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To cite this version:
Anthony Bardou, Thomas Begin, Anthony Busson. Multi-Armed Bandit Algorithm for Spatial Reuse in WLANs: Minimizing Stations in Starvation. 23ème congrès annuel de la Société Française de Recherche Opérationnelle et d’Aide à la Décision, ROADEF’22, 2022, Lyon, France. hal-03643750

HAL Id: hal-03643750
https://hal.archives-ouvertes.fr/hal-03643750
Submitted on 16 Apr 2022

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Multi-Armed Bandit Algorithm for Spatial Reuse in WLANs: Minimizing Stations in Starvation

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Mots-clés: reinforcement learning, starvations, spatial reuse, clear channel assessment.

1 Introduction

Nowadays, access to WLANs is often regarded as a basic service. However, despite its importance, very few WLANs run at their maximum efficiency. Their current deployments often contain a dense number of access points (APs), which can have a major impact on the WLANs’ performance because of the listen-before-talk property of 802.11. The recent amendment to the 802.11 standard (802.11ax or Wi-Fi 6) could be a game-changer as it enables WLANs to dynamically modify the transmission power of APs (a.k.a. $TX\_PWR$) as well as their CCA (Clear Channel Assessment) threshold (a.k.a. $OBSS/PD$). In this work, we frame the proper tuning of these two parameters as a Multi-Armed Bandit problem, which allows us to derive an efficient and robust data-driven solution using Thompson sampling, an original sampling of WLAN configurations, and a tailor-made reward function assessing their quality.

2 Methods

2.1 Reward Function

In order to converge quickly to an efficient WLAN configuration in the configuration space $C = ([−82, −62] \times [1, 21])^{NA}$ (with $NA$ the number of APs in the WLAN), our reinforcement learning agent must be able to assess the quality of a given configuration through a reward function. We propose a reward function $R$ which is based on the stations’ (STAs) effective and attainable throughputs ($T_i$ and $T_A^i$), $T^+$ and $T^−$ the sets of STAs not in starvation and in starvation (defined by $T_i < αT_A^i$ for a fixed $α \in [0, 1]$) and the number of STAs in the WLAN $N_S$. It is defined in Equation 1.

$$R(c) = \frac{|T^−| \prod_{j \in |T^−|} \frac{T_j}{T_A^j} + |T^+| \left( N_S + \prod_{j \in |T^+|} \frac{T_j^+}{T_A^j} \right)}{N_S(N_S + 1)}$$

This reward is bounded between 0 and 1 and mainly increases with the reduction of starvations in the WLAN. We suppose that $R$ is sufficiently smooth over the discrete configuration space $C$, that is: $\exists δ \in [0, 1], \forall c_i, c_j \in C, |R(c_i) − R(c_j)| \leq δ||c_i − c_j||_1$. This property allows us to split our problem into two independent tasks, (i) look for promising configurations in $C$ to fill a reservoir, done by a first agent, the sampler, and (ii) find the best configuration within the reservoir, done by a second agent, the optimizer.

2.2 Sampler and Optimizer

The sampler exploits the smoothness property of the reward to build a mixture of hyperspheres centered on the best configurations found so far. When triggered, the agent samples a configuration on the surface of these hyperspheres and updates its state, as shown in Figure 1.
The optimizer is another agent which tries to find $c^* = \arg \max_{c \in S} E[R|c]$, with $S$ the reservoir filled by the sampler when requested. To do so, it tries to approximate the reward distribution (supposed Gaussian) of each configuration $c$ with an iterative Bayesian update of a Normal-Gamma prior with parameters $(\hat{\mu}_i, \hat{\lambda}_i, \hat{\alpha}_i, \hat{\beta}_i)$. At each step, Thompson sampling uses the beliefs of the agent to select the configuration to test.

3 Results

Our strategy was tested using the realistic network simulator ns-3 [1] and compared with other state-of-the-art solutions such as [2, 3] in full buffer bidirectional (uplink and downlink) traffic on realistic network topologies based on the highly-dense WLAN deployed by Cisco in its offices in San Francisco [4]. Our results show a significant, rapid and lasting improvement of all the performance metrics considered, by factors ranging from 38% to 140% when compared with the default configuration of 802.11 as shown in Figure 2. We can also observe significant improvement when compared to state-of-the-art solutions.

 Références