Machine Learning-based Joint TX Power and RX Sensitivity Control for Overlapping Basic Service Set Interference Mitigation in Dense IoT Wireless Networks

Jin-Min Lee, Hye-Yeon Shim, Il-Gu Lee

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Jin-Min Lee
csewa56579@gmail.com
Sungshin Women's University

SUNGSHIN WOMEN'S UNIVERSITY

IARIA

Jin-Min Lee

Author Information

- Ph.D. Candidate, CSELAB
- Future Convergence Technology Engineering
- Sungshin Women's University

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M.S. Course in Future Convergence Technology Engineering,
Sungshin Women's University, Seoul, Korea

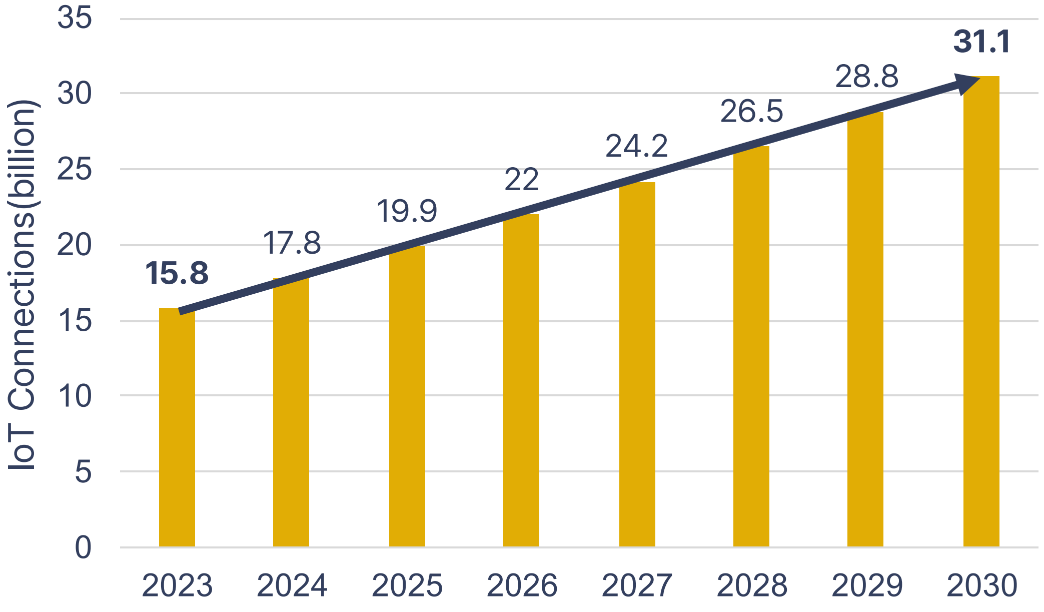
2018. 03 ~2021.08

B.S Course in Convergence Security Engineering,
Sungshin University, Seoul, Korea

Research Areas

- Secure IoT and Wireless Networking for Next-Generation Networks
- Digital ID Technologies
- AI Convergence Technologies
- Convergence Security

01 Background & Motivation



Projected Global IoT Connections Growth (2023-2030)

IoT growth → OBSS environments frequent

- Multiple BSS sharing same/adjacent channels
- Results in strong interference and degraded QoS

Performance Degradation in OBSS

- OBSS environments cause **severe channel interference**
- Leads to reduced throughput, higher latency, and unstable link quality

Limitations of Existing Soluntions

- Prior studies use blocking links or time-division methods.
- These reduce throughput & SR rates, fail to adapt to real time traffic, and **ignore RX sensitivity.**

Proposed Approach

- OBSS is treated not as a constraint but as **a resource to manage**
- Propose **ML-based joint control of TX power and RX sensitivity**
- Support both **centralized (global optimization) and distributed (local prediction scalability)**

02 Problem Statement

1 Conventional Methods

- Focus mainly on **TX power control**, rarely consider RX sensitivity.
- Rely on **static probability models**, unable to adapt to real-time traffic dynamics.
- Result: **Fail to mitigate interference** effectively in dense IoT networks.

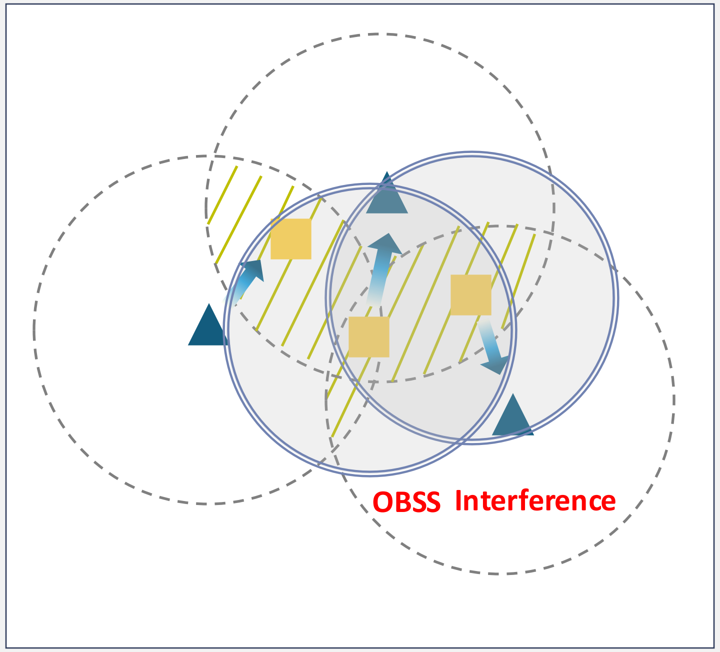
2 Limitations

- Cause **significant throughput and SR degradation** (up to 40% loss in heavy OBSS).
- **Do not capture receiver-side effects**, leading to unstable SINR.
- **Poor scalability** in high-density deployments.

“How to mitigate interference while simultaneously improving throughput and SR in dense IoT networks?”

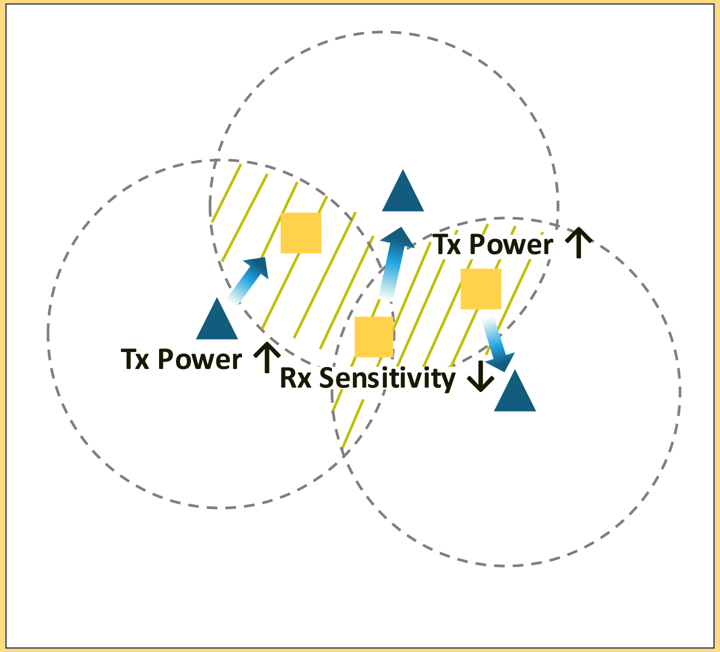
03 Proposed Scheme

Problem



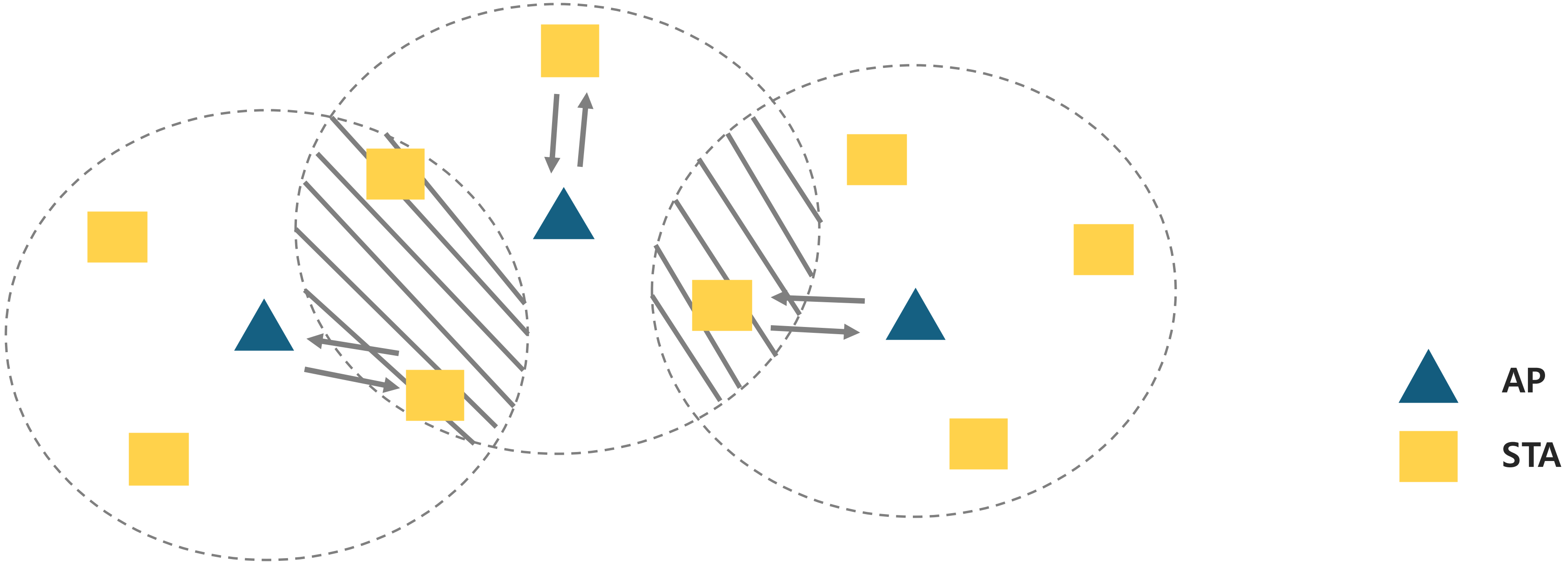
- OBSS interference occurs from shared same/adjacent channels
- Throughput degradation

Proposed Solution



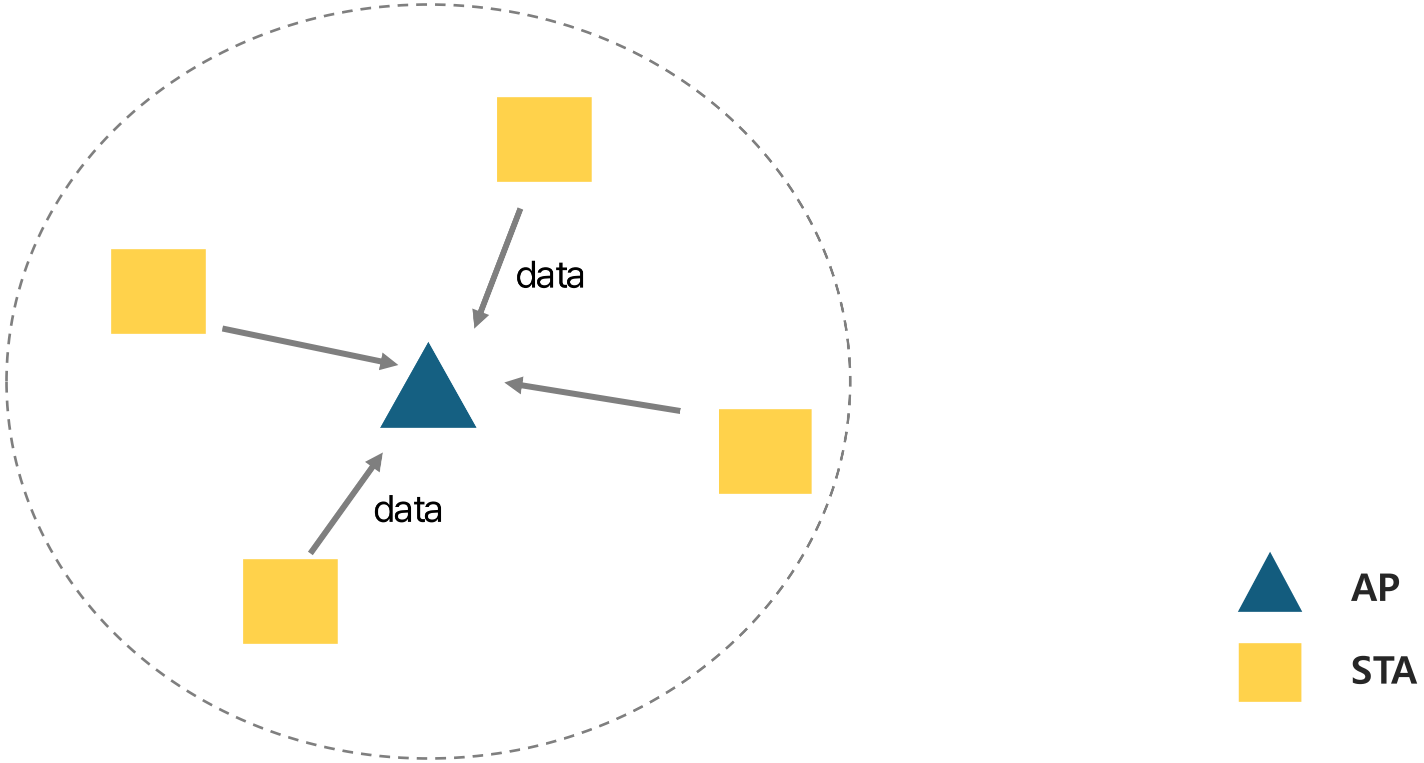
- ML-based distributed control
  - TX Power (on sender side)
  - RX Sensitivity (on receiver side)
- Interference ↓, Throughput ↑

① Network simulation



- Each AP communicates with its associated STAs within its BSS.
- Overlapping BSS areas cause co-channel interference among APs and STAs.

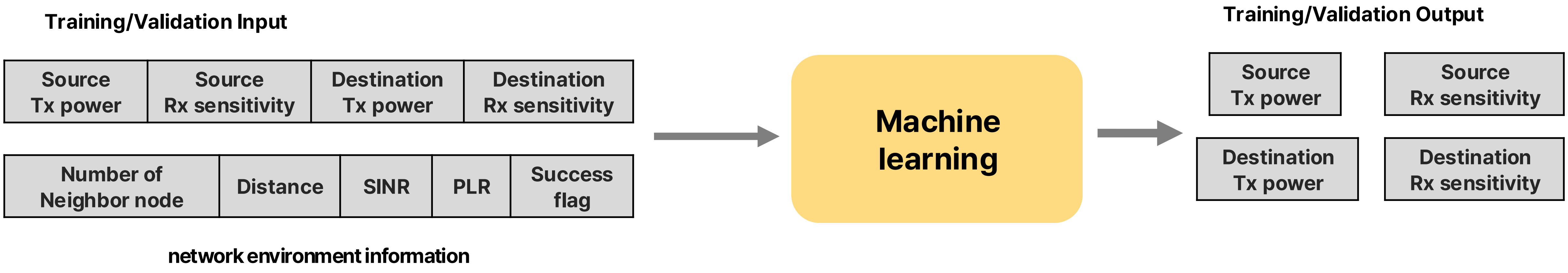
② data collection



- Each AP collects local network information such as TX/RX parameters, number of neighboring nodes, distance, SINR, PLR, and success flag for training.

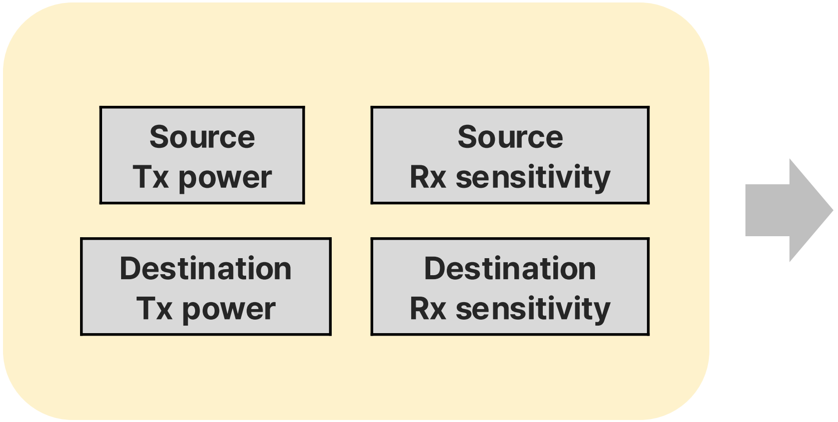
03 Proposed Scheme

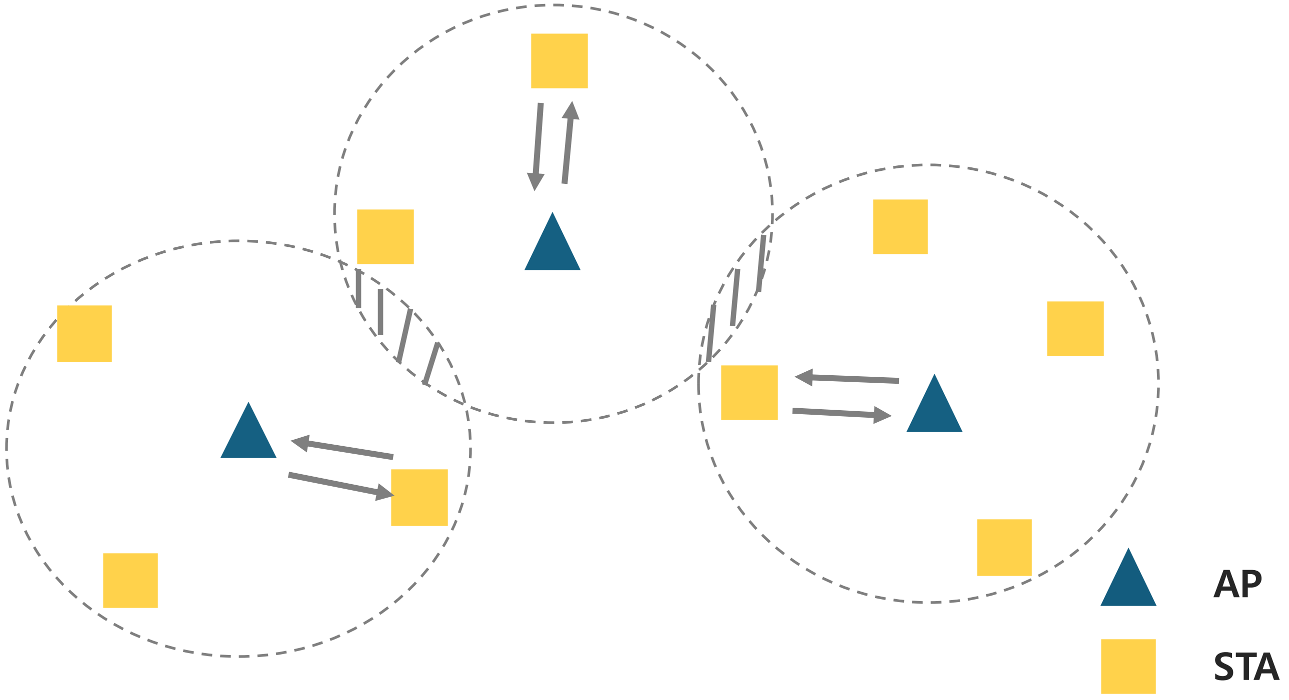
③ Machine learning



- The ML model learns the optimal TX power and RX sensitivity that minimize interference and maximize throughput.

④ Machine learning based TX/RX parameter control

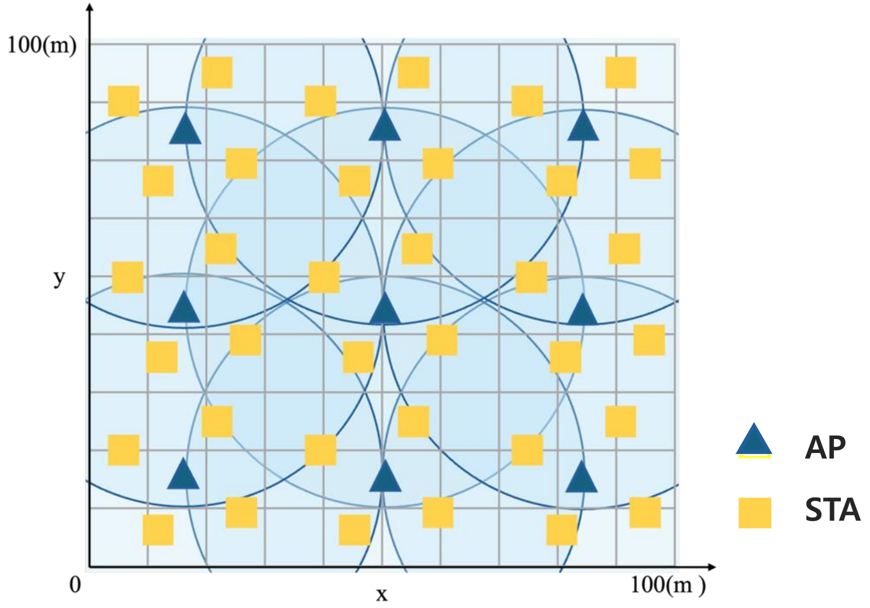




- Each AP dynamically adjusts TX power and RX sensitivity based on the learned model, reducing interference and improving throughput.

04 Simulation Model

Network Topology



- **100m × 100m area**, single 20 MHz channel (2.4 GHz)
- 9 APs in 3×3 grid (33.33 m spacing), **4 STAs per AP**
- **Co-channel interference** due to overlapping coverage

Model Parameters

Channel model
Log-distance path loss with shadow fading (σ = 4 dB)

Noise model
Thermal noise (N = –94 dBm)

Performance metric
Downlink/uplink SINR (includes AP & STA interference)

05 Experimental Environment

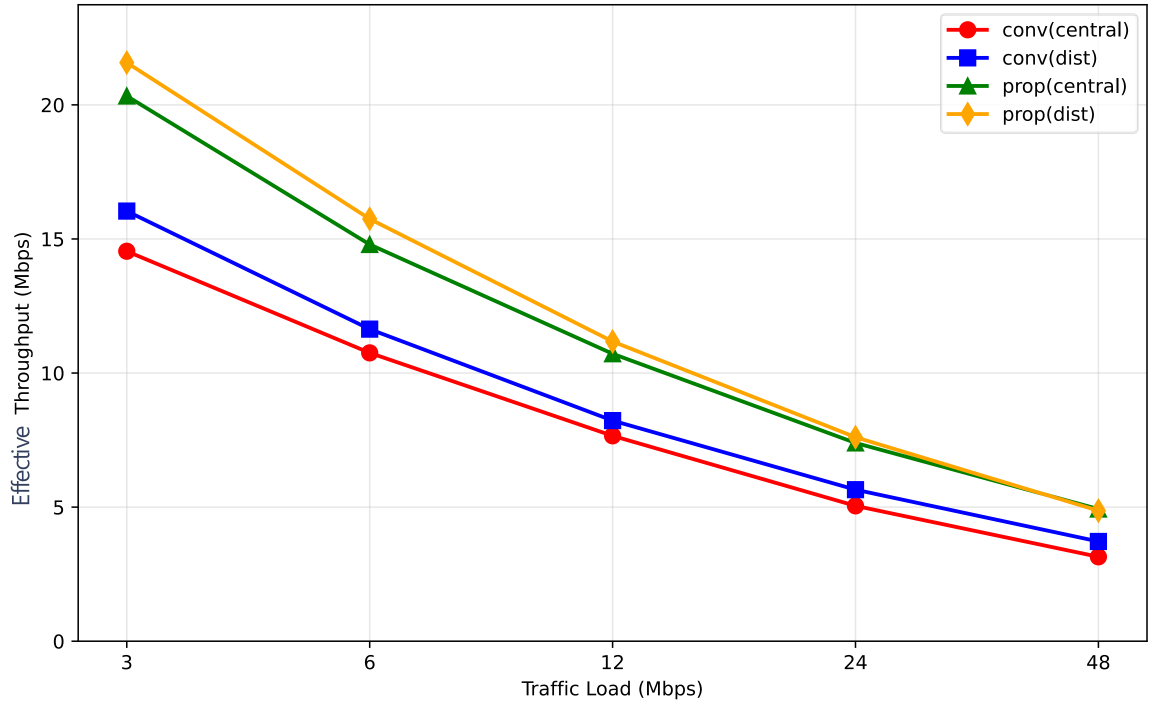
Experimental Setup

- Traffic Loads: 3, 6, 12, 24, 48 Mbps
- Runs: Each test 10 seconds, repeated 1000 times
- Metrics Evaluated:
  - Effective Throughput (Mbps)
  - Measured SINR (dB)
  - Control overhead (s)

Evaluated Methods

Control techniques		Description
Conv	central	Conventional method controlling **Tx power** in a **centralized technique**
	dist	Conventional method controlling **Tx power** in a **distributed technique**
Prop	central	Proposed method controlling **Tx power and Rx sensitivity** in **a centralized technique**
	dist	Proposed method controlling **Tx power and Rx sensitivity** in a **distributed technique**

06 Evaluation Result – Effective Throughput

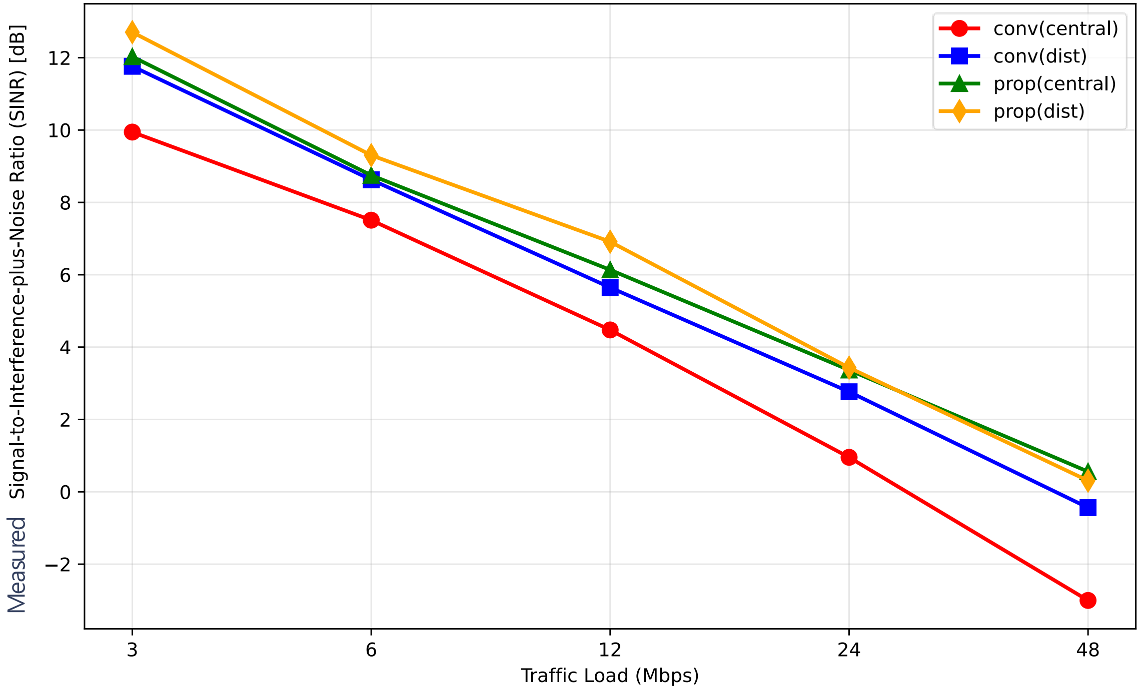


- Effective Throughput ↑ 47.1%
- Distributed > Centralized
  46.4% ↑ under low load
- Stable even under heavy traffic

$$T_i = R_{MCS}(SINR_i) \times (1 - PLR_i)$$

i: i-th simulation round
T_i: Effective throughput measured at round i
$R_{MCS}(SINR_i)$: MCS selection function that maps the measured $SINR_i$to the corresponding PHY data rate (IEEE 802.11ac, 20 MHz, MCS 0–9); selects the highest MCS level satisfying the SINR threshold.
$SINR_i$: Measured SINR at round i
PLR_i: Packet loss ratio at round i

06 Evaluation Result - Measured SINR

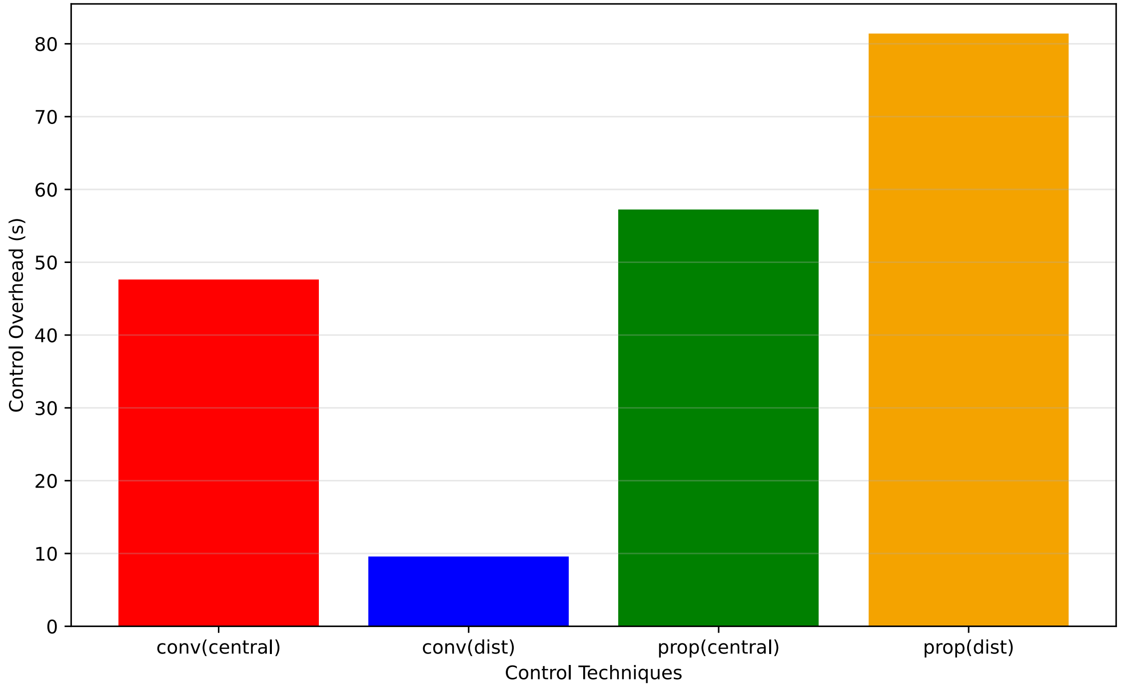


- Measured SINR ↑ 29.6%
- Distributed: consistent improvement
- Ensures higher link quality

$$SINR_{DL(i,j)} = \frac{P_{rx(i,j)}}{N_i + I_i}, \qquad SINR_{UL(i,j)} = \frac{P_{rx(j,i)}}{N_j + I_j}$$

$P_{rx(i,j)} = P_{tx(j)} - PL(i,j)$: The received signal power
$P_{tx(j)}$: The TX power of AP_j
$PL(i,j)$: The path loss between AP_j and STA_i
N_i: The noise power at STA_i
I_i: The interference from the other APs and active STAs

Evaluation Result – Control Overhead



- Distributed control overhead ↑ due to prediction overhead
- Still scalable in real deployments

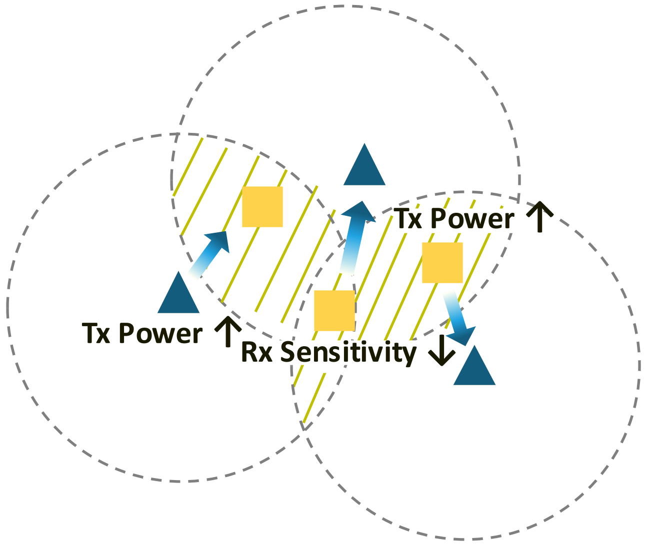
$$\begin{aligned} &Control\ Overhead \\ &= ML\ prediction\ +\ file\ I/O \\ &+ SINR\ calculation\ of\ the\ network \end{aligned}$$

06 Conclusion and Future work

Conclusion

- ML-based joint TX/RX control mitigates OBSS interference
- The distributed approach achieves **47.1% higher throughput and 29.6% better SINR t**han conventional methods.
- It maintains **stable link quality under heavy traffic**, demonstrating strong **potential for real-world deployment**.

ML-based joint control of TX power and RX sensitivity



Future work

- Use ns-3 for realistic distributed simulation
- Apply reinforcement learning for adaptive control
- Validate in real WLAN deployments

Thank you!

Jin-Min Lee
csewa56579@gmail.com
Sungshin Women's University