Journal of Theoretical and Applied Information Technology
30th November 2021. Vol.99. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DELAY REDUCTION THROUGH SECONDARY USER COOPERATION IN SPECTRAL HANDOFF

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ABSTRACT

An inadequate selection of spectral opportunities within a cognitive radio network can lead to an increase in the spectral handoff rate and thus increase delay in the communication of the secondary user. The purpose of the present article is to assess the performance of the delay level in a cognitive radio where secondary users cooperate by exchanging information over the spectral occupation frequency band. Using the SAW and Naïve Bayes algorithms for decision-making tasks, the obtained results reveal a significant reduction in the delay of the communication from secondary users when they cooperate between them.

Keywords: *Cooperation, Delay, Spectral decision, Handoff, Cognitive radio.*

1. INTRODUCTION

The general principle of CR consists on granting access to the spectrum in dynamic manner through the opportunistic exploration of the space-time dimensions of the network. In contrast with traditional networks, CR has two types of users. While the licensed or primary user (PU) pays to use a certain frequency band, the unlicensed or secondary user (SU) makes opportunity-based use of the spectrum whenever it is available [1]–[4].

In order to implement a dynamic and opportunistic access, cognitive radio networks (CRN) adopt a management model that can perform smart adaptations based on learning processes and information exchange [5]. This model is known as the cognitive cycle (Figure 1).

According to figure 1, the cognitive cycle can be characterized by six elements:

- Environment: This is the structure of the network and the surrounding environment which includes physical channels, other users, devices, networks and any other object that can affect network conditions such as meteorological conditions, obstacles, economic indicators and trade rules.

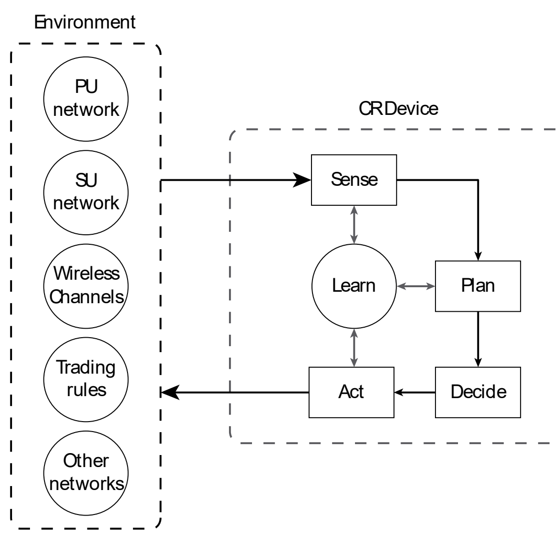

Figure 1: Cognitive cycle [5]

- Sense: It detects and watches over the environment focused on variables such as interference levels, spectral bands, physical propagation parameters within channels and locations of PU and SU.
- Plan: SU plan and assess before making decisions.
- Decide: SU make the decision to access the spectrum based on knowledge, learning and the actions taken by other users.

- Act: SU act over the medium based on the decisions made.
- Learn: This learning tool enables follow-up on the information related with the network and environmental conditions. The system is able to learn, predict, plan and decide in a smart manner.

Spectral decision-making is a key aspect of CRN. However, it has not been as researched as other functions of the cognitive cycle [1], [6]. Decision-making is a process that seeks to choose the best spectral alternative among a finite set of possibilities, allowing SU to generate a sequence of actions intended to meet the defined goals [7], [8]. Improper decision-making can significantly affect parameters such as service quality, latency, throughput, reliability, signalization, PU interference, energy efficiency, bandwidth, SINR and error rate [9]–[12].

The present research assesses the performance in terms of average delay according to the level of information shared between SU within a CRN with a collaborative spectral decision-making model. The goal is to determine the percentage of information to be shared in order to deliver efficient results.

Hence, a segmentation structure is used that includes five collaboration levels (10%, 20%, 50%, 80% and 100%) between SU. The spectral occupation data correspond to a Wi-Fi frequency band, derived from a previous metering campaign and organized in the form of a power matrix. In order to analyze the decision-making process, two multi-criteria techniques are implemented: Naïve Bayes and Simple Additive Weighting (SAW), due to the results previously shown [9], [11], [13], [14].

2. RELATED WORK

The method for decision making based on multiple criteria (MCDM) has been the most widely used in research work on SH, [15] [16] [17] [18] [19]. MCDM fundamental issues are diverse but share common characteristics, such as, alternatives to select the multiple Decision Criteria (DC) describing the options, and a set of weights representing the relative importance of each DC [20]. Therefore, MCDM is a suitable mathematical tool for modeling the process of handoff different MCDM methods have been proposed in the literature for the handoff, such as, Simple Additive Weighting (SAW) [21], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [21], Multiplicative Exponent Weighting (MEW) [22], Grey Relational Analysis (GRA) [23], Elimination and Choice Translating Priority (ELECTRE) [24], Weighted Markov Chain (WMC) [25] and, Multi-criteria Optimization and Compromise Solution (VIKOR) [26]. For instance, the authors in [20] present an extensive comparative study of the MCDM methods previously mentioned. The performance of each method is evaluated under three different applications, voice, data and cost constraints. The authors also perform an analysis of the sensitivity of each method and its computational cost in terms of the number of floating-point operations. The results show that the VIKOR y MEW algorithms have the best performance for the three applications tested.

The research carried out that orients their efforts towards reducing the delay in cognitive radio networks, the vast majority present proposals with a single simulation scenario, with random spectral occupancy data and with centralized decision making. All of the above does not allow obtaining an adequate analysis close to reality in distributed cognitive radio networks, where cooperation and the exchange of information between SU resulting relevant to make assertive decisions. For this reason, the present research work presents a proposal based on decision-making through collaborative work between SUs, with real spectral occupancy data, captured in previous measurement campaigns, and in eight different simulation scenarios.

3. METHODOLOGY

The structure of the collaborative model consists on sectioning the training matrix based on a given number of users. The following section presents a detailed description of the implemented strategy.

A general description of the collaborative model is presented in Figure 2. The logic of the algorithm consists on segmenting the training matrix (input data) based on two parameters: User Relation and Number of Users. The output parameters of the model are the segmented power matrix for training, the total number of users in which the matrix was sectioned (User Full) and the users that will participate in training (User Simulation).

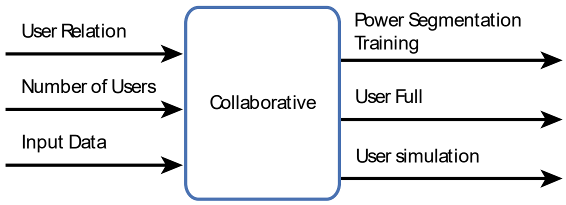

Figure 2: General overview of the collaborative model.

3.1 Naïve Bayes

Naive Bayes is a model that depends on the interaction of different nodes in order to generate learning in each node involved in the process, through the Bayesian approach, it is a probabilistic learning technique, it provides exact inferences and estimates complete probability models, where a priori knowledge or results are used to build an updated model.

One of the main considerations for the selection of prediction models is that there are multiple characteristics or criteria that can improve prediction. A structure based on Naïve Bayes assumes that the presence of a particular feature is in no way related to the presence of any other feature, even if one of these features depends on the other.

The proposed model takes as an input variable a spectral occupation training matrix. Before being used in the predictor training process, the spectral information passes through the spectral information processing block, which converts the data into dichotomous series where a "0" represents channel occupancy and a "1" represents availability of channel. With this information processing the Naive Bayes algorithm is trained.

The model is divided into four stages, Figure 3 presents the block diagram of the proposed model.

The first stage corresponds to the modules "Project Information", "Collaborative Module", "Multi-User Module" and "Parameters Module"; the second consists of two functions: (1) "Naive Bayes Algorithm", (2) "Channel allocation prediction". To calculate the cost and gradient parameters that adjust the predictor, the first function uses the vector ASINR, ETA and AP as variables. The second function performs an assignment of the channel occupation by assigning "1" and "0", which generates a BW availability prediction matrix as an output variable. The fourth stage compares the matrices to determine the predictive indicators. Finally, in the fourth stage, the evaluation results are processed and the relevant indicators are displayed graphically.

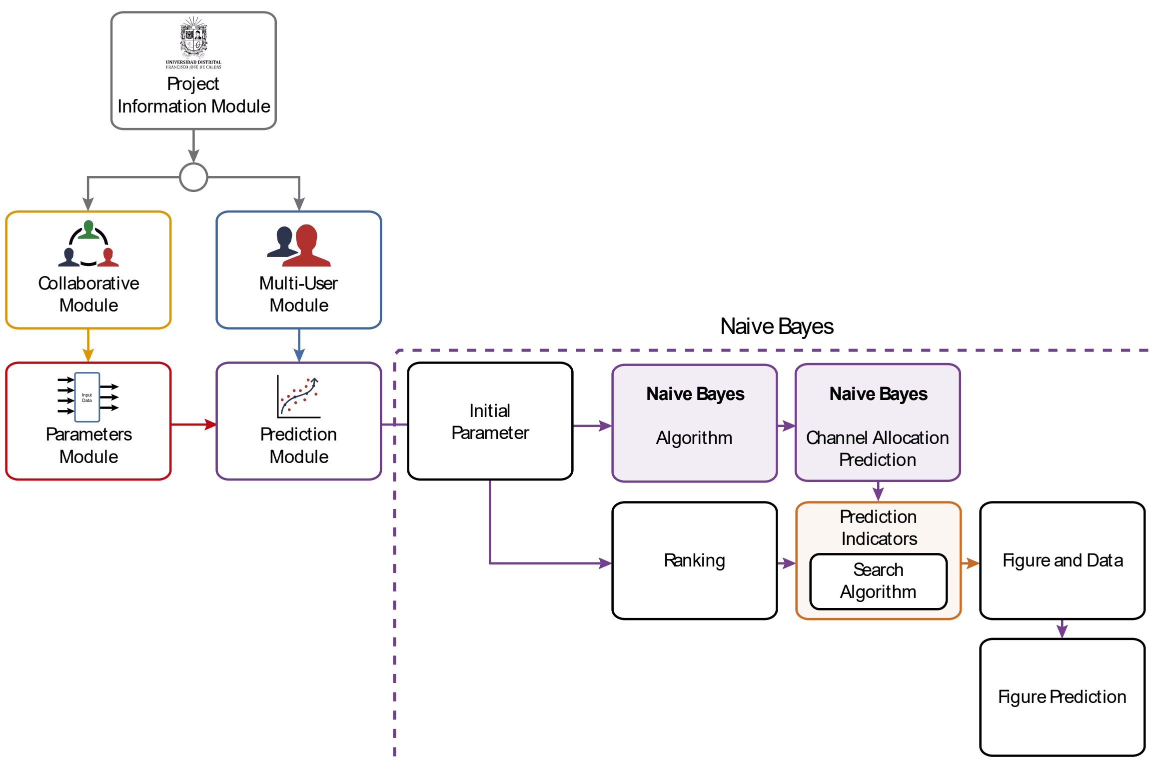

Figure 3: Naive Bayes model

3.2 SAW

To analyze the decision-making process based on the chosen collaborative strategy, the multi-criteria technique (MCDM) known as Simple Additive Weighting (SAW) is implemented [9], [13]. Additonally, the analysis is carried out based on the service type: real time (RT) and better effort (BE).
This algorithm develops a decision matrix comprised of criteria and alternatives; for each intersection of the matrix, the algorithm assigns a weight based on the criteria set by the designer. This delivers a score for each assessed SO, and obtain a ranking that includes all the alternatives. The SO with the highest score is ultimately chosen [13], [27], [28] by using Equation (1) where ri,j belongs to the matrix and the sum of weights is equal to 1.

$$u_i = \sum_{j=1}^{M} \omega_i r_{i,j} \quad \forall i \in 1,\ldots,N \qquad (1)$$

The steps required to develop this algorithm are: (1) to identify the goals and different alternatives; (2) to assess the alternatives; (3) to determine the weights from each combination; (4) add the aggregated values based on preferences; and (5) analyze sensitivity [13].

The assessment of the performance of the proposed collaborative model is carried given the number of unsuccessful handoffs, i.e., when the SU cannot materialize handoff since the respective spectral opportunity is currently occupied [11].

4. RESULTS

The results are presented through a comparative analysis regarding the average accumulative delay (AAD), for five collaboration levels: 10%, 20%, 50%, 80% and 100%, two levels of traffic: high traffic (HT) and low traffic (LT), two types of service: real time (RT) and better effort (BE), and two types of networks GMS and Wi-Fi. This generates 8 different evaluation scenarios:

- ✓ GSM-RT-HT
- ✓ GSM-RT-LT
- ✓ GSM-BE-HT
- ✓ GSM-BE-LT
- ✓ Wi-Fi-RT-HT
- ✓ Wi-Fi -RT-LT
- ✓ Wi-Fi -BE-HT
- ✓ Wi-Fi -BE-LT

Figures 4 and 5 shows the average delay for a transmission of an information package of 9,000 kB using Naïve Bayes algorithm as a multi-criteria technique for the four scenarios of GSM and Wi-Fi, respectively. While, Figures 6 and 7 shows the average delay for a transmission of an information package of 9,000 kB using SAW algorithm as a multi-criteria technique for the four scenarios of GSM and Wi-Fi, respectively.

From the analysis of figures 4, 5, 6 and 7, it is initially observed that, according to what was expected, the average delay level decreases as the level of cooperation between secondary users increases, although for some scenarios said improvement, quantitatively, it is not so significant.

Figure 4 shows a high similarity in the delay levels for the same type of traffic, that is, for high traffic the delay behaves very similar for both a real-time and best-effort application. The same happens with the low type of traffic, the delay behavior is similar between RT and BE. However, when the behavior of the delay level between the two types of traffic is analyzed, differences of up to 29% are observed, the low traffic scenarios being the ones that present the best performance, that is, the lowest average delay level. This can be explained by the greater number of spectral opportunities at low traffic levels.

Figure 5 shows a behavior of the average delay with very high values compared to figure 4. This can be explained by the fact that the Wi-Fi network (Figure 5) has a more stochastic behavior of its traffic pattern in comparison with the GSM network (Figure 4). Additionally, the percentage difference between the delay values for high and low traffic is only 9%.

Figure 6 shows a behavior similar to figure 4, with the difference that in the case of Naive Bayes (figure 4) it has a better performance than for SAW (figure 6), with an improvement in the reduction of the level of delay of the 14%.

Figure 7 shows that except for the RT-HT scenario, the average delay is reduced in all the other scenarios as the collaboration level increases. This increase corresponds to 11,24% for the BE-LT case, 7,86% for the RT-LT case and 5,66% for the BE-HT case.

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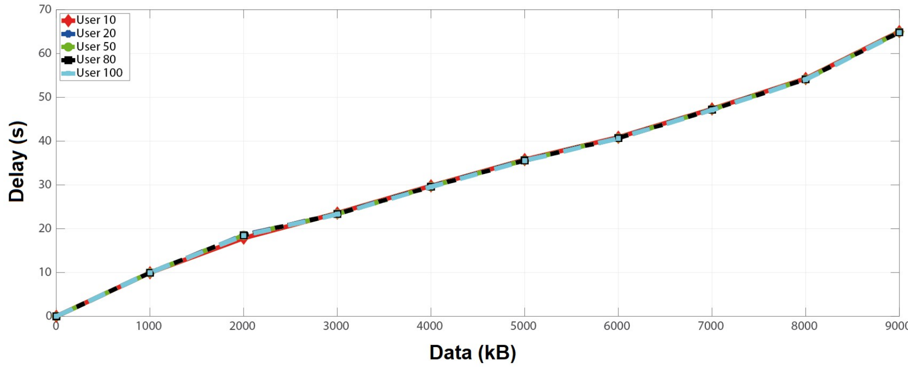
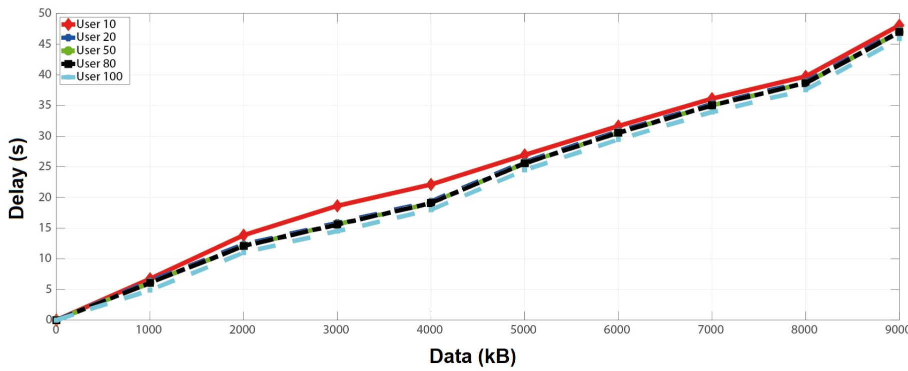
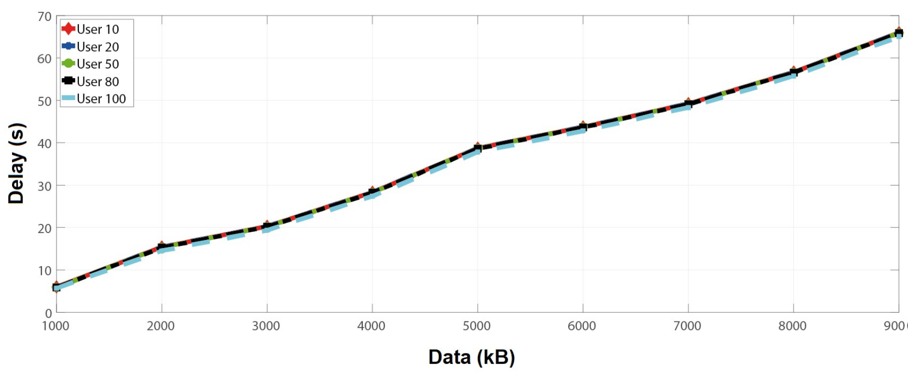


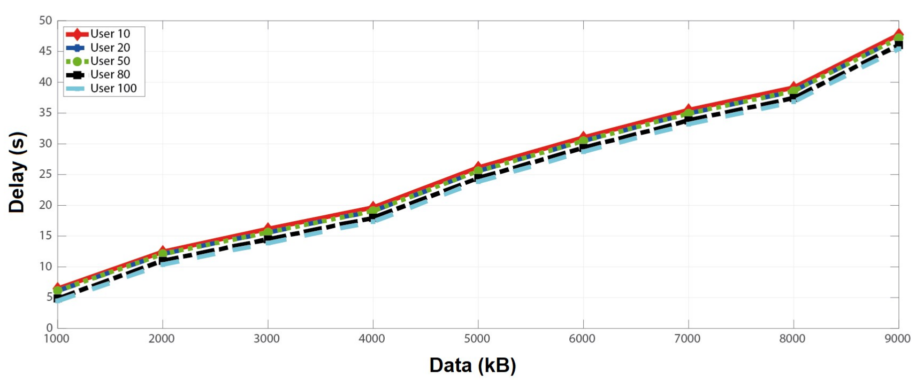
a. GSM RT HT



b. GSM RT LT



c. GSM BE HT



d. GSM BE LT

Figure 4: AAD in GSM for the Naïve Bayes algorithm

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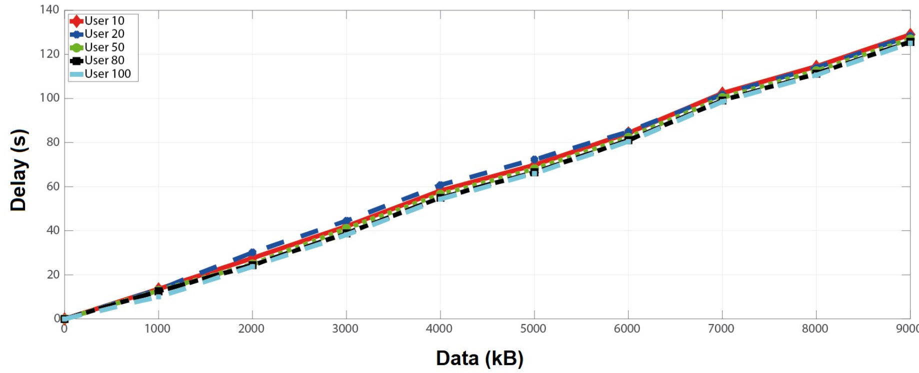
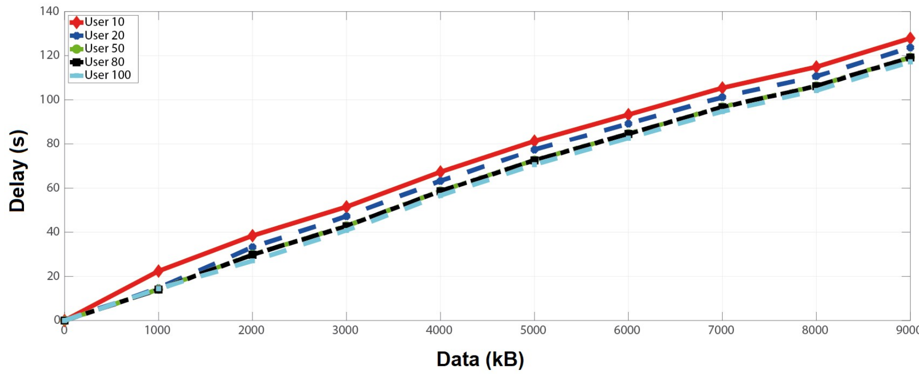
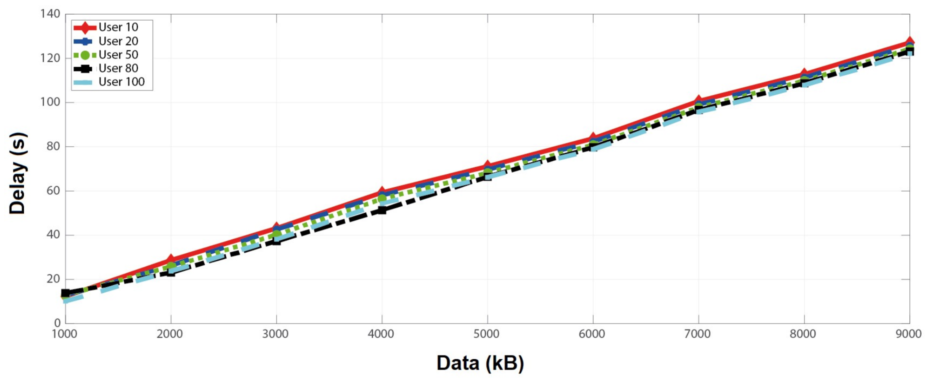


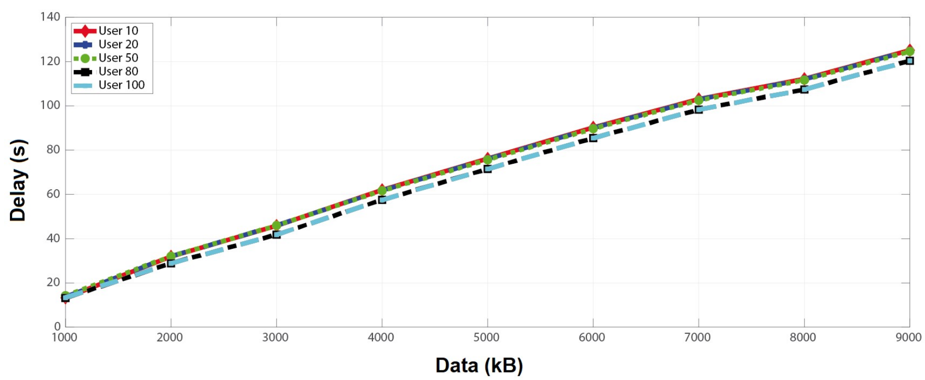
a. Wi-Fi RT HT



b. Wi-Fi RT LT



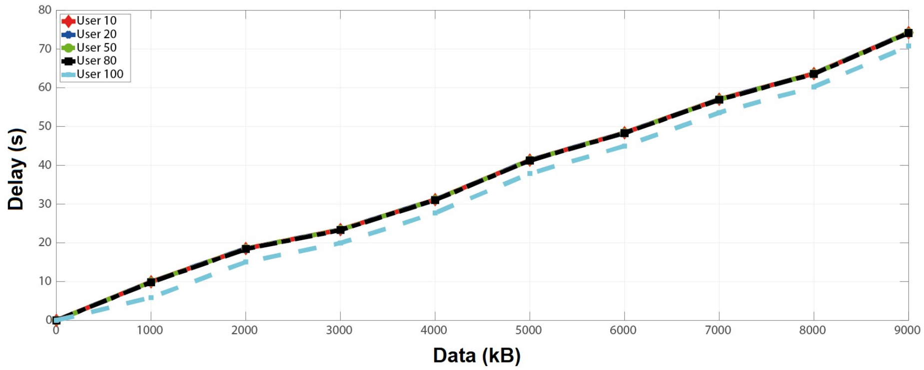
c. Wi-Fi BE HT



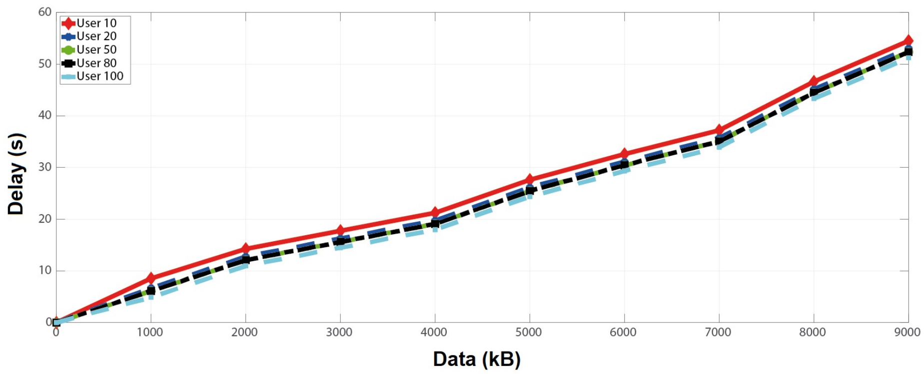
d. Wi-Fi BE LT

Figure 5: AAD in Wi-Fi for the Naïve Bayes algorithm

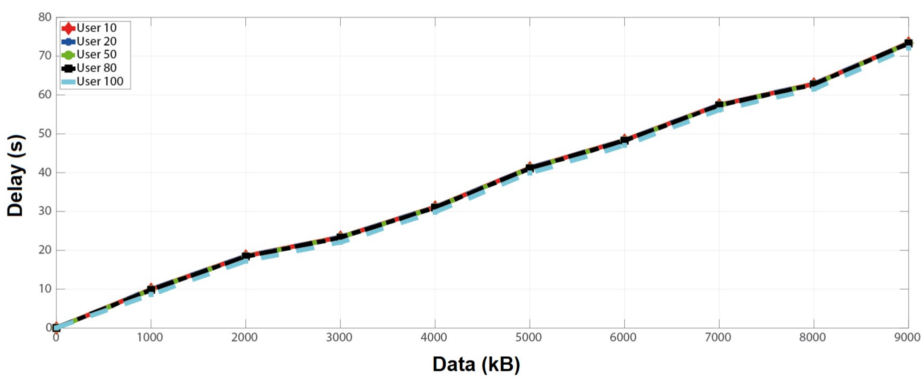
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



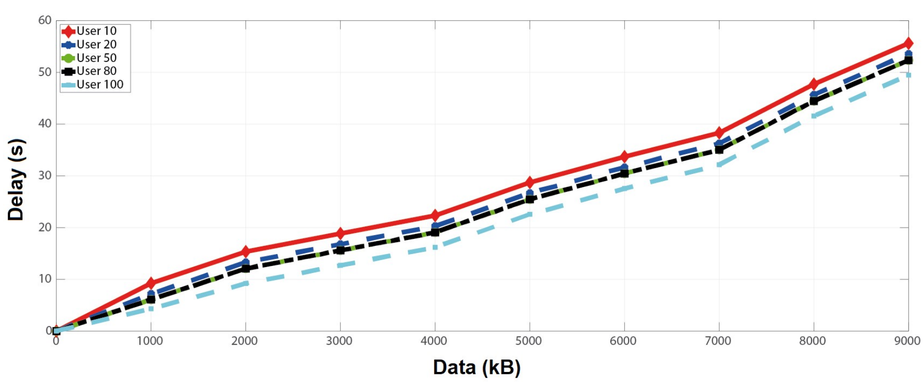
a. GSM RT HT



b. GSM RT LT

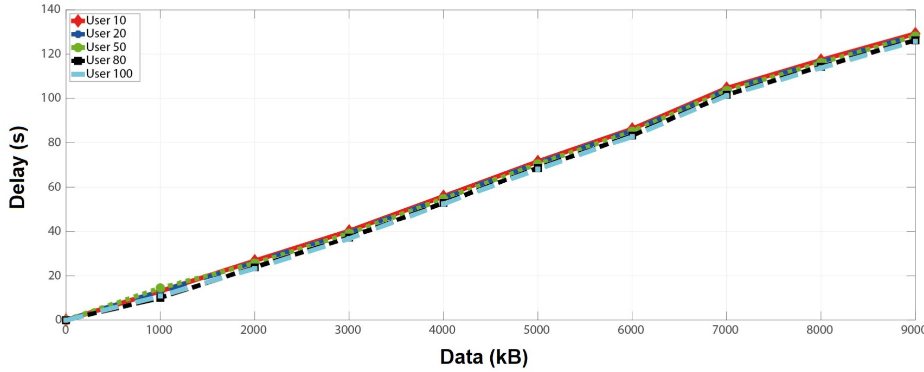


c. GSM BE HT

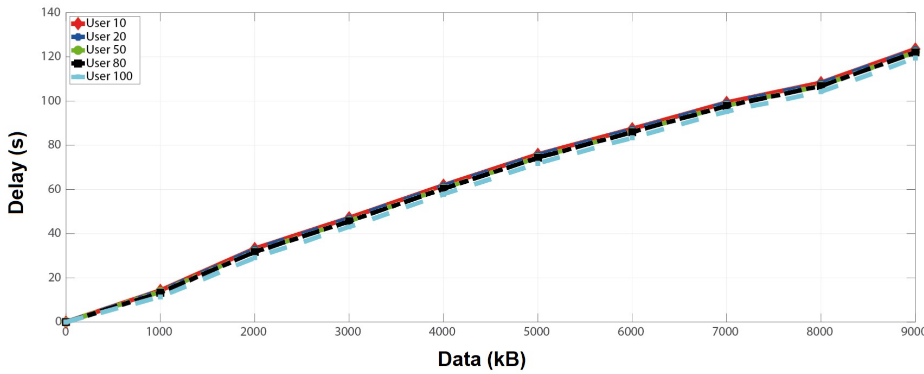


d. GSM BE LT

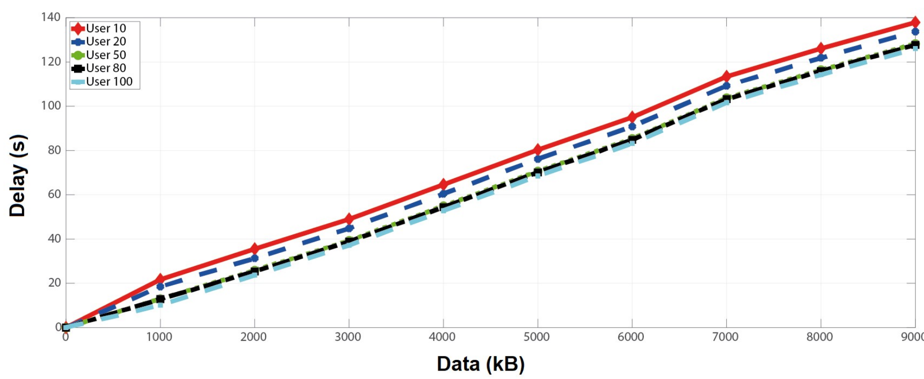
Figure 6: AAD in GSM for the SAW algorithm



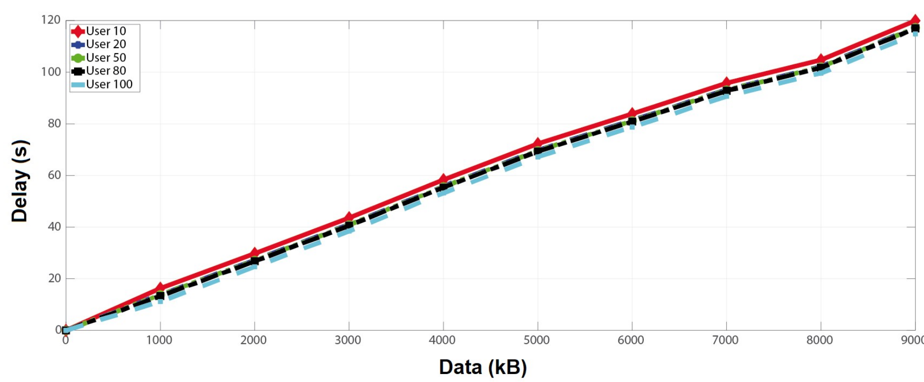
a. Wi-Fi RT HT



b. Wi-Fi RT LT



c. Wi-Fi BE HT



d. Wi-Fi BE LT

Figure 7: AAD in Wi-Fi for the SAW algorithm

It is concluded that performance in terms of average delay is better the higher the level of cooperation and also is superior in low traffic compared to high traffic, which is explained by less spectral opportunities.

Another interesting finding is that the delay value is highly similar between BE and RT, under the same traffic level. In terms of the percentage of collaboration between users, it can be stated that the impact lies between 10% and 12% depending on the corresponding scenario.

Finally, the increase in the level of cooperation does not produce in several scenarios a significant reduction in the average level of delay.

According to the results achieved in the developed work, there are advantages and disadvantages compared to the related works in the current and previously developed literature. In summary, the advantages of the proposal developed in this work are:

- ✓ Eight different simulation scenarios
- ✓ Two different levels of traffic: low and high
- ✓ Two different types of applications: RT and BE
- ✓ Two different types of networks: GSM and Wi-Fi
- ✓ Simulation with real spectral occupancy data
- ✓ Five different levels of cooperation and information exchange between SU
- ✓ The results of two algorithms, one predictive and the other reactive, are compared.

In the same way, the proposal developed in the present work has the following disadvantages:

- ✓ There is no centralized spectral information storage unit
- ✓ Other evaluation metrics such as number of handoffs, bandwidth or throughput are not analyzed
- ✓ Various types of algorithms are not analyzed
- ✓ It is not taken into account in multi-user access to the spectrum.

5. CONCLUSIONS

The collaboration level can lead to significant changes in the performance values for the SAW algorithm. The reduction of delay ranges from 7% to 13%, depending on the collaboration level. However, the exchange rate is relatively low.

In CRN, SU must make smart decisions in terms of spectrum variation and the actions performed by other SU. The challenge lies on making decisions for a DCRN by granting the nodes the capacity to learn from the environment, proposing the strategies that allow SU to exchange information in a cooperative or competitive manner.

ACKNOWLEDGMENTS

The authors would like to thank the Center for Research and Scientific Development of Universidad Distrital Francisco Jose de Caldas and Colciencias, for supporting this research project.

FUNDING

This research was funded by Center for Research and Scientific Development of Universidad Distrital Francisco Jose de Caldas and Ministerio de Ciencia, Tecnología e Innovación - Minciencias.

AUTHOR CONTRIBUTIONS

Conceptualization, C.H. and D.G.; methodology, C.H.; software, D.G and F.M.; validation, F.M. and C.H.; formal analysis, C.H., D.G. and F.M.; data curation, C.H.; writing—original draft preparation, D.G.; writing—review and editing, C.H., F.M. and D.G.; project administration, C.H. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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