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

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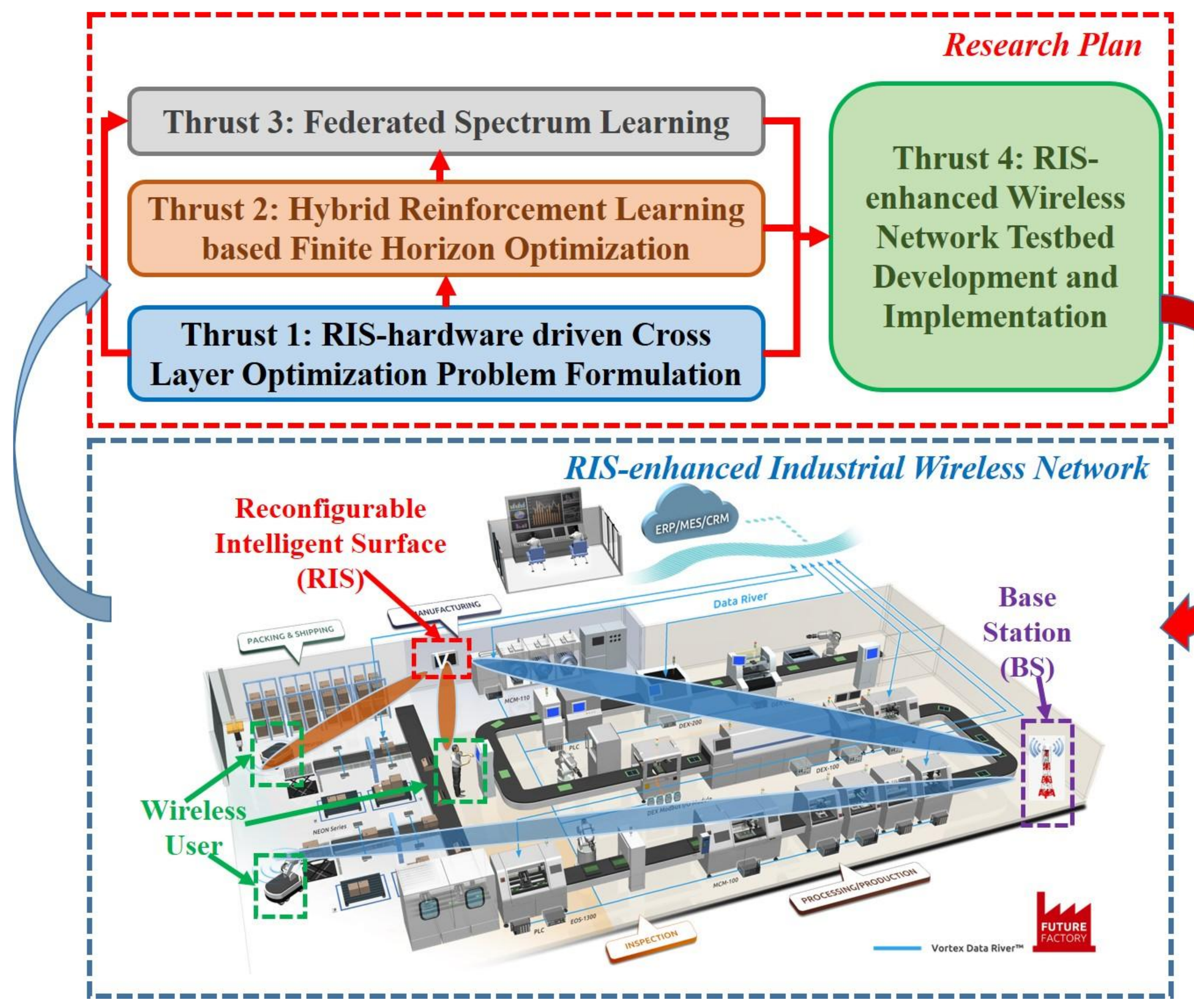
Overview

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 complex environment?**

Technical Approach and Results

Dynamic resource allocation optimization for Social Internet of EV Charing with causal RL

Goal: To optimize dynamic optimal resource allocation for large scale social internet of EV charging network.

Approach:

Solution 1: Formulate the dynamic optimization problem for RIS-aid wireless network to support data exchange among social IoEVs.

Solution 2: Develop causal structure based RL algorithm to learn dynamic optimal resource allocation online and rapidly.

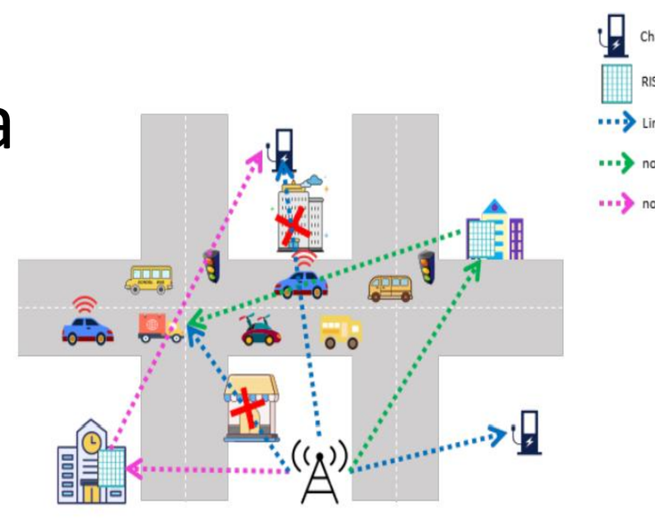


Figure 1. RIS-assisted wireless electric vehicle charging network.

Causal structure RL-enhanced RIS assisted and resource allocation for large scale IoEVs

Algorithm 1 Causal factor extraction based on a self-attention mechanism

```
Input: State set of each subcarrier s_j^t, ∀j; subcarrier neighborhood sets L_i, ∀i; weight matrix W_i; attention vector l
Position Encoding:
Initialize the position encoding for each state vector to consider the sequence order.
Encoder:
for each time step do
    Concatenate the state vectors of all subcarriers into a matrix X.
    for encoder layer do
        Pass the output through a feed-forward neural network layer to capture non-linear relationships.
        Compute the self-attention scores for each subcarrier's state vector.
        Apply the self-attention mechanism to obtain the weighted sum of each user's state representation.
    end for
    Obtain the causal factor for each subcarrier from the final encoder layer output.
end for
return Causal factor for each subcarrier.
```

Algorithm 2 CF-A3C-based resource allocation optimization algorithm

```
Input: Global network parameters θ^global, number of threads N_threads
Initialize global network parameters θ^global
for thread = 1 to N_threads in parallel do
    Initialize thread-specific environment and network parameters θ^local ← θ^global
    Initialize episode counter episodes = 0
    while not done do
        Receive initial observation state s_1
        Put state s_t into the causal factor extraction network to obtain causal factor z_t
        for t = 1 to T_max do
            Select action a_t = π(z_t|θ^local) using policy network
            Execute action a_t and observe reward r_t and new state s_{t+1}
            Put state s_{t+1} into the causal factor extraction network to obtain causal factor z_{t+1}
            Perform gradient ascent on global network parameters using the observed transition
            Synchronize local network parameters with global network parameters
        end for
        Increment episode counter episodes
    end while
end for
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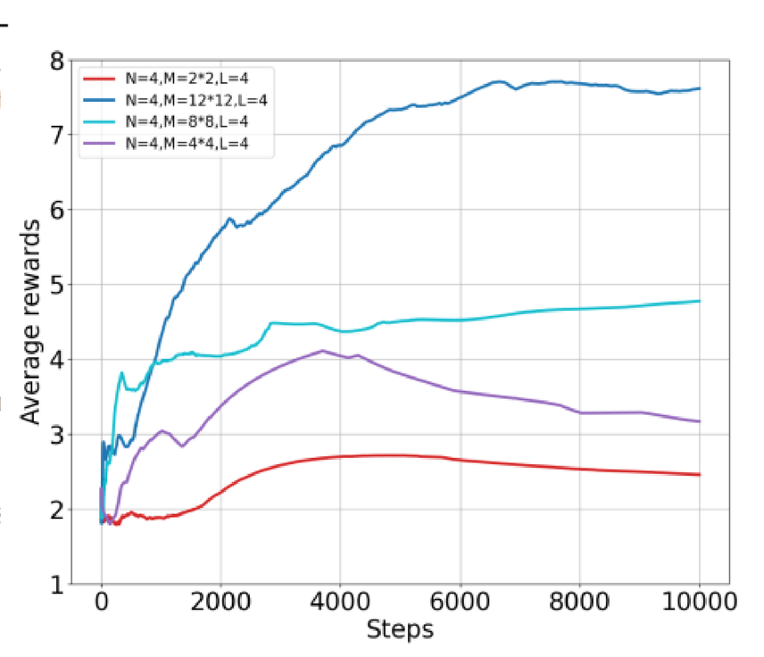
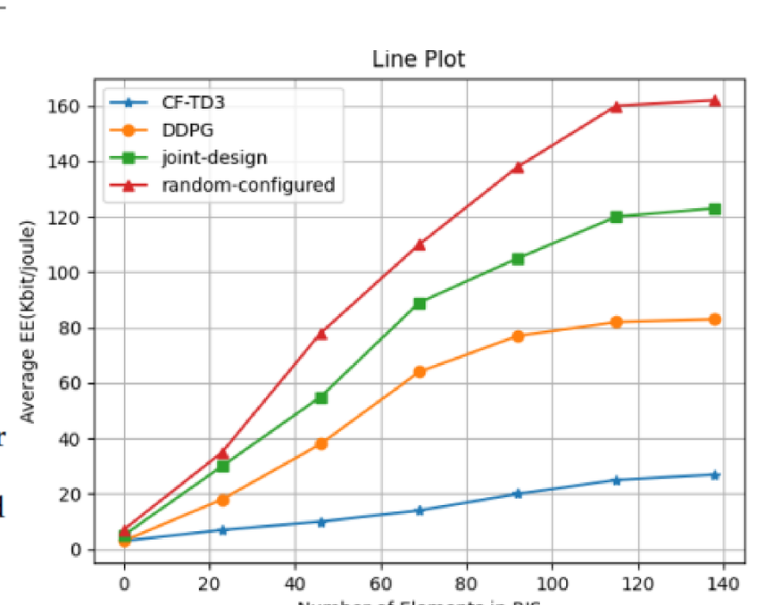


Average rewards vs. num. of RIS units



Average EE vs. num. of RISx with different methods.

Integrated channel estimation and resource allocation for RIS-assied wireless network (A bilevel optimization with hierarchical RL approach)

Goal: Obtain a novel theoretical foundation and algorithm to address integrate channel sensing and resource allocation for RIS-assisted wireless network.

Approach:

Solution 1: Develop a novel bi-level optimization theory with *i) Top Layer:* solve the intelligent resource allocation with sensed channel from bottom layer, *ii) Bottom Layer:* estimate the wireless channel based on assigned resource allocation from top layer.

Solution 2: Develop a hierarchical reinforcement learning technique to solve the bilevel channel sensing and resource allocation optimization problem with i) NN-based channel estimator for bottom layer, and ii) Actor-critic RL based resource allocation for top layer.

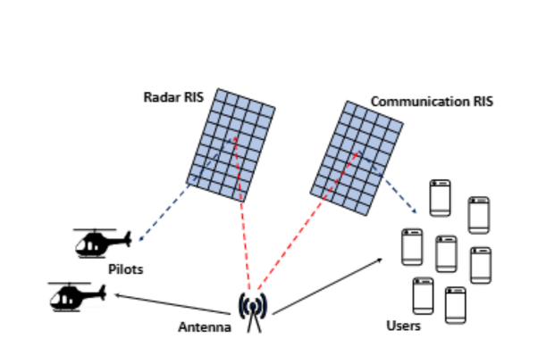
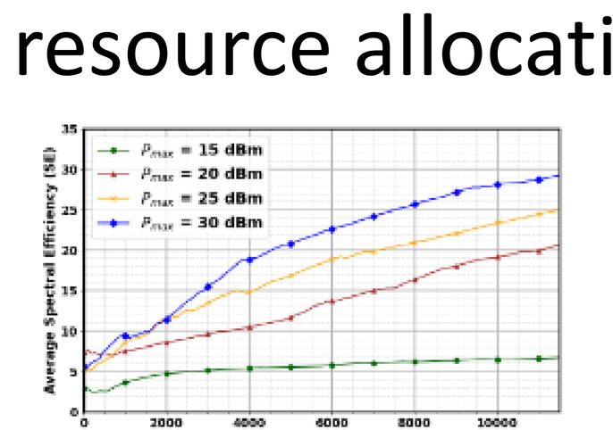


Fig. 1: Dual purpose RIS for communication and sensing



(b) Average SE over time steps under different values of P_{max}

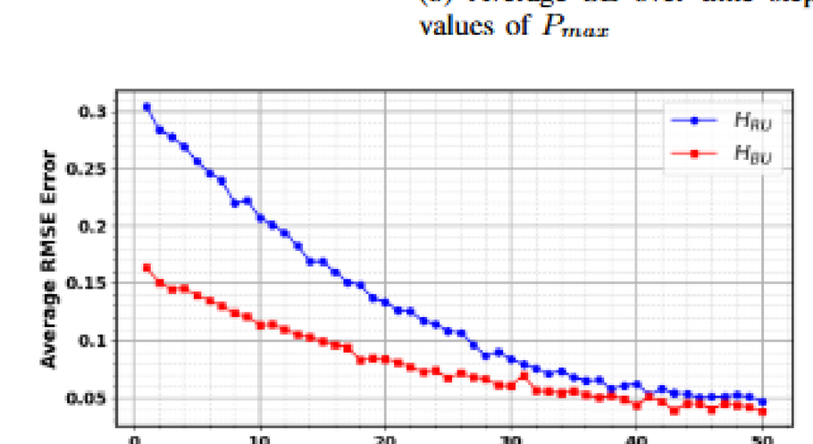


Fig. 2: The channel gain estimation error averaged over all RIS and users

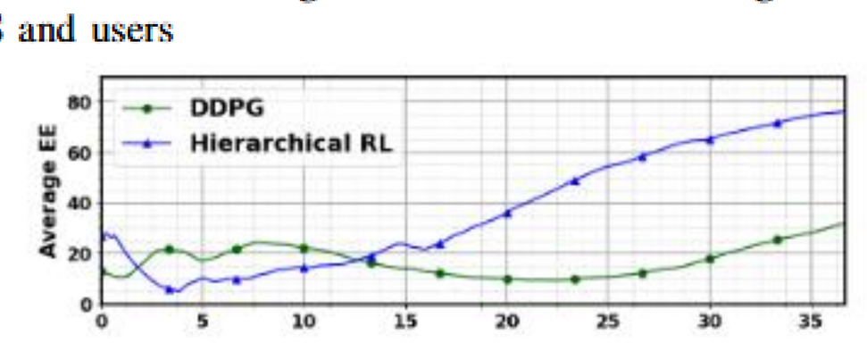


Fig. 4: Average energy efficiency with the confirmations $N = 16$, $N_{\mathrm{UE}} = 16$, and $N_{\mathrm{RIS}} = 8$

Algorithm 1 Hierarchical Reinforcement Learning based Joint Optimal Dynamic Resource Allocation and Wireless Channel Estimation: A Bi-Level Optimization Algorithm

1. Initialize N, N_{RIS}, M, N_{UE} and Pilots number.
2. Initialize channel gain matrices and antenna vectors.
3. Initialize weights for wireless channels estimation: $\hat{W}_{BU,k}$ and $\hat{W}_{RU,l,k}$. Actor-Critic RL: $\hat{W}_{Q,i}$, $\hat{W}_{\phi,i}$ and $\hat{W}_{P,i}$
4. Initialize errors: e_k^{p1}, $e_k^{p2,l}$, $e_{Q,i}$, $e_{\phi,i}$ and $e_{P,i}$
5. Initialize thresholds: δ_k^{p1}, $\delta_k^{p2,l}$, $\delta_{Q,i}$, $\delta_{\phi,i}$ and $\delta_{P,i}$.
6. **while** TRUE **do**
7. At time t
8. Beginning of lower-level optimization
9. **while** $((e_k^{p1} \geq \delta_k^{p1})$ and $(e_k^{p2,l} \geq \delta_k^{p2,l}))$ **do**
10. Update NN weights using (16) and (17).
11. Update wireless channel estimation error using (14) and (15).
12. **end while**
13. Pass lower-level cost function and weights to the upper level.
14. Beginning of upper-level optimization.
15. **while** $e_{Q,i} \geq \delta_{Q,i}$, $e_{\phi,i} \geq \delta_{\phi,i}$ and $e_{P,i} \geq \delta_{P,i}$ **do**
16. Update actor-critic NN weights using (22), (25) and (27).
17. Update approximation errors (21), (24) and (26).
18. **end while**
19. $\mathbf{\Phi} \leftarrow \hat{\mathbf{W}}_{\phi,i}^T(t)\psi(.)$, $\mathbf{P} \leftarrow \hat{\mathbf{W}}_{P,i}^T(t)\vartheta(.)$.
20. Update $t = t + T$
21. Estimate new wireless channel and observe wireless network performance based on fine-tuned energy-effective transmit power allocation at BS and phase shift matrices design at RISs.
22. **end while**

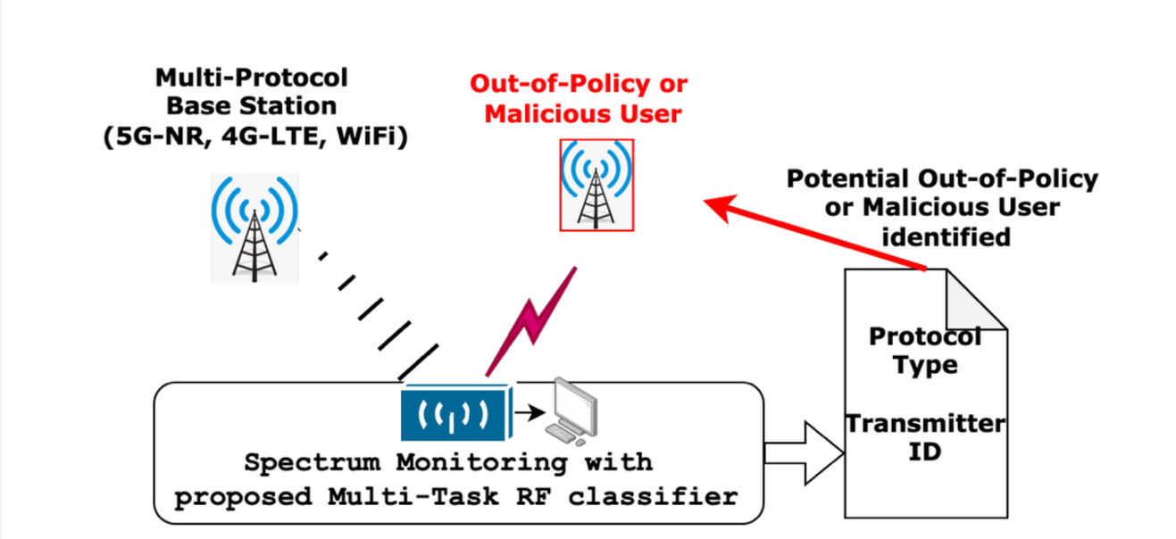
Transmitter Identification and Protocol Categorization in Shared Spectrum via Multi-Task RF Classification at the Network Edge

Goal: Develop a robust framework for transmitter identification and protocol categorization via RF signal classification in shared spectrum environments.

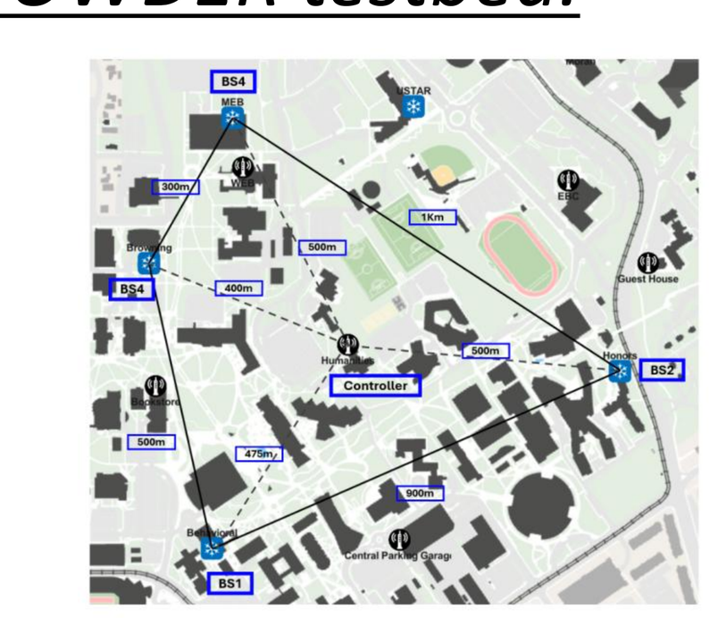
Approach:

(i) A multi-task RF classifier using Convolutional Neural Network (CNN) is designed to tackle critical challenges such as overlapping signal characteristics and environmental variability. The proposed method employs a multi-channel input strategy to extract meaningful signal features, achieving remarkable accuracy.

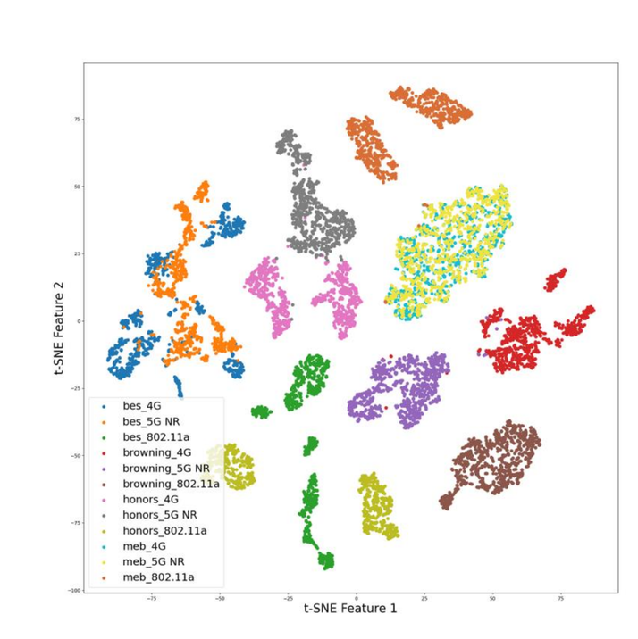
(ii) Unlike existing methods that focus on narrow dimensions or individual tasks, this research aims for joint classification by simultaneously analyzing protocols, base stations, and their combinations. *Data is from NSF POWDER testbed.*



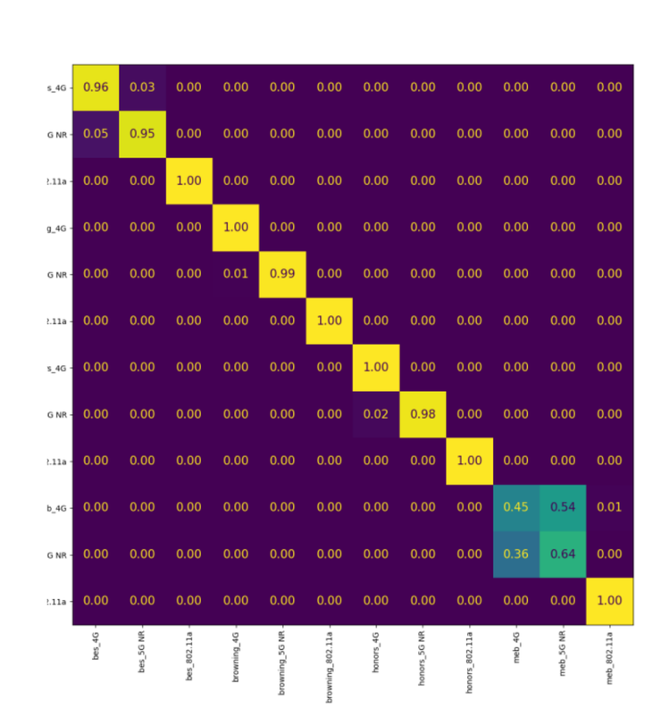
Motivating example for transmitter identification and protocol categorization in shared spectrum



NSF POWDER testbed for data collection: The dataset consist of 120 signals each with 3 million IQ samples across 2 different days with 60 signals sampled per day with a total of 4 base stations and 3 protocols. The transmission protocols are WiFi, 4G LTE, and 5G NR.



Joint T-SNE embeddings



Joint Confusion Matrix

Class	Precision	Recall	F1-Score
bes_4G	0.93	0.97	0.96
bes_5G NR	0.97	0.93	0.95
bes_802.11a	1.0	1.0	1.0
browning_4G	0.98	0.99	0.99
browning_5G NR	0.99	0.99	0.99
browning_802.11a	1.0	1.0	1.0
honors_4G	0.97	0.99	0.98
honors_5G NR	0.99	0.97	0.98
honors_802.11a	1.0	1.0	1.0
meb_4G	0.56	0.40	0.47
meb_5G NR	0.56	0.71	0.62
meb_802.11a	0.99	1.0	0.99
Accuracy	0.92		

TABLE III
JOINT CLASSIFICATION PERFORMANCE

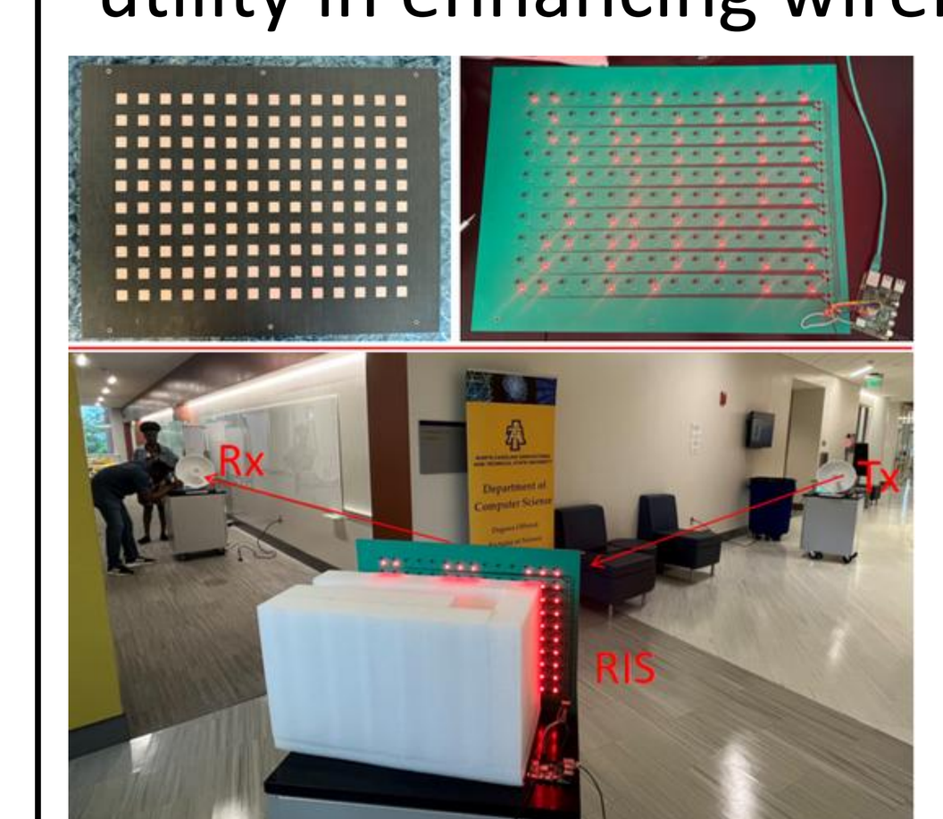
RIS Hardware Development and Wireless System Testbed (Abdullah, Binbin)

Goal: Develop the RIS hardware and conduct system level experiments to characterize the RIS-assisted wireless communication system.

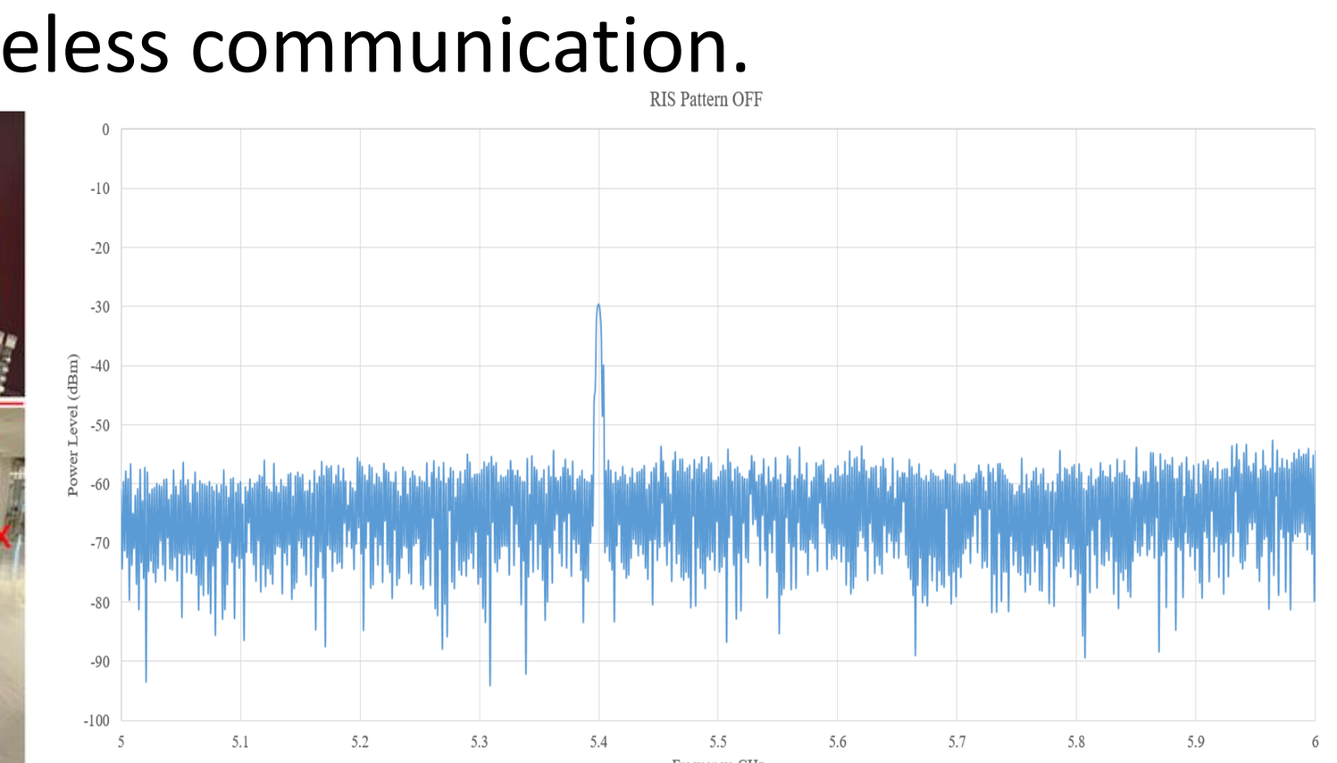
Approach:

(i) Designed a wideband binarily controlled RIS operating at 5-6 GHz by leveraging stacked patch structures as the reflector element and PIN diodes as the binary switch. Two 140-element arrays are designed and prototyped.

(ii) Both indoor measurements at NCAT and outdoor measurements at NSF POWDER site were conducted. Consistent results of 10-15 dB signal strength boost has been observed for both cases, validating the RIS design and its utility in enhancing wireless communication.

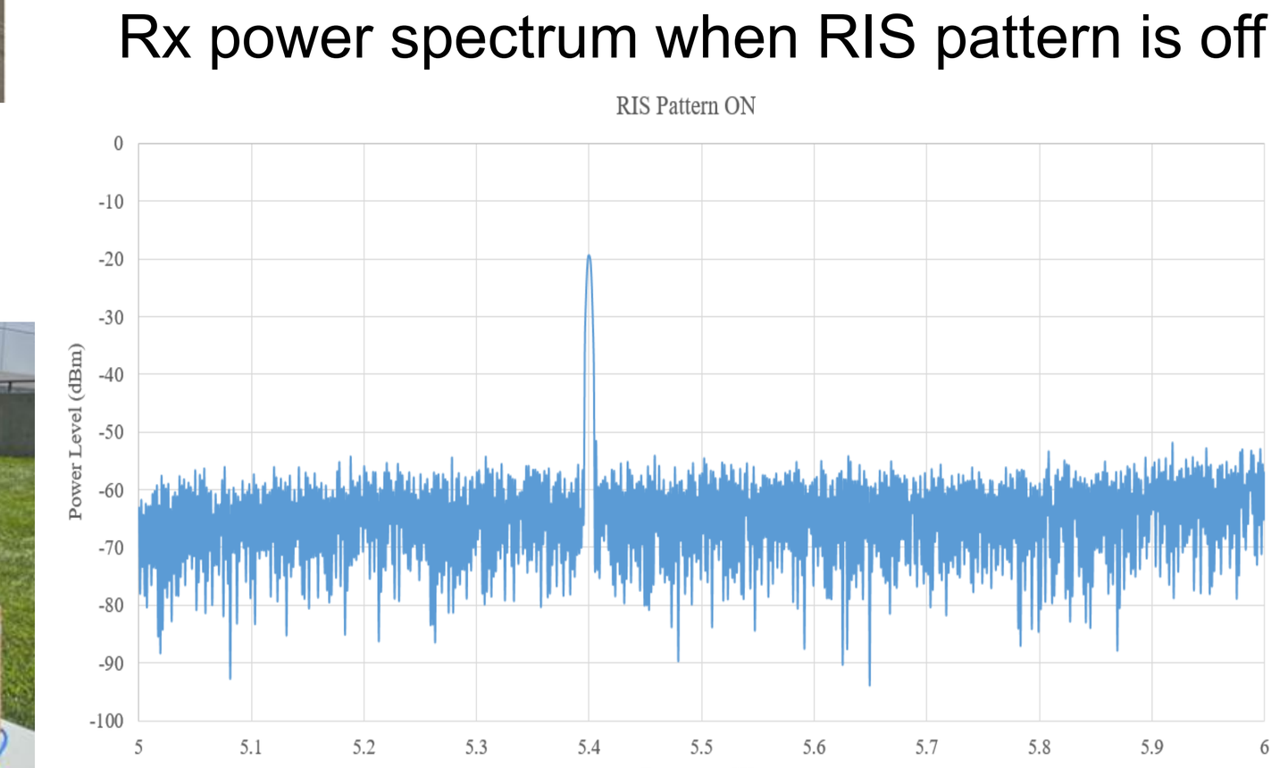


RIS hardware with 140 binary elements and the indoor test at NCAT



Rx power spectrum when RIS pattern is off

RIS outdoor measurement at NSF POWDER site in Utah



Rx power spectrum when RIS pattern is on
(10dB+ signal strength boost is observed)

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Selected Products

1) Yuzhu Zhang, and Hao Xu. "Distributed Data-Driven Learning-Based Optimal Dynamic Resource Allocation for Multi-RIS-Assisted Multi-User Ad-Hoc Network". Algorithm, vol. 17, no. 1, pp. 45, 2024.
2) Yuzhu Zhang, and Hao Xu. "Reconfigurable-Intelligent-Surface-Enhanced Dynamic Resource Allocation for the Social Internet of Electric Vehicle Charging Networks with Causal-Structure-Based Reinforcement Learning." Future Internet, vol. 16, no. 5, pp. 165, 2024.
3) Shawon Dey, Lijun Qian, and Hao Xu. "Joint Channel Sensing and Dynamic Resource Allocation for Multi-RIS assisted Wireless Networks: A Bilevel Optimization Approach." In *2025 IEEE Military Communications Conference (MilCOM)*, to appear. IEEE, 2025.
4) T. Abdul-Quddoos, T. Sharmin, X. Li, L. Qian, "Transmitter Identification and Protocol Categorization in Shared Spectrum via Multi-Task RF Classification at the Network Edge," The Third Workshop on Machine Learning and Deep Learning for Wireless Security, ICC 2025.
5) K. Mensah-Bonsu, B. Yang, A. Eroglu, H. Xu and L. Qian, "1-bit Wideband Reconfigurable Intelligent Surface Design at Sub-6 Band," 2024 International Applied Computational Electromagnetics Society Symposium (ACES), Orlando, FL, USA, 2024, pp. 1-2.