Building AI-native Protocols from the Inside: The Case of Wi-Fi

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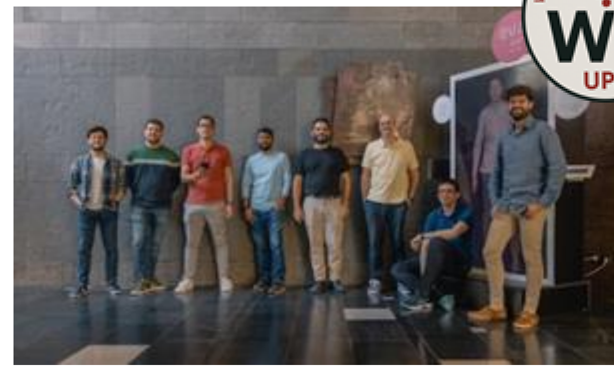
AI and Machine Learning in Communication Networks

Wireless Networking Research Group @ UPF



Team:

- Prof. Boris Bellalta, Prof. Francesc Wilhelmi
- 4 PhD students (+2 from Q4-2025)
- 1 Research engineer
- + Master and undergraduate students

Research lines:

- Wireless Networking in Unlicensed Bands
  - Wi-Fi 7/8 technologies
- The future of the unlicensed
  - Beyond Wi-Fi 8, AI-native networking, DLT/Blockchain
- Applications: XR streaming over Wi-Fi

Ongoing projects:

- MAX-R (HE), Wi-XR (AEI), MLDR (Chistera EU)

maxR
Mixed Augmented and Extended Reality Media Pipeline

Wi-XR
Low-latency Wireless Networking for interactive XR applications

MLDR
A Machine Learning-Driven Radio Interface

Agenda

1. Introduction to AI-native Wi-Fi
2. AI-driven MAC & PHY enhancements
3. Towards AI-native 802.11
4. Toolset for advancing towards AI-native networks

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AI-Native Networks: The What & The Promises

1 Definition [1]

- *"In AI-native networks, AI is deeply integrated into the network's architecture and, which is key for handling core operations"*
- *"AI-native networks should have: cognitive ability, problem-solving capability, learning ability, and autonomy"*

2 Expectations

- Proactive, self-optimizing, and self-healing capabilities
- Enhanced performance, higher efficiency, reduced operational costs, improved security, higher flexibility, etc.

3 Needs

- Enhanced and specialized data collection and processing (e.g., traffic patterns, customer/device behavior, environment, application usage…)
- Ability to run AI operations (new computing/communication architectures, parallelization, etc.)
- New measurement and validation tools & processes

[1] FG-AINN-I-038-R5: Study of characteristics of artificial intelligence native telecommunication networks

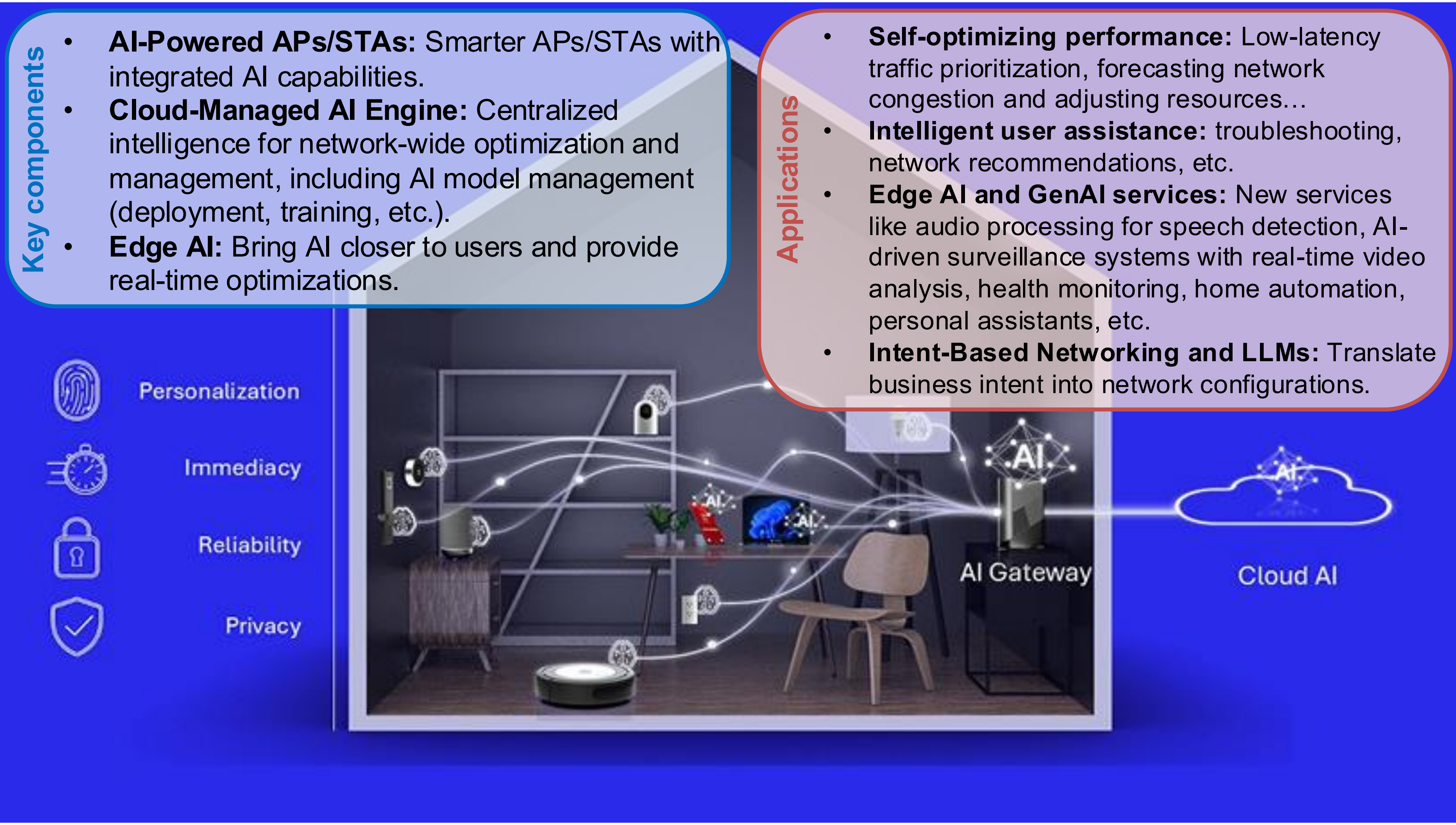
AI-Native Wi-Fi: High-level definition

Key components

- **AI-Powered APs/STAs:** Smarter APs/STAs with integrated AI capabilities.
- **Cloud-Managed AI Engine:** Centralized intelligence for network-wide optimization and management, including AI model management (deployment, training, etc.).
- **Edge AI:** Bring AI closer to users and provide real-time optimizations.

Applications

- **Self-optimizing performance:** Low-latency traffic prioritization, forecasting network congestion and adjusting resources…
- **Intelligent user assistance:** troubleshooting, network recommendations, etc.
- **Edge AI and GenAI services:** New services like audio processing for speech detection, AI-driven surveillance systems with real-time video analysis, health monitoring, home automation, personal assistants, etc.
- **Intent-Based Networking and LLMs:** Translate business intent into network configurations.



Source: Qualcomm (https://www.qualcomm.com/news/onq/2024/10/how-ai-can-unlock-the-future-of-wireless-networking)

Our focus today: 802.11 MAC & PHY

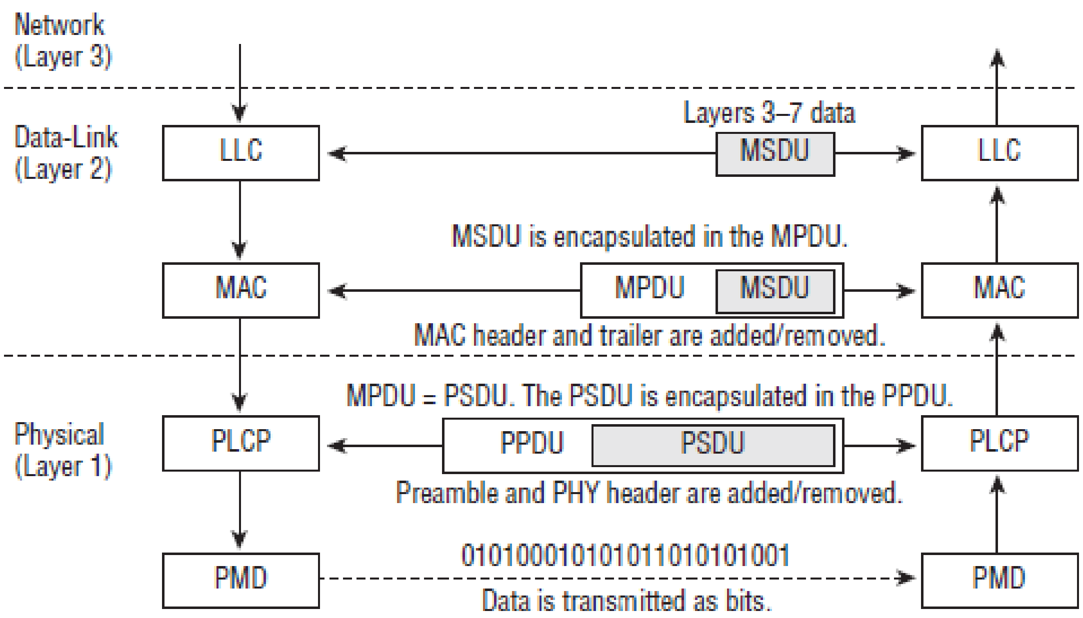
IEEE 802.11 architecture:

L2

- Link-Layer Control (“upper MAC”): network discovery, onboard users, measurement & reporting, mobility, etc.
- Medium Access Control (”lower MAC”): channel access, framing, retransmissions, error detection, etc.

L1

- Physical Layer Convergence Procedure (PLCP): Carrier sensing, clear channel assessment, handle PLCP Protocol Data Unit (PPDU), etc.
- Physical Medium Dependent (PMD): TX/RX (modulation/demodulation, encoding, etc.)



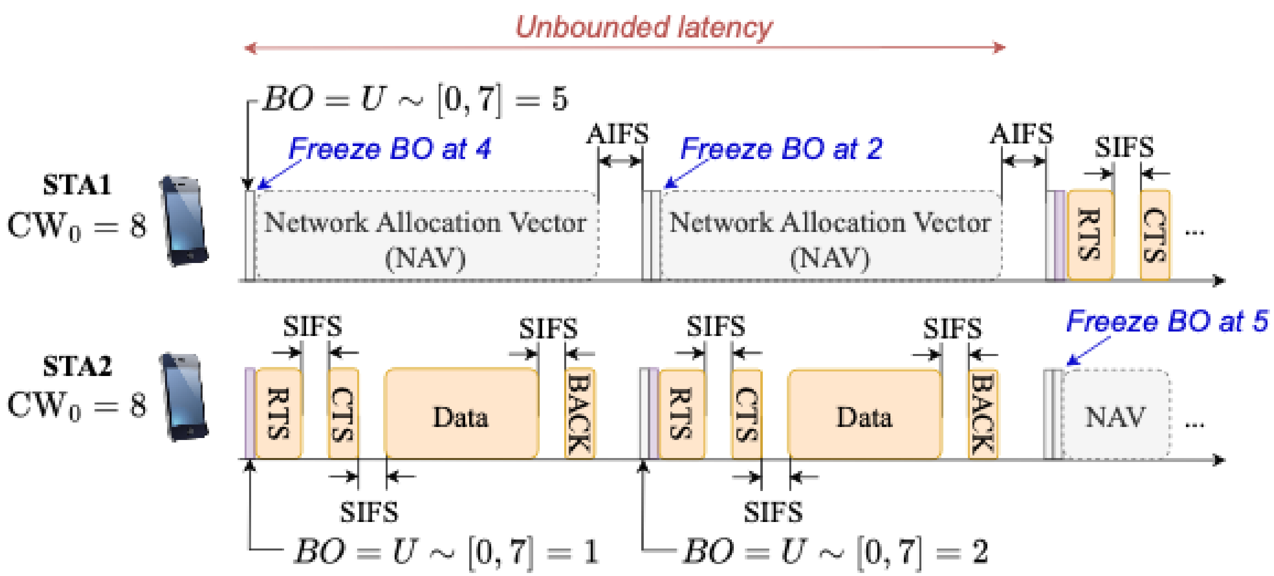
Need for AI in 802.11: Current 802.11 MAC & PHY

Wi-Fi design principles:

- Listen Before Talk (LBT)
- DCF: CSMA/CA + BEB + ARQ
  - EDCA: DCF + Multiple Access Categories for Traffic Differentiation
  - RTS/CTS mechanism reduces collision time

Limitations of traditional MAC & PHY:

- MAC: Fixed contention windows, reactive retransmissions, limited visibility into queueing and prioritization needs…
- PHY: Static power control, fixed channel operations, limited MCS adaptation, inefficient CSI acquisition…



*The performance of a Wi-Fi network **depends** on the activity of **other devices/networks** within its coverage, and operating in the same channel*

Result: Inefficient spectrum use, higher latency, and lower throughput, especially in dense or noisy environments.

Need for AI in 802.11: Wi-Fi Evolution and Use Cases

802.11n (Wi-Fi 4)
- 2.4 and 5 GHz band operation
- 4x4 SU-MIMO
- Packet aggregation, 64-QAM

802.11ac (Wi-Fi 5)
- Primarily 5 GHz band operation
- 8x8 SU-MIMO, DL MU-MIMO
- Channel bonding, 256-QAM

802.11ax (Wi-Fi 6/6E)
- 2.4, 5, and 6 GHz band operation
- OFDMA, UL & DL MU-MIMO
- TWT, 1024-QAM

802.11be (Wi-Fi 7)
- 320 MHz channels, 4096-QAM
- Improved OFDMA, R-TWT
- Multi-Link Operation

802.11bn (Wi-Fi 8)
- Improved Roaming
- Power saving mechanisms
- Multi-AP Coordination

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Improving Tx Rates

Radio Resource Management

Latency

Reliability

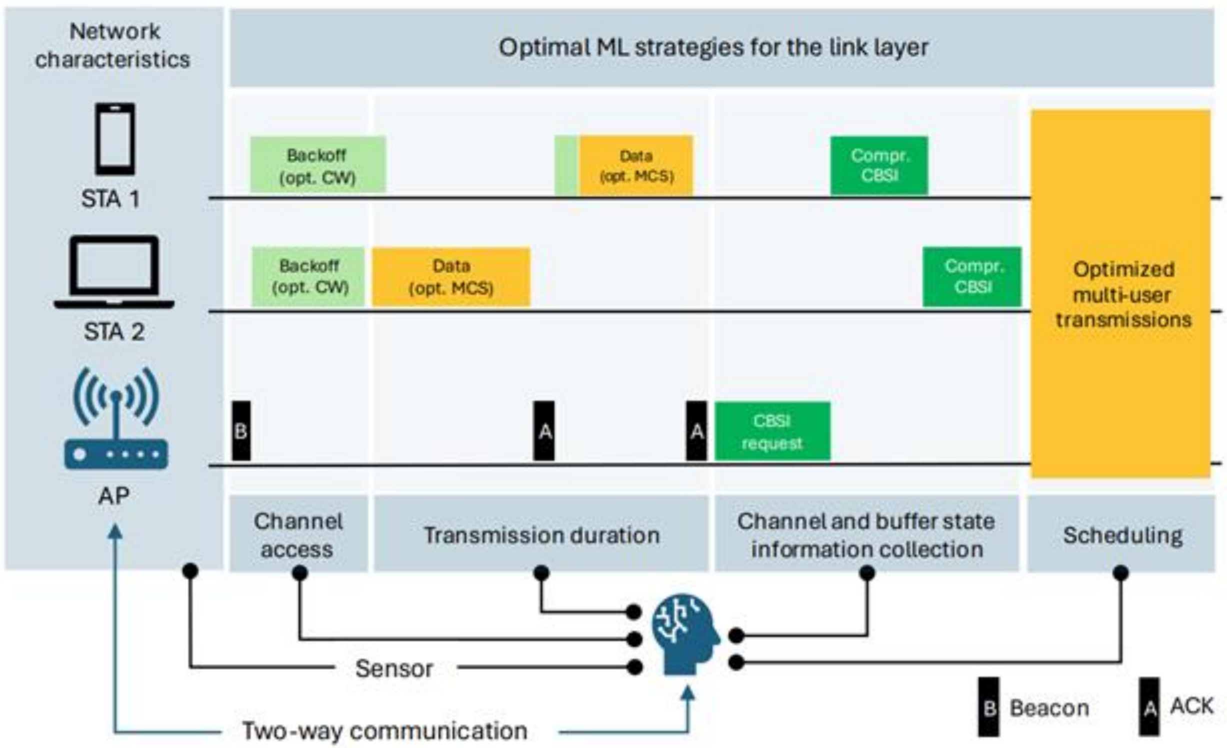
+ Complexity



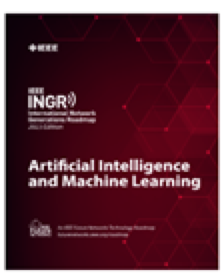
Wide range of use cases & scenarios: smartphones, laptops, gaming & TV, smart home, business networks, smart grid, industrial IoT, healthcare, AR/VR/XR, supply chain, warehouse, manufacturing Industry...

AI-Native Wi-Fi: An IEEE 802.11 (MAC/PHY) perspective

AI/ML-native radios envision to replace 'expert'-based designs by ML models able to adapt to every particular situation



PHY	Channel coding/decoding, modulation constellation design, equalization, mitigation of RF hardware impairments, etc.
Lower MAC	Interactive protocols & radio resource management: channel access, transmission duration set-up, error detection, channel & buffer state collection, scheduling, etc.
Upper MAC	AP selection, roaming, link management, onboarding, etc.



IEEE INGR AI/ML 2024

Open access version: Bellalta, Boris, Katarzyna Kosek-Szott, Szymon Szott, and Francesc Wilhelmi. "Towards an AI/ML-defined Radio for Wi-Fi: Overview, Challenges, and Roadmap." arXiv preprint arXiv:2405.12675 (2024).

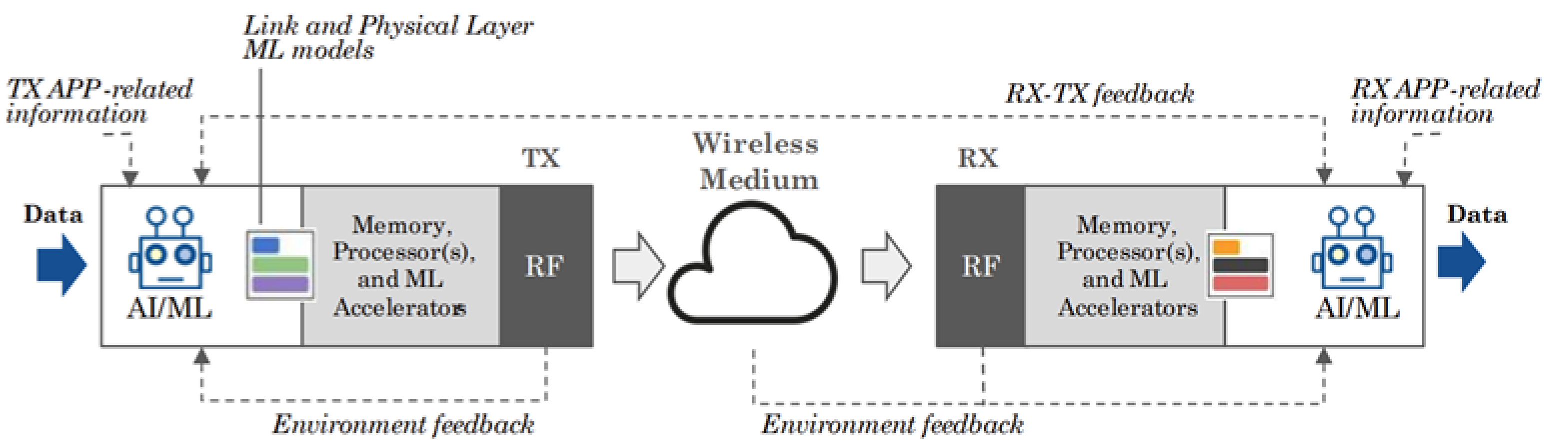
AI-Native Wi-Fi: An IEEE 802.11 (MAC/PHY) perspective

Data collection:

- PHY Data: Signal-to-Noise Ratio (SNR), Received Signal Strength Indication (RSSI), Channel State Information (CSI), channel utilization, interference, error rates, preamble detection, etc.
- MAC Data: Packet loss rates, retransmission counts, queue depths, contention metrics, airtime utilization per device, frame types, etc.

AI-based MAC & PHY:

- Optimization: Drive communication mechanisms like channel access, signal TX/RX, error control…
- Prediction: Predict future channel conditions, traffic changes, interference activity…
- Classification: Identify traffic types and applications, types of interference (Wi-Fi vs non-Wi-Fi)…
- Anomaly Detection: Detect unusual MAC/PHY behavior that indicates a problem (e.g., a sudden increase in retransmissions, persistent high contention).



Bellalta, Boris, Katarzyna Kosek-Szott, Szymon Szott, and Francesc Wilhelmi. "Towards an AI/ML-defined Radio for Wi-Fi: Overview, Challenges, and Roadmap." arXiv preprint arXiv:2405.12675 (2024).

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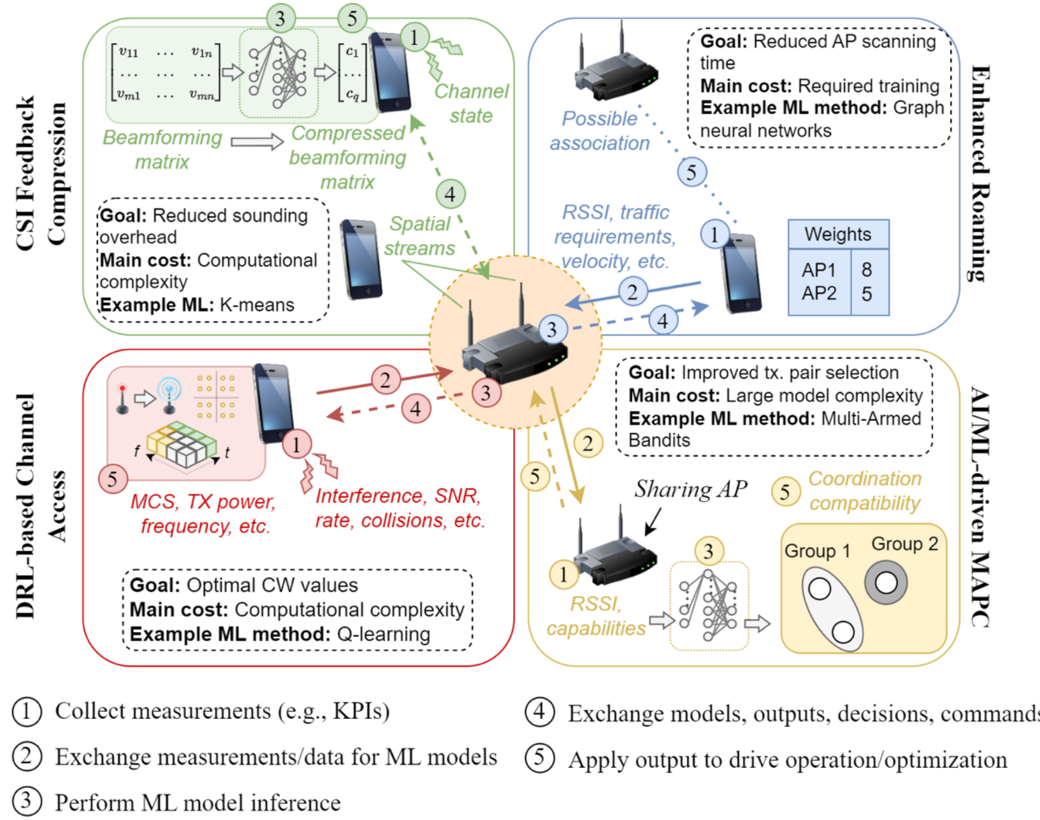
Standardization Efforts on AI/ML within IEEE 802.11

Past and current status:

- [July 2022] The IEEE 802.11 establishes the AIML TIG
- [Mach 2024] The TIG delivers a [report](https://www.ieee802.org/11/Reports/aiml_update.htm) on AI/ML for Wi-Fi use cases
- [Mach 2024] The TIG becomes an IEEE 802.11 Standing Committee (SC)
- [July 2025] 1st SC report

Use cases:

- CSI feedback compression based on Neural Networks
- AIML-based Roaming Enhancements
- DRL-based Channel Access
- ML-driven MAPC
- AI/ML model sharing



Wilhelmi, F., et al. (2024).[Machine Learning & Wi-Fi: Unveiling the Path Towards AI/ML-Native IEEE 802.11 Networks](). IEEE COMMAG 2024.

<https://www.ieee802.org/11/Reports/aiml_update.htm>

AI-driven MAC & PHY: CSI Feedback Compression

Problem:

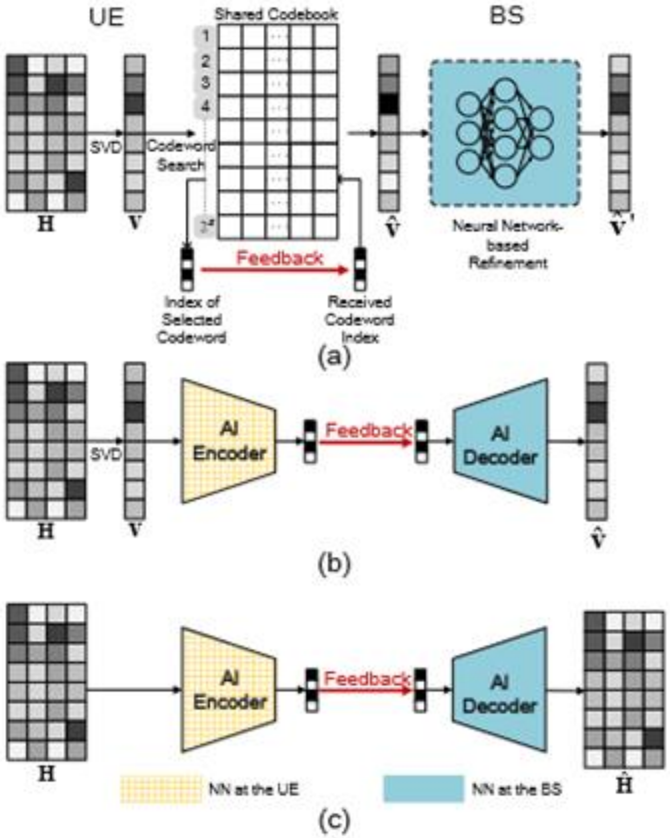
- In 802.11ax/be, the AP uses a sounding sequence for beamformee/beamformer communication
- Sounding feedback airtime overhead increases with new features (e.g., MAPC + many spatial streams)

Approach:

- Sounding feedback airtime overhead increases with new features (e.g., MAPC + many spatial streams)

Benefit from ML

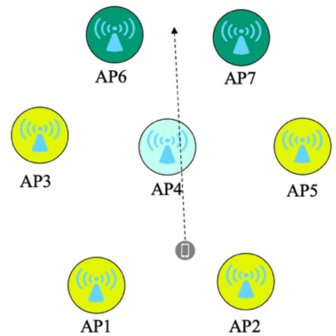
- CSI compression
- Faster operation
- Improved throughput

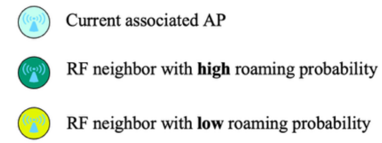


Guo, Jiajia, et al. "AI for CSI feedback enhancement in 5G-advanced." *IEEE Wireless Communications* (2022).

AI-driven MAC & PHY: Enhanced Roaming

IEEE 802.11-23/0433r2: AIML-based Roaming Enhancements Use Case





AP	weight
AP7	0.4
AP6	0.3
AP5	0.1
AP3	0.1
AP2	0.05
AP1	0.05

<u>Problem:</u>

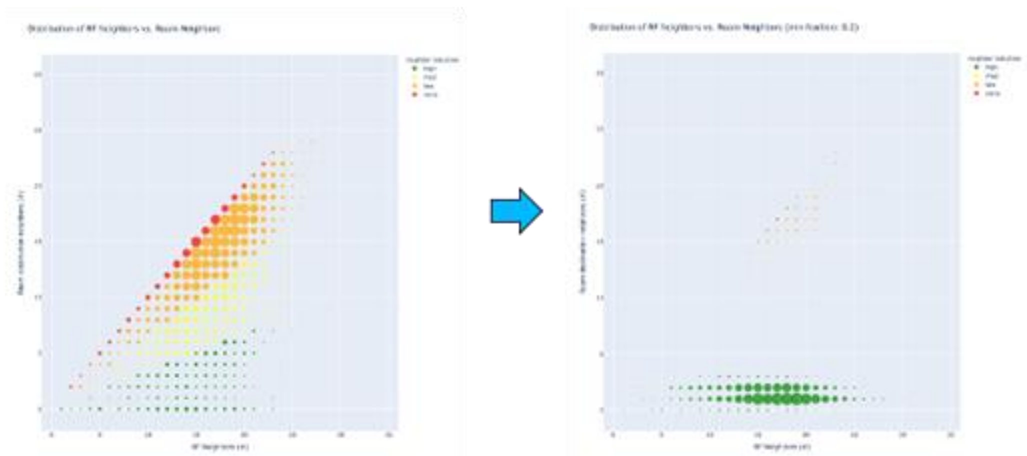
- Roaming in dense environments can lead to very high roaming times
- Based on 802.11k (roaming)

<u>Approach:</u>

- AI/ML is used to determine the probability of a client roaming to a specific AP, based on the learned client roaming patterns
- AI/ML is used to reduce the size of the neighbor report list returned to STAs

<u>Benefit from ML:</u>

- STA devices can discover good neighbors for roaming quickly
- Reduce the latency experienced by clients when they are operating in a highly roaming environment



**Each circle indicates a group of APs having the same number of RF and roam neighbors*

The neighbor list could be reduced by more than 66% on 88% of the APs

AI-driven MAC & PHY: DRL-based channel access

Problem:

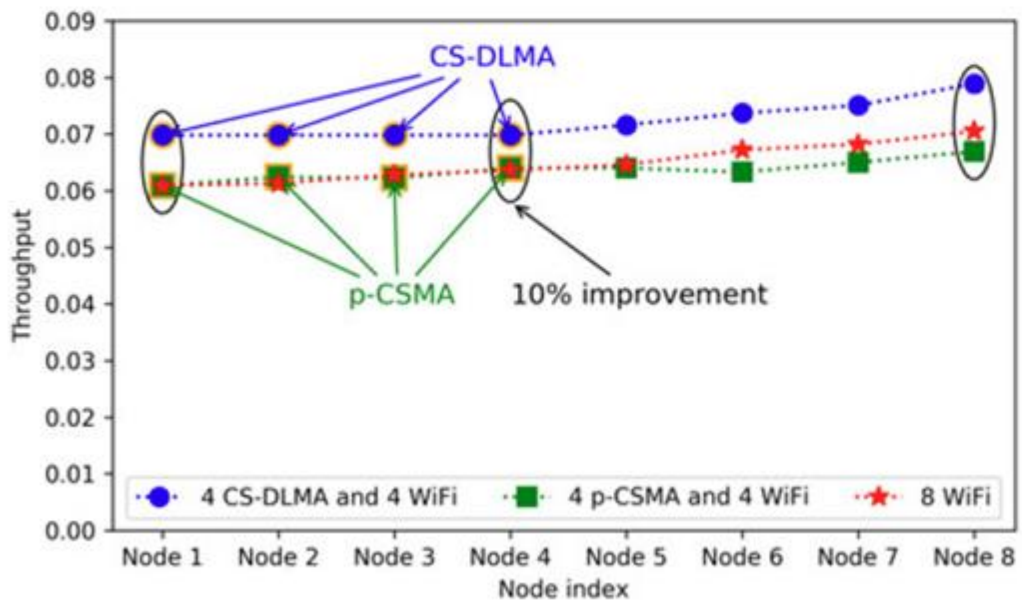
- Current channel access methods based on CSMA/CA lack efficiency and fairness

Approach:

- DRL is applied to derive the channel access policies whereby devices decide to transmit or not based on the environment

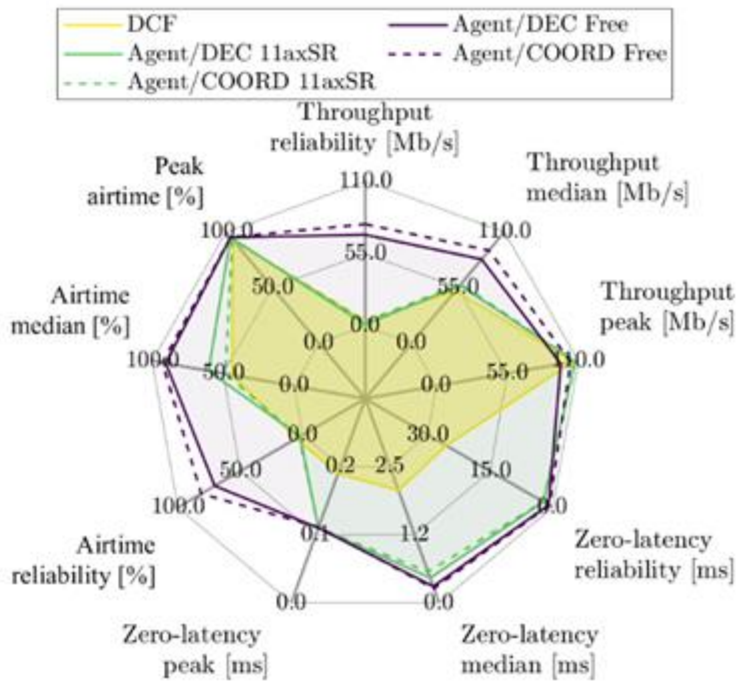
Benefit from ML:

- Enhance spectrum efficiency by reducing “empty” and “collision” slots



Y. Yu, S. C. Liew and T. Wang, "Non-Uniform Time-Step Deep Q-Network for Carrier-Sense Multiple Access in Heterogeneous Wireless Networks," in IEEE Transactions on Mobile Computing, vol. 20, no. 9, pp. 2848-2861, 1 Sept. 2021

AI-driven MAC & PHY: Enhanced Spatial Reuse

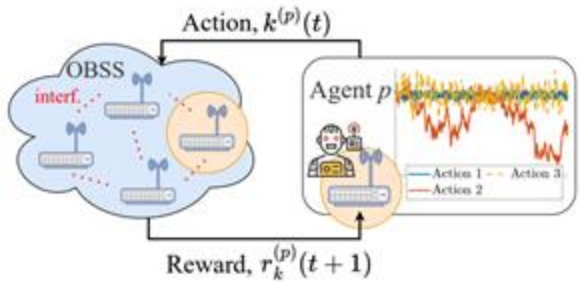


Problem:

- Enable multiple simultaneous transmissions using transmit power control

Approach:

- RL-based SR parameters optimization
- 11axSR-constrained vs Free
- Cooperation (COORD) or not (DEC) depending on communication between agents



Evaluation:

- Throughput (Mb/s), Latency (ms), Airtime (%)
- Reliability, Median, and Peak

- 11axSR/DEC and 11axSR/COORD lead to similar results because the IEEE 802.11 standard already enforces fairness
- Free can improve DCF's throughput, latency, and airtime, especially in terms of reliability
- Free/COORD leads to better results than Free/COORD, which motivates the need for exchanging information

Wilhelmi, F., et al. (2024). Machine Learning & Wi-Fi: Unveiling the Path Towards AI/ML-Native IEEE 802.11 Networks. *IEEE COMMAG 2024.*

Wilhelmi, F., et al. Coordinated Multi-Armed Bandits for Improved Spatial Reuse in Wi-Fi. arXiv preprint arXiv:2412.03076 (2024).

AI-driven MAC & PHY: Intelligent Prioritization & Scheduling

Problem:

- Schedule transmissions from *N* APs simultaneously
- Leverage Spatial Reuse & TDMA
- Joint scheduler: MAPC signaling protocol (~802.11bn)

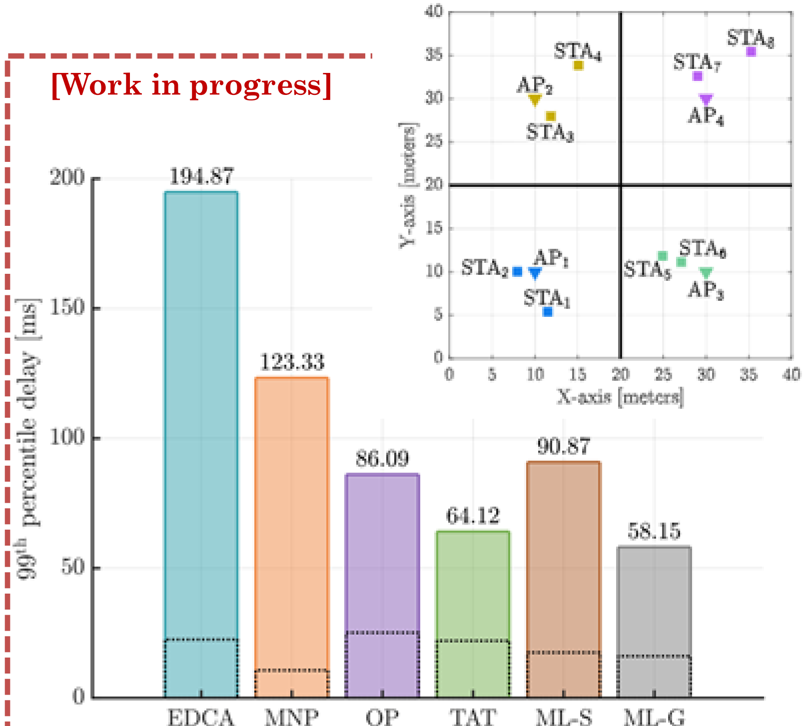
Approach:

- Deep Reinforcement Learning (DRL)
  - **State:** queue depth, current/past worst-case delays, current/past traffic load…
  - **Reward:** Combination of average and worst-case latency
  - **Action:** Select a group of devices to be scheduled in the upcoming TXOP

Evaluation:

- ML-S (trained in single deployment) & ML-G (trained in multiple deployments) vs Heuristic methods[1]
- Scenarios with 4 APs and 16 stations, with Poisson (75 Mbps) & Bursty (25 Mbps) traffic profiles

[Work in progress]



Nuñez, David, et al. "**Empowering Multi-Access Point Coordination through Machine Learning-based Scheduling**"

- ➢ ML-S: Fails to generalize well—but not too badly—due to being trained in a single deployment.
- ➢ ML-G: Outperforms expert-based designs

[1]Nuñez, David, Pasquale Imputato, Stefano Avallone, Malcolm Smith, and Boris Bellalta. "**Enabling Reliable Latency in Wi-Fi 8 Through Multi-AP Joint Scheduling.**" IEEE Open Journal of the Communications Society (2025).

AI-driven MAC & PHY: Dynamic CW adjustment

Problem:

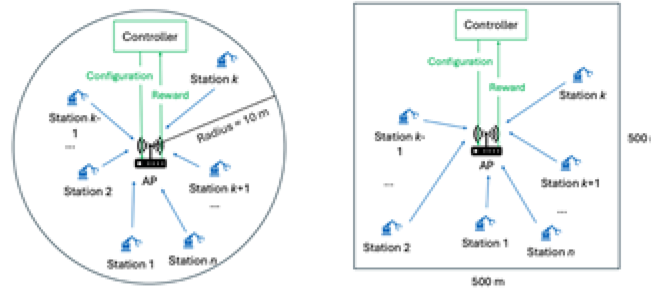
- Improve the performance of Wi-Fi networks for different scenarios and requirements

Approach:

- RL-based channel access with dynamic CW adjustment and RTS/CTS on/off

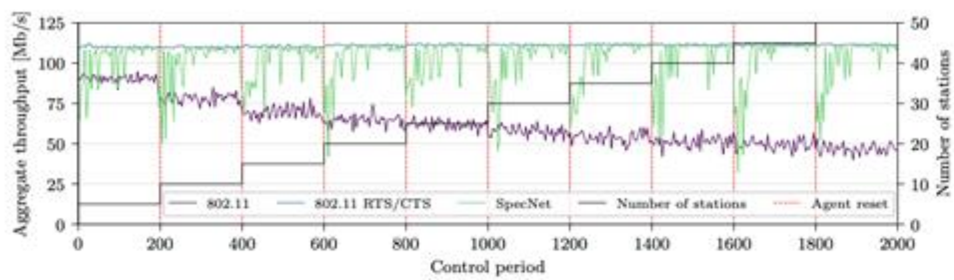
Evaluation:

- Different scenarios & needs
  - High throughput
  - Low latency
  - Massive communications
- Evaluate the throughput and fairness of the proposed solution

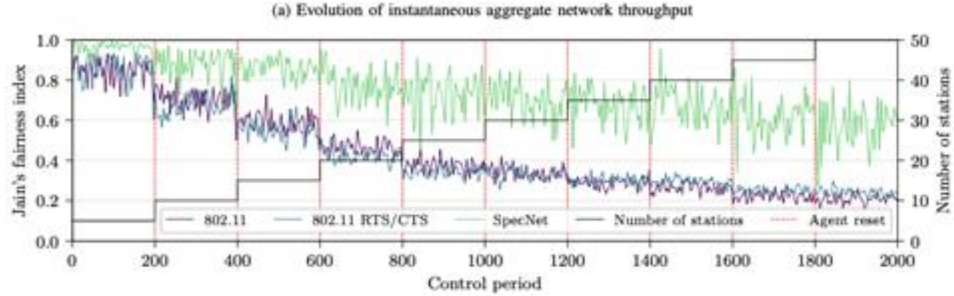


(a) (b)

Scenario	No. of stations	Packet size (payload)	Load per station	MCS
High throughput	5 – 50	1500 B	120 Mb/s (full buffer)	11
Low latency	4	1500 B	20 Mb/s	11
Massive communication	250	256 B	46 kb/s	0



(a) Evolution of instantaneous aggregate network throughput



(b) Evolution of instantaneous fairness

Szczech, Kamil et al. "Towards Specialized Wireless Networks Using an ML-Driven Radio Interface." arXiv preprint arXiv:2502.20996 (2025).

upf. **AI-driven MAC & PHY:** Sensing

Problem:

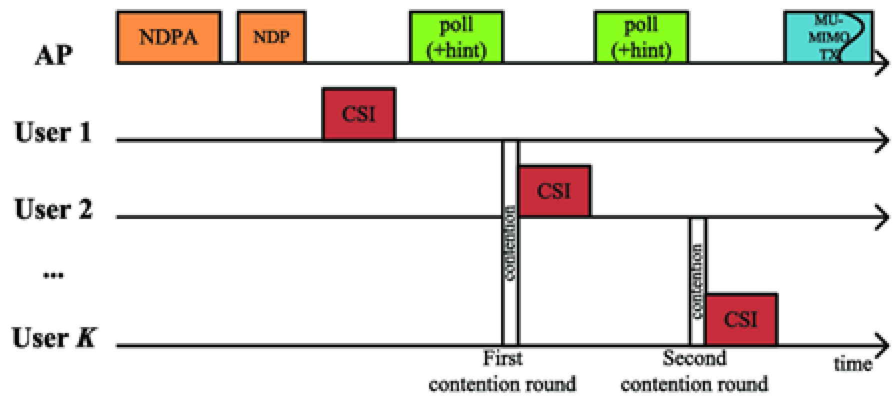
- Wi-Fi sensing leverages existing Wi-Fi signals (CSI - Channel State Information) to perceive and analyze environmental changes (e.g., human movement).

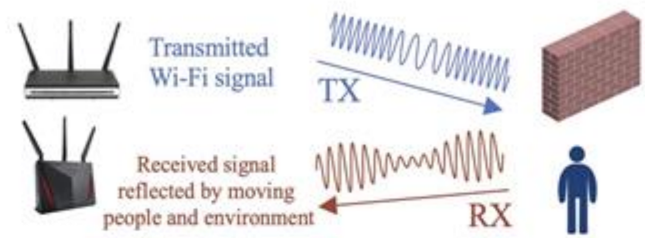
Approach:

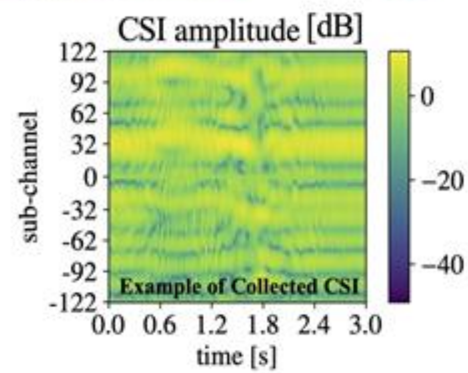
- Interpret the complex Wi-Fi signal variations (reflection, absorption, diffraction) when affected by objects in their path.

Applications:

- Human activity recognition (fall detection, gesture/pose detection, breathing and heart rate monitoring, etc.)
- Intrusion detection
- Through-wall sensing



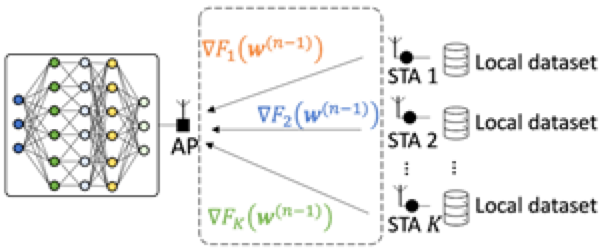




Channel State Information (CSI): Detailed, fine-grained data about the path characteristics (amplitude and phase) of Wi-Fi signals as they travel from transmitter to receiver.

Francesca Meneghello, Nicolò Dal Fabbro, Domenico Garlisi, Ilenia Tinnirello, Michele Rossi, "CSI Dataset for Wireless Human Sensing on 80 MHz Wi-Fi Channels", IEEE Dataport, October 30, 2022, doi:10.21227/xbhv-f125

AI-driven MAC & PHY: Over-the-air computation

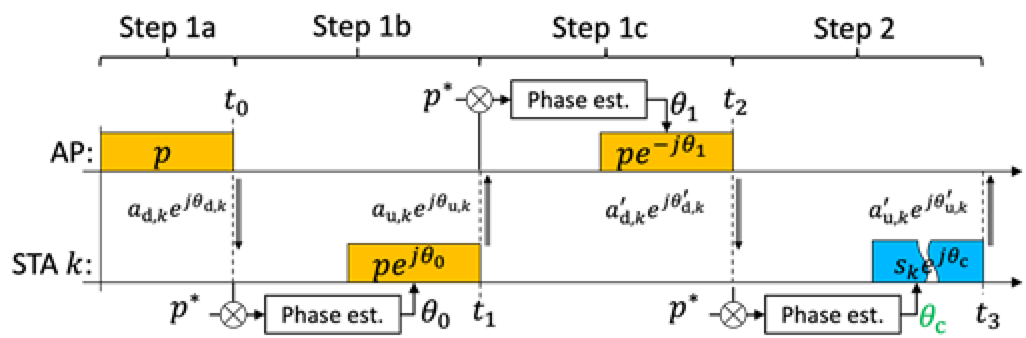


- OAC leverages interference from simultaneous transmissions for ML model aggregation/averaging
- The medium performs the computation (signal superposition)
- The underlying communication infrastructure needs to be aware of the mechanism:
  - Schedule devices
  - Synchronization
  - Power control

Challenge: The transmitted symbols (e.g., gradients) from all STAs should add up coherently on the AP side.

*The Carrier Frequency Offset (CFO) represents the difference between the expected carrier frequency of the signal and the actual frequency received by the receiver (leads to inter-carrier interference (ICI)).

Solution: Add training sequences in the preamble and pilot signals in the data field to estimate CFO and remove it.



IEEE802.11-25/304r0, Feasibility Study of Phase-Synchronization for Wireless Federated Learning on WLAN (March 2025)

The AIML SC is preparing use cases for enabling AIML in WLANs for the IEEE 802.11 AIML SC 1st Technical Report Draft

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How to make an AI use case successful

1 Performance

- What are the expected gains (e.g., throughput, latency, retransmissions)
- How generalizable and scalable the mechanism is (e.g., scenario dependency)
- How stable the performance is and what are the worst-case scenarios

2 Required overheads

- How much additional signaling is required to operate the mechanism
- How often do ML model updates (e.g., from the cloud) need to be provided
- Data collections & Retraining needs

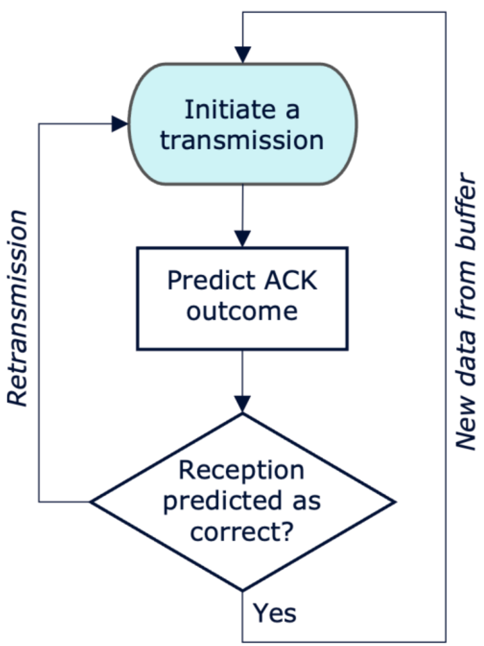
3 Compute needs & implications

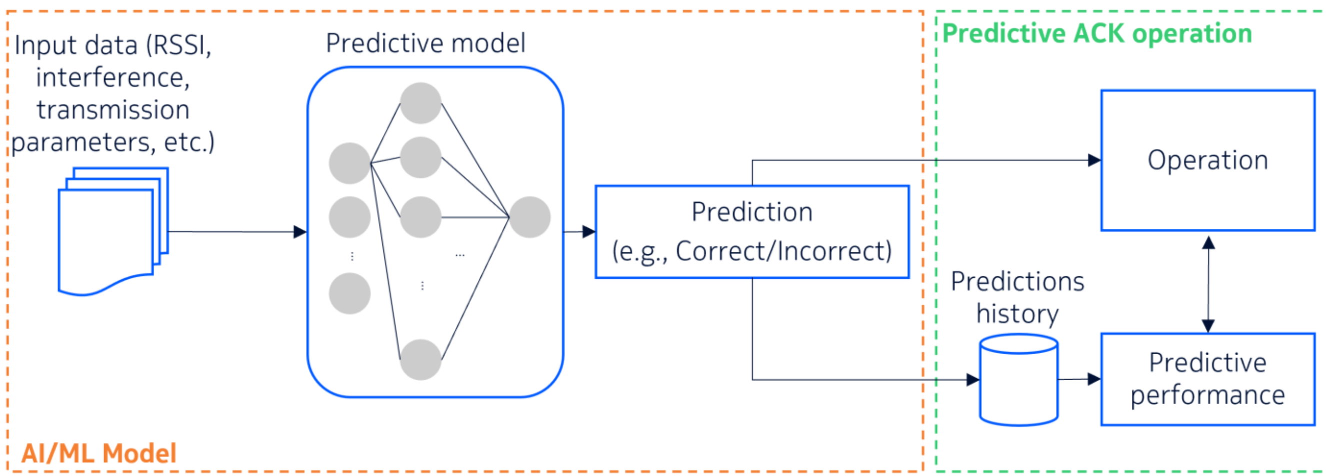
- How much compute/memory resources are required to run the mechanism
- What is the energy footprint associated with the mechanism
- Security and safety of the added processes (e.g., data exchanges, resilience)

Example mechanism: AI-based Error Control

Basic steps:

- Define a **mechanism** (e.g., data collection and processing, training vs inference phases)
- Define the **required signaling** (e.g., discovery and setup, operation, teardown)
  - In 802.11, the ACK Policy (2 bits) for the current frame is informed in the QoS Control Field

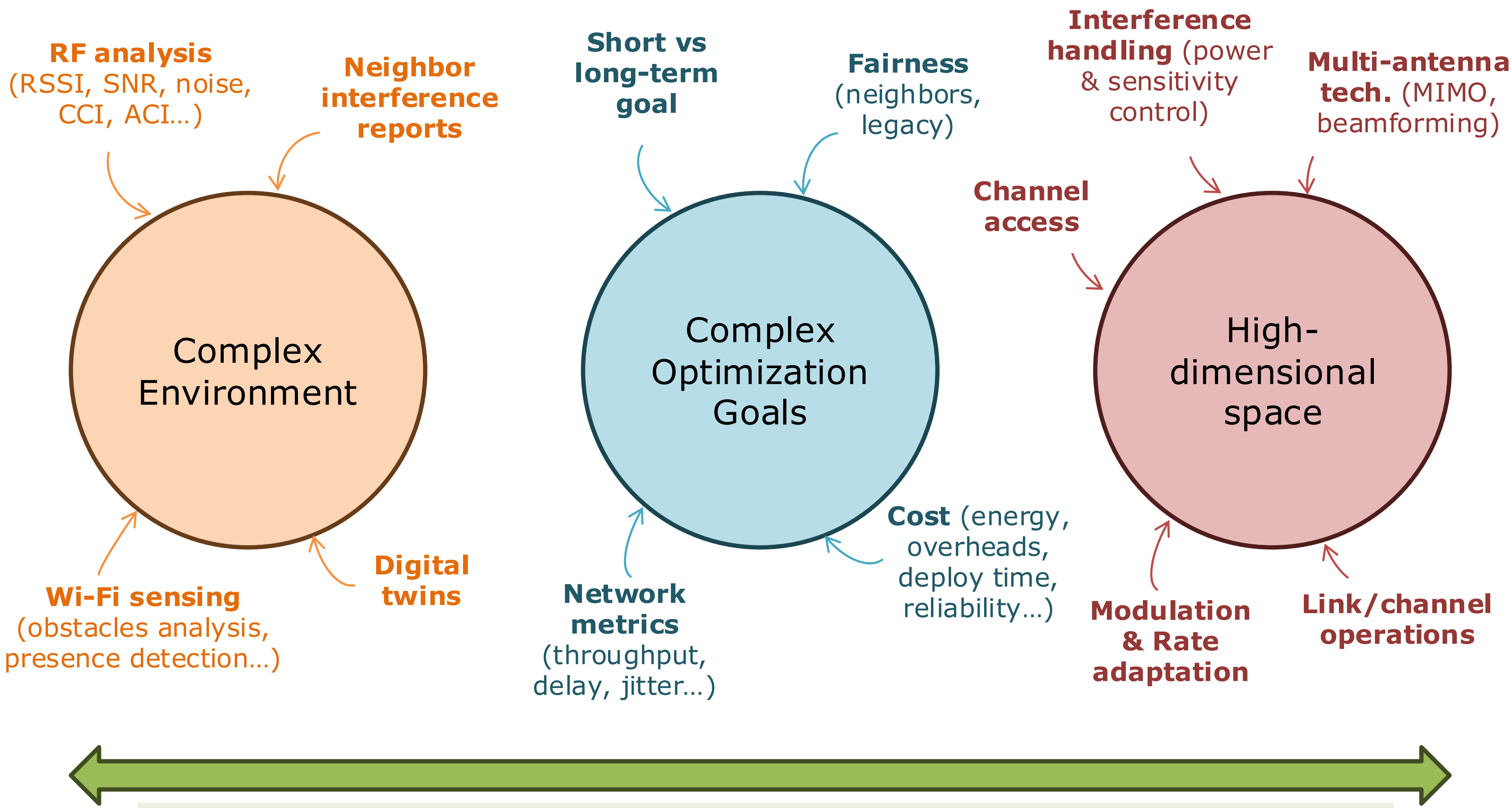




Further operations are required for:

- Ensuring mechanism’s correctness (e.g., self-healing, deactivation)
- Providing (re)deployment options
- …

From AI-based Error Control to Full AI-based MAC/PHY



- Complex relationships but the revolution is on fully leveraging all the aspects
- Different AI solutions are required at different levels of participation (e.g., provide insights/forecasts, digest complex data, apply changes)

From AI-based Error Control to Full AI-based MAC/PHY

Features that AI can unlock for a proactive, predictive, and adaptive MAC/PHY:

1. **Smart error correction:** Enhancing HARQ or other error correction methods (e.g., adjust the type of redundancy based on channel conditions).
2. **Application-specific optimization:** Integrating application-specific information would allow learning different policies.
3. **Cross-layer design:** Finding relationships between layers (e.g., impact of PHY conditions on MAC errors) for a fully-aware cross-layer design.
4. **Link and transmission parameters adaptation:** MCS change, spatial stream adjustment, antenna elements optimization (e.g., for beamforming), transmit power adjustment, etc.
5. **Channel access:** Decide when to transmit based on detailed channel information and selected capabilities.
6. **Other enhancements** like dynamic fragmentation and aggregation can be applied (e.g., to address temporary bad conditions).

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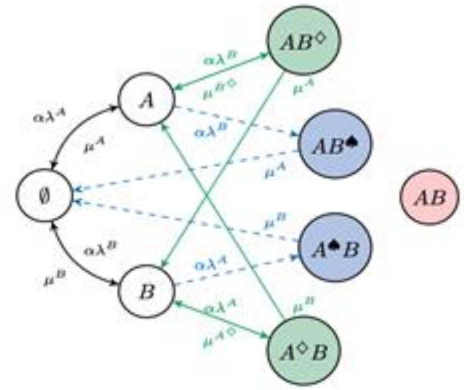
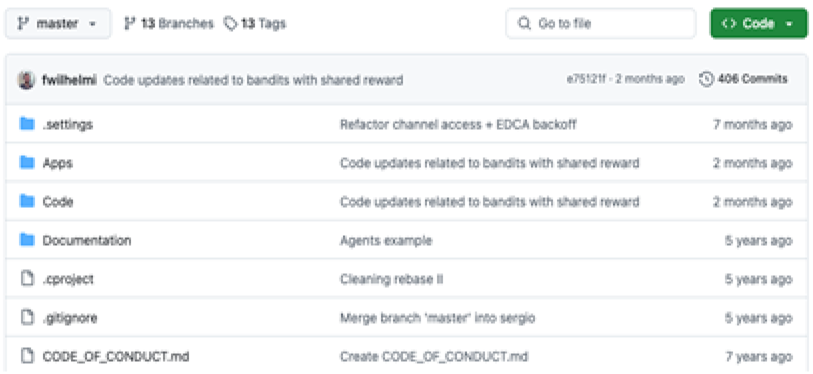
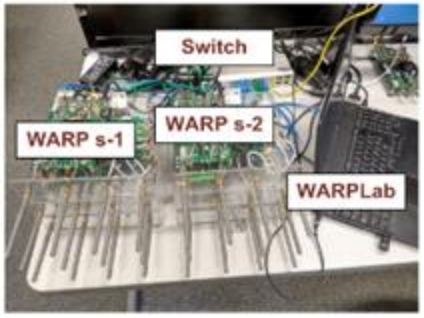
4. **Toolset for advancing towards AI-native networks**

Required toolset

- Analysis, stochastic processes, queueing models
  - e.g., SFCTMN (framework for creating and solving CTMNs)
- Simulation with **AI/ML integration**
  - e.g., Komondor (with AI/ML support and upcoming Wi-Fi 8 and beyond features)
- Experimentation:
  - VR + Wi-Fi platform
  - SDRs (e.g., WACA, openwifi)
  - Experimental testbeds (e.g., OpenWrt devices)

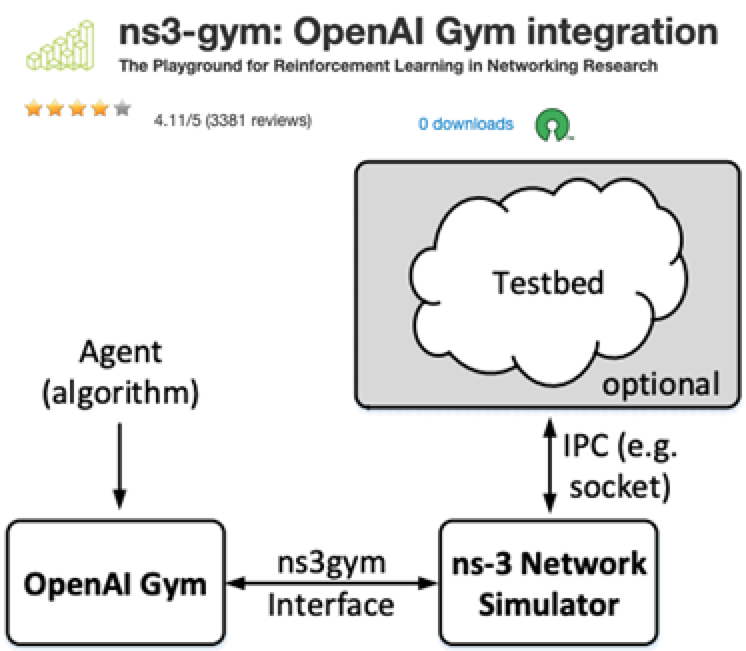


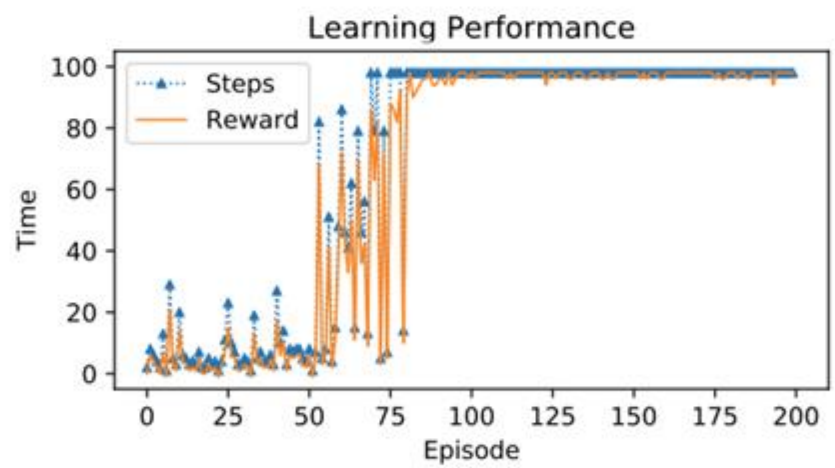




Tools for AI-Native MAC & PHY: ns-3

- Full TCP/IP stack, Wi-Fi, community validated, open-source
- Not all 11ax features are yet implemented; some 11be ones are in development (developing new features requires expertise and time)
- AI/ML support with ns3-gym (OpenAI Gym integration)



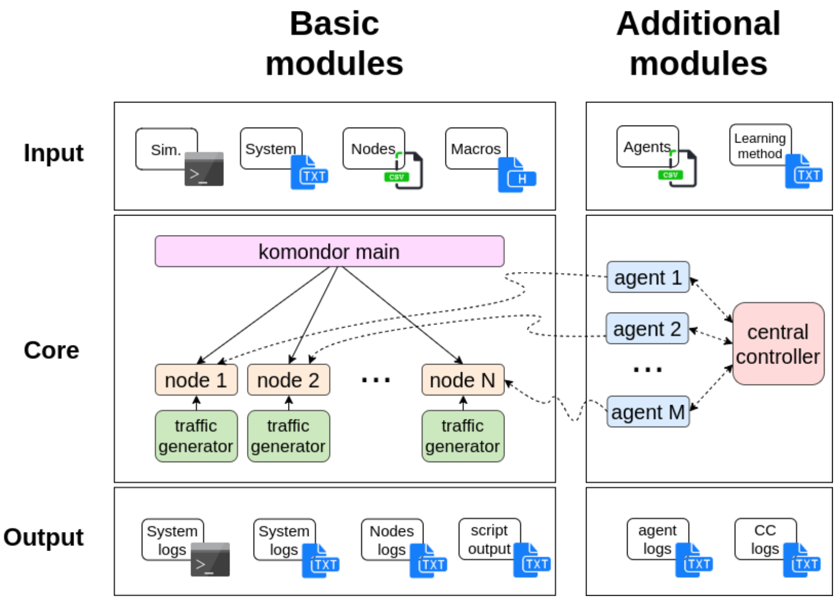


P. Gawlowicz and A. Zubow, "ns-3 meets OpenAI Gym: The Playground for Machine Learning in Networking Research", MSWiM, 2019.

Tools for AI-Native MAC & PHY: Komondor

- Tool to simulate IEEE 802.11 networks and more
  - Low-complexity (simplified PHY/MAC)
  - Fast simulations – Very large deployments
  - Low-cost implementation of novel features, e.g., 11ax SR
  - Generate results on specific 802.11 features
- Includes "in-house" AI/ML operations
  - Fast prototyping of new AI-based features (e.g., AI-driven channel access, spatial reuse, channel bonding, etc.)
  - Suitable for creating datasets
- Future support for:
  - ML libraries written in python (e.g., pytorch)
  - MAC protocol learning

Open-source: [GitHub - wn-upf/Komondor: Komondor Wireless Networks Simulator]



Good adoption in academia

- Cited/used in >50 research works (source: [Google Scholar])
- Used in two editions of the ITU AI Challenge as a data generator [1], [2]

Wilhelmi, F. et al. (2021). Machine Learning for Performance Prediction of Channel Bonding in Next-Generation IEEE 802.11 WLANs. *ITU Journal on Future and Evolving Technologies, Volume 2 (2021), Issue 4 , Pages 67-79.*

Wilhelmi, F. et al. (2022). Federated Spatial Reuse Optimization in Next-Generation Decentralized IEEE 802.11 WLANs. *ITU Journal on Future and Evolving Technologies, Volume 3 (2022), Issue 2, Pages 117-133.*

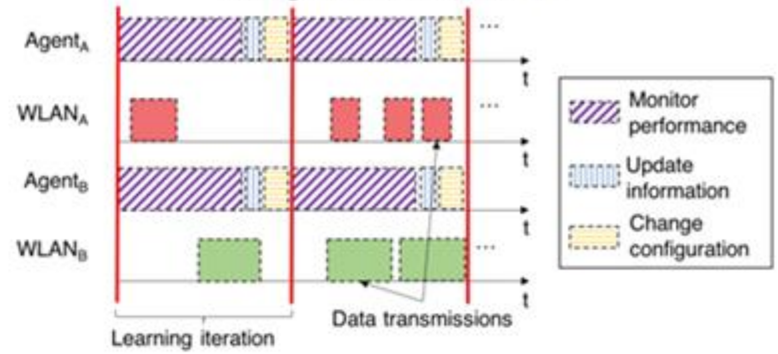
Barrachina-Munoz, S., Wilhelmi, F., Selinis, I., & Bellalta, B. (2019, April). Komondor: A wireless network simulator for next-generation high-density WLANs. *In 2019 Wireless Days (WD) (pp. 1-8). IEEE.*

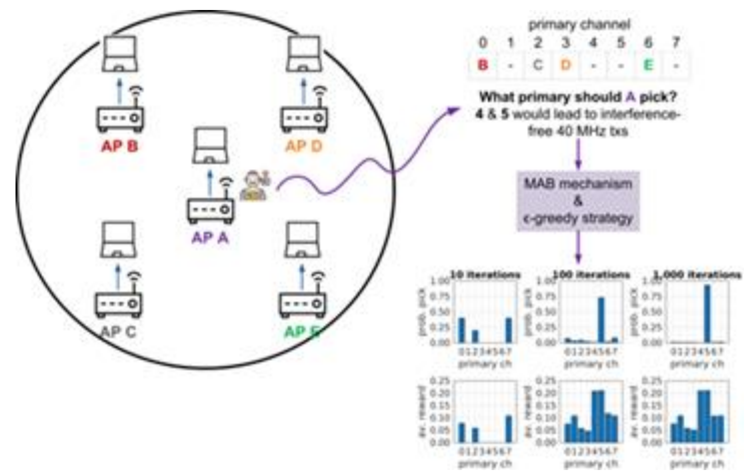
Tools for AI-Native MAC & PHY: Komondor

Online learning agents in Komondor

- The operation of AP and non-AP devices can be ruled by agents during simulations
- Agents run during the simulation
  - Monitoring performance (passive/reactive)
  - Internal operation (e.g., training/inference)
  - Submit configuration changes to devices
- Centralized, distributed, and decentralized modes
- An example:
  - Online learning is used by **AP$_A$** to decide the best primary channel
  - Scenario dependency (awareness of channels' statuses)

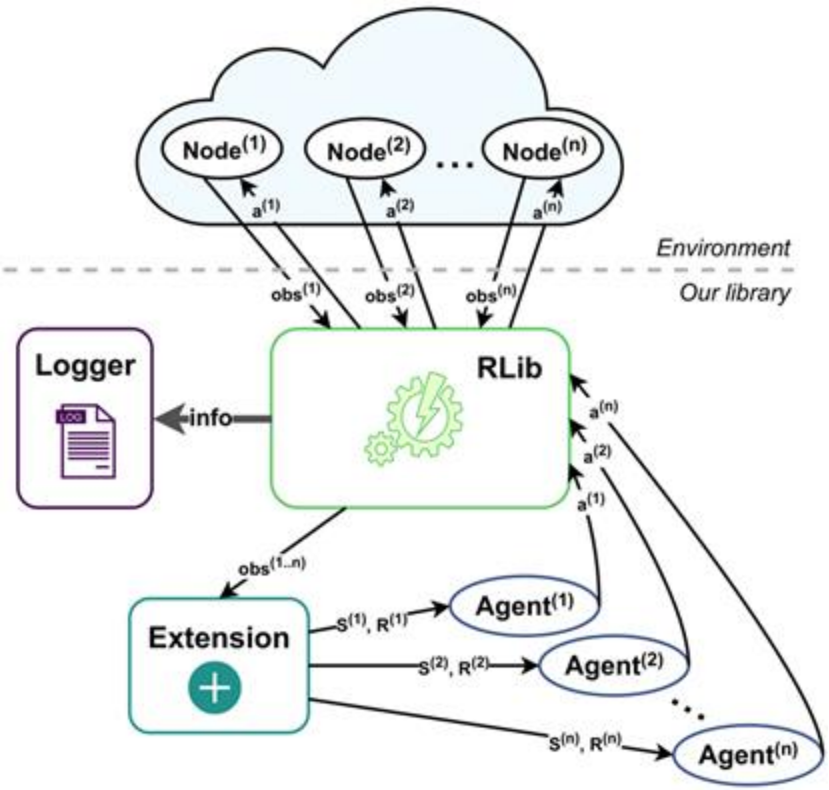
(a) Agents embedded to APs





Tools for AI-Native MAC & PHY: Reinforced-lib

- Open-source & easy to use
- Extensive documentation
- Support for simple (MABs) and deep RL
- Export to embedded devices
- Provided examples
    - MAB rate selection
    - DQN CW selection



pip install reinforced-lib

https://github.com/m-wojnar/reinforced-lib

Wojnar, M., Szott, S., Rusek, K., & Ciezobka, W. (2024). Reinforced-lib: Rapid prototyping of reinforcement learning solutions. SoftwareX, 26, 101706.

Tools for AI-Native MAC & PHY: Datasets

- The existence of open-source and standardized datasets is essential for training and comparing ML algorithms
- Very few datasets are currently available
- Examples:
  - (Herzen et al.) **throughput** and on basic performance metrics (e.g., **received power, channel width**) collected in a small testbed
  - (Karmakar et al.) **throughput** achieved under 5 **link configuration parameters** (i.e., channel bandwidth, MCS, guard interval, MIMO, and frame aggregation) and the channel quality measured as SNR
  - (Chen et al.) **User load** in a large-scale campus Wi-Fi network

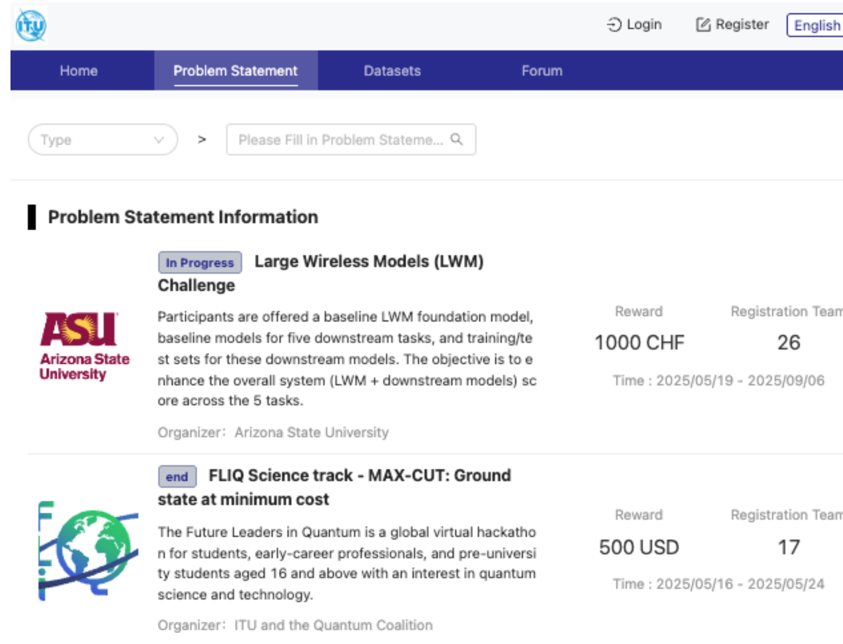
More info
in this survey:

It would be beneficial to have standardized datasets, standardized means for sharing datasets (preserving privacy), and standardized procedures for data collection (to build new datasets)

ITU-T Correspondence Group for datasets applicable for AI/ML in networks (CG-datasets)

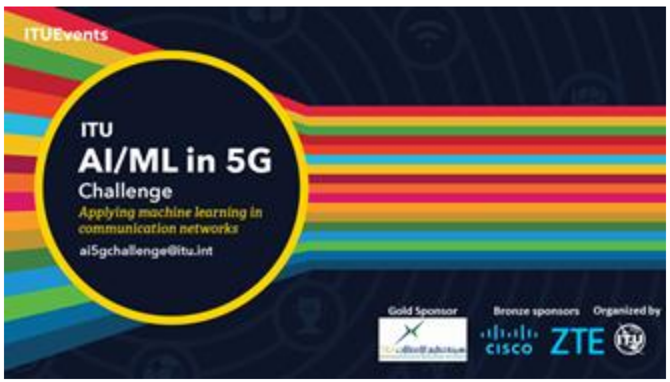
Tools for AI-Native MAC & PHY: Synthetic datasets

https://challenge.aiforgood.itu.int



Komondor-generated datasets:

- 2020 ITU AI Challenge - IEEE 802.11ax Dynamic Channel Bonding (DCB) dataset♦
- 2021 ITU AI Challenge - IEEE 802.11ax Spatial Reuse (SR) dataset♦



Wilhelmi, F., Góez, D., Soto, P., Vallés, R., Alfaifi, M., Algunayah, A., ... & Bellalta, B. (2021). Machine learning for performance prediction of channel bonding in next-generation IEEE 802.11 WLANs. *ITU Journal on Future and Evolving Technologies, Volume 2 (2021), Issue 4, Pages 67-79*.

Wilhelmi, F., Hribar, J., Yilmaz, S. F., Ozfatura, E., Ozfatura, K., Yildiz, O., ... & Bellalta, B. (2022). Federated spatial reuse optimization in next-generation decentralized IEEE 802.11 WLANs. *ITU Journal on Future and Evolving Technologies, Volume 3 (2022), Issue 2, Pages 117-133*

♦Wilhelmi, F. (2020). [ITU-T AI Challenge] Input/Output of project "Improving the capacity of IEEE 802.11 WLANs through Machine Learning" [Data set]. Zenodo. https://doi.org/10.5281/zenodo.4106127

♦Wilhelmi, F. (2021). [ITU AI/ML Challenge 2021] Dataset IEEE 802.11ax Spatial Reuse (v1.3) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5656866

Thank you

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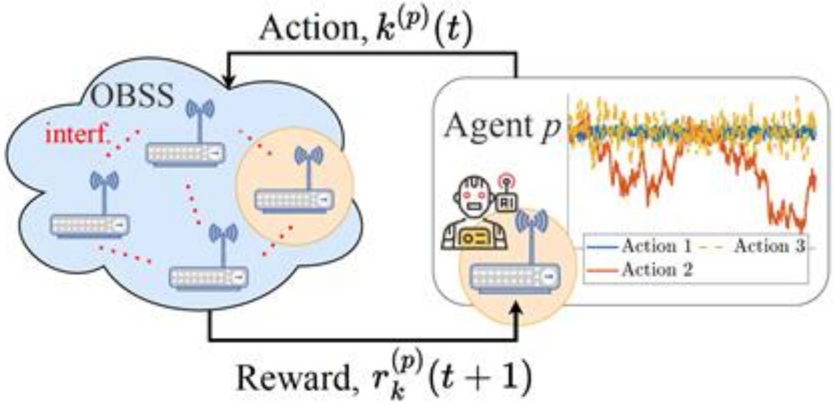
AIML-based Multi-AP Coordination

Example

- ML agent driving Spatial Reuse (SR)
- MAPC allows agents collaborating to learn better strategies than selfishly

Mechanism (Iterative Steps)

- Agents play an action among a set of actions (transmit power and sensitivity combinations)
- Agents obtain a signal (e.g., throughput), which depends on the joint action profile
- Agents share the signal with the others to generate a collaborative reward
- Considered exploration-exploitation strategies: e-greedy, Thompson sampling



Wilhelmi, F., Bellalta, B., Szott, S., Kosek-Szott, K., & Barrachina-Muñoz, S. (2024). Coordinated Multi-Armed Bandits for Improved Spatial Reuse in Wi-Fi. *arXiv preprint arXiv:2412.03076*.

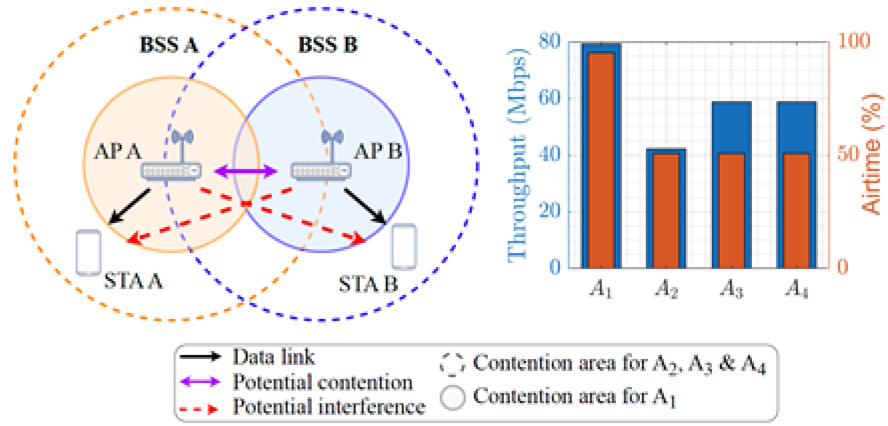
AIML-based Multi-AP Coordination

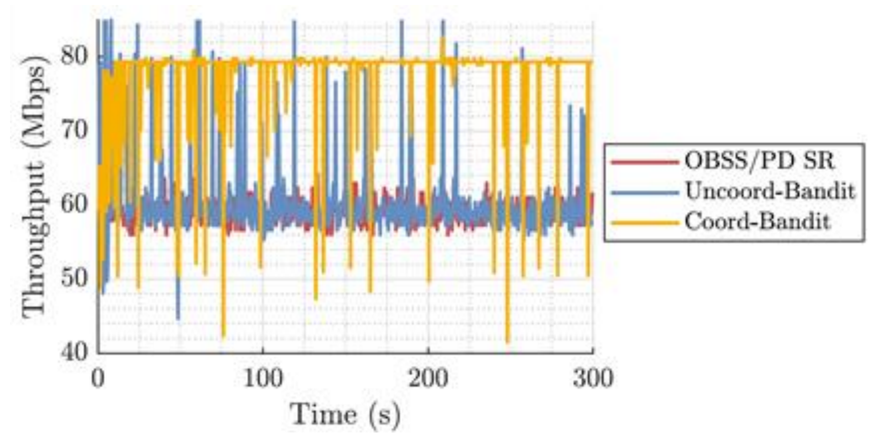
Scenario

- Two BSSs with one AP and one STA each
- 1 agent per BSS
- 4 different actions

Comparison

- **OBSS/PD SR:** Baseline operation, included in 802.11ax.
- **Uncoordinated bandits:** Each agent learns selfishly
- **Coordinated bandits:** Agents share their performance to compute a cooperative reward.





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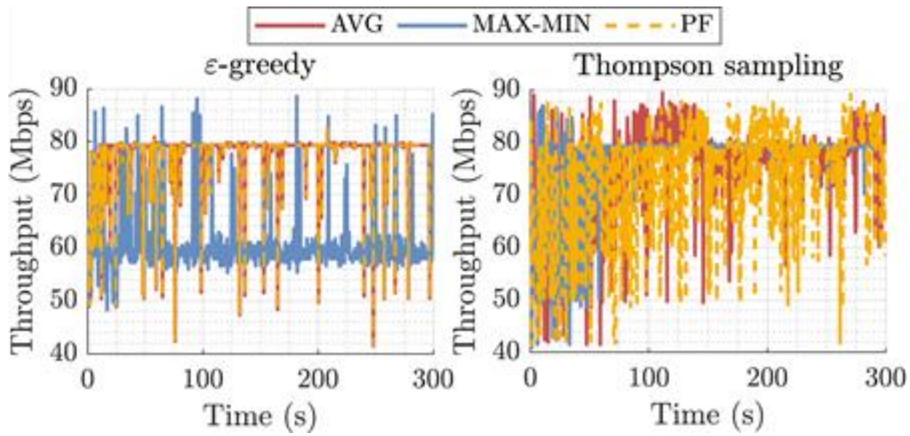
AIML-based Multi-AP Coordination

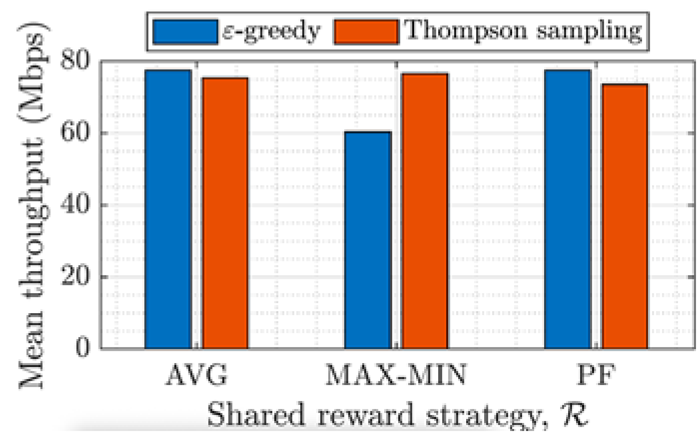
Scenario

- Two BSSs with one AP and one STA each
- 1 agent per BSS
- 4 different actions

Sharing reward strategies

- **Average, AVG:** The shared reward is calculated as the average value of each individual reward.
- **Max-min, MAX-MIN:** The shared reward is computed as the minimum value of each individual reward.
- **Proportional fairness, PF:** The shared reward is calculated as the sum of the logarithms of each individual reward.





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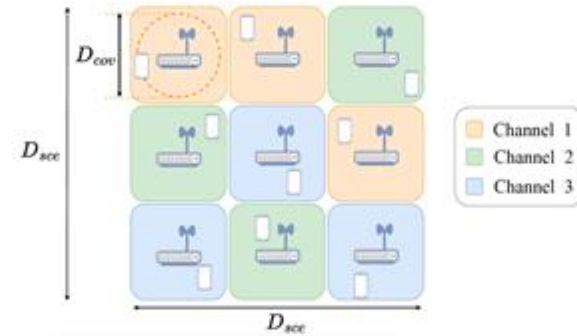
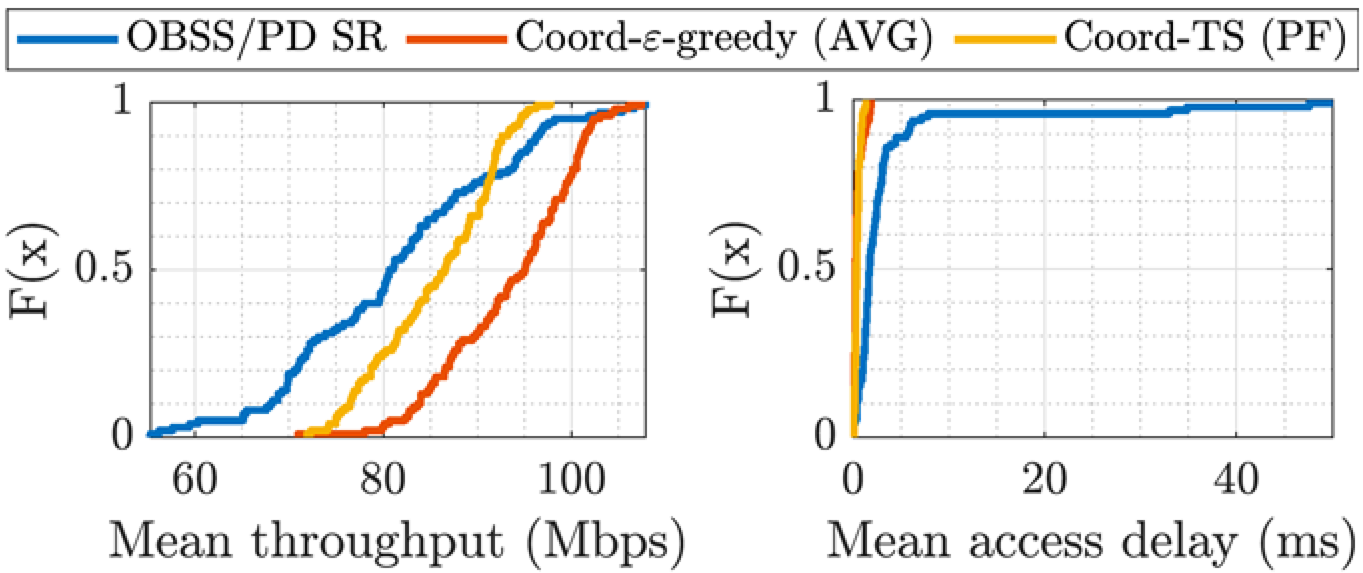
AIML-based Multi-AP Coordination





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