**IEEE P802.11**

**Wireless Local Area Networks**

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| Source | Marco Hernandez, YRP-IAI, Japan; CWC Oulu Univ. Finland. | Marco.Hernandez@ieee.org |
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**Revision History**

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# Introduction

Artificial Intelligence-Machine Learning (AIML) techniques are increasingly adopted by a wide range of industries very successfully.

Although AIML techniques in general may be considered mature nowadays, some of the relevant aspects of the technology are still evolving while new complementary techniques are frequently emerging.

 AIML capabilities are now applied to the telecommunication industry, including wireless networks, as a key enabler for a wide range of features and functionalities that maximize efficiency and bring intelligence and automation in various domains of communication networks.

Hence, the goal of this report is to explore the feasibility to apply AIML technologies to local area networks and 802.11 networks.

802.11 networks are expected to meet new challenges of consistent optimization of and increasing numbers of KPIs. Those include latency, reliability, connection density of devices, user experience, and energy efficiency in a shared spectrum.

AIML provides a powerful tool to help implementers and vendors improve network management and user experience by analyzing the collected data and making automatic inferences and actions based on a trained model or self-learning approach to improve targeted KIPs.

In this report, the AIML TIG explores the benefits of augmenting the air interface with features enabling improved support of AIML-based algorithms for enhanced performance and reduced complexity and overhead.

The enhanced performance depends on the particular use case under consideration. It may include improved throughput, robustness, reliability, and user experience, especially in dense scenarios and coexistence scenarios with other technologies sharing the same spectrum.

The report describes the study of a few carefully selected use cases, assessing performance in comparison with conventional methods and highlighting how an AIML potential specification impacts such performance.

The report lays the foundation for future 802.11 use cases leveraging AIML techniques.

The goal of the considered use cases is to identify an AIML framework, including functional requirements of AIML architecture, which can be used as a baseline in subsequent projects. Also, the report identifies areas where AIML could improve the performance of air-interface functions of 802.11.

Also, the report identifies the requirements for an adequate AIML model characterization and description for subsequent evaluations. Various levels of evaluation between the APs and STAs is considered.

The identification of KPIs will give a better understanding of the attainable gains and associated complexity requirements.

Finally, the impact will be assessed to improve the overall understanding of what would be required to enable AIML techniques for the air interface of 802.11 deployments.

# Functional framework for standarization

The functional requirements required for an AIML-enabled 802.11 specification are as follows:

* AIML algorithms and models are implementation specific and out of the scope of an 802.11 specification.
* The focus is on AIML functionality and corresponding types of inputs and outputs.
* The report studies representative use cases, each with specific input, output, model training (if applicable), and model inference functionality.
* When applicable, the report focuses on the analysis of the data needed at the model training function from the data collection function, while the aspects of how the model training function operates are out of scope.
* The report focuses on the analysis of data needed for the model inference function from the data collection functionality, while the aspects of how the model inference function works are out of scope. The AIML functionality resides in the 802.11 architecture and depends on deployment and the specific target use case.
* The model training and model inference functions must request specific information for training (if applicable) and execute the AIML inference model. The nature of such information depends on the use case and the AIML algorithm. However, a potential standard should specify the required signaling and data format to and from the AIML inference model.
* The model inference function should signal the outputs of the model only to entities that have explicitly requested them, or entities that take actions based on the output from the model inference function.
* The specific AIML algorithm used in a model inference function must be initially trained (if applicable), validated, and evaluated by the model training function before deployment.
* Cyber-security and privacy protection should be considered.

Figure 1 illustrates the AIML functional framework.



**Figure 1**⸺AIML-based Functional framework.

* The Data Collection is a function that provides input data to the Model Training and Model Inference functions. Data collection may include data preparation, i.e., data pre-processing and formatting depending on the use case and the heavy task of carefully labeling data for supervised learning or finding patterns in unlabeled data for unsupervised learning. Examples may include measurements from STAs and APs, or feedback from the Actor function.
* Model Training is a function that performs the AIML model initialization, training (if applicable), validation, and testing. **The Model Update** signaling delivers an updated or trained model to the Model Inference function. **The Model Deployment** signaling is an initialized, trained (if applicable), validated, and tested AIML model to the Model Inference function. Details of the Model Deployment and Model Update procedures are use case-specific and out of scope.
* The Model Inference is a function that provides the AIML model or algorithm inference output (predictions or decisions) based on the data provided by the Data Collection function and trained data from the Model Trained function, when applicable. It may provide **feedback** to the Model Training function. Details of inference output and feedback are use-case specific and out of scope.
* The Actor is a function that receives the output from the Model Inference function and triggers or performs corresponding actions. The actions may be directed to other entities or the Actor function itself. Feedback data may be required to derive training data or inference data or to monitor the performance of the AIML Model and its impact on the 802.11 deployments by updating KPIs and performance indicators.
* We expect the Access Point implements the AIML functional framework, but it does not preclude implementations at stations or the cloud.

## 802.11 standardization

Figure 1 illustrates the workflow of AIML-based 802.11 applications running at the PHY and/or MAC specification.

The Training Model, Inference Model, and Actor Actions are implementation dependent left for vendors to innovate.

An 802.11 specification should describe the required signaling and data formats for inputs and outputs of the blocks of Figure 1 and the procedures for the Data Collection and the executed Actions by the PHY or MAC depending on the target use case.

## Data collection

TBD

# Use cases and standard impact.

## ~~CSI~~

### ~~Use case description.~~

### ~~KPIs~~

### ~~Solution~~

### ~~Evaluation~~

~~The evaluation methodology. Performance benefits of AIML based algorithms for the use case.~~

~~The Training Model phase (including initialization, training (if applicable), validation, and testing) requires the evaluation of performance of related KPIs. Performance indicators need to be collected and analyzed.~~

~~The performance of the Inference Model function needs evaluation against the target KPIs to identify performance gains and situations where the AIML model requires re-training and testing.~~

### ~~Standard impact assessment~~

~~Note: the selection of use cases for this report targets the formulation of a framework to apply AIML to the air-interface of 802.11. The selection itself does not intend to provide an indication of a normative project.~~

## Dynamic spectrum sharing and coexistence.

### Use case description.

The wireless spectrum is getting even more crowded with an increasing number of devices and services. In the unlicensed spectrum case, the situation is more daring with the incorporation of IoT, unlicensed cellular network, and new transmission requirements in 802.11 applications. The situation requires efficient utilization of the spectrum in a shared ecosystem, where devices from different vendors and with different priority levels share a common set of spectrum bands.

In this coexistence scenario, detecting other signals of interest, or at least recognizing the presence of signals of a specific modulation type, is significant for dynamic spectrum-sharing techniques.

Spectrum sensing techniques have been developed to achieve spectrum awareness for some years. They have found widespread applications in the 3.5 GHz citizens broadband radio service band, the 6 GHz unlicensed band, the Industrial, Scientific, and Medical (ISM) frequency bands, and the 60 GHz mm-wave bands, among others.

Currently, a diversity of coexisting devices is unable to demodulate each other’s signals, and in the best case, may only have a beacon-length sensing duration to infer such information to minimize any outage for a higher-priority transmission. Hence, lightweight, and fast signal classification techniques are needed.

AIML techniques support efficient spectrum sensing and signal detection. A potential 802.11 specification could specify the framework under which implementation dependent AIML solutions will work by specifying dataset generation, storage, and processing procedures to support the development and evaluation of AIML-based spectrum awareness techniques.

AIML spectrum sensing, and signal classification infer the presence of other wireless systems sharing the same spectrum, reacting by manipulating system parameters according to a given policy under a collaborative or uncollaborative scheme for interference mitigation and avoidance. The use case will improve performance and coexistence of 802.11 deployments in the presence of inter-interference and intra-interference with the power of AIML. Something that current specifications are lacking.

The use case assumes operation in dense scenarios (malls, arenas, stadiums, etc.) or where interference is a sensitive issue like industrial or defense.

The Inference Model in part works as a spectrum manager responsible for coordinating spectrum access among different users across APs.

The Inference Model relies on advanced sensing capabilities (signal identification, interference mitigation) to detect and locate available spectrum bands and monitor the usage of existing spectrum bands. It may work in a collaborative way across APs or uncollaborative way with other wireless systems like unlicensed 3GPP specs for 5G/6G.

The information is used to allocate spectrum resources dynamically to different users in real-time optimizing KPIs (maximizing reliability while minimizing interference).

Please understand, the use case is for when interference is an issue.

### KPIs

The requirement to enable an AIML model is the availability of performance metrics (KPIs) along with historical data as inputs to the AIML model. The sophistication and deployment of a particular AIML model depend on the use case at hand. That is, dealing with coexistence with other wireless technologies or with a high density of 802.11 devices, or both. In either case, with high or variable traffic demands.

### Solution

The generic workflow of the operational steps in the lifecycle of an AIML model is shown in the Figure 2.



**Figure 2⸺** AIML operational workflow.

#### **Data collection**

#### **Preprocessing**

#### **Training**

#### **Data update**

#### **Validation**

#### **AIML inference**

#### **Actos actions**

### Evaluation

AIML enables spectrum sensing and signal classification for interference mitigation or avoidance combined with intelligent scheduling of resources and power saving. It allows dynamic fair and efficient channel access on unlicensed and unmanaged spectrum sharing.

The impact of the AIML model application on 802.11 deployments is on high-density scenarios, perhaps with several APs, like malls, schools, institutions, and arenas, to guarantee user experience and availability of services. AIML enables control and monitoring of resources across APs such as beams, modulation & coding, bandwidth, size of contention window, and use of channel bands, depending on traffic demands, the density of 802.11 devices, and the density of other wireless systems operating in the same spectrum.

Smart APs would be able to make predictions and act upon them so that 802.11 devices enable the creation of dynamically adaptable clusters based on learned data and traffic requirements. This will improve efficiency and reliability of 802.11 deployments.

#### **Challenge**

Develop effective mechanisms for collecting, structuring, and analyzing the volumes of data generated by the AIML model in a potential 802.11 specification. Early adopters who find solutions to these challenges will emerge as clear frontrunners.

*Work in progress.*