

Data Driven Learning and Optimization in Reconfigurable Intelligent Surface Enabled Industrial Wireless Network for Advanced Manufacturing

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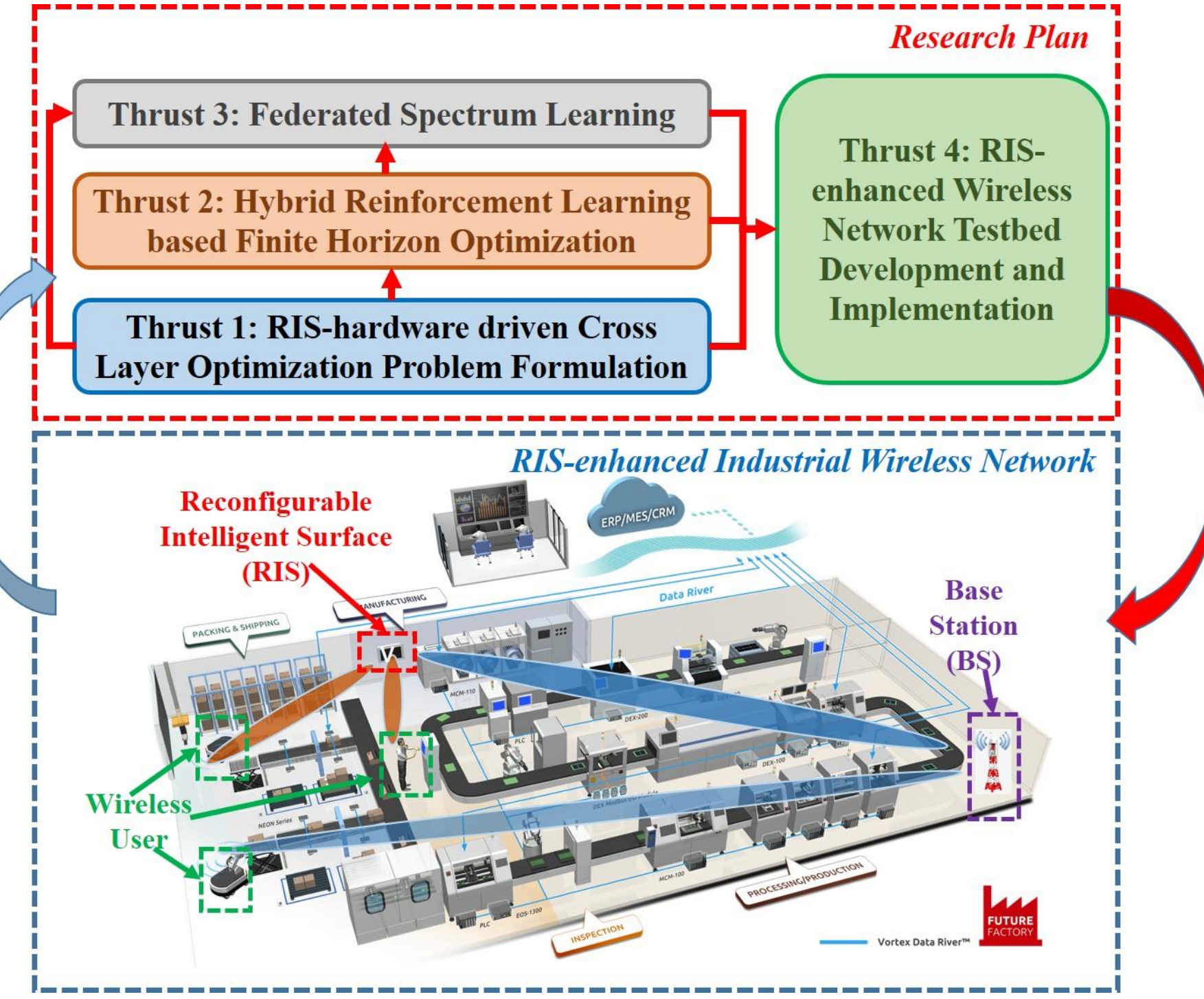
Overview

Project Goal

Address fundamental research challenges required for transcending industrial wireless network from **theoretical optimistic** vision to practical and **implementable reality**.

Technical Objectives

1. Formulate a hardware-driven cross-layer optimization problem for RIS-enhanced wireless network with **hardware constraints**
2. Design data-enabled learning algorithm to solve the formulated **cross-layer optimization** problem
3. Develop distributed computational efficient learning mechanism to reduce the **network risk** during learning
4. Develop and experimentally characterize various **RIS implementation** for wireless networks.



Challenges

1. **Stringent latency requirement** in wireless network for control and automation units in industrial environment
2. **Nonstationary Spectrum sharing** among coexisted mobile users (e.g., mobile robot, human operators) and stationary users (e.g., fixed machinery, etc.).
3. **Dynamic security requirement** for control and automations units in distributed industrial environment

Driving application **Optimal, Secured, and Dynamic Wireless Network for Industrial 4.0**

A key issue is **how to balance optimality, security, time-efficiency in wireless network management that can be used for industrial 4.0 even under dynamic and uncertain industrial environment?**

Technical Approach and Results

Dynamic resource allocation optimization (A causal RL approach)

Goal: Obtain real-time dynamic optimal resource allocation for time-varying RIS-enhanced network.

Approach:

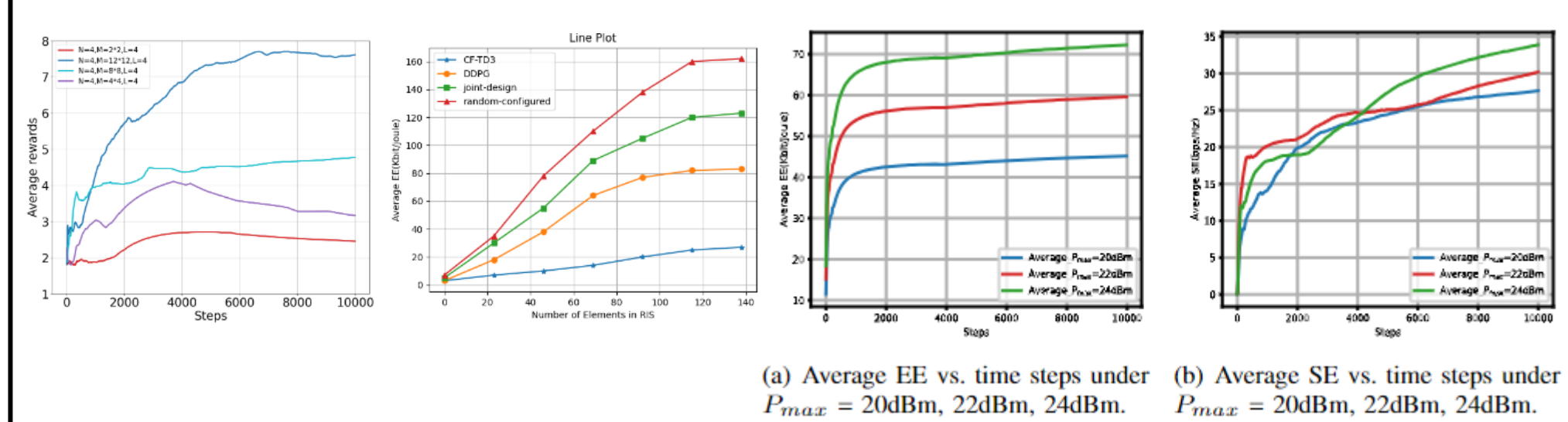
Solution 1: Formulate the time-varying dynamic optimization problem for UAV-assisted RIS-aid wireless network.

Solution 2: Develop causal reinforcement learning algorithm to learn dynamic optimal resource allocation online and rapidly.

Causal RL-enhanced Two-phase UAV-assisted RIS placement and resource allocation optimization

Algorithm 1 Deep Reinforcement Learning Based Intelligent Mobile UAV Placement (Phase 1)

1. Do K -means clustering for all users positions, get centers for different clusters $\{u_{i,1}, \dots, u_{i,K}\}$.
2. Assign all mobile UAV relay and base stations their own cluster centers.
3. Do Deep Q Network (DQN) learning within each UAV-enhanced RIS-assisted wireless network relay network.
4. Set memory pool P_t for each UAV-enhanced RIS-assisted wireless network relay. Set action-value function Q_t for each UAV-enhanced RIS-assisted wireless network relay with random weights.
5. For episode $e = 1$ to M do
6. Set sequence $s_{i,t} = u_{i,1}$ and get $\phi_{i,t} = \phi(s_{i,t})$.
7. For $t = 1$ to T do
8. With probability ϵ randomly get $a_{i,t}$ from $A_{i,t}$. Otherwise select $a_{i,t} = \arg \max_{a \in A_{i,t}} Q_t(\phi_{i,t}, a; \theta)$.
9. Execute action $a_{i,t}$ in simulator and get reward $r_{i,t}$.
10. $r_{i,t}(\theta) = \theta(\sum_{j=1}^K r_{i,t,j} U_{i,t,j}(\theta)) / \sum_{j=1}^K U_{i,t,j}(\theta)$.
11. Set $s_{i,t+1} = s_{i,t} \cup a_{i,t}$ and preprocess.
12. $\phi_{i,t+1} = \phi(s_{i,t+1})$.
13. Store transition $(\phi_{i,t}, a_{i,t}, r_{i,t}, \phi_{i,t+1})$ in D_t .
14. Sample random minibatch of transitions $\{(\phi_{i,j}, a_{i,j}, r_{i,j}, \phi_{i,j+1})\}$ from D_t .
15. Set $\tilde{s}_{i,j} = \{r_{i,j}, \phi_{i,j+1}\}$ for terminal $\phi_{i,j+1}$.
16. Perform a gradient descent step on $\{(\tilde{s}_{i,j}, Q_t(\phi_{i,j}, a_{i,j}; \theta))\}$.
17. end for
18. end for



Distributed learning based intelligent resource allocation for multi-RIS-assisted MANET (A multi-player multi-armed bandit approach)

Goal: Obtain intelligent resource allocation for mobile ad-hoc network in a distributed manner.

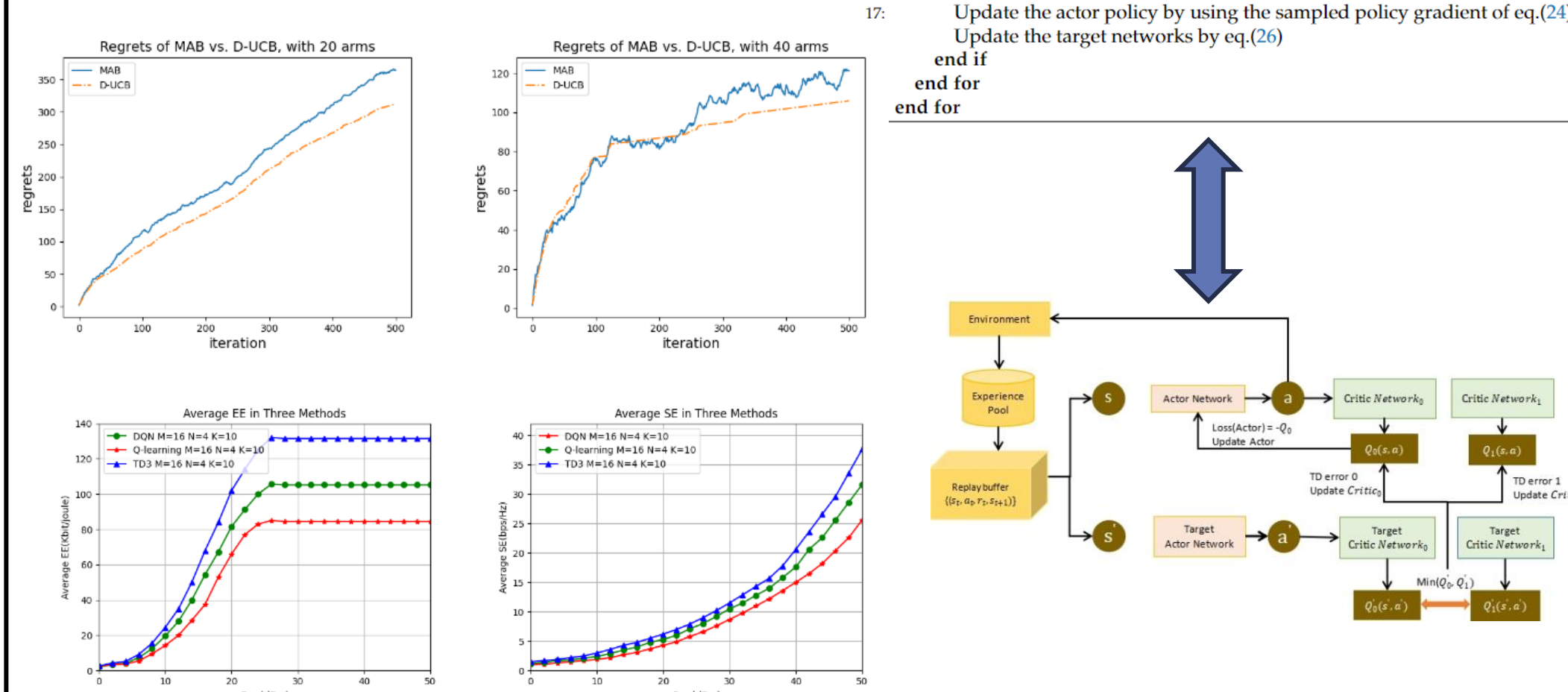
Approach:

Adopt a multi-player multi-armed bandit approach to handle distributed intelligent resource allocation. Then, use TD3 learning algorithm to solve multi-player MAB.

TD3 distributed learning based intelligent resource allocation for MANET

Algorithm 1 DUCB Algorithm

1. Input: Number of agents N and arms A .
2. Initialization/Initialize the following variables:
3. for $i = 1$ to N do
4. Initialize $K_{i,t}$ array $K_{i,t}$ and D -UCB $_i$ (initialize to 0 for all arms)
5. end for
6. Choose exploration parameter $C = 2$
7. for $t = 1$ to T do
8. for $i = 1$ to N do
9. Execute arm $A_{i,t}$ and observe the reward $R_{i,t}(t)$, where $R_{i,t}(t)$ is getting from the inner loop Alg2.
10. Update the estimated mean reward $X_{i,t}(t)$ for the selected arm $A_{i,t}$ using the eq.(14)
11. Calculate the D -UCB $_i$ index using (15)
12. end for
13. end for



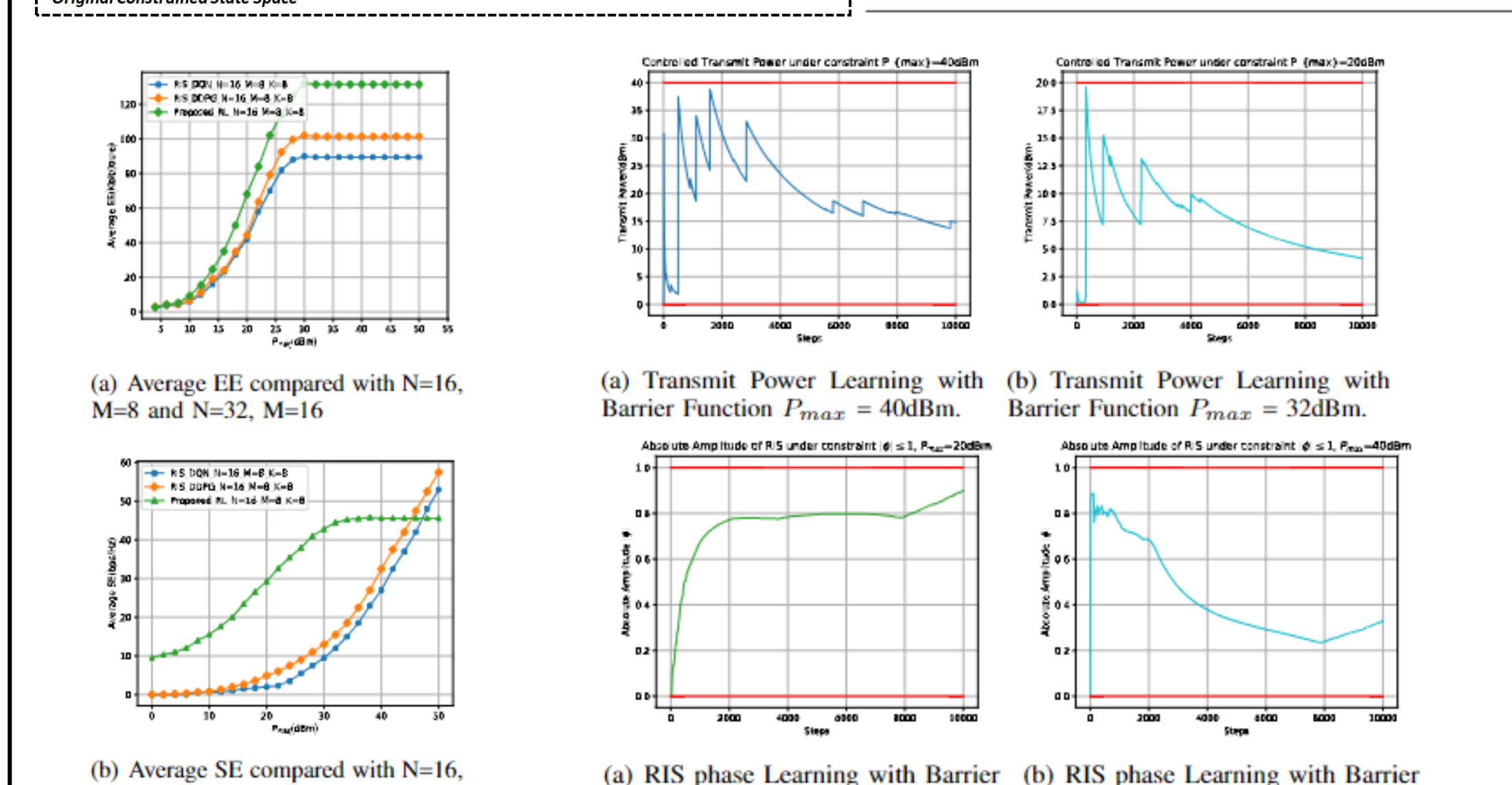
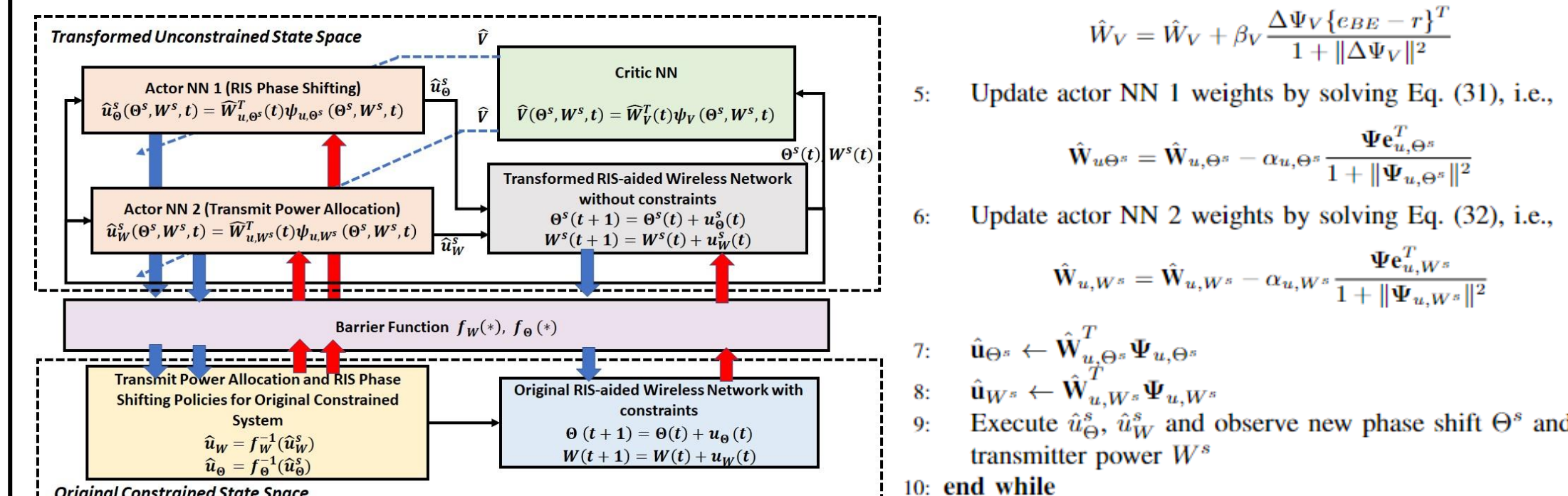
Dynamic resource allocation for RIS-aided MIMO wireless network with hardware limitations (A barrier function approach)

Goal: Obtain feasible cost-effective dynamic resource allocation for RIS-aided MIMO wireless network with limitation from RIS hardware.

Approach:

Adopt a barrier function mechanism and incorporate with actor-critic reinforcement learning (RL) to find dynamic resource allocation for RIS-aided MIMO wireless network with RIS hardware limitations.

Actor²-Critic-Barrier RL based dynamic resource allocation

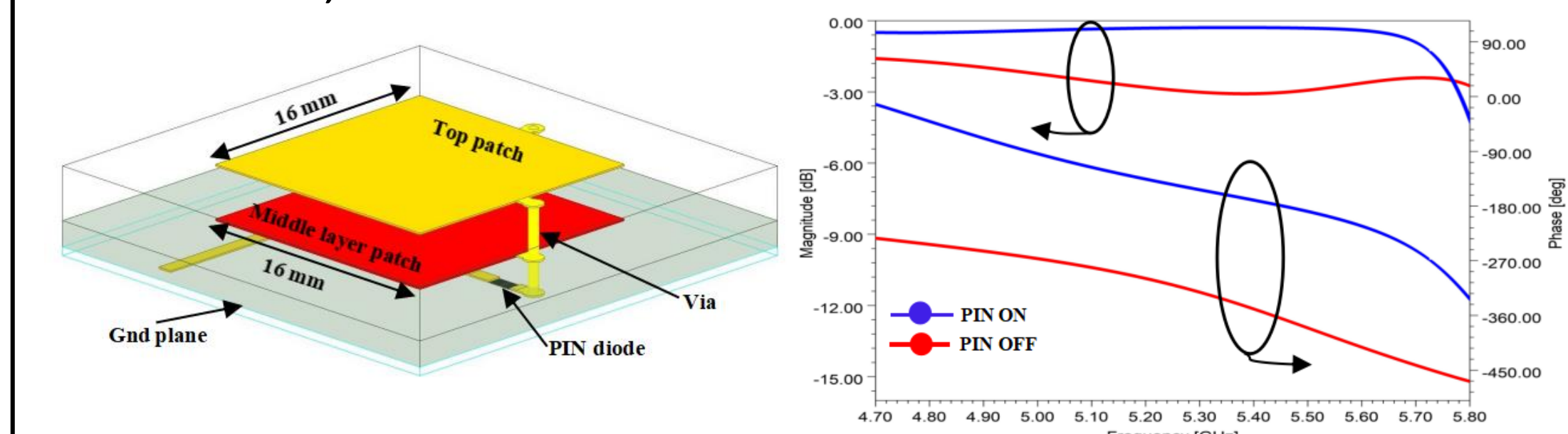


RIS Hardware development and wireless system testbed

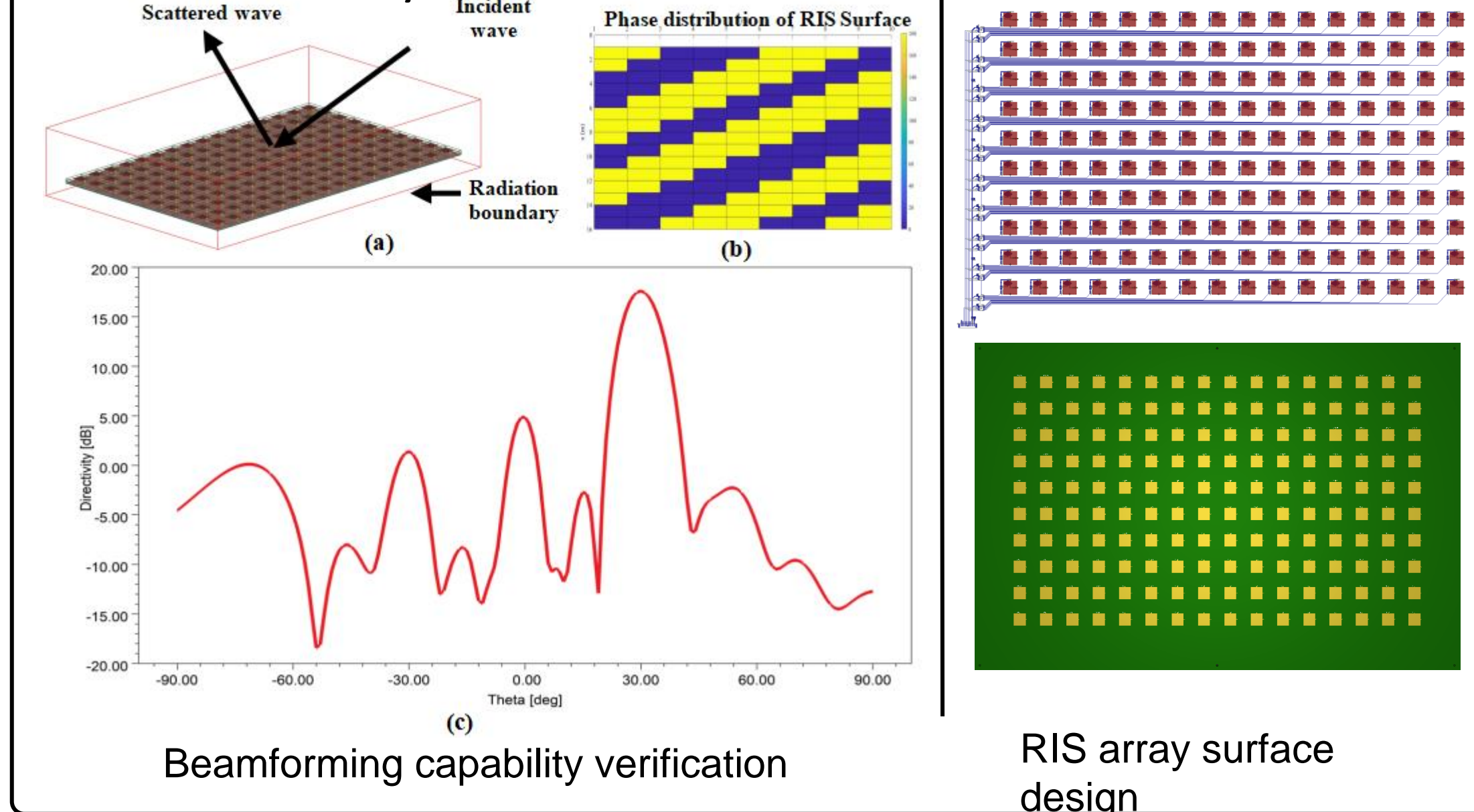
Goal: Design a wideband binary RIS surface at Sub-6 band, and use it for RIS-assisted wireless communication system test.

Approach:

A two-layer stacked patch structure is used to broaden the bandwidth of the RIS element. A 1-bit PIN diode is employed to reconfigure the phase states, and a phase difference of is observed over the frequency range of 4.81 – 5.77 GHz, a 19.2% fractional bandwidth.



(a) RIS unit element
(b) phase/magnitude response
For system level test, a 16x10 array is designed and has been verified for its beamforming capability. A prototype is under fabrication for system level test.



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Selected Products

- 1) Yuzhu Zhang, and Hao Xu. "Optimal Dynamic Resource Allocation for Multi-RIS Assisted Wireless Network: A Causal Reinforcement Learning Approach." In 2024 International Conference on Computing, Networking and Communications (ICNC), 2024.
- 2) Yuzhu Zhang, and Hao Xu. "Decentralized Learning based Optimal Design for RIS-assisted Multi-User Ad-Hoc Network: A Multi-Player Multi-Armed Bandits Approach." In 2024 International Conference on Computing, Networking and Communications (ICNC), 2024.
- 3) Zhang, Yuzhu, Lijun Qian, and Hao Xu. "Joint Optimal Placement and Dynamic Resource Allocation for multi-UAV enhanced Reconfigurable Intelligent Surface Assisted Wireless Network." In 2023 International Conference on Computing, Networking and Communications (CCNC), pp. 1-6. IEEE, 2023.

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