Predicted Contention Resolution in 802.11ax Based on Reinforcement Learning

Mohammed AZZA [a], Amina TAOULI [b]
[a] Ecole Superieure en Informatique, Sidi Bel Abbes, Algeria
m.azza@esi-sba.dz.

[b] Ecole Superieure en Informatique, Sidi Bel Abbes, Algeria
a.taouli@esi-sba.dz.

Abstract: in this paper, we exploits the spatial reuse SR mechanism of IEEE 802.11ax by integrating the color scheme to predict, adapts the OBSS/PD threshold, and adjusts the transmission power level. With the rapid development of modern technology, networks of communication have turned into a complex and colossal system. The new network technology, such as WIFI 6, is committed to providing more great performance and improvements where the density and complexity of the network will more increase and new requirements and problems will appear. In this solution, we propose a prediction reinforcement-learning model in network traffic based on the dynamic exponential smoothing model and optimises the smoothing coefficient of the model through the hyperbolic cosine. Moreover, our solutions based on the network traffic prediction improve the many parameters such as throughput and de delay. The simulation results show that the advantage of prediction model with optimised hyperbolic cosine has a high accuracy and stability in dense scenario.

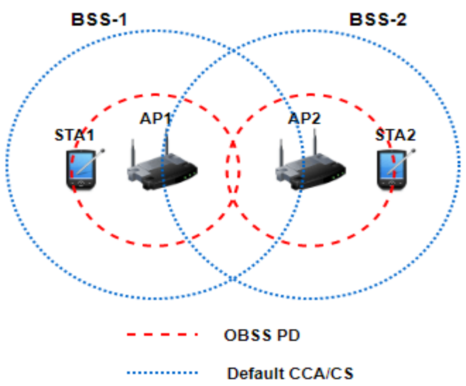
Keywords: IEEE 802.11ax, Reinforcement learning, WLAN, Throughput, Hyperbolic cosine.

1. Introduction

With the rapid development of communication network Wireless local area networks (WLANs) have been growing and becoming essential in modern technology such as the Internet of Things (IoT). Due to the increase of mobile devices the Institute of Electrical and Electronics Engineers (IEEE) is committed to providing more great performance and improvements with many amendments. Moreover, the recent applications such as health monitoring and real-time multimedia application require high throughput and low latency. Many challenges are treated in 802.11 standards such as transmission and collision in dense networks, energy efficiency and enhancing higher throughput. Many times the performance is influenced due interference and the use of the same channel with other mobile nodes.

The IEEE 802.11ax standard called Wi-Fi 6 modified the functionality of PHY and MAC layers. It also includes modifications for backward compatibility with older standards based on IEEE 802.11n in the 2.4 GHz band and IEEE 802.11n/ac in the 5 GHz band [1]. With the definition of High Efficiency WLANs, it is becoming gradually common to find multiple Basic Service Sets (BSS) in the same coverage areas. Wi-Fi 6 increases the data rate and capacity of access points (AP) by transmitting 10 bits at a time with the 1024-QAM modulation OFDM method compared to Wi-Fi 5. IEEE 802.11ax propose a rate-control algorithm it exploits both BSS color and spatial reuse (SR) techniques to adjust the rate relying on packet loss ratio thresholds. Based on the loss ratio thresholds, it tunes the rate, the overlapping basic service sets/packet detect (OBSS/PD) threshold, and the transmission power with an approach similar to the one in [2]. The OBSS/PD SR operation is illustrated in Figure.1 for two overlapping (APs). It used when the channel quality is fair because is more susceptible to noise. Modulation and coding schemes (MCS) define 11 indices so it combine with it and profits from an modulation called dual-carrier modulation (DCM) to improve interference in long distance[3].

Figure.1 showing the percentage



Actually, with the growth of computer performance, the field of artificial intelligence (AI) has also skilled rapid expansion. The techniques such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) have been tested and applied in various fields, and are usually in the research of communication networks [4].

DAMYSYS and THOMPSON SIMPLING

Damysus [2] is an algorithm that select a throughput aware that SNR conditions for example. It also exploits the SR mechanism of IEEE 802.11ax by integrating the color scheme, which adapts the OBSS/PD threshold and jointly adjusts the transmission power level.
A more sophisticated algorithm than the previous one are called Thomson sampling [5], it used to select the best network configuration which assumes that for a given MCS (transmission rate r_j), the j is the number of successful transmissions follows the binomial distribution with unknown probability of success q. To estimate the value of q_j given the transmission success statistics, we take the beta (B) distribution with parameters ($1+\alpha_j$, $1+\beta_j$), where α_j and β_j are the numbers of successful transmissions and unsuccessful for MCS_j. At the beginning, $\alpha_j=\beta_j=0$ $\forall j$ for all MCS uniformly distributed probability. Then, α_j is incremented at each successful transmission, and βj is incremented at each failure. Whenever, for qj is estimate from the following beta distribution:

$$p(q_j) = \frac{q_j^{\alpha} \cdot (1-q_j)^{\beta}}{B(\alpha_j,\beta_j)} \qquad 1$$

The Rate control based on Thompson sampling selects an $\mathrm{MCS}_j = \arg\max_j (q_j \times r_j)$.

In this section, we elaborate on the latest standard by 802.11ax outlining and his feature individually. Next, we study some works in literature in Section 2. Finally, we explain our solution and system model and some results after the simulation.

2. RELATED WORKS

The authors proposed a new link adaptation technique based on a multidimensional Kalman filter to predict via the channel conditions an optimal value of the MCS index and the repetition rate. They have improved network performance degradations due to the higher level of interference introduced into the channel [6].
A new analytical framework for the 802.11ax MAC protocol is provided by authors called a Markov-chain-based models are developed to represent the behavior of the 802.11ax nodes, and both non-saturated traffic conditions and co-existence with the legacy nodes are considered in [7, 8]. Some work analysed the impact of sensitivity tuning and transmission power control in wireless networks.
The most prominent of the former are SINR-based methods [9] to characterize radio links via stochastic geometry (SG) to model the random nature of dense wireless networks.
They improved dynamically the transmission power of APs as well as their Clear Channel Assessment threshold, it has used a multi-armed bandit problem, which allows an efficient and robust data based solution using Thompson sampling, an original sampling of WLAN configurations, and a rewards function.[5].
An tutorial has proposed by Khorov et al in[10], it explain in detail many challenges which should be resolved in order to implement the standards 802.11ax. First, the authors described how to select the optimal operation in dense environment, transmit power and the energy saving. Furthermore, it finds the balance between energy consumption and throughput with an effective contention window size to balance the transmission

The authors aimed to maximize the performance of next-generation WLANs by increasing the number of parallel transmissions with federated learning. They modelled the SR operation using Continuous Time Markov Networks (CTMNs) by a new type of inter-BSS interactions that can result from applying SR in an OBSS. In particular, they simulated BSSs with a single STA and BSSs with multiple STAs, including node mobility, complex uplink/downlink traffic patterns, or heterogeneous deployments. [11].
Deep learning approaches are extended for increasing the efficiency and throughput of 802.11The majority of studies use CNN and GNNs [12] . the VGG16 is utilized to determine the type of interference The power control concern in K-user interference channels is addressed in paper [13]. The authors [14] created an Interference Graph Convolutional Networks (IGCNet), whose principal advantage is to capture the interference channel's iteration invariance attribute. An unsupervised optimization algorithm was proposed to learn optimal PA strategies has proposed to minimize the impact of interference on dense transmissions.

3. SYSTEM MODEL

First, the main objective of our solution is to maximize the network throughput after to finding the optimal OBSS/PD threshold cited in equation 2. For this purpose, we aim to create a Reinforcement neural network model that predicts the rate of each STA in the given BSS for a chosen OBSS/PD threshold within a certain range, thus one can improve the OBSS/PD threshold using the RNN architecture. We used several features retrieved from the simulator output files namely OBSS/PD configuration, RSSI, throughput, SINR and of each STA. Table 1 provides an overview of the entire dataset.

$$TX\,PWRmax = TX\,PWRref - (OBBSS/PD - OBSS/PDmin); \qquad 2$$

Table.1. Association between father's educational qualifications of prospective teachers in their awareness on

parameters	values
$OBSS/PD_{max}$	−62 dB
$OBSS/PD_{min}$	−82 dB
Num. STAs	1-10
Num. APs	2-6
Minimum distance between APs	10m
Training	1-10 STAs
Test	1-10 STAs

The dataset selected [15] contains the information of 3,000 IEEE 802.11ax deployments (divided into two different scenarios) to which the basic service set (BSS) of interest applies different OBSS/PD thresholds possible in the context of the operation spatial reuse (SR). 21 OBSS/PD values are considered for each deployment, and some of the deployments include data from different STA locations. The files provided are used for Machine Learning (ML) training.
After, we propose an improving Thompson sampling approach by taking account that the quality of the channel may change over time. We propose the hyperbolic cosine to enhance the exponential smoothing function and the calculation of numbers of successes and failures. Specifically, we use exponential smoothing after each operation such as:

$$\begin{aligned} \alpha_j(t) &= \alpha_j(t - \Delta t) \cdot e^{\frac{\Delta t}{\omega}} + 1 \text{ if success} \\ \alpha_j(t) &= \alpha_j(t - \Delta t) \cdot e^{\frac{\Delta t}{\omega}} \qquad \text{if failure} \\ \beta_j(t) &= \beta j(t - \Delta t) \cdot e^{\frac{\Delta t}{\omega}} + 1 \text{ if failure} \\ \beta_j(t) &= \beta_j(t - \Delta t) \cdot e^{\frac{\Delta t}{\omega}} \qquad \text{if success} \end{aligned} \qquad 3$$

4. PERFORMANCE EVALUATIONS

We have evaluated the performance of our approach using a.NS-3.32 simulator with the "ns3-ai" module, its facilitate us to carry out studies that are more difficult or impossible to carry out with real systems, to study the behaviour of the system in a highly controlled way in an environment reproducible much more precisely and much more efficiently.Ns3-ai [16].

In figure.2, we compare the algorithms according to the average throughput between the nodes on the network. In most scenarios, one seeks to maximize the throughput in the network in an efficient and fast way, to give a clearer

idea of the performance of the "Minstrel" and "Thompson Sampling" algorithms, they are also compared with the "Constant Rate" algorithm (constant bit rate) but which requires changes to the standard is therefore not applicable in the real world.
We note that "Minstrel" presents a notable improvement against the basic "constant rate", but the throughput remains too unstable and too variable to consider it effective. However, the "Thompson Sampling" algorithm is much more stable and gives a very high throughput that rivals the performance of the ideal.

Figure.2 Related works comparison

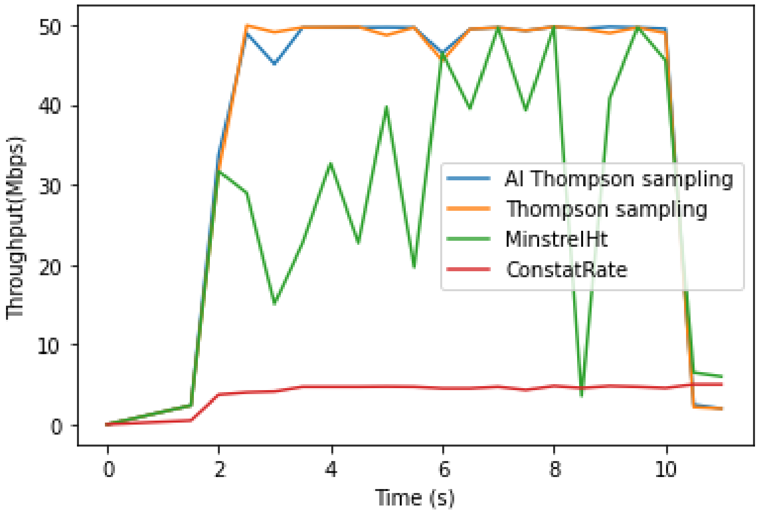
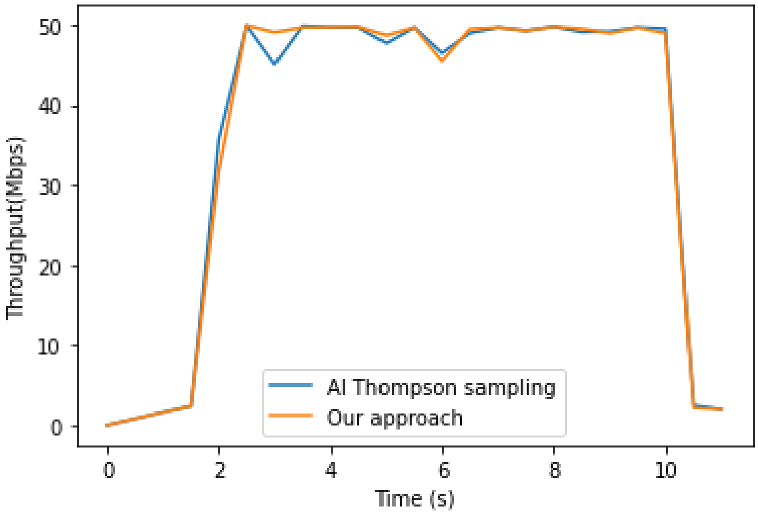
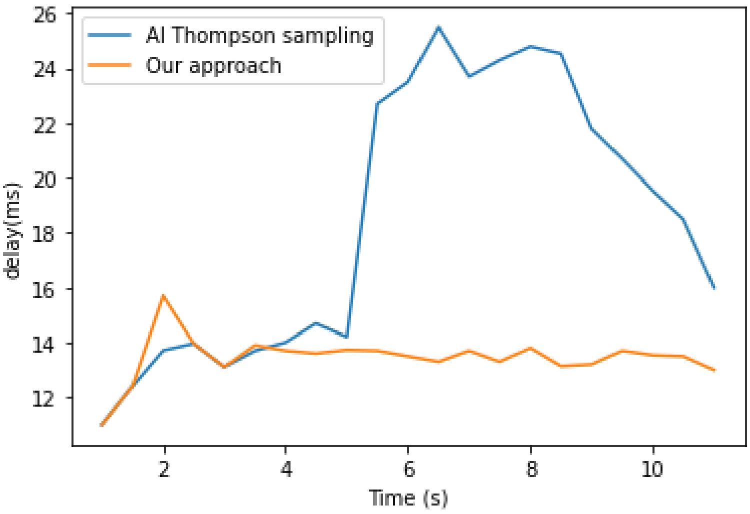


Figure.3 Throughput comparison



By modifying the smoothing function from exponential to hyperbolic cosine and the calculation of the numbers of successes and failures. An interesting result illustrated in figure.3 is obtained. Our approach generates similar throughput values compared to its equivalent, but considerably improves the stability and the predictability of the delay figure.4. This result is an improvement that depends very largely on the quality of the channel and on the smoothing function, which remains a very approximate method which tries to model a rather random parameter and dependent on the outside world and on a considerable number of external factors (the channel quality).
Nevertheless, this demonstrates that the improvement of the “Thompson Sampling” algorithm remains possible and that these algorithms do not guarantee to obtain an optimal solution, but remain acceptable, in most cases.

Figure.4 delay comparison



5. Conclusion

In this paper, we have provided the problem of transmission rate selection in modern Wi-Fi networks. According to new spatial reuse algorithms proposed in the latest IEEE 802.11ax amendment. we study the 3 algorithms and we find that there is always opportunity for improvement the throughput in 802.11ax. The module allows the study and the improvement of these algorithms and existing standards in the world of network communications by using several learning techniques and other heuristic methods, which makes it possible to obtain very practical algorithms that facilitate the parameterization and optimization of traffic on very complex networks in terms of topology and general heterogeneity. In this paper, we enhance the Thompson Sampling algorithm by the cosinus heperbolic and is very efficient and gives very satisfactory results. However, RL is abilities to be a very powerful advantage for network traffic management. However, the development of new standards and algorithms must be approved. In this study we consider all the possible practical cases on which one can come beneficiate.

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