ML5G-I-176: Adoption of the ITU-T's Architecture in IEEE 802.11 WLANs

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Outline

NOTE: this work is based on the work in *Wilhelmi et al. "A Flexible Machine Learning-Aware Architecture for Future WLANs"* [1].

Goals

1. Proof-of-concept adoption of the ITU-T's architecture
2. Insights on specific underlay (IEEE 802.11 WLANs)
3. Impact on academia

Scope

1. Realization of the ML pipeline in WLANs
2. Fast adoption: main challenges & current mechanisms
3. ML Architecture-enabled use cases in WLANs (PHY & MAC)

Outline

Learning approaches

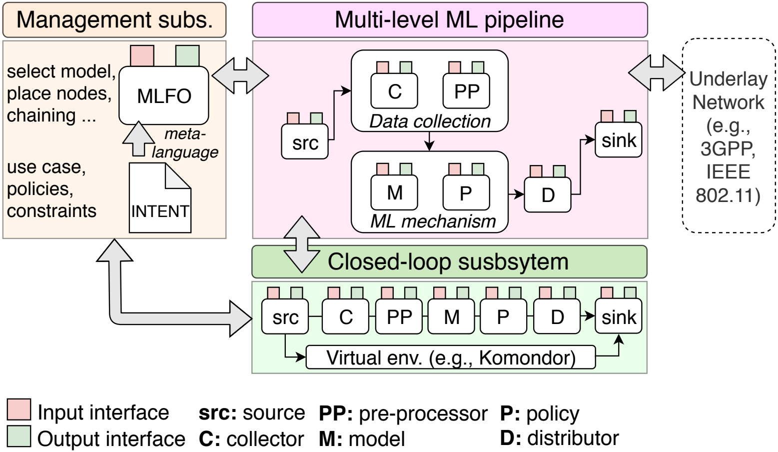

Figure 1: ITU-T's logical ML architecture for future networks [2].

Outline

Deployment modes in IEEE 802.11 WLANs

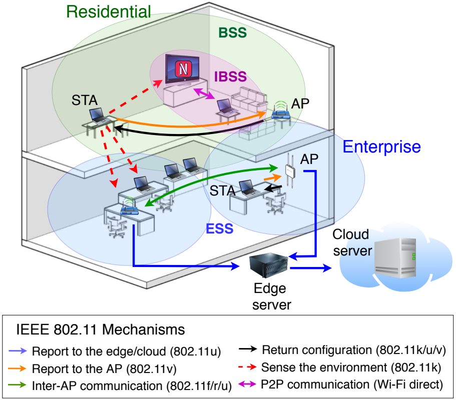

Figure 2: Deployment modes in IEEE 802.11 WLANs.

Flexible technology:

- Ad-hoc (IBSS)
- Residential (BSS)
- Enterprise (ESS)

Computation paradigms:

- Edge-oriented
- Cloud-oriented

The ITU-T's flexible architecture fits perfectly

ML-enabled use cases (I)

- OFDMA-based smart network slicing
- Cloud-Based User Association and Handover
- Inference-Based Coordinated Scheduling
- Reinforcement Learning-Based Spatial Reuse
- ...

ML-enabled use cases (II)

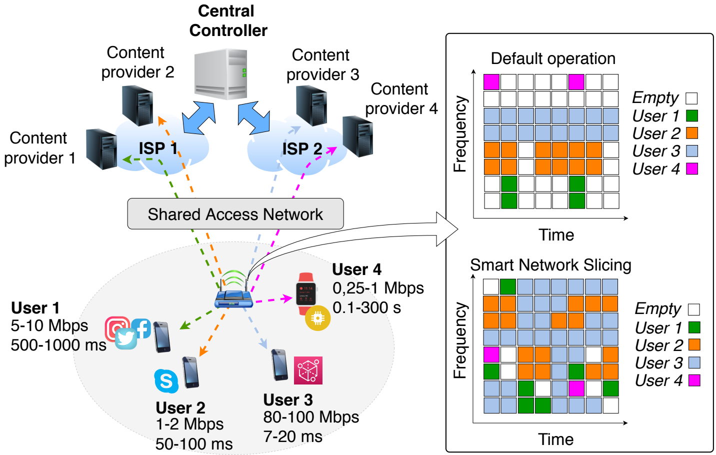

Figure 3: ML-oriented network slicing OFDMA.

Outline

Challenges

Compute a solution

- Network dynamics (users' mobility, variable traffic patterns...)
- Adversarial setting unleashed
- Legacy devices
- Limited computation and storage resources

Enable communication-based ML models

- Limited communication resources (unlicensed band)

Other inter-domain challenges

- Security
- Interoperability

Opportunities for fast adoption

Feature	Amendments	Opportunities for ML application
Information gathering	802.11k/r/v	A given ML mechanism can use information about the network topology or RF measurements to infer the behavior of other devices or to extract important environmental characteristics.
Interoperability	802.11f/u	Interoperability with other networks can be used to perform coordinated operations (e.g., scheduling, resource allocation). Besides, inter-AP communication procedures can enable centralized/coordinated mechanisms (e.g., federated learning).
Security	802.11w	ML mechanisms can use management frames that are protected so that a higher level of security is granted.
Validation	802.11t	Performance evaluation in WLANs through test metrics can be of great utility to define optimization goals within the ML operation.

Hybrid AP (re)association and handover

- Function generation (prediction) at the cloud
- New situations handled at the edge
- Re-adjustment of the model based on new data (online)

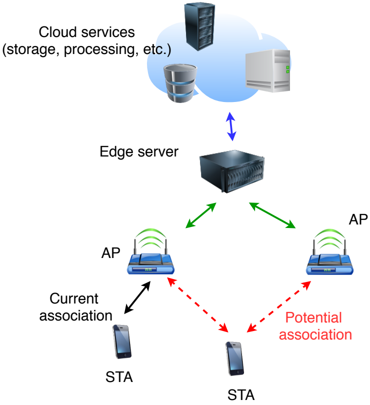

Figure 4: Hybrid AP (re)association and handover.

Realization example

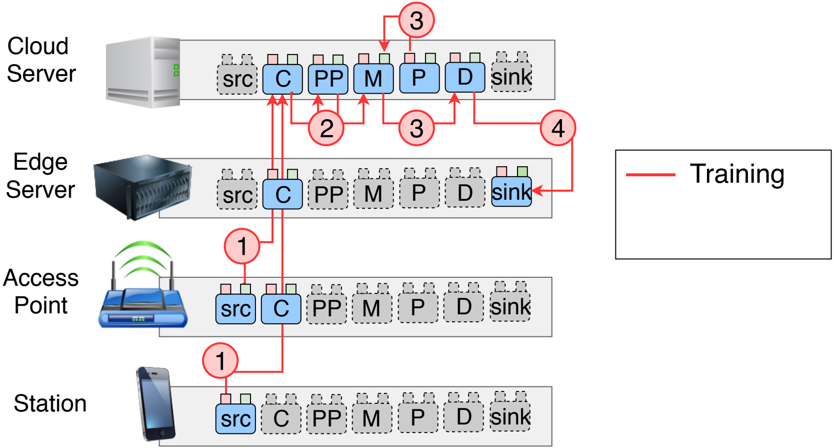

Figure 5: Realization of the ITU's ML architecture for IEEE 802.11 WLANs through a hybrid ML-based solution for AP (re)association and handover.

Realization example

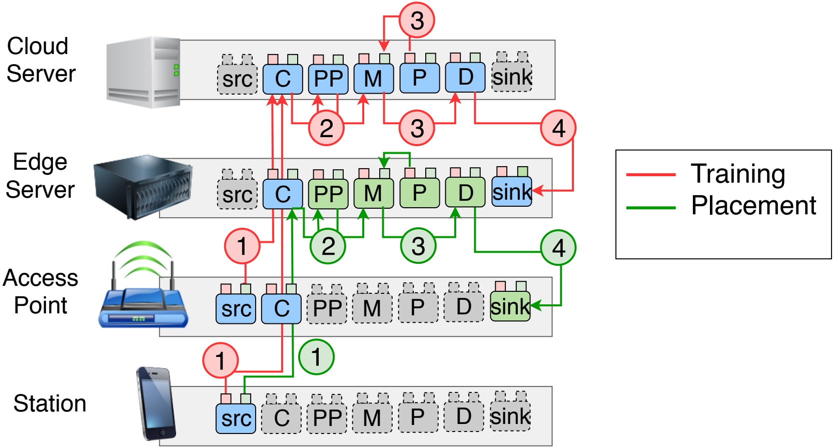

Figure 6: Realization of the ITU's ML architecture for IEEE 802.11 WLANs through a hybrid ML-based solution for AP (re)association and handover.

Realization example

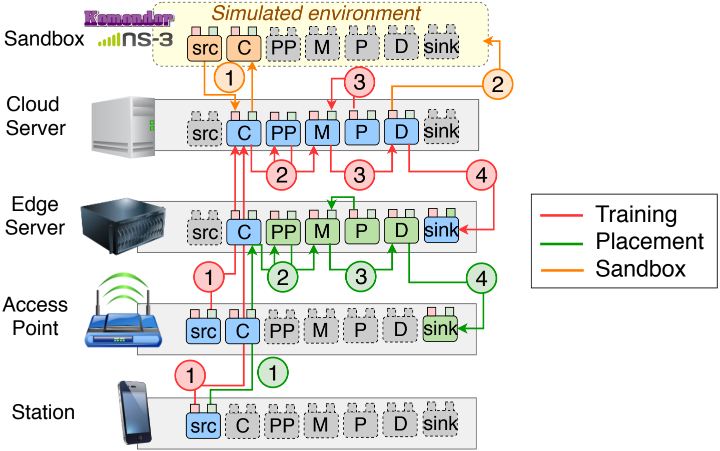

Figure 7: Realization of the ITU's ML architecture for IEEE 802.11 WLANs through a hybrid ML-based solution for AP (re)association and handover.

Management and Orchestration in WLANs

- The MLFO deploys, monitors & orchestrates the ML operation [3]
- Some responsibilities:
  - Process use case information from intents
  - Ensure that use case requirements are met
  - Identify entities and provide chaining
  - React to misbehavior
- Some specific challenges:
  - Network devices on/off: also APs in WLANs
  - Synchronization: bigger challenge for independent BSSs
  - Lack of information: legacy devices
  - Adversarial setting: address clashing interests

Management and Orchestration - Example

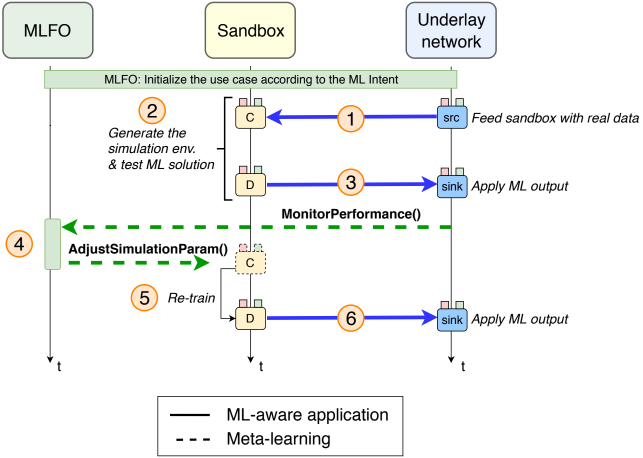

Figure 8: MLFO operation for adjusting the sandbox parameters based on its accuracy for representing the actual performance of the network.

Outline

Conclusions

Conclusions

- ML as an intrinsic part of future networks (5G/6G)
- Role of the ITU-T's ML-aware architecture

Open issues

- Data handling (*how and where to store data? how to assess the expiry of data?*)
- Orchestration (*behavior of several ML approaches in conjunction, ML operation distribution, heterogeneity...*)
- Robustness (*how to deal with uncertainty? how to prevent network failures?*)

Future contributions

- Potential and pitfalls of network simulators as a sandbox

Any questions?

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References

Wilhelmi, F., Barrachina-Muñoz, S., Bellalta, B., Cano, C., Jonsson A., & Ram, V. (2019).

"A Flexible Machine Learning-Aware Architecture for Future WLANs", *arXiv preprint arXiv:1907.04141*.

Barrachina-Muñoz, S., Wilhelmi, F., Selinis, I., & Bellalta, B. (2019).

"Komondor: a Wireless Network Simulator for Next-Generation High-Density WLANs", *in 2019 Wireless Days (WD)*. IEEE, pp. 1–8.

ML5G-I-172 (2019).

"Requirements, architecture and design for machine learning function orchestrator"