IEEE P802.11
Wireless LANs

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| Proposed IEEE 802.11 AI/ML TIG Technical Report Text for the Distributed Channel Access Use Case |
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Abstract

This document contains the proposed technical report of IEEE 802.11 AI/ML TIG, especially for the distributed channel access use case.

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1. **Introduction**
	1. Terminology
	2. Background information
2. **AI/ML Use Cases for IEEE 802.11**

Note: use cases potentially can be organized into different categories

Note: use cases potentially can identify KPIs

* 1. **Use case 1: CSI feedback compression**
	2. **Use case 2: Distributed channel access**

In 802.11, the fundamental access method of the MAC used by STAs is a Distributed Coordination Function (DCF) known as carrier sense multiple access with collision avoidance (CSMA/CA). A STA is required to sense the wireless medium before transmitting. If it finds that the medium is continuously idle for a minimum specified duration, the STA is then permitted to start transmission of a frame after waiting for an additional random backoff. The range of the generated random backoff counter is bounded by the Contention Window. The initial range is set between 0 and the Contention Window minimum value (CWmin) . If there is collision, the contention window is doubled until it reaches the maximum Contention Window size (CWmax) in order to furhter reduce collisions.

Higher throughput and lower latency have been an inevitable trend in WLAN for more than a decade as mentioned in [3] [4] [5] [6] . An efficient channel access protocol is fundamental to achieve this goal. However, the analysis in [7] shows that current contention-based access protocol suffers large performance degradation in dense deployments. The binary exponential backoff leads to short-term unfairness [8] , i.e., consecutive unsuccessful transmissions lead to worse latency perfomance. Therefore, more efficient channel access schemes are needed to increase throughput and to reduce latency and jitter.

Some studies [9] [10] [11] [12] have shown that AI/ML based channel access schemes can efficiently improve throughput/channel efficiency and reduce latency and jitter. For example, Centralized Contention window Optimization with Deep reinforcement learning (CCOD) [9] , applied Deep Q Network (DQN) or Deep Deterministic Policy Gradient (DDPG) contribute to contention window optimization. Simulation results show that the throughput improvement of CCOD over standard 802.11, ranges from 1.5% (for 5 stations) to 40% (for 50 stations). In [10] , QMIX-advanced Listen-Before-Talk (QLBT) is proposed for distributed channel access and improves the performance by leveraging the powerful learning capability of deep neural networks. Experimental results show that QLBT increases the channel efficiency by 18% and reduces the lantency and jitter by 25% and 90% on average.

This use case proposes to apply AI/ML techniques to distributed channel access to improve throughput and reduce latency and jitter.

KPIs considered in this use case are proposed as follows:

1. **Throughput**
2. **Latency and jitter**
3. **Fair coexistence**

An evaluation methodology needs to be established.

* 1. Use case 3
1. **Requirements and Potential Features Analysis (high level)**
	1. Requirements
2. Use case 1: CSI feedback compression
3. Use case 2: Distributed channel access
4. Fair coexistence with legacy 802.11
	1. Support fair coexistence with legacy 802.11 channel access schemes.
5. Performance should follow the guidiance below:
	1. **Throughput improvement measured at MAC data service access point (SAP)**: Achieve throughput improvement compared to 802.11be for different scenarios.
	2. **Latency and jitter reduction**: Achieve latency and jitter reduction compared to 802.11be for different network sizes. Latency is the time from when a packet enters the queue to when it is successfully transmitted. Jitter is the standard deviation of the latency.
	3. **Additional complexity introduced by AI/ML**: Minimize the additional complexity, e.g., computation complexity, introduced by AI/ML process.
	4. Potential features analysis
6. **Technical feasibility analysis**
	1. Standards impact
7. Use case of CSI feedback compression
8. Use case of distributed channel access

The standards impact may include:

* Define the parameter exchange between AP and non-AP STAs, e.g., capability indication, data report to facilitate training, neural network parameters, etc.
	1. Technical feasibility
1. Use case of CSI feedback compression
2. Use case of distributed channel access

 The following metrics will be studied:

* + 1. **Backwark compatibility**: The STAs that support an AI/ML based channel access scheme shall support the legacy 802.11 channel access scheme.
		2. **Data availability and accesibility**: There are some STAs that are able to use data to perform AI/ML model training and/or inference [13] . The data used for model training and/or inference shall be accessible for these STAs. Extra data and model exchange may be required to support model training and/or inference.
		3. **Hardware/software capability**: The STAs that support AI/ML based channel access shall have the hardware and software capability to support AI/ML algorithm(s). The STAs that support model training may require higher computation capabilities. Extra data and model exchange may be required to support model training and/or inference.
1. **Summary**
2. **References**
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