A Flexible Machine-Learning-Aware Architecture for Future WLANs

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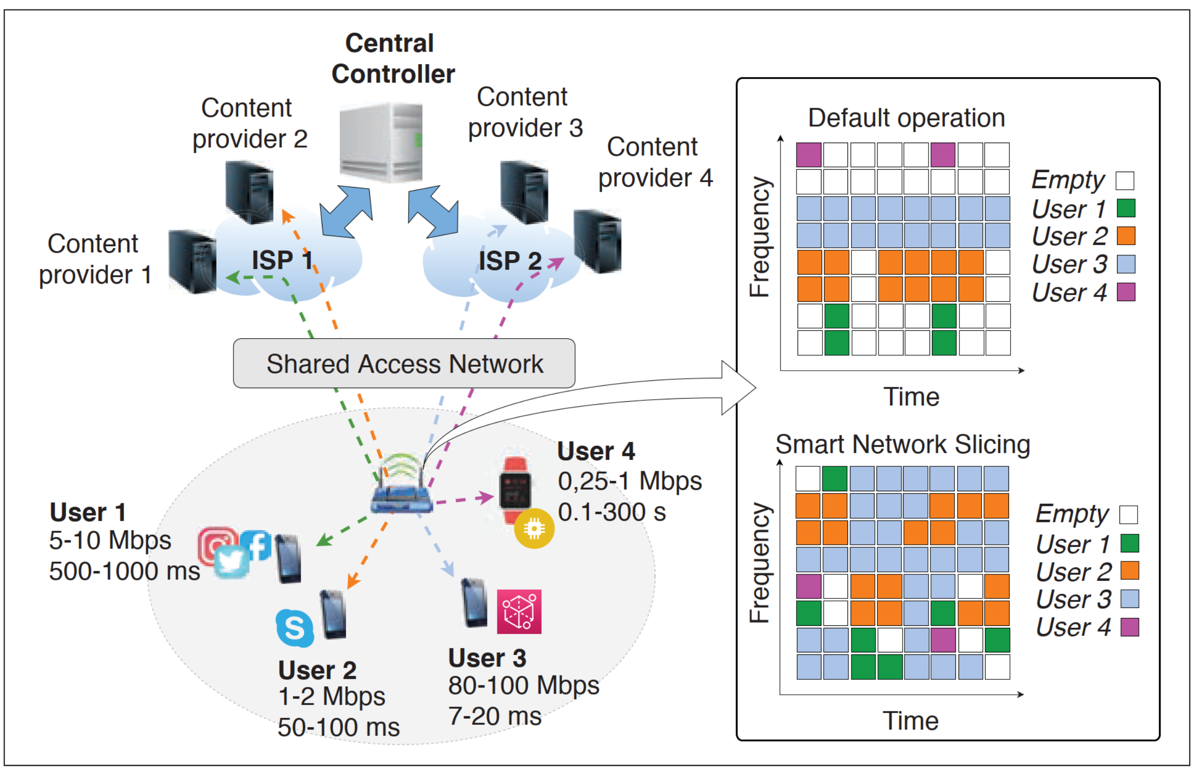
- Challenge of future communication
  - bandwidth: 10-20Gbps
  - latency: < 5ms
  - loss: packet-error rate < 1e-5
  - scalability: 1e6 per km^2
- Paradigm shift in designing for network planning, operation and management
  - empower on cognitive and context-aware capacity
  - need additional information: environment sensors, camera.

Machine-Learning-enabled use cases in WLANs

OFDMA-Based Smart Network Slicing

- network slicing: allows virtually separating network resources to meet diverse application requirements
- thru resource allocation in OFDMA.
- ML **predicts on the user requirements** to optimize access network
- predict resource requirement by ML, allocated to ofdma resource



- 5G network slicing is a network architecture that enables the multiplexing of virtualized and independent logical networks **on the same physical network infrastructure**. Each network slice is an isolated end-to-end network tailored to fulfil diverse requirements requested by a particular application.

Cloud-Based User Association and Hand-over

- HO typical rely on the strongest signal first (SSF) mechanism
  - has loading balancing issue
  - performance loss in dense BSSs
- provide contextual information such as traffic load.
- **mobility pattern prediction** using ML to empower association and HO process

Inference-Based Coordinated Scheduling

- WLAN deployments can be chaotic
  - complex scenarios where inter-BSS inter-actions prevent the existing scheduling approaches from ensuring a minimum quality of service
- Thru coordinated **ML-assisted scheduling**, different APs can trigger uplink/downlink transmissions from/to the appropriate stations (STAs)
  - increasing the network throughput while
  - reducing the number of packet collisions

Reinforcement-Learning-Based Spatial Reuse

Future Network

- FG-ML5G was
- November 2017 by its parent group, ITU-T Study Group 13
- to study the integration of ML mechanisms into future networks.

Multi-level machine learning pipeline

- Source (Src)
- Collector©
- Pre-processing(PP)
- Model(M)
- Policy§: constrain of guideline delimit behavior of model.
- Distributor(D): spread ML output across all corresponding targets.
- Sink:

Closed-loop subsystem

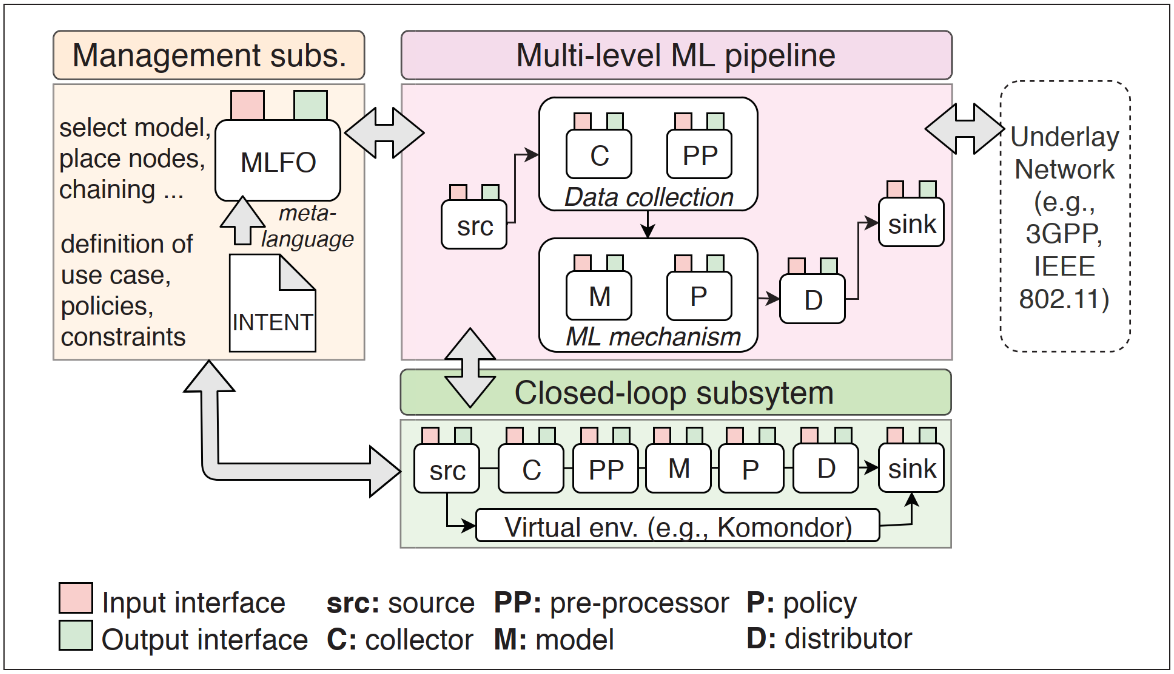


Figure 2. ITU's logical architecture for future networks [2]. Entities contain input/output interfaces for communication, while the ML intent is a declarative file with information related to the use case.

ML-aware arch for IEEE WLAN

WLAN two deployment classes

- Residential
- Enterprise

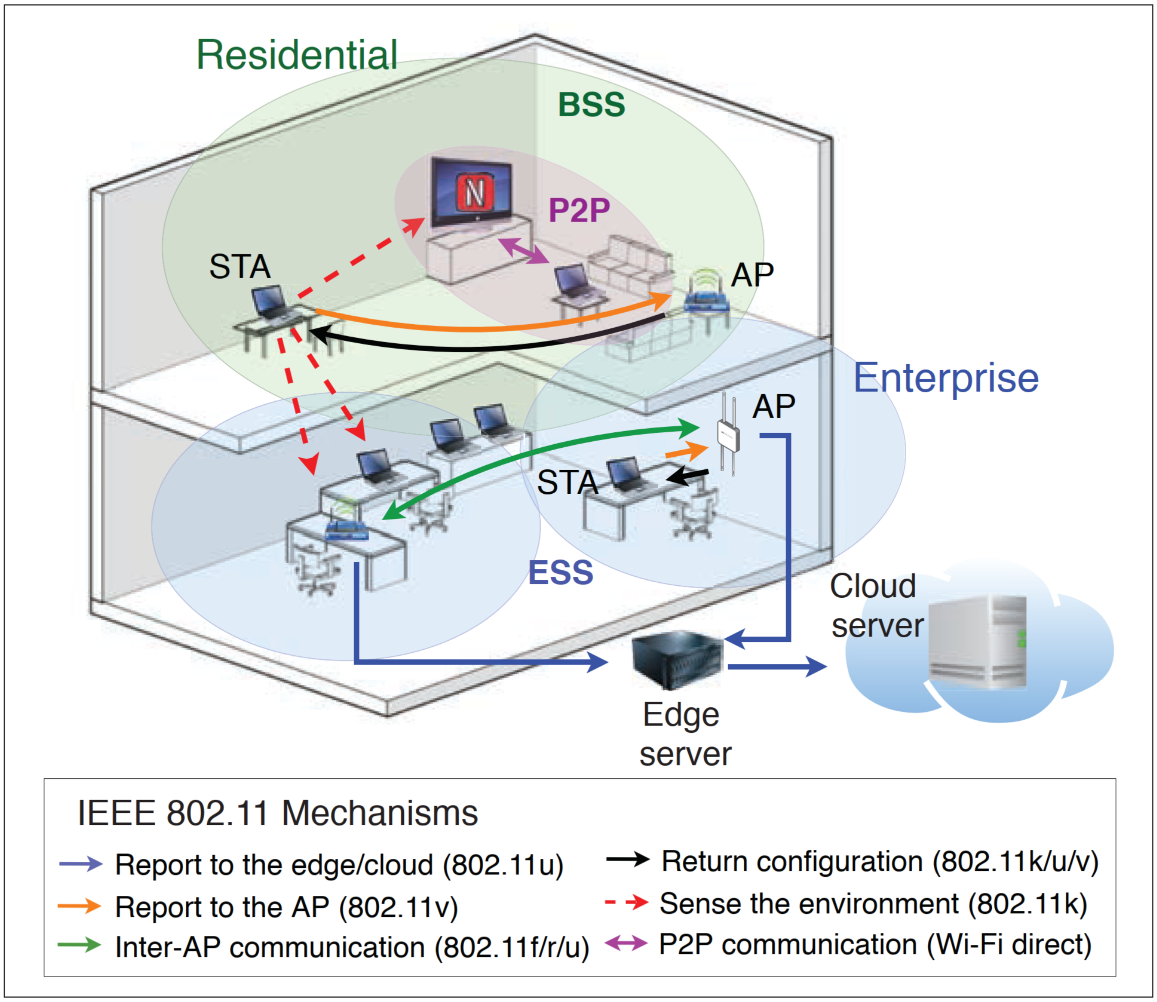


Figure 3. Enterprise and residential-like deployments and complementary IEEE 802.11 mechanisms to enable the utilization of ML.

Challenges

- Non-stationary:
  - channel fluctuations, mobility user, varying traffic made netwrok dynamiclly,
  - **continuous re-training** ML.
- Limited Communication Resources:
  - unlicensed bands shared resource, ML mechanism may be fail or delay due to conjunction.
  - ML operation must be **robust and resilient**.
- Limited Computation and Storage Resources:
  - scarce resource in WLAN special in residential environments
  - ML needs computation-efficient procedures, limited resources for online learning.
- Adversarial Environment
  - chaotic in overlapping BSSs
  - competition among agents may lead to an adversarial setting
  - different ML mechanisms in multi-vendor devices, leading to clashing interests.
- Legacy Devices

Computation Paradigm in IEEE 802.11 WLANs

- Cloud-oriented: high computational and storage resources
  - relay on management of data and the corresponding synchronization, availability, and heterogeneity issues
- edge-oriented:
  - lack powerful computation and storage resources
  - only allow using simple and lightweight computing ML algorithms
  - for real-time ML applications that manage local (and even highly varying) information.

Realization

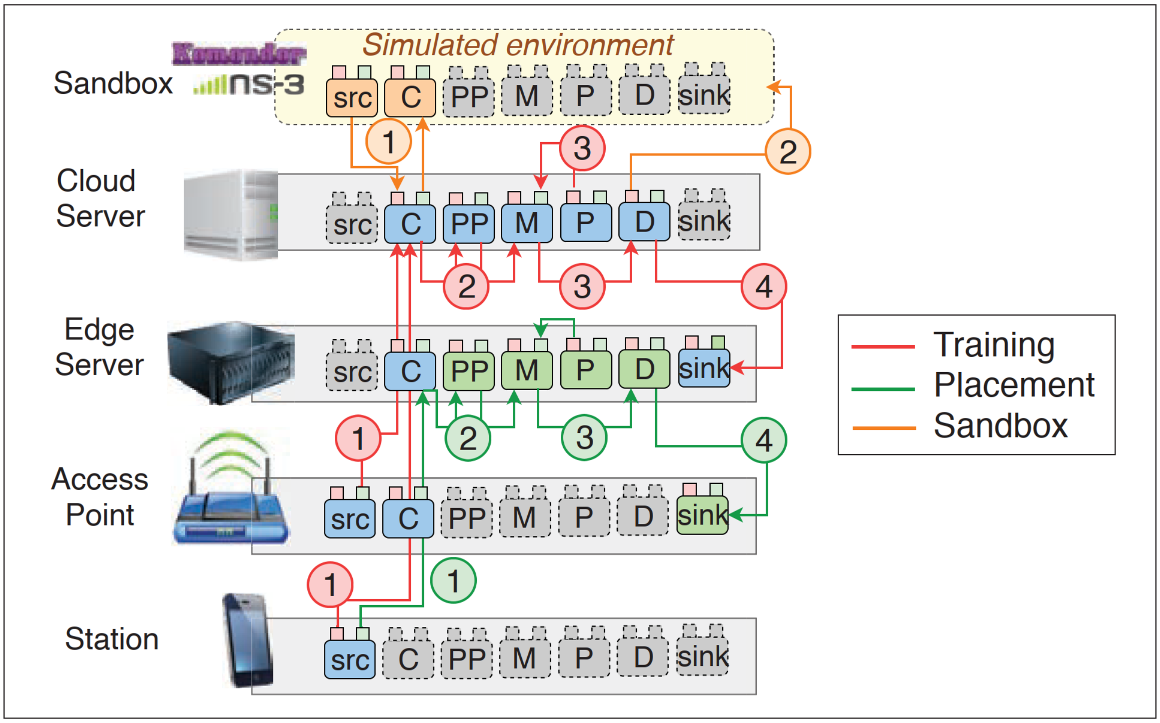


Figure 4. Realization of ITU's ML architecture for IEEE 802.11 WLANs through a hybrid ML-based solution for AP (re)association and handover.

- Training procedure
  1. Data collection
     - from different ap,sta, collects
     - user info, performance, application data, channel states,…
  2. Pre-processing
  3. Model generation
  4. Output distribution
- Placement
  - Handle new requests
  - Pre-processing
  - Run the ML solution
  - apply solution
- Sandbox(simulated environment!)
  - Generate data for training
  - Preliminary model testing

Example study: AP association/HO problem

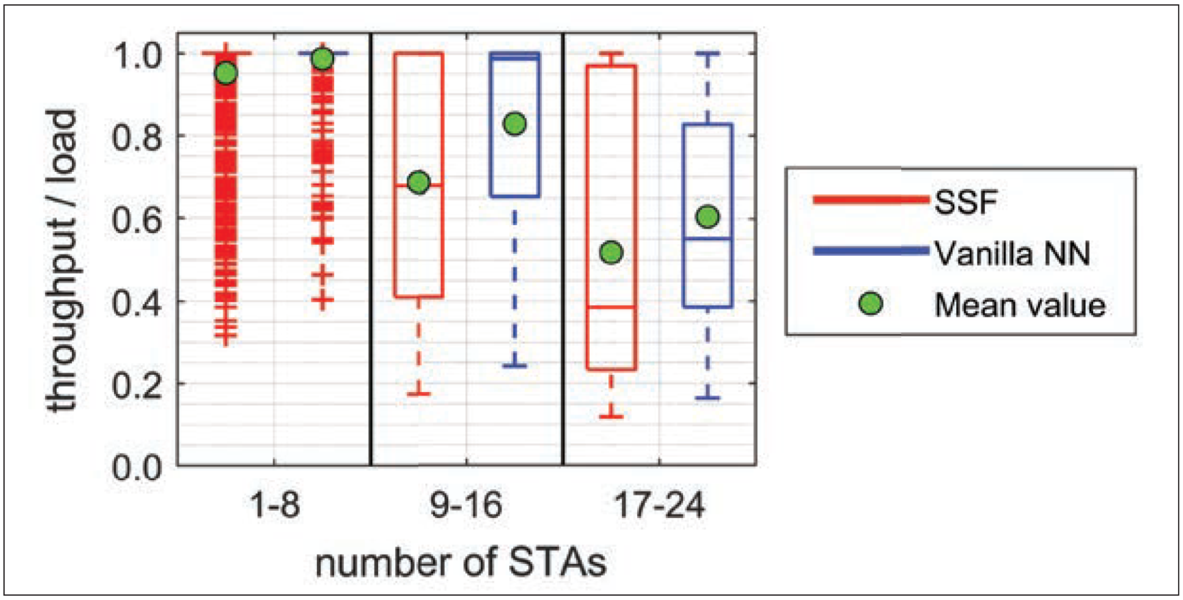


Figure 5. Performance evaluation of the AP association problem in WLANs: SSF vs. neural network (NN). The mean performance of each mechanism is represented by a green dot.