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Interference Analysis in a Multiuser Predictive Spectral Model

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Abstract

Interference is one of the most relevant aspects at the time of spectrum sharing in technologies such as cognitive radio. The objective of this article is to analyze and evaluate the level of interference when multiple secondary users access the spectrum simultaneously using the Naive Bayes algorithm as a decision-making tool. To achieve this, the interference behavior is analyzed with a single secondary user and then with ten simultaneous secondary users, both scenarios take into account variables such as the level of traffic and random secondary users. The results show a strong level of direct correlation between interference and the level of traffic, in relation to the number of users accessing the spectrum simultaneously or with the number of random secondary users.

Keywords: Handoff, Spectrum, Interference, Cognitive radio, Multiuser

I. INTRODUCTION

During the last decade, CRN research focused its efforts on the spectrum detection function, which is why there are various developments in this regard in the current literature [1]–[5]. In comparison with the previous function, the spectrum decision (decision making) has been little studied despite its importance in improving the performance of wireless networks [6]–[8], due to the relevance within the CRN , it is required to propose methodologies that guide their objectives to the decision-making process.

The basic component of a cognitive decision is a function of learning environment, reasoning and awareness. The decision techniques should seek to maximize globally or at least locally, the use of the spectrum and the operating parameters [9]. Decision-making models have multiple techniques, some deterministic and others probabilistic, their applications are diverse and cover large areas of science. In telecommunications networks, decision-making theories allow solving allocation problems, however, like many areas of engineering, it is limited by the application system. In the case of CRNs, the models developed focus their efforts on solving problems of centralized architectures [6], [10]–[12], therefore, it is necessary to identify models that improve the decision-making process for other types of architectures with infrastructure such as decentralized architectures.

In CRNs, SUs must make intelligent decisions based on the variation of the spectrum and the actions taken by other SUs, under this dynamic, the probability that two or more SUs choose the same channel is high, especially when the number of SU is greater than the number of available channels, due to the negative externality of the network, the more SU select the same channel, the lower the utility that each SU can obtain and the number of interferences due to simultaneous access will be greater [13] . To model the network under practical parameters in reality, it is necessary to analyze the access of multiple users simultaneously. The decision-making process between users who interact in the same environment (multi-user) is a multi-objective optimization problem, which is generally difficult to analyze and solve with classical optimization models [14], [15]. For centralized and distributed networks (ad-hoc networks), methodologies with good results are found [16]–[18], however, for the DCRN, few research works have been carried out [8], [19], and the available proposals assume that there is no network externality, that is, that the reward of an SU is not affected by the actions of other SU. Therefore, to obtain a more practical network model in reality, it is necessary to take into account how the decisions made by an SU affect the other users of the network.

The present work analyzes and evaluates the level of interference in a cognitive radio network during the selection of spectral opportunities from a predictive process carried out through the Naive Bayes algorithm. The evaluation of the interference level is carried out from the quantification of the number of handoffs with interference carried out during a 9-minute transmission of information for a single secondary user, 2 SU, 4 SU, 6 SU, 8 SU and for 10 SU, accessing simultaneously. In both cases, the performance is analyzed in a controlled environment with only primary users and for a chaotic environment with random PU and SU, additionally, there are two levels of traffic: high (HT) and low (LT), corresponding to previously captured spectral occupancy traces. To evaluate the prediction level, the number of perfect handoffs, made just before the PU's arrival and anticipated, made well in advance of the PU's arrival, are also taken into account.

This article is organized as follows, in section 2 the Naive Bayes technique is described; section 3 presents the results achieved; in section 4 the analysis of results is carried out; and finally, section 5 presents the conclusions.

II. NAÏVE BAYES

In simple terms, a Naïve Bayes classifier assumes that the presence of one characteristic in particular does not relate in any way with the presence of any other characteristic. Even if one these characteristics depend on each other or the existence or other characteristics, all these properties contribute independently. One of the advantages is the utility to operate over large datasets and even surpass highly sophisticated classification methods.

The Bayes theorem allows the calculation of the posterior probability P (c | x), P(c), P(x) and P (x | c) in equation (1).

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \quad (1)$$

Where:

- P (c|x) is the posterior probability of class c (c, target) given the predictor (x, attributes).
- P (c) is the previous probability of the class.
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According to equation (1) and considering our independent variables AP and AAT as it was described in previous paragraphs as well as the dependent variable or class (in the specific case, it is the channel availability that will be denoted as occupied or available), we have equations (2) and (3).

$$posterior(ocp) = P(occ)p(TED \mid occ)p(PD \mid occ)/evidence \quad (2)$$

$$posterior(ava) = P(ava)p(TED \mid ava)p(PD \mid ava)/evidence \quad (3)$$

Where "occ" is occupied and "ava" is available.

III. RESULTS

Figures 1 to 4 describe the handoff number with interference (AAI), the number of anticipated handoffs (AAU) and the number of perfect handoffs (AAP), in conventional mode and in real mode for the Naive Bayes model, during a transmission of 9 minutes, with a trace of HT and LT, in a GSM network, for 2 different multi-user structures (1 SU and 10 SU), the other results are presented in table 1.

Finally, Table 1 presents the comparative percentages of the performance of the Naive Bayes model with multi-user access in conventional mode and the real mode for 1, 2, 4, 6, 8 and 10 users. The above, for each of the AAI, AAU, AAP evaluation metrics.

Table 1. Multiuser Benchmarking for Interference in Naive Bayes

Multi-user Features	AAI-HT	AAI-LT	AAU-HT	AAU-LT	AAP-HT	AAP-LT	Score
MSU1 - Conventional	52.6	75	100	100	100	44.67	78.71
MSU2 – Conventional	68.18	100	47.17	65.66	98.65	52.63	72.05
MSU4 – Conventional	86.89	82.76	26.77	52.01	91.26	79.57	69.88
MSU6 – Conventional	92.19	60	23.24	50.33	85.42	97.34	68.09
MSU8 – Conventional	95.65	50.51	22.34	47.08	82.89	100	66.41
MSU10 – Conventional	100	40.27	22.04	43.65	81.79	96.26	64
Score Conventional	**82.59**	**68.09**	**40.26**	**59.79**	**90**	**78.41**	**69.86**
MSU1 – Real	47.35	62.5	100	100	100	45.93	75.96
MSU2 – Real	79.89	100	40.98	49.67	97.51	58.41	71.08
MSU4 – Real	76.27	58.82	23.73	53.43	89.84	94.02	66.02
MSU6 – Real	80.54	50	23.27	49.06	83.49	100	64.39
MSU8 – Real	87.73	28.99	21.3	45.24	82.51	97.76	60.59
MSU10 – Real	100	31.65	21.26	37.35	81.01	94.98	61.04
Score Real	**78.63**	**55.33**	**38.42**	**55.79**	**89.06**	**81.85**	**66.51**
Global Score HT	**80.61**	**NA**	**NA**	**57.79**	**89.53**	**NA**	**75.98**
Global Score LT	**NA**	**61.71**	**39.34**	**NA**	**NA**	**80.13**	**60.39**

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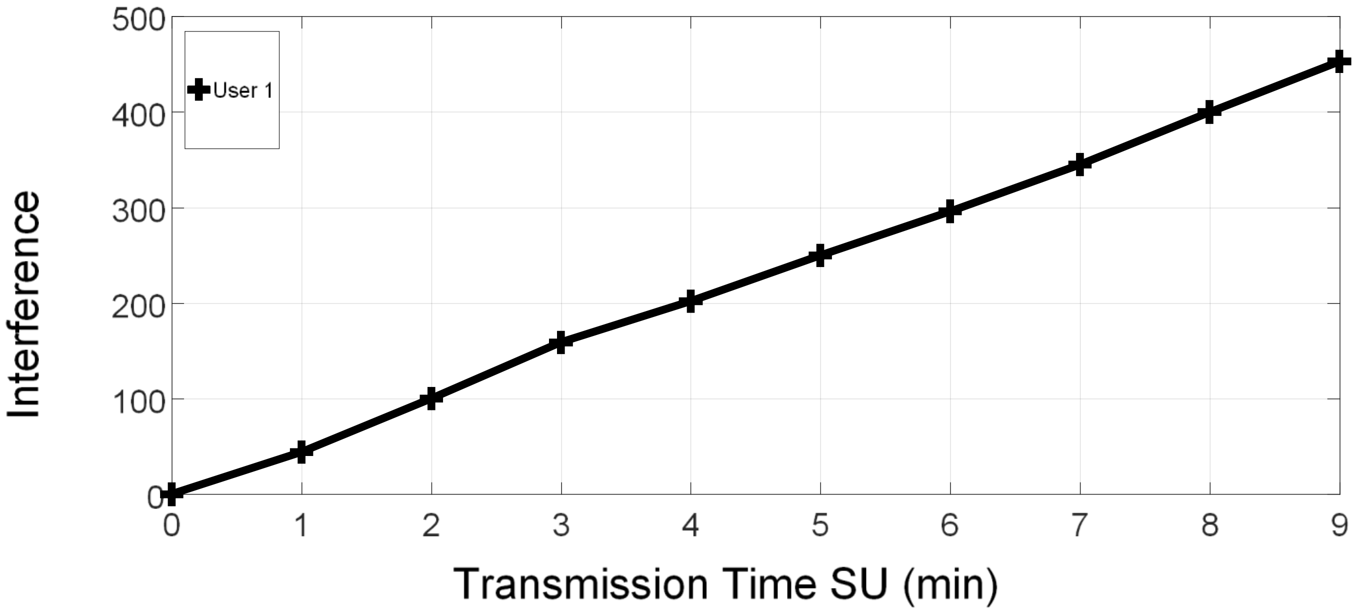
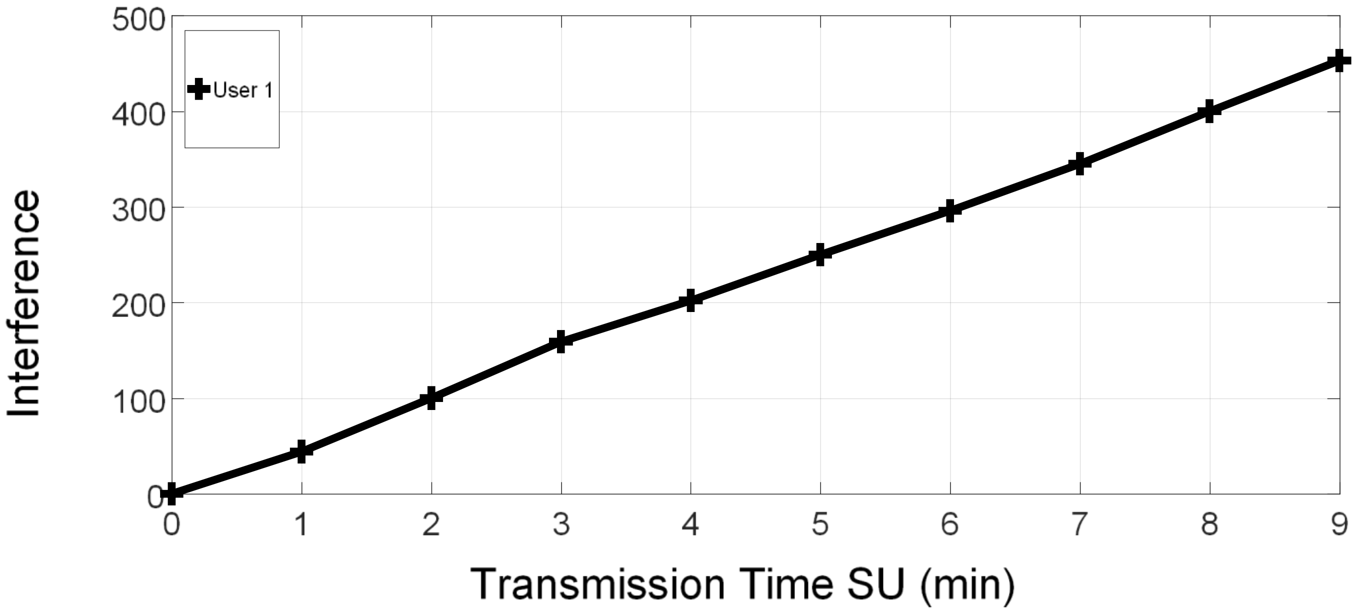


a. Conventional mode in HT



b. Real mode on HT

Fig. 1. Naive Bayes AAI with 1 SU in HT with and without additional random SU

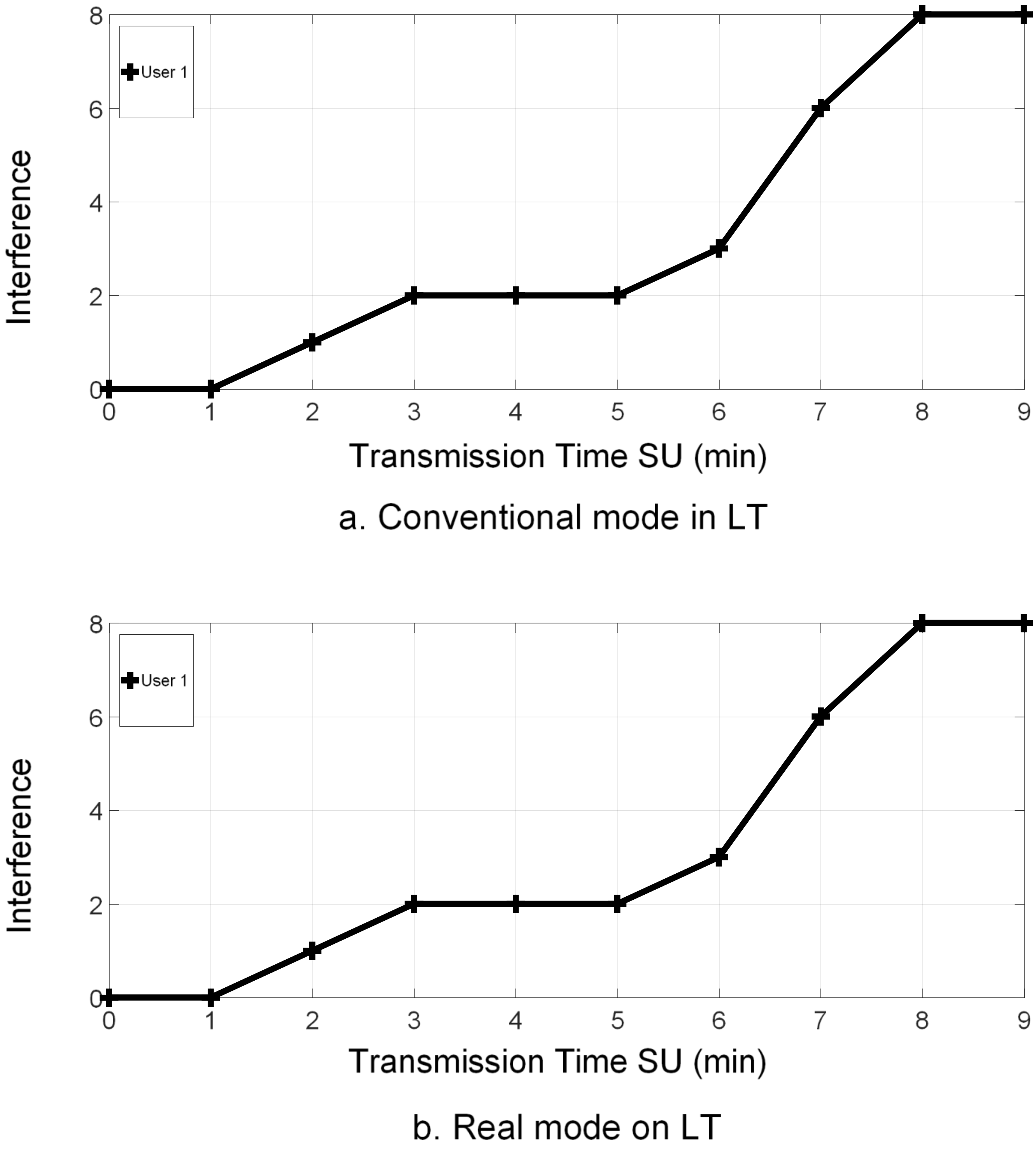


Fig. 2. Naive Bayes AAI with 1 SU in LT with and without additional random SU

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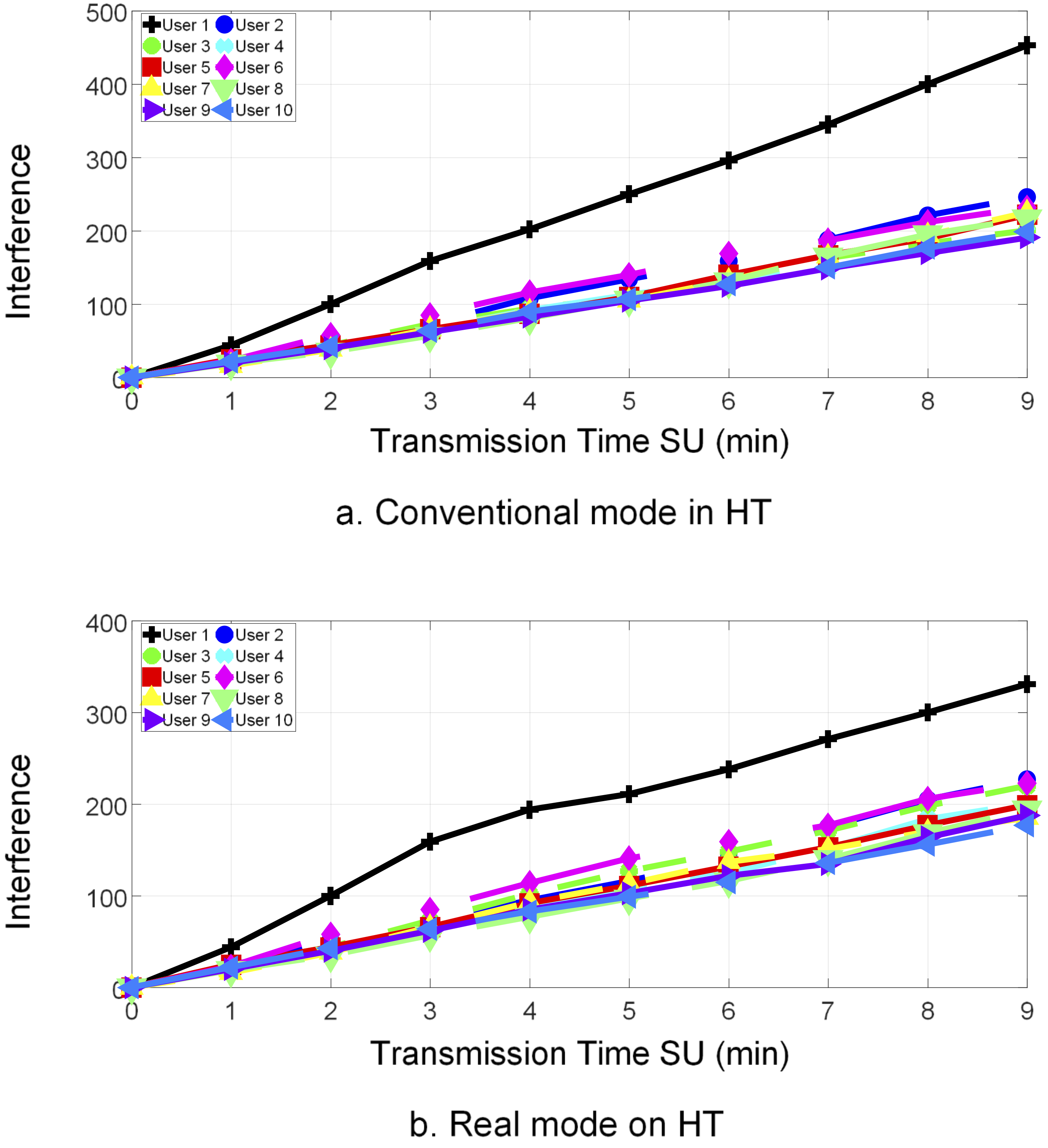

Fig. 3. Naive Bayes AAI with 10 SU in HT with and without additional random SU.

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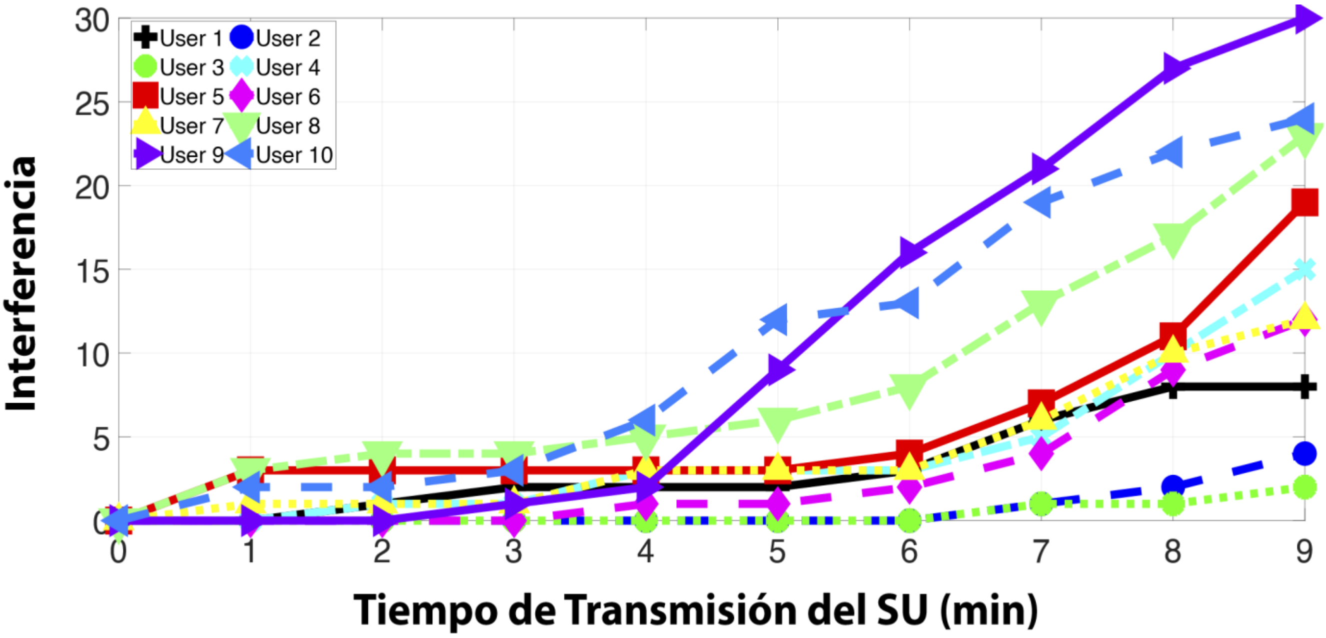
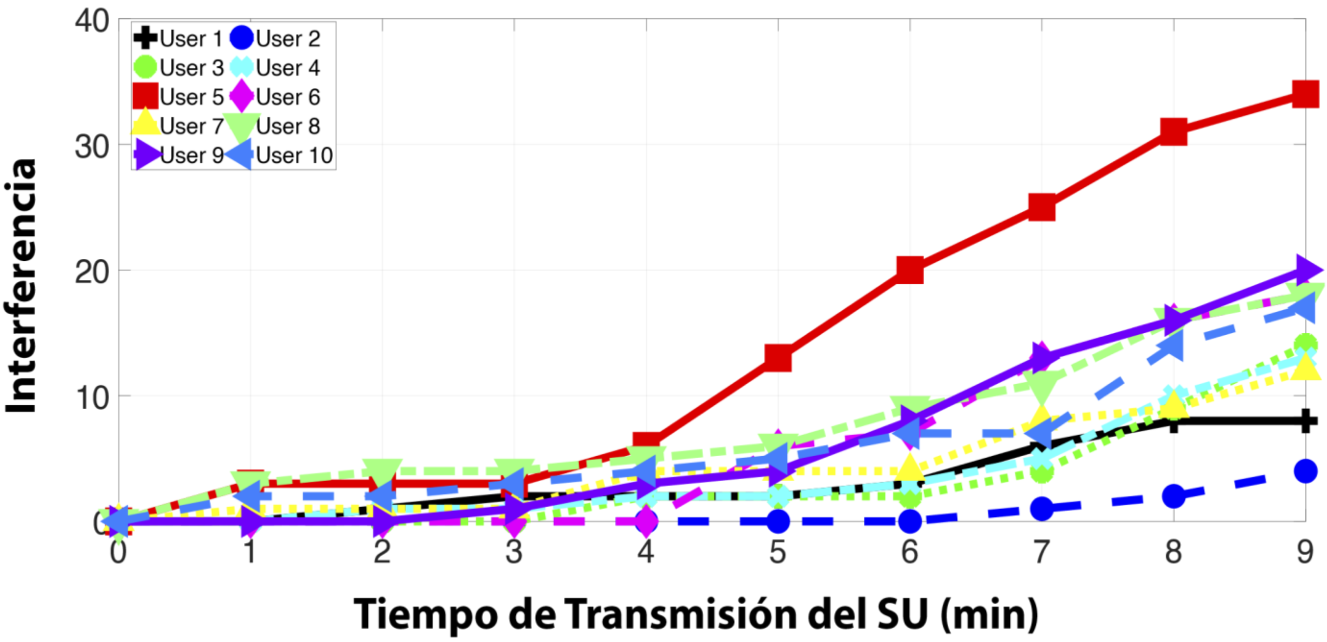


a. Modo Convencional en LT



b. Modo Real en LT

Fig. 4. Naive Bayes AAI with 10 SU in LT with and without additional random SU

IV. DISCUSSION

For the evaluation of the multi-user Naive Bayes model, HT and LT traffic are used, in conventional mode and real mode, for 1 and 10 users. The evaluation metric is: AAI, AAU and AAP. The results of the evaluation identify that as the number of users increases, the performance of each of the models decreases, obviously, the spectral opportunities will be fewer and more difficult to locate.

According to the level of traffic, when observing Figures 1, 2, 3 and 4, it can be seen that there is a lower level of interference for LT compared to HT; in the case of a user, there is 56 times more interference in HT than in LT; and in the case of 10 SU, there is 10 times more interference in HT than in LT. But when random SUs is included, the behavior of spectral opportunities becomes more chaotic, the previous percentages remain at similar values. This shows that it is easier to make adequate predictions in non-chaotic environments, especially with LT, because there is a greater number of spectral opportunities.

In the case of AAU for a non-chaotic environment, LT performance is 50% better compared to HT, and for chaotic environments this value drops slightly to 44%. In the case of AAP, there is no marked difference between the level of HT and LT.

V. CONCLUSIONS.

According to the results achieved, the level of interference is directly and strongly affected by the level of traffic, in a directly proportional way. Regarding the number of secondary users that simultaneously access the spectrum, although the greater the number of secondary users, the higher the level of interference, in the first place, this is not strictly fulfilled, since close values of secondary users can have performances similar, but in the same ordinal sequence; secondly, the variations of the interference levels oscillate around 70 handoffs for high traffic and 30 in the case of low traffic.

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