Machine Learning & Wi-Fi: Unveiling the Path Towards AI/ML-Native IEEE 802.11 Networks

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***Abstract*—Artificial intelligence (AI) and machine learning (ML) are nowadays mature technologies considered essential for driving the evolution of future communication systems. Simultaneously, Wi-Fi technology has constantly evolved over the past three decades and incorporated new features generation after generation, thus contributing to increased complexity. As such, researchers have observed that AI/ML functionalities may be required to address the upcoming Wi-Fi challenges that will be otherwise difficult to solve with traditional approaches. This paper discusses the role of AI/ML in current and future Wi-Fi networks and depicts the ways forward. A roadmap towards AI/ML-native Wi-Fi, key challenges, standardization efforts, and major enablers are also discussed. An exemplary use-case scenario is provided to showcase the potential of AI/ML in Wi-Fi at different adoption stages.**

***Index Terms*—Artificial Intelligence, IEEE 802.11, Machine Learning, Wi-Fi**

I. Introduction

The IEEE 802.11 standard (commercially known as Wi-Fi), since its first release in 1997, has accompanied humanity by providing an entry point to a connected world through wireless local area networks. Wi-Fi is continuously evolving together with its users, their applications, and habits. As a result, it has been and continues to be the most popular technology for residential connectivity. In addition, the technological evolution of Wi-Fi—which has included a plethora of physical (PHY) and medium access control (MAC) enhancements—has enabled it to expand to other domains beyond residential, including enterprise and industry.

At this point, communication systems are expected to enable new verticals such as Industry 5.0, autonomous vehicles, or smart cities, where unprecedented levels of performance and reliability are required. However, the current incremental-based status quo on evolving wireless communications standards and technologies seems to be insufficient for such stringent performance targets. Moreover, the underlying complexity and the incurred overheads of the latest mechanisms adopted in communication systems (e.g., massive antenna arrays) demand innovative ways of operating networks, which must now hoard self-configuration capabilities [1].

All these factors call for a revolutionary paradigm shift, which can be potentially achieved by artificial intelligence (AI) and machine learning (ML). AI/ML is a computer programming paradigm that allows learning functions (or models) directly from data or experience, instead of defining them statically. AI/ML has revolutionized and boosted many domains like computer vision thanks to its ability to exploit complex characteristics from data, thus allowing it to solve problems that are hard to solve by hand. So now the question is to what extent can AI/ML reshape future wireless communications. Will AI/ML be applied to support the operation of communications networks? Will it be used as part of the current communications protocols, as a way of enhancing performance? Or will AI/ML be used to create new communication protocols from scratch?

In recent years, we have witnessed an exponential growth in the utilization of AI/ML in Wi-Fi. In academic research, AI/ML has been extensively studied to showcase potential, provide a better understanding of its trade-offs, and foresee its viability when applied to Wi-Fi use cases. A survey of approaches proposed by researchers for enriching 802.11 with AI/ML solutions is given in [2]. As for industry, AI/ML can already be found in commercial Wi-Fi devices as a product differentiator feature. However, it fulfills only a limited set of functionalities, mostly oriented to enhance the operator's management experience (e.g., network analytics and assisted troubleshooting) or for basic equipment self-configuration (e.g., automatic channel selection). AI-powered solutions like HPE Aruba Networking Central are currently based on proprietary implementations, some of which leverage non-AI/ML-specialized standardized protocols and data formats—such as the Broadband Forum (BBF) User Services Platform (USP) data models—to enable data collection and remote device configuration. The main drawback of these kinds of proprietary solutions is that they are far from the Wi-Fi core, thus their potential for improving Wi-Fi is limited.

In view of the high expectations of AI/ML for Wi-Fi, in this paper, we shed light on the status and future evolution of the IEEE 802.11 tied to AI/ML, starting from current developments to potential AI nativeness. We identify the main challenges and enablers for pursuing such an evolutionary path, emphasizing on standardization gaps and required actions to be taken. In addition, we provide simulation results to showcase the benefits that AI/ML can in its different adoption stages bring to Wi-Fi. Based on past and future milestones on AI/ML, Fig. 1 depicts the envisioned roadmap for AI/ML adoption in Wi-Fi and we later discuss this roadmap in detail.

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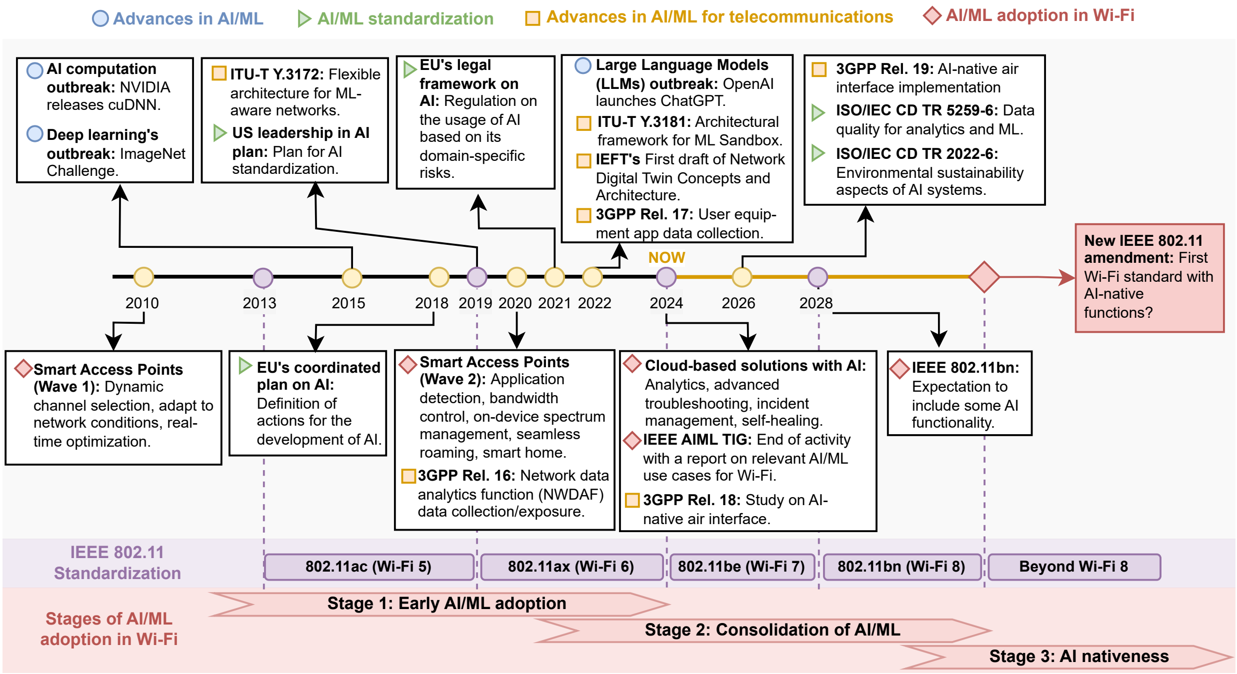

Figure 1: Roadmap of Wi-Fi towards AI nativeness.

II. Current AI/ML in IEEE 802.11 Standardization

The first standardization steps towards AI-native Wi-Fi operation were recently taken by the IEEE 802.11 AIML Topic Interest Group (TIG), which produced a technical report describing relevant use cases of AI/ML in for 802.11 networks [3]. This report can influence other groups and standards within 802.11, particularly 802.11bn (Wi-Fi 8), hence potentially leading to the definition of new mechanisms, signaling, infrastructure, and interfaces to enable AI/ML functions within the IEEE 802.11 standard. Furthermore, legacy IEEE 802.11 mechanisms may need to be modified to integrate AI/ML native operations. It should be noted that the technical use cases defined by the AIML TIG are well aligned with the corresponding efforts of 3GPP, which in Rel-18 focuses on enhancements to data collection and signaling (to support AI/ML-based network energy savings, load balancing, and mobility optimization) and lists promising areas of interest for AI/ML implementations (e.g., channel state information, beam management, and positioning [4]).

The following is an outline of the use cases defined by the AIML TIG (Figure 2), including channel state information (CSI) feedback compression using neural networks (NNs), enhanced roaming assisted by AI/ML, deep reinforcement learning (DRL)-based channel access, multi-access point coordination driven by AI/ML, and AI/ML model sharing.

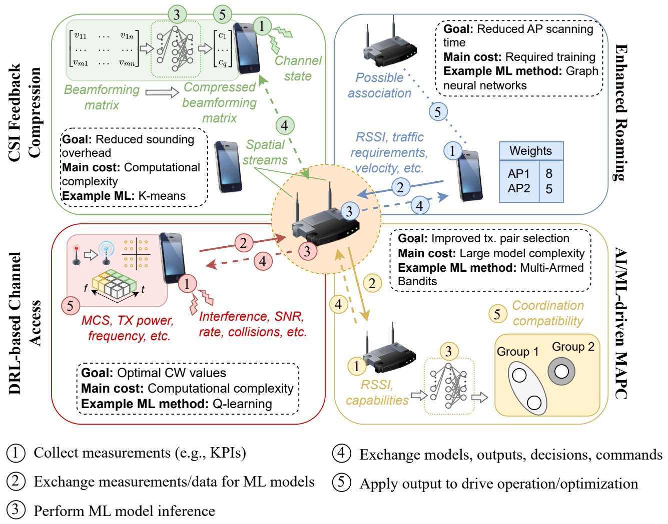

Figure 2: An overview of the AIML TIG use cases [3].

A. CSI Feedback Compression

The first use case concerns improving the operation of beamforming in multiple input, multiple output (MIMO) systems, which is one of the most appealing techniques for sustaining the continuously increasing gains in Wi-Fi, both from capacity and reliability perspectives. Beamformed transmissions, however, come at a high cost in terms of overheads because they require precise CSI to steer the signal toward the desired direction. CSI reports include information from each spatial stream used, which limits the scalability of beamforming. Wi-Fi 7 currently supports up to 8 spatial streams and Wi-Fi 8 targets support for up to 16. Thus there is an urge for enhancing the current signaling for MIMO, especially if multi-access point coordination (MAPC) combines streams from multiple access points (APs) for performing joint transmissions, as in coordinated beamforming (C-BF).

The overheads incurred by MIMO can be substantially reduced using ML. In particular, deep learning-based auto-encoder architectures can potentially reduce the dimensionality of the channel state matrices. Alternatively, since CSI may be similar for stations located close to each other, clustering methods such as k-means could be helpful.

ML-based CSI feedback compression is illustrated in the top-left corner of Fig. 2, where the station collects the channel measurements (#1) and then applies a local NN to compress the information (#3), thus leading to a compressed beamforming matrix (#5). It should be noted that additional upfront signaling would also be required to support the exchange of AI/ML models (e.g., a trained NN) and other relevant information for the use case (#4). However, this cost can be later offset by the reduced sounding overheads. Thus, the main cost of introducing AI/ML-based feedback compression remains in the computational complexity of the ML methods.

B. Enhanced Roaming Assisted by AI/ML

Another use case considered by AIML TIG concerns improving roaming, i.e., the handover of a client station between APs. The station decides to switch based on reports received from neighboring APs. In dense AP deployments, ML can assign weights (representing the probability of roaming to a given AP, based on learned station movement patterns) to each nearby AP to appropriately prioritize the APs during the scanning procedure. ML can also predict the received signal strength indicator (RSSI) level at which the scanning procedure should start to achieve faster and more reliable roaming.

This use case is shown in the top-right corner of Fig. 2, where the station collects information on neighboring APs (#1) and feeds the ML model implemented at the AP with its roaming decisions and local conditions (#2). This allows enhancing a candidate AP weight list and predicting the optimal RSSI threshold for starting the scanning procedure using ML methods (#3). Based on updated information (#4), the station can make better roaming decisions (#5).

Besides the appropriate computational resources available at the AP for model training and execution, such a solution would require additional signaling in the form of extending existing 802.11 management frames (such as 802.11k neighbor report frames or 802.11v handover management frames).

C. DRL-based Channel Access

This use case involves improving the distributed channel access method, which in 802.11 originates from the CSMA/CA multiple access protocol. Numerous ML-based modifications to this protocol have been proposed in the literature to improve its operation [2], especially in the case of dense deployments. Recently, solutions using reinforcement learning methods have emerged, which can learn optimal parameter values, e.g., contention window (CW) settings, for given network conditions.

This use case is presented in the bottom-left corner of Fig. 2. Based on the information collected from stations (#2), an AP can perform ML inference (#3) and update currently used 802.11 settings (#4).

The report in [3] emphasizes that when implementing standardized solutions in this area, fair channel access conditions must be ensured for all stations, including those implementing legacy solutions. Additionally, the computational complexity and the associated overhead should be minimized.

D. MAPC Driven by AI/ML

The next use case pertains to the functionality of MAPC, which involves coordinating simultaneous transmissions by multiple APs in overlapping networks. The MAPC feature is planned in the upcoming 802.11bn amendment, which will be developed by the Ultra-High Reliability (UHR) study group [5]. Simultaneous coordinated transmissions can be achieved, for example, through appropriate resource allocation within orthogonal frequency-division multiple access (OFDMA) or intelligent beamforming [6]. ML can support MAPC by either distributed or centralized selection of the non-interfering AP-station pairs.

Fig. 2 illustrates the ML-based MAPC use case in the bottom-right corner. The MAPC procedure is started by the so-called sharing AP (#1), which collects reports from neighboring shared APs regarding network and traffic conditions (#2). These reports are intended to help the sharing AP in selecting groups of APs and stations that can transmit simultaneously. The sharing AP uses ML methods to select and configure an appropriate MAPC transmission strategy (OFDMA, beamforming, or other) for the final transmission phase (#3). As a result, the sharing AP informs the shared APs about its decision (#4).

ML-supported MAPC may require additional signaling (e.g., to request missing data), however, its amount may be reduced if the implemented AI/ML model will predict network and traffic conditions. Additionally, it is expected that the trained AI/ML models can be shared between APs to improve the general MAPC convergence.

E. Model Sharing

AIML TIG defines a separate, generic use case to efficiently share and distribute AI/ML models and their parameters over 802.11 networks. This use case considers centralized, distributed, and federated learning as well as centralized or distributed AI/ML model generation and refinement. To this end, the report [3] recommends utilizing the broadcast nature of 802.11 transmission along with the emerging 802.11bc (Enhanced Broadcast Services) amendment.

III. Towards a native, pervasive AI in IEEE 802.11 WLANs: The evolution path for Wi-Fi

The AIML TIG technical report described above does not finalize the standardization activities within the IEEE 802.11 Working Group (WG). The TIG has recently transformed into the AIML standing committee (SC), which will continue reviewing and analyzing the feasibility and need for AI/ML in Wi-Fi. This, obviously, dampens the euphoria in AI for Wi-Fi, but at the same time reveals that the overarching goal of AI-native Wi-Fi must be taken cautiously. Nevertheless, the AIML SC will now serve as a liaison point on AI/ML topics and foster new collaborations with other standards-developing organizations (SDOs) like ITU, ETSI, or 3GPP, who have already worked on AI/ML standardization for several years [7], [8], thus boosting innovation and, therefore, bringing AI/ML adoption closer. In what follows, we overview the most relevant challenges of AI/ML adoption in Wi-Fi in the post-AIML TIG landscape, from which we derive a possible standardization roadmap for Wi-Fi towards AI nativeness and highlight key enablers for adoption, summarized in Fig. 1.

A. AI/ML in Wi-Fi: Standardization Challenges

1) Backward compatibility: A relevant Wi-Fi-specific challenge is the backward-compatible premise of IEEE 802.11, whereby AI/ML-driven operations should take into account legacy devices, thus ensuring fairness in access to shared resources. One potential way forward is defining new greenfield bands for AI/ML-based protocols, hence not disrupting legacy devices operating in different bands. This approach, however, entails involving spectrum regulators like ITU or FCC and requires strongly motivating the release of novel bands. As for legacy coexistence, AI/ML solutions should be properly designed and exhaustively tested to ensure that the AI/ML-operating devices are not disrupting legacy devices. For that, entities on top of IEEE 802.11 would be required to be involved, including the Wi-Fi Alliance, which is in charge of Wi-Fi certifications and which would need to introduce novel testing and certification track procedures for AI/ML.

2) ML computations and overheads: The data-driven condition of AI/ML methods makes them really computationally intensive, thus leading to extra computation and communication needs. In terms of computation, hardware-constrained APs or stations would need to handle most of the ML operations, including data processing and ML model training and inference. Therefore, either their computational capabilities would need to be significantly extended, or computational support would be required (e.g., from the cloud). In terms of *storage and communication*, ML models require from tens to hundreds of megabytes. Moreover, depending on the ML training and inference approach adopted (e.g., distributed learning), the overheads may dramatically increase due to the communication among ML components. In federated learning (FL), for instance, different ML clients iteratively communicate the model weights acquired through local training. Therefore, the use of ML models may turn out to be unfeasible if the computation and communication requirements are unbearable.

3) Continuous development and integration: ML model performance highly depends on the data with which the models are trained, thus requiring continuous monitoring and updating. Such volatility calls for flexible ML model deployment options, so that models can be updated at the targeted hardware on a plug-and-play basis. The plug-and-play approach has strong implications for the way IEEE 802.11 operates, as it would require the unification and opening of deeply rooted interfaces on the chipsets. With standardized ML-specialized procedure interfaces, vendors could implement their own AI/ML-based functionalities on top. This is aligned with 3GPP's vision for Rel-18, which states that the definition of AI/ML models is expected to be part of the implementation, and left out of the standard [9]. For example, in data rate selection algorithms, where the 802.11 standard only defines transmission rates, each vendor could implement independent ML methods for selecting the actual rates to be used.

4) Interoperability: The implementation heterogeneity of ML solutions can cause conflicts and lead to fairness issues, especially if ML optimizations would impact channel access rules. Additionally, if ML is applied to manipulate how information is transmitted (e.g., build fields of the transmitted frames or decide on the information they provide), this can potentially lead to a lack of interoperability between devices produced by different vendors. In this regard, it is important from the point of view of IEEE 802.11 standardization to clearly define the bounds of operation for AI/ML and to standardize new fields, so that the underlying principles of Wi-Fi (e.g., fair channel access) are guaranteed and interoperability is provided. Furthermore, the developed AI/ML methods will need to meet regional laws, e.g., ETSI defines strict channel access rules in European unlicensed bands.

5) General concerns on AI/ML: Besides networking-specific challenges, AI/ML may raise broad concerns in the areas of security, explainability, and ethics [10]. AI has progressed at a fast pace in recent years, even faster than regulations on AI use. As a downside, AI may cause harm due to a large set of reasons (e.g., lack of explainability, misuse, poor data used for training, bad design, etc.), thus leading to misbehavior. As a result, AI may lead to unexpected insecure actions, thus potentially compromising security for mission-critical applications. Other relevant threats of AI include aspects related to privacy (e.g., potentially derived from ML model and data transfer). In particular, the proliferation of specialized parties with expertise in AI/ML may lead to the establishment of marketplaces for trading raw ML models, trained models, and training data. The main issue of this is that manufacturers, vendors, and operators are reluctant to run unknown code on their devices and networks. To address the above-mentioned perils of AI and make it secure, ethical, and trustworthy, substantial standardization efforts (i.e., developed outside the IEEE 802.11 standard) are required. Some relevant areas include enforcing trust in AI, creating of datasets for training and validating ML models, developing new AI testing techniques, establishing performance benchmarks, or creating open platforms such as AI testbeds.

B. AI/ML in Wi-Fi: Adoption and Standardization Roadmap

Knowing that AI/ML can improve Wi-Fi's performance and unlock novel use cases and functionalities, it is crucial to examine how the IEEE 802.11 standard and other SDOs can sustain such evolution. Owing to the challenges listed above, the journey towards AI-native Wi-Fi is not simple and short, and will only be realized as a result of several years of research and joint efforts in a complex regulatory, standardization, and industrial ecosystem. In our roadmap, we identify three potential stages of adoption (highlighted at the bottom of Fig. 1), depending on the degree of integration and involvement of AI/ML in the Wi-Fi protocol:

1) **Early AI/ML adoption:** AI/ML solutions developed on top of the 802.11 standard for providing additional

support (e.g., enhanced troubleshooting, analytics) and limited optimization capabilities (e.g., dynamic channel selection, radio resource management). At this stage, we find commercial solutions such as smart APs, some of which integrate basic AI/ML functionalities, or cloud-based managed Wi-Fi networks for residential and industrial deployments with AI/ML features.

2) **Consolidation of AI/ML:** The latest efforts in 802.11 standardization (identification of use cases on AI/ML for Wi-Fi) and the proliferation of Wi-Fi products with AI/ML (e.g., Qualcomm's AI-optimized Wi-Fi 7 chipset FastConnect 7900), underscore the willingness to integrate AI/ML deeper into Wi-Fi. Such efforts suggest that we are now entering into a second phase of adoption that might culminate in updates of the 802.11 protocol to allow the integration of vendor-specific AI/ML features (e.g., ML-based CSI compression).

3) **AI nativeness:** The last stage of adoption envisages AI/ML built-in the IEEE 802.11 PHY and MAC so that AI/ML is applied to drive specific or chained sets of operations, for protocol learning, or even to replace entire parts of the PHY or MAC specifications. This stage goes beyond the current way of developing standards and solutions (building self-AI/ML protocols [11]), so its success depends on many advances in the regulation, improvement, trustworthiness, and optimization of AI/ML. In standardization, AI nativeness can be achieved by expanding the current protocols to support AI/ML operations, thus leading to new procedures and interfaces to enable ML pipelines (cf. 3GPP's AI-native air interface [9]).

C. Key Enablers for AI/ML Adoption in Wi-Fi

We next identify three key enablers for the adoption of AI/ML in Wi-Fi.

1) AI/ML-aware infrastructure: AI/ML solutions differ from classical methods (e.g., handcrafted solutions or closed models) in their operational processes, which particularly focus on data utilization. AI/ML processes—data collection, data processing, model deployment, model training/inference, ML output application—need to be considered to extend the current network's infrastructure, thus requiring the creation of new elements and interfaces [12]. Several SDOs have already provided guidelines and defined requirements for adopting AI/ML processes in telecommunications systems (cf. the ITU-T Y.3172 and ETSI GS ENI 005 frameworks). Likewise important is data handling and processing, which are crucial to the effective functioning of AI/ML but also to equip networks with cognitive capabilities. Therefore, several standardization activities started to prepare the ground in 2017 by introducing elements and procedures for introducing data gathering and processing capabilities to networks (cf. the 3GPP network data analytics function and ITU-T Y.3174 specification). Finally, the adoption of AI/ML in networks also calls for a paradigm shift in the current telecommunication ecosystem. A clear example lies in the need for establishing ML marketplaces, where models and data could be exchanged and traded among multiple interested parties, thus allowing to leverage the expertise of ML experts (cf. ITU-T Y.3176).

Several key requirements for supporting AI/ML in Wi-Fi are discussed in [3]. The 802.11 architecture should be extended to support the operation of ML agents, i.e., processes that execute specific ML algorithms, but an open question remains whether a *single advanced agent* should operate within a single device or *multiple cooperating, simpler agents* (e.g., each supporting a single functionality) should be used. Additionally, the 802.11 will need to define protocols and programming interfaces for data and code exchange. For example, a network controller might require transmitting agent code and installing it through a programming interface at APs or stations. Support for a typical control loop (observing the network state, making decisions, and deploying the selected action), often required in ML-based solutions, will also be necessary.

2) Trustworthy AI/ML: As previously indicated, trust in AI/ML is a must. In this regard, AI ethics are important for defining procedures and tools to develop secure AI applications (cf. the *US leadership in AI plan* or the *EU's coordinated plan on AI*). To enforce trust in AI/ML, explainable AI (XAI) is useful for understanding black-box ML methods better by explaining the behavior and outputs of AI models. Other appealing paradigms for trustworthy AI/ML are ML sandboxes and network digital twins (NDT). An ML sandbox allows for secure training, testing, and evaluating ML solutions before they are applied to production environments [13], whereas NDTs are digital replicas of a network that can fulfill the purposes of ML sandboxes. ML sandboxes and NDTs have started to be considered by different SDOs, cf. ITU-T Y.3181 and IETF's document on NDT concepts and architecture. Finally, trustworthy AI/ML involves the definition and generation of high-quality data, which is essential to ensure the proper training of robust and ethical AI/ML models. For that, there must be progress on the standardization of datasets and evaluation scenarios to confirm the validity of AI/ML solutions (cf. the work in progress ISO/IEC CD TR 5259-6).

3) Advances in AI/ML: The progress made in the field of AI/ML strongly influences the interest in adopting it in networks. For instance, the outbreaks in AI computation with the introduction of optimized hardware for deep learning around 2015 generated excitement in many other fields, including telecommunications. More recently, the outbreaks of generative AI and large language models (LLMs) have fueled the telecom industry with new use cases and extended capabilities [14], thus re-shifting the previous vision on AI/ML adoption. Apart from the advances in AI/ML per se, AI/ML optimization (e.g., model compression, quantization) is indispensable to make AI/ML adoption feasible. In Wi-Fi, for instance, AI/ML components are expected to mainly run in hardware-constrained AP and stations, which prevents using heavy models and keeping large datasets in memory. The communication overheads required to sustain the AI/ML operation are also critical in networks, so specialized types of signaling (e.g., new traffic classes for ML) might be defined in the upcoming years.

IV. Use Case Results: From On-Top Intelligence to AI-Native WLANs

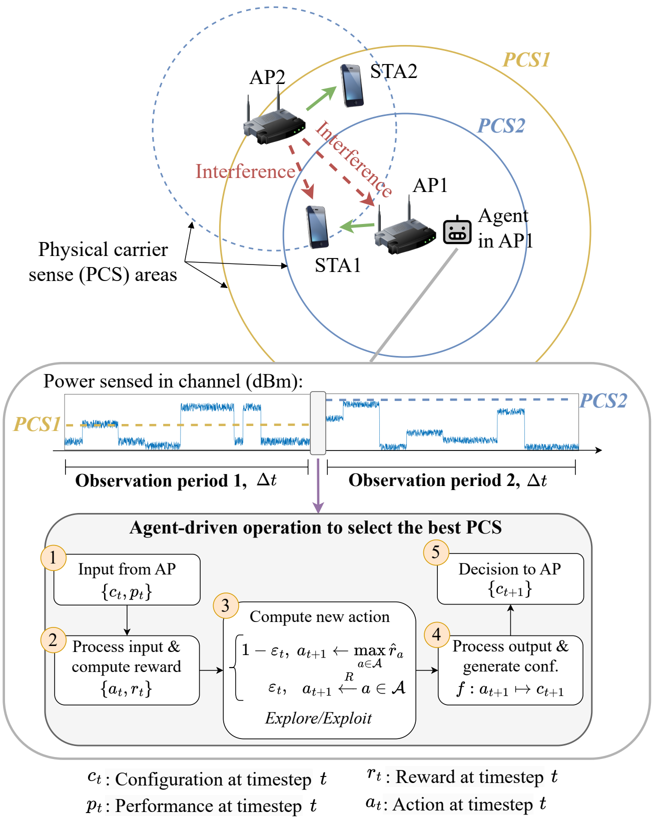

Figure 3: Use case scenario for showcasing the performance of different AI/ML agent-based solutions in 802.11 networks.

To showcase the benefits that AI/ML could bring to Wi-Fi at different stages of adoption, we study the use case of ML-based spatial reuse (SR). The considered use case is depicted in Fig. 3, where agents autonomously optimize the performance of a given basic service set (BSS) deployment by collecting measurements and applying configuration changes in a decentralized fashion. The implementation is based on multi-player multi-armed bandits, so that each AP in an overlapping basic service set (OBSS) is controlled by an independent agent that follows a given exploration-exploitation maximization policy [15]. To capture different degrees of maturity for AI/ML adoption in Wi-Fi, we consider:

1) **Constrained SR** (`11axSR`): The agent is constrained to the SR operation defined in IEEE 802.11ax, so it learns the best carrier sensing (sensitivity) threshold, $C \in [-82, -62]$. Note that the selection of C entails a transmit power limitation, where the maximum allowed transmit power is inversely proportional to C.
2) **Unconstrained SR** (`Free`): The agent freely adjusts both the carrier sensing and the transmit power to maximize performance. Through this approach, the fairness in channel access is implicit in the agents' rewards, thus in their expected behavior [15].

In both cases, spectrum regulations (e.g., maximum emitted power) apply. Moreover, with the advent of MAPC in Wi-Fi 8, we define two types of rewards to be used by the agents: decentralized (`DEC`), whereby each agent attempts to maximize its throughput selfishly (no coordination), and coordinated (`COORD`), whereby agents share their performance among them, thus aiming to maximize the max-min throughput. The proposed use case is simulated using Komondor, an IEEE 802.11 simulator including agents operation. The simulation parameters are in Table I.[1]

Table I: Simulation parameters.

	Parameter	Value
Scenario	Num. of random deployments, N	100
	Deployment side size, D	150 m
	Number of BSSs, N_{BSS}	4
	Traffic model, λ	Full-buffer
	Simulation time, T	100 s
PHY/MAC	Central frequency, f_c	6 GHz
	Bandwidth, B	20 MHz
	Default transmit power, P_{default}	20 dBm
	Default carrier sensing, S_{default}	-82 dBm
	Min. contention window, CW_{min}	16
	Max. contention window stage, s_{max}	5
	Maximum aggregated MPDUs, N_{agg}	64
	Data frame length, L	12 kb
Agents	Transmit power levels, $\mathbf{P}$	$\{5, 10, 15, 20\}$ dBm
	Carrier sensing levels, $\mathbf{C}$	$\{-82, -78, -74, -70, -66, -62\}$ dBm
	Action-selection strategy	ε-greedy
	Initial ε, ε_0	1
	Exploration adaptation, $f_\varepsilon(\cdot)$	$\varepsilon_t = \varepsilon_0/\sqrt{t}$

The results achieved by each approach are shown in Fig. 4. They are compared against the baseline without agents (`DCF`) for three relevant metrics, namely throughput, latency, and airtime. In all presented cases, reliability (25th percentile), median (50th percentile), and peak (75th percentile) are provided. As shown, the `11axSR`-constrained agent approach provides slightly better results than legacy `DCF` in terms of throughput, which can be attributed to the intrinsic limitations of the 802.11ax SR specification, which is conservative by design. Notwithstanding, `11axSR` agents allow to significantly enhance the zero-latency reliability by selecting the proper value of C. When it comes to the unconstrained agents approach (`Free`), we observe that the reliability and median gains substantially outperform both `DCF` and `11axSR` settings, thus proving the potential of an AI-native approach.

Regarding agent coordination through MAPC, `COORD` provides more benefits in the `Free` case, where agents have more freedom in accessing the channel and adapting the transmit power to be used. In that case, `COORD` enforces fairness through a shared reward, thus preventing starvation situations. The `DEC` approach, in contrast, may lead to unfairness as a result of the greediness of each individual agent, which is worsened in asymmetric deployments [15]. Finally, in `11axSR`, `COORD` leads to moderate enhancements as any possible value of C intrinsically includes fairness as a result of the protection mechanisms established by the 802.11ax SR operation. In that case, the `DEC` approach becomes a feasible low-complexity option (no communication is needed) thanks to the bounds provided by the IEEE 802.11 standard.

Considering that the room for improvement for physical carrier sense and transmit power control solutions is somewhat

[1]The source files used in this paper are available at https://github.com/mlwifitutorial/towards_ai-native_wifi. Accessed on May 2, 2024.

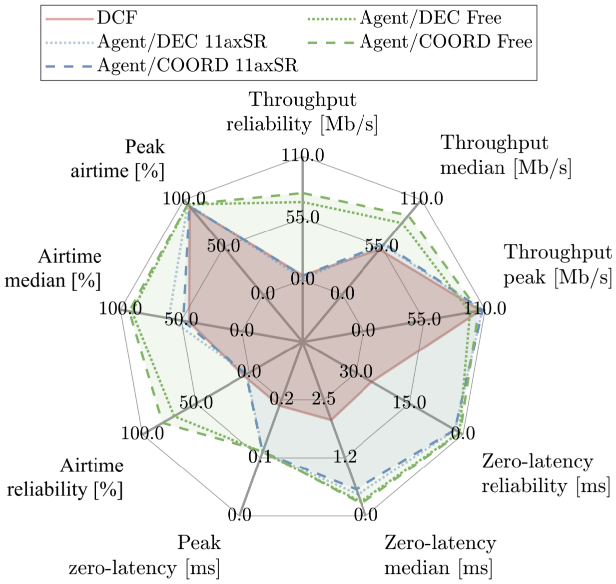

Figure 4: Performance across different metrics achieved by each approach.

limited in dense scenarios like the one showcased in this paper due to high interference regimes, the performance achieved by the unconstrained AI/ML-driven SR turns out to be promising and serves as an illustrative example for motivating AI-native communications. Moreover, the presented experiments are based on decentralized multi-armed bandits, so action-selection is still done individually (even if agents share a reward), thus the gains provided by AI/ML could potentially be higher if more sophisticated solutions were considered.

V. Conclusions

We have shown the ongoing standardization efforts and outlined a tentative roadmap towards future AI/ML-native Wi-Fi interfaces. Based on the provided list of related challenges, we conclude that the success and speed of development of AI/ML-native Wi-Fi interfaces will mainly depend on future standardization efforts to ensure the effectiveness, feasibility, and trustworthiness of the solutions developed by Wi-Fi vendors. This standardization process will require great care, as it is necessary to not only define appropriate interfaces precisely but also possible constraints (e.g., sets of parameters/functions/modules that can be modified) and security mechanisms. Overall, the definition and development of AI/ML-native Wi-Fi is still in its early stages and will certainly require answers to many open questions, however, it promises tempting performance improvements.

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