Improving Spatial Reuse in High-Density Wireless Networks through Learning

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ABSTRACT

Popularity of IEEE 802.11 Wireless Local Area Networks (WLANs) leads to massive deployments in which few frequency resources must be shared, resulting in inefficiency in dense environments. The behavior of the protocols that grant access to the medium, which are based on Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA), is inefficient in dense deployments, and prone to generate issues such as the Hidden-Terminal and the Exposed-Terminal problems. Therefore, the overall throughput may be considerably reduced due to collisions and/or starvation. As the complexity of Wireless Networks in terms of variability prevents to computationally find the optimal configuration for a given network, we aim to use Reinforcement Learning (RL) to find close-to-optimal solutions adaptively.

MOTIVATION

Context:

▪Wireless traffic evolution

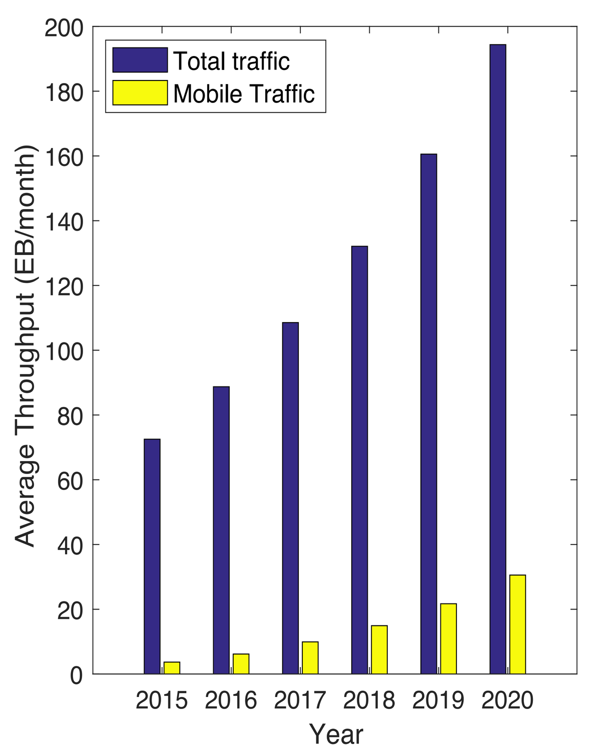


Figure 1: IP Traffic Evolution & Wireless Traffic proportion [1]

▪Explosion of the RL field

Challenges:

- Dynamic Power and Sensitivity Adjustment to improve *Spatial Reuse*

Previous work:

- Dynamic Sensitivity Control (DSC) is under discussion to become part of the upcoming IEEE 802.11ax standard for High-Efficiency WLANs (HEWs)

COEXISTENCE ISSUES

Root causes:

- Non-optimal resource allocation
- Selfish configurations

Main consequences:

- Throughput degradation
- Unfairness
- Scalability issues

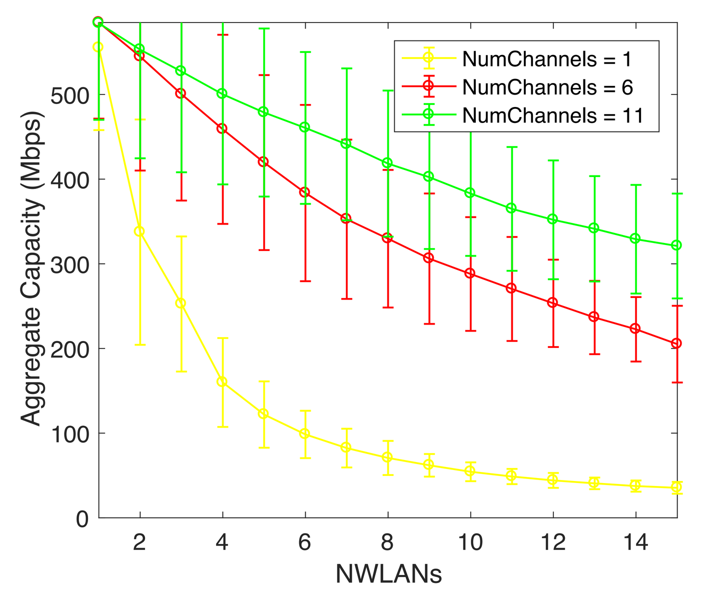


Figure 2: Aggregate capacity in an OBSS vs Number of coexistent WLANs

CHALLENGES

Adjust wisely both **TPC** (Transmission Power Control) and **CCA** (Clear Channel Assessment)

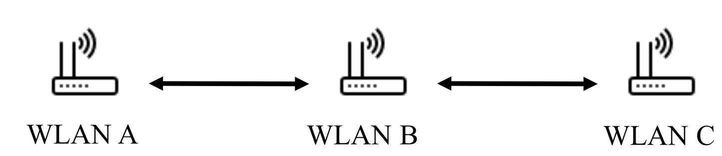
Action	Effect		
	Parallel Transmissions	Data Rate	Collisions probability (by hidden node)
↑ TPC	↓	↑	↓
↓ TPC	↑	↓	↑
↑ CCA	↓	-	↓
↓ CCA	↑	-	↑

Table 1: Effects of modifying TPC and CCA

PROBLEM CHARACTERIZATION

Continuous Time Markov Networks (CTMN) [2]:

- Obtain the Theoretic Throughput for a given configuration
- Graphical visualization of possible states (at $s_{i,j}$ nodes i and j are transmitting)



$$\pi_s = \frac{\prod_{i \in s} \frac{\lambda_i}{\mu_i}}{\sum_{s \in \Omega} \prod_{i \in s} \frac{\lambda_i}{\mu_i}}$$

$$\Gamma_i = L \sum_{s \in S} \mu_{n_{i,s}} \pi_s$$

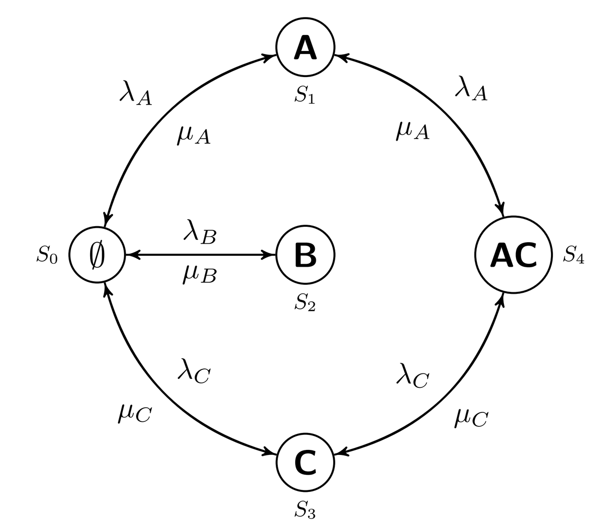
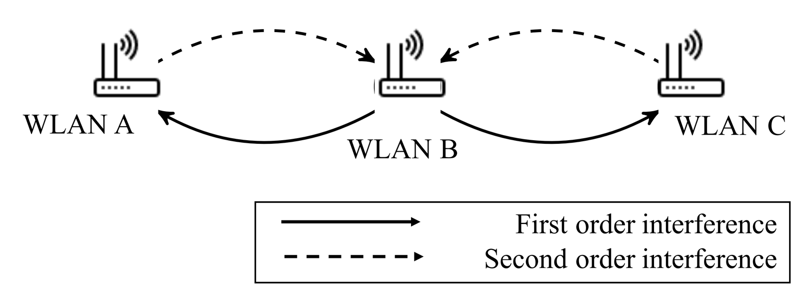


Figure 3: Markov Network - 3 WLANs with direct interferences

Considerations:

- Complexity increases very fast
- Asynchronous hidden hard to model easily appear with complexity



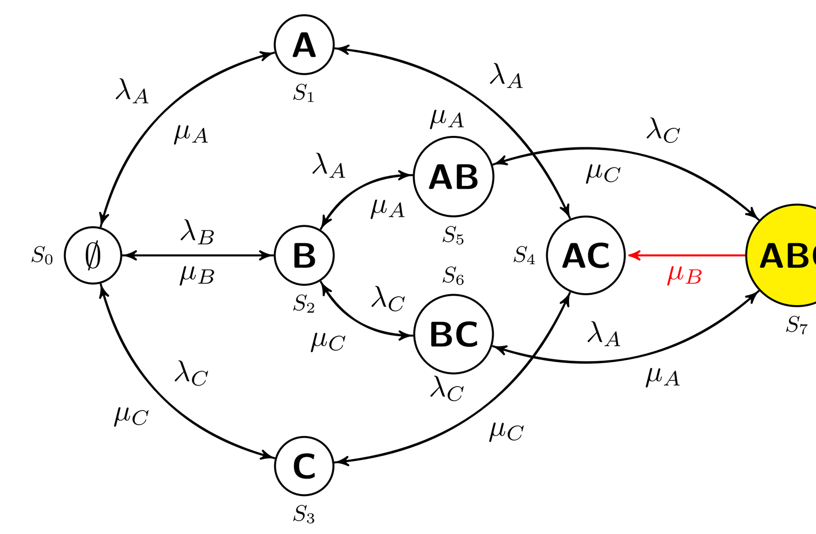
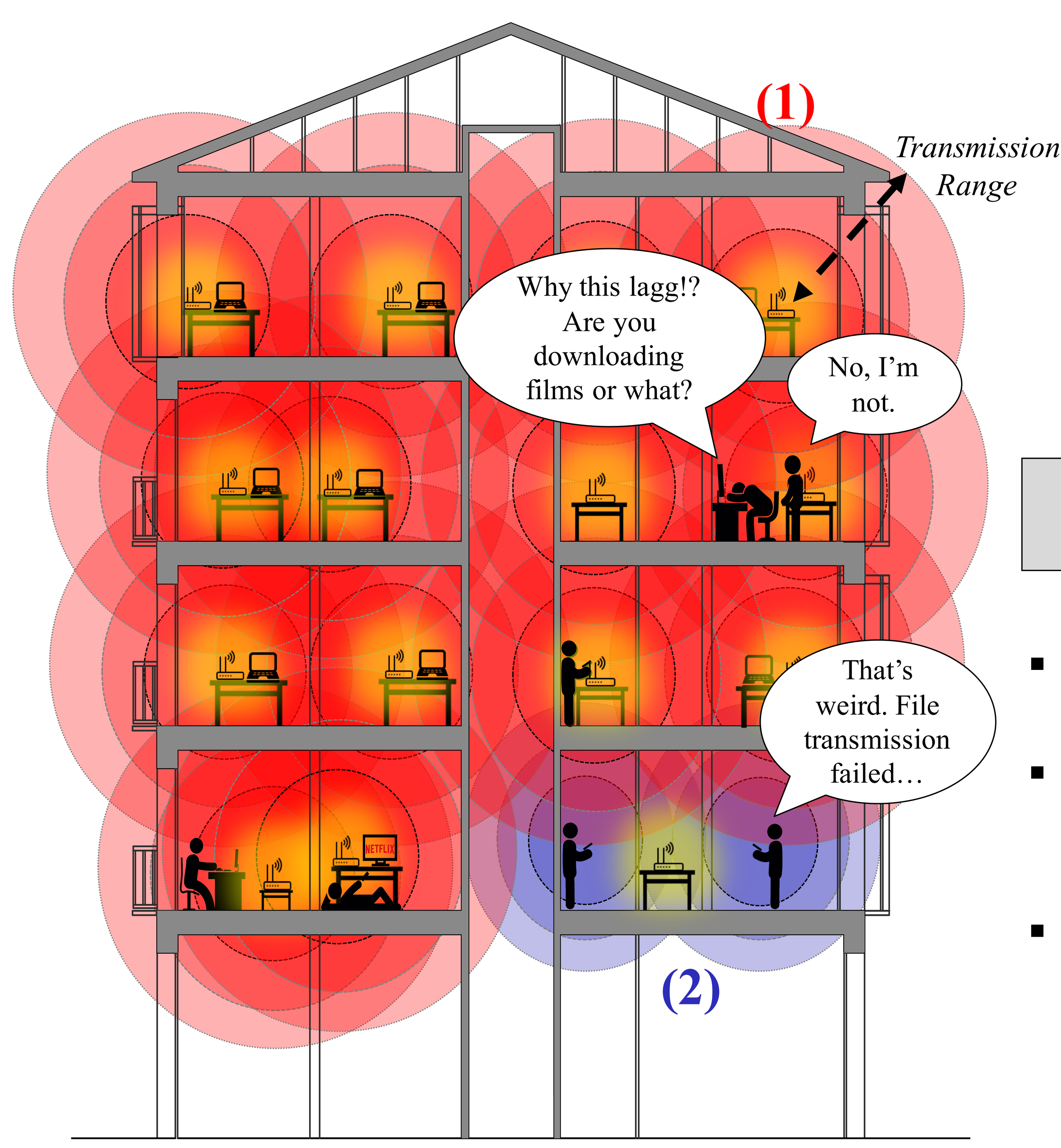


Figure 4: Markov Network - 3 WLANs with additive interferences

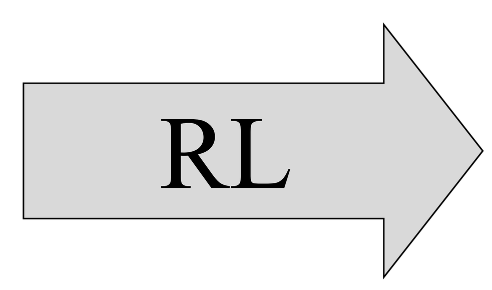


(1) Exposed-Terminal problem

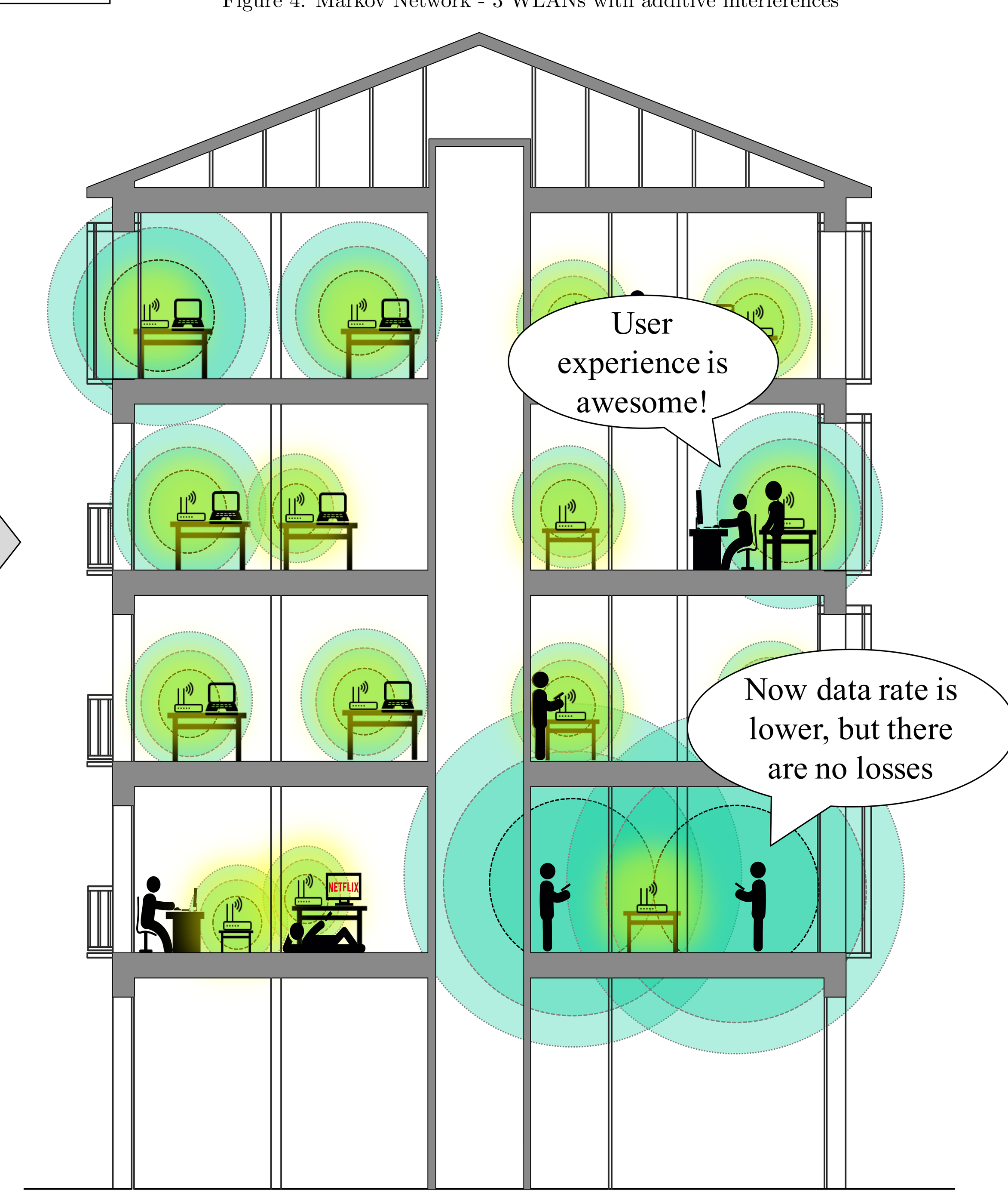
- **Causes:** To high power transmitted and very high sensitivity
- **Consequences:** Throughput decays very fast with the number of coexistent nodes

(2) Hidden-Terminal problem

- **Causes:** CSMA fails - nodes out of reach
- **Consequences:** Collisions may harm the throughput



- Empower devices with agents
- Learn from the environment and take decisions
- Potential of Multi-Armed Bandits framework



MULTI-ARMED BANDITS [3]

GOAL: Given $\langle \mathcal{A}, \mathcal{R} \rangle$, minimize the expected regret to exploit resources as much as possible (obtain the highest possible throughput in each WLAN)

- $\mathcal{A}$ is the set of arms (set of pairs CCA-TPC)
- $\mathcal{R}$ is the set of probability distributions of the rewards associated to each arm (varies in function of the neighbours' actions)
- After an action $a \in \mathcal{A}$ is played, a reward R_a is generated by the environment (depends on the throughput experienced after taking action a)

CONCLUSIONS

The Spatial Reuse problem in High-Density Wireless Networks can be solved by allocating resources dynamically, but its variability and complexity prevent to use exhaustive methods to solve it.

Thus, we aim to dynamically tune the CCA and TPC of a WLAN through the experience acquired by using Reinforcement Learning methods.

ONGOING WORK

Komondor simulator [4]

- WN Simulator based on COST [5]
- Simulate behaviour of advanced features in IEEE 802.11ax
- Open repository: https://github.com/wn-upf/Komondor

TPC/CCA problem formulation

- State of the art
- Analytical model to understand underlying interactions
- Previous steps to design RL techniques to be applied on agents

REFERENCES

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[3] Auer, Peter, Nicolo Cesa-Bianchi, and Paul Fischer. Finite-time analysis of the multiarmed bandit problem. Machine learning 47.2-3 (2002): 235-256.

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[5] G. Chen and B. K. Szymanski, "Reusing Simulation Components: COST: A Component-oriented Discrete Event Simulator," in Proceed- ings of the 34th Conference on Winter Simulation: Exploring New Frontiers, ser. WSC '02. Winter Simulation Conference, 2002, pp. 776–782.

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