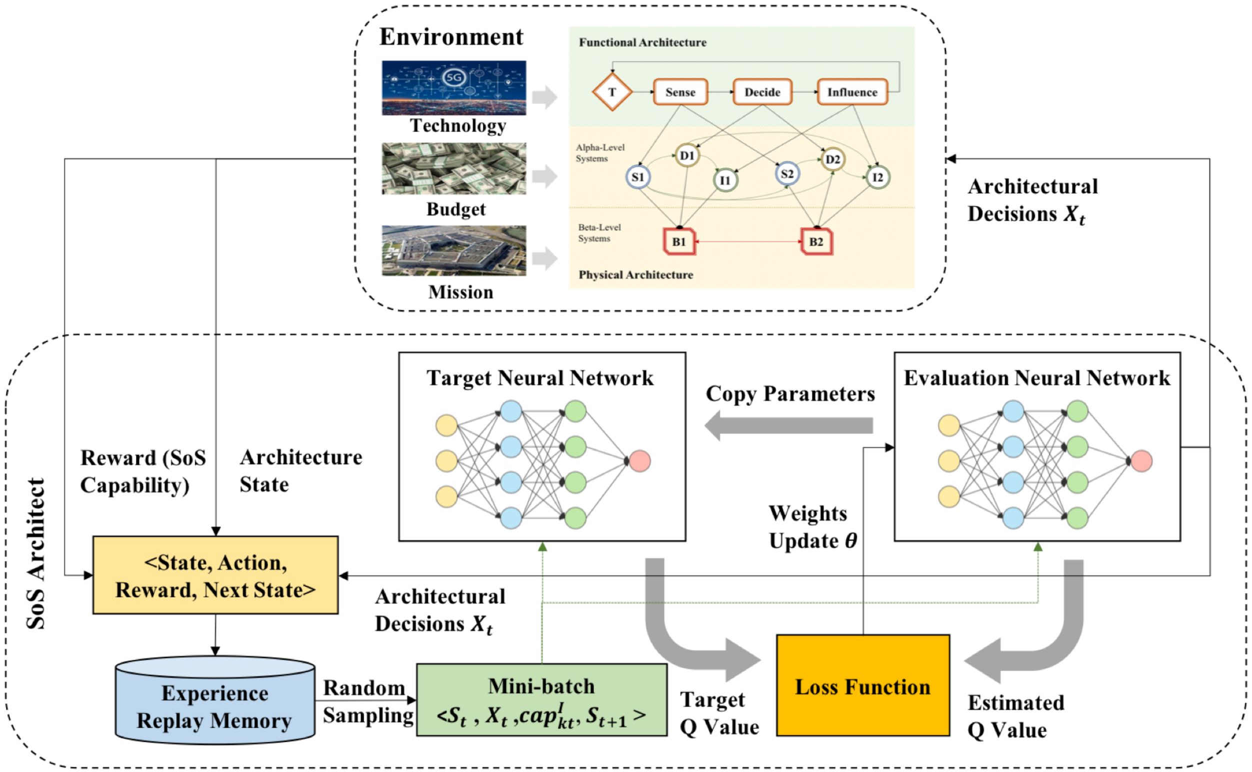
Approach: Deep Reinforcement Learning (DRL)

Brief Introduction to Reinforcement Learning



- No supervisor → Learning based on feedback and improvement
- Sequential decision-making
- Q learning
  - Value-based learning algorithm that updates the action-value function Q(S,X) based on Bellman Equation
  - Simple problems can directly use Q-Table Q(S,X) to calculate and store the maximum expected future rewards for action at each state
  - For high-dimensional problems, Q-Table is insufficient

Approach: Deep Reinforcement Learning (DRL)



$$Loss(\theta_n) = \mathrm{E}\left[\left(\left(cap^I_{kt} + \gamma \max_{X_t} \bar{Q}_{t+1}(S_{t+1}, X_{t+1}; \theta_n^-) - \bar{Q}_t(S_t, X_t; \theta_n\right)\right)^2\right]$$

Bellman Equation

$$Q_t(S_t, X_t) = \mathrm{E}\left[cap^I_{kt} + \gamma \max_{X_{t+1}} Q_{t+1}(S_{t+1}, X_{t+1})\right]$$

Techniques: Deep Q Network (DQN)

- Q learning
- Functional approximator: Convolutional Neural Network (CNN)
- Experience replay: remove correlation between observation sequences
- Target network + evaluation network
- Parameter noise: support exploration

Illustrative Study

Mosaic Warfare

- Decompose monolithic multi-mission units into a larger number of smaller elements
- Distributed maritime operations
  - ISR USV, C2 USV and AMD USV with different TRLs
- Interdependency
  - Left: inherent (L = 0.1, M = 0.4, H = 0.8)
  - Right: interop (L = 0.1, M = 0.5, H = 1)

Candidate systems and input parameters

Example	Sys	Self-Cap Limit	Initial Self-Cap	Dev Rate	Cost (m$)
ISR USV Class A Radar I	S1	40	40	(0,0)	80
ISR USV Class B Radar I	S2	40	40	(0,0)	120
ISR USV Class A Radar II	S3	50	40	(1,1)	110
ISR USV Class B Radar II	S4	50	40	(1,1)	130
ISR USV Class A Radar III	S5	60	36	(2,1)	150
ISR USV Class B Radar III	S6	60	36	(2,1)	180
ISR USV Class C Radar III	S7	70	35	(3,1)	160
……	…	…	…	…	…

Interdependency between sensor-decider system pairs

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
S1	HL	HL	HL	HL	HL	HL	ML	ML	ML	ML	ML	ML	LL	LL
S2	HL	HM	HL	HM	HM	HM	MM	MM	MM	MM	MM	MM	LM	LM
S3	HL	HL	HL	HL	HL	HL	ML	ML	ML	ML	ML	ML	LL	LL
S4	HL	HM	HL	HM	HM	HM	MM	MM	MM	MM	MM	MM	LM	LM
S5	HL	HM	HL	HM	MM	MM	MM	MM	MM	MM	LM	LM	LM	LM
……	…	…	…	…	…	…	…	…	…	…	…	…	…	…

ISR: Intelligence, Surveillance and Reconnaissance; AMD: Air and Missile Defense; USV: Unmanned Surface Vehicle; TRL: Technology Readiness Level

Illustrative Study

Hyperparameters	Values
Mini-batch size	512
Discount factor	0.9
Q learning rate (stepsize)	0.8
Experience replay memory size	10000
Target network update frequency	500
CNN network layer	4
CNN learning rate	0.001
Optimizer	Adam
Activation function	ReLU
Noise	N(0,1)

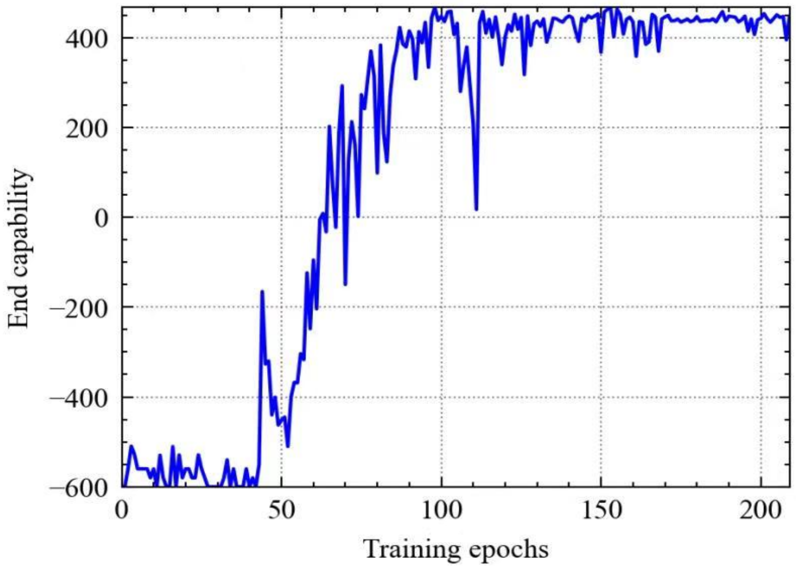
Additional Input

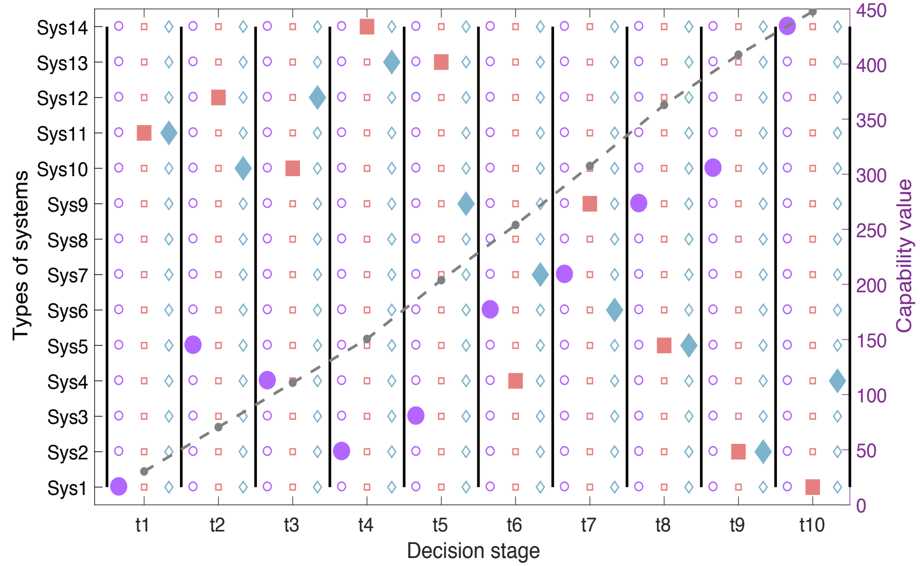
- Horizon: 10 stages
- Budget: 1000 m$ initially; receives additional 500 m$ each stage
- Intermediate requirement: Stage 3 >= 100 units; Stage 6 >= 250 units

Environment

- Python 3.7
- PyTorch machine learning library
- AMD Ryzen-2600X CPU
- 16GB 3000MHZ memory
- GeForce RTX-2080 GPU
- WIN 10 operating system

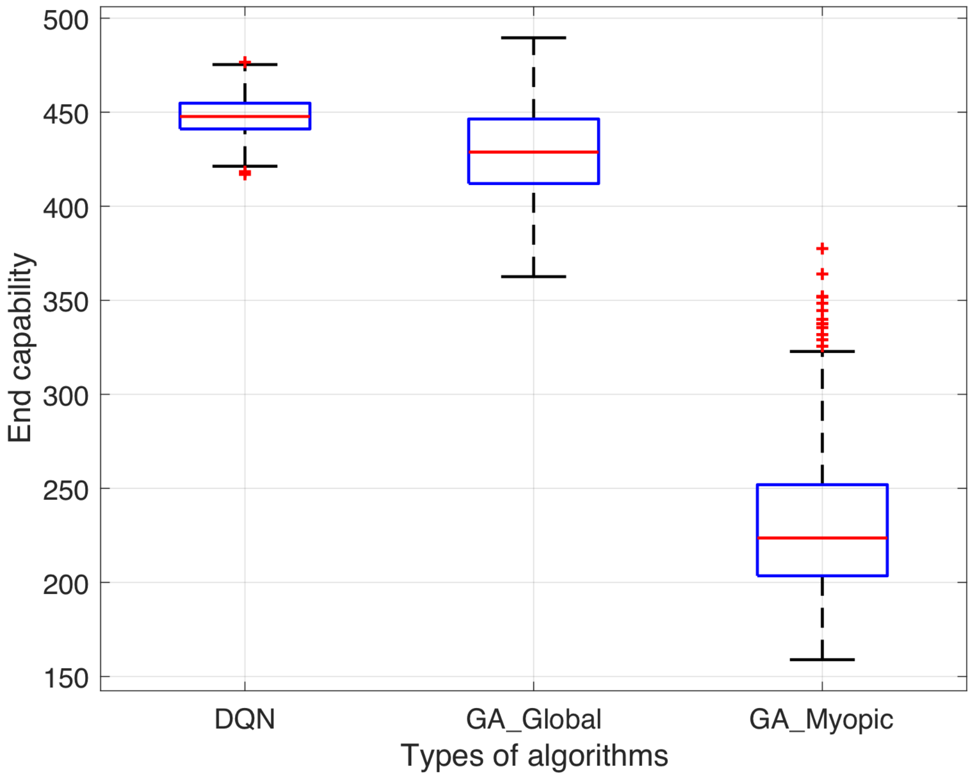
Illustrative Study





- Left: training curve tacking total capability of combat SoS.
  - Capability of the entire SoS architecture converges after around 150 training epochs.
  - Fluctuation still exists but remains stable and the MSE loss function stays around 2.
- Right: most often suggested architectural path and resultant capability (circle: S; square: D; diamond: I).
  - Decider systems and influencer systems with advanced technologies are often selected at the beginning whereas sensor systems with high readiness level are selected.
  - SoS architect agent is smart enough to choose those systems with large potentials in the future.

Illustrative Study



- **DQN algorithm** provides the largest average capability value of 448 units and lowest standard deviation of 10 units.

  → DQN provides more stable solution in an uncertain environment
- **GA_Global** provides slightly lower average capability value (429 units) and larger standard deviation (24 units) than DQN algorithm.
- **GA_Myopic** offers lowest capability value of 232 units since it only sees the current situation without any consideration of future possibility.

- **GA_Global:** assumes full predictability of future information and establishes a big optimization problem containing all architectural path decisions at ten stages.
- **GA_Myopic:** only considers now and does not account for any information from the future.

Conclusion & Future Work

- Conclusion
  - Developed DQN algorithm to support the SoS architectural path selection under uncertainty;
  - Built a simple parametric model to capture the impact of interdependency on SoS capability;
  - Applied the method to a synthetic USV-centered naval AMD SoS.
- Future Work
  - Assumption relaxation, such as one system for one type of function;
  - Development of more effective DRL algorithms and techniques;
  - Robust and resilient architectural path selection.

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