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Benchmarking spectral handoff rate performance in cognitive wireless networks with real multi-user access

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ABSTRACT

Cognitive radio (CR) has proven to be an excellent alternative to the problem of inefficient spectrum use in wireless networks. However, the vast majority of proposals found in the current literature are restricted to the access of a single secondary user (SU) to the network, and the few proposals with multiple access do not take into account the access of other primary users (PUs) during the opportunistic transmission of the SU. The objective of this work is to perform a comparative evaluation of the spectral handoff (SH) rate in cognitive wireless networks with multi-user access in an environment with other PUs interacting. To carry out this evaluation, four SH models with better performance were selected: deep learning (DL), feedback fuzzy analytic hierarchy process (FFAHP), simple additive weighting (SAW), and Naïve Bayes (NB), which were validated according to the metric of the number of total handoffs, under four scenarios given by the combination of the following parameters: low spectral availability, high spectral availability, active presence of others SUs, and passive presence of others SUs. The results show that each model performs well according to the scenario in which it is executed, suggesting an adaptive multi-model as a proposal.

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1. INTRODUCTION

The idea behind cognitive radio (CR) stems from the understanding that the radio frequency spectrum is a finite resource, which is often significantly underutilized. This underutilization results in diminished overall spectrum efficiency. As noted in various studies, CR technology aims to fulfill the increasing bandwidth (BW) demands of modern devices through its ability to dynamically reconfigure itself. Consequently, the operation of a cognitive network (specifically regarding the allocation and deallocation of radio resources) is inherently complex. This complexity arises because the network nodes must continuously adapt their behavior based on the local information available about their surrounding environment [1]-[4].

Cognitive radio networks (CRNs) have been proposed as a viable solution to address the issue of spectral scarcity by allowing secondary users (SUs) to temporarily utilize unused spectrum segments, known as spectral opportunities (SOs). This access is provided on the condition that primary users (PUs) do not experience any degradation in their quality of service. A significant challenge within this context is managing spectral handoffs (SHs) (or the switching of channels among CRs) efficiently, with the aim of minimizing the frequency of these handoffs during extended communication periods [5]-[8].

Moreover, it is critical to consider scenarios where multiple SUs simultaneously seek to opportunistically access the licensed spectrum held by PUs. In such cases, effective multi-user access strategies must be developed to account for the unpredictable arrival and departure of PUs during the ongoing transmissions of SUs. This dynamic behavior necessitates sophisticated approaches to ensure seamless communication and optimal use of the available spectrum [9]-[13].

Building upon the aforementioned context, this study aims to conduct a comparative analysis of the SH rate in cognitive wireless networks featuring multi-user access within a realistic environment. Specifically, this environment includes PUs dynamically entering and exiting the licensed spectrum during the opportunistic utilization by SUs. For this evaluation, four SH models demonstrating superior performance were chosen: deep learning (DL), feedback fuzzy analytic hierarchy process (FFAHP), simple additive weighting (SAW), and Naïve Bayes (NB). These models were assessed based on the total number of handoffs (AAH) under four distinct scenarios, characterized by the following combinations of parameters: low spectral availability (high traffic or HT), high spectral availability (low traffic or LT), active presence of SUs (real mode), and passive presence of SUs (conventional mode). In the current literature we do not find related works that consider a realistic multi-user environment with dynamic behavior of the PUs.

The structure of this study is organized into five sections. Section 2 provides a detailed description of the research methodology, including the selection of SH models, experimental design, decision-making criteria, and performance metrics. Section 3 presents the results obtained from the analysis and offers a comparative examination of the evaluation metrics. Section 4 focuses on the discussion of these results, interpreting the findings in the context of the objectives set forth. The final section summarizes the main conclusions of the study, highlighting the key contributions and potential areas for future research.

2. METHOD

This section outlines the methodology employed in the research. It begins with a detailed description of the experimental design, which forms the foundation of the study. Following this, the criteria used for decision-making in selecting the optimal frequency channel or spectral opportunity (SO) for executing the SH are explained. Next, the section provides an overview of the specific handoff (HS) models that were chosen for evaluation. Finally, it concludes with a presentation of the performance metrics that were applied to facilitate the comparative analysis of these models.

2.1. Experiment design

The comparative evaluation of the selected SH models was conducted using a simulation tool previously developed for this purpose. This tool utilizes real spectral occupancy data gathered from a measurement campaign carried out in Bogotá, Colombia [14]. The simulation tool reconstructs the spectrum occupancy patterns over time by employing experimental data traces recorded in the GSM band, providing a close approximation of the real behavior of PUs within the simulated environment. This approach enables a more accurate assessment of each algorithm’s actual performance [15], [16]. The data set used in the simulation reflects one month of continuous observation collected in Bogotá D.C., Colombia [14].

When a SU intends to transmit for φ minutes, the simulation tool follows a structured sequence of steps. First, it updates the decision criteria (DC) values based on information available before the current time instant, referred to as $\tau 0$, when the SU requests access to the spectral resource. Second, the tool ranks the SOs according to the scores generated by the decision-making algorithm under evaluation. Third, the SO with the highest rank is selected and assigned to the SU, initiating its transmission. Fourth, at time $\tau 1$, the tool checks the database of captured and processed data to determine whether the selected SO remains available. Since SH models rely solely on the probability of availability (AP) rather than real-time availability data, if the SO is still accessible, the cumulative handoff metric (AAH) is incremented by one, and the next step is executed. If not, the alternative handoff metric (AAFH) is incremented, and the next ranked SO is chosen, returning to the previous step.

The tool then performs a continuous check at each time step (TS) to verify if the SO currently in use by the SU remains available. If, at any time τk, a PU demands the selected SO, rendering it unavailable according to the database, and the elapsed time, calculated as $\Delta\tau = \tau k - \tau 1$, is less than 60 seconds, the system selects the next SO in the ranking and returns to the prior step. If this condition is not met, $\tau 0$ is updated to reflect the new current time, and the entire procedure begins anew. If, after a duration of ζ seconds, no suitable channel is found, the communication is deemed to have failed.

2.2. Decision criteria

All handoff (HS) models utilized in this study relied on four key DC to identify the optimal channel for SH: the AP, the estimated time of availability (ETA), the signal-to-noise ratio (SINR), and the BW. These criteria were derived from spectral data that had been previously collected. To accurately perform the evaluation, it was crucial to compute values for each of the four DC (AP, ETA, SINR, and BW) for every entry in the training matrix, given that the SH algorithms did not have any pre-existing knowledge of these values.

The AP variable offers a normalized representation of the duty cycle for each of the 500 potential SOs present in the matrix. The ETA variable calculates the average duration for which each channel remains continuously available. This is determined by first identifying all periods during which a channel is continuously accessible, followed by calculating the mean of these durations for each channel.

The SINR variable quantifies the average ratio of signal power to the noise floor, which reflects the quality of the channel. The BW variable denotes the average BW for each channel. Since all channels have an identical BW of 100 kHz, the BW variable does not provide significant differentiation in its basic form. To enhance the relevance of the BW criterion, the BW for each potential SO was expanded to incorporate up to four adjacent channels on both sides, assuming they were continuously available, thus creating a broader, composite channel. Although all channels in the GSM band typically have a BW of 200 kHz, due to the specific technical parameters set on the spectrum analyzer during the measurement campaign, the spectral occupancy data was captured in segments with a fixed BW of 100 kHz.

2.3. Handoff models

A review of the current literature on SH in CRN was conducted to identify suitable algorithms for comparison with the newly developed algorithms presented in this study. The selection process took into account the performance outcomes reported for these algorithms, along with their underlying mathematical principles and the clarity of their methodologies, which facilitate reproducibility. Multi-criteria decision-making (MCDM) methods were chosen as they offer a robust mathematical framework for modeling the SH process in situations involving multiple variables, providing a highly effective approach for evaluating and selecting SOs [1], [17]-[20]. Due to their proven efficacy, MCDM methods have been widely applied in SH contexts. The specific algorithms selected for comparison in this study are FFAHP, NB, SAW, and DL [1], [21]-[28].

2.3.1 FFAHP

The FFAHP algorithm is designed to enhance the accuracy of selecting SOs. To achieve this goal, FFAHP utilizes feedback from previously conducted SO evaluations to refine its selection process. The choice of SO is determined by analyzing both current spectral data and historical assessment results.

The spectrum data detection process involves capturing key parameters, such as frequency, signal power, and time intervals. These measurements are influenced by settings on the spectrum analyzer, including the resolution bandwidth (RBW), the frequency span, and the sweep time [14], [16]. All the acquired data are systematically stored in a dedicated database. The processing unit periodically calculates the values for the DC (such as AP, ETA, SINR, and BW) and normalizes these values on a scale from 0 to 100. The FFAHP algorithm then utilizes this normalized data to assess each SO. The score assigned to each SO, indicated by i, is determined using (1), where the score ranges between 0 and 100, with 100 indicating the highest possible score. Figure 1 illustrates the design and workflow of the FFAHP algorithm.

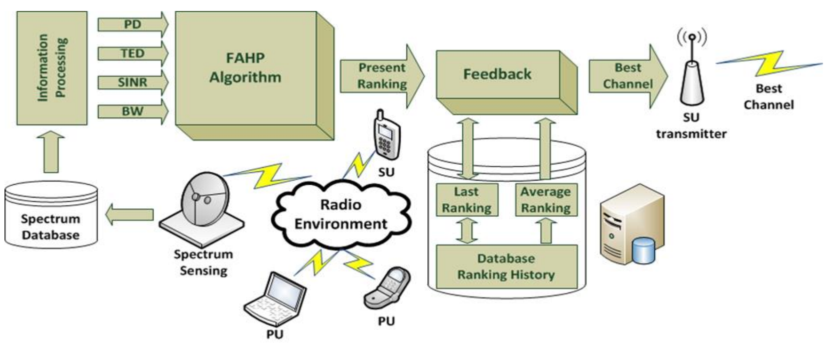


Figure 1. Schematic representation of the proposed FFAHP algorithm

At this stage of the process, each SO is initially ranked based solely on the current values of the DC. However, the SO that ranks highest at this point may not ultimately be chosen, as the final evaluation incorporates weighted adjustments using historical survey data. The feedback mechanism integrates the current survey results (PS) for each SO with both the most recent survey data (LS) and the average survey results (AS) collected over the preceding hour. These weighted inputs are then used to compute a final ranking for each SO. The method for calculating this final ranking is outlined in (1).

$$Final\_Score = \alpha \times PS + \beta \times LS + (1 - \alpha - \beta) \times AS \quad (1)$$

Here, α and β are coefficients within the range [0,1], and the term "Final_Score" represents the final survey value assigned to each SO. The SO with the highest final score is chosen to initiate data transmission for the SU. Subsequently, the feedback mechanism updates the last survey (LS) value by transferring the present survey (PS) value and recalculates the AS value to reflect the new LS value. If the chosen SO is found to be occupied, the FFAHP algorithm resets the LS value to zero for that particular SO [21].

2.3.2. Naïve Bayes

A key factor in selecting an appropriate prediction model is its ability to incorporate multiple characteristics or criteria that enhance the accuracy of predictions. This is important because during the training phase, various criteria such as AP, ETA, SINR, and BW can be used, all of which contribute to improving the prediction performance [22], [25].

Given this context and the principles of NB theorem, it can be concluded that the independent variables, or predictors, in this specific scenario are AP and ETA, while the dependent variable, or the class to be predicted, is channel availability. The NB model is particularly effective for predicting multiple classes because it operates under the assumption that each predictor is independent of the others. In other words, a NB classifier assumes that the presence or absence of a particular feature is not influenced by any other feature. Even when some features may have dependencies, the model treats all these characteristics as if they contribute independently to the outcome. One of the main benefits of this approach is its capacity to efficiently handle very large datasets.

Bayes' theorem offers a framework to calculate the posterior probability $P(c|x)$ using the prior probabilities $P(c)$, $P(x)$, and the likelihood $P(x|c)$, as shown in (2).

$$\mathrm{P(c|x)} = \frac{\mathrm{P(X|C)P(c)}}{\mathrm{P(x)}} \quad (2)$$

Where:
- $P(c|x)$ represents the posterior probability of the class c (the target variable) given the predictor x (the input features).
- $P(c)$ denotes the prior probability of the class.
- $P(x|c)$ is the likelihood, or the probability of the predictor given that the class is known.
- $P(x)$ indicates the prior probability of the predictor.

Using (2) and considering the independent variables (AP and ETA) as outlined in earlier paragraphs, along with the dependent variable or class, which in this context is the channel's status (either "occupied" or "available"), we can derive the expressions presented in (3) and (4).

$$\mathrm{Posterior(occupied)} = \frac{\mathrm{P(occupied)p(TED|ocuppied)p(PD|occupied)}}{\mathrm{evidence}} \quad (3)$$

$$\mathrm{Posterior(available)} = \frac{\mathrm{P(available)p(TED|available)p(PD|available)}}{\mathrm{evidence}} \quad (4)$$

Where "evidence" would be given by (5).

$$\mathrm{evidence} = \mathrm{P(occupied)p(TED \mid ocuppied)p(PD \mid occupied)} + \mathrm{P(available)p(TED|available)p(PD|available)} \quad (5)$$

2.3.3 Simple additive weighting

The algorithm creates a decision matrix that incorporates multiple attributes and possible alternatives. For each intersection within this matrix, a weight is allocated according to the designer's predefined criteria. This process of assigning weights enables the calculation of a score for each SO under evaluation, resulting in a prioritized ranking of all potential alternatives. The SO that achieves the highest score in this ranking is selected as the optimal choice. The mathematical representation of an alternative, denoted as $\boldsymbol{A}_i$, is presented in (6).

$$u_i = \sum_{j=1}^{M} \omega_i \, r_{i,j} \quad \forall i \in 1, \ldots, N \qquad (6)$$

Here, $r_{i,j}$ represents an element within the matrix, and the total of all assigned weights equals 1. The steps involved in developing this algorithm are as follows: (1) identify the objectives and potential alternatives; (2) perform an evaluation of these alternatives; (3) assign weights to each combination based on their importance; (4) calculate the aggregated values according to the established preferences; and (5) conduct a sensitivity analysis to assess the robustness of the results. In several studies, the SAW method has been applied to identify the optimal SO within a GSM frequency band, to assess the number of handoffs executed, and to compare the performance with that of other spectrum allocation algorithms [1].

2.3.4 Deep learning

A comprehensive description of the DL algorithm employed in this study can be found in reference [24].

2.4. Evaluation

The performance of the selected handoff (HS) models was evaluated using four specific metrics: the total number of channel changes (AAH), the number of interfering channel changes (AAI), the number of anticipated channel changes (AAU), and the number of perfect channel changes (AAP). These metrics were assessed under two traffic levels (high (HT) and low (LT)) as well as for two types of SU behavior: passive (conventional mode) and active (real mode).

To conduct a comprehensive multi-user evaluation, the selected SH models were applied across four different scenarios: (1) conventional mode with HT, (2) real mode with HT, (3) conventional mode with low traffic (LT), and (4) real mode with low traffic (LT). For each scenario, the performance of the SH model was analyzed with varying numbers of simultaneous users, specifically for 1, 2, 4, 6, 8, and 10 users. Given the volume of data, complete results are summarized in tables provided in the results section, while the figures primarily illustrate the behavior for the case of 10 users.

Table 1 outlines the evaluation metrics used to assess the performance of the SH models, including AAH, AAI, AAU, and AAP. The table details the acronyms, definitions, descriptions, and types of evaluation metrics, indicating whether a metric represents a benefit (where a higher value is better) or a cost (where a lower value is preferred). The term "average" in the context of evaluation metrics reflects that these results are based on the mean values obtained from multiple experiments. While the AAH metric applies to all HS models, the other metrics are specific to the NB prediction model.

Table 1. Evaluation metrics for HS models

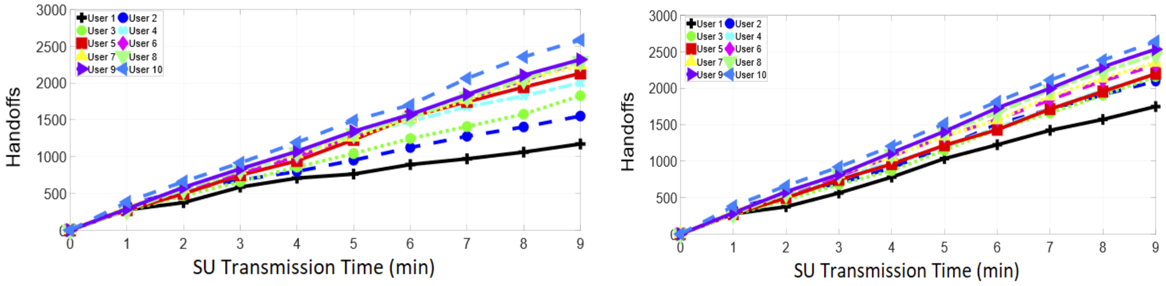
Acronym	Name	Description	Evaluation metric type
AAH	Cumulative average handoff number	This is the total number of handoffs performed during the 9 minutes of SU transmission	Cost
AAI	Cumulative average interference handoff number	It is the total number of reactive handoffs performed once the PU arrives, during the transmission time of the SU	Cost
AAP	Cumulative average perfect handoff number	It is the number of non-interference handoffs performed very close to the arrival of the PU, but without causing interference to the latter, during the transmission time of the SU	Cost
AAU	Cumulative average anticipated handoff number	It is the number of non-interference handoffs performed well in advance of the arrival of the PU, during the transmission time of the SU	Cost

To facilitate the comparative analysis of each algorithm, the relative values (in percentage) of each evaluation metric were calculated. For the cost metrics, the relative value (Rel) of algorithm i was calculated based on the absolute value (Abs) and the minimum value (Min) of the evaluation metric, as described in (7).

$$X_i^{Rel} = \frac{X_i^{Min}}{X_i^{Abs}} \times 100\% \qquad (7)$$

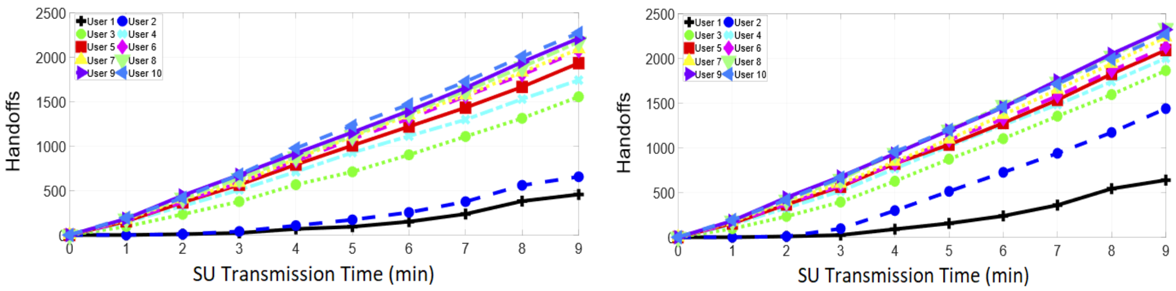
3. RESULTS

Figures 2 to 9 describe the results for each of the HS models. Figure 2 shows deep learning with 10 SUs in HT with and without additional random SUs, Figure 2(a) conventional mode in HT and Figure 2(b) real mode in HT. Figure 3 shows deep learning with 10 SUs in LT with and without additional random SUs, Figure 3(a) conventional mode in LT and Figure 3(b) real mode in LT. Figure 4 shows FFAHP with 10 SUs in HT with and without additional random SUs, Figure 4(a) conventional mode in HT and Figure 4(b) real mode in HT; Figure 5 shows FFAHP with 10 SUs in LT with and without additional random SUs, Figure 5(a) conventional mode in LT and Figure 5(b) real mode in LT. Figure 6 shows Naïve Bayes AAH with 10 SUs in HT with and without additional random SUs, Figure 6(a) conventional mode in HT and Figure 6(b) real mode in HT; Figure 7 shows Naïve Bayes AAH with 10 SUs in LT with and without additional random SUs, Figure 7(a) conventional mode in LT and Figure 7(b) real mode in LT; Figure 8 shows SAW AAH with 10 SUs in HT with and without additional random SUs, Figure 8(a) conventional mode in HT and Figure 8(b) real mode in HT; Figure 9 shows SAW AAH with 10 SUs in LT with and without additional random SUs, Figure 9(a) conventional mode in LT and Figure 9(b) real mode in LT. Each figure shows the SH models' results during a 9-minute transmission, with a trace of HT and LT in conventional and real modes on a GSM network.



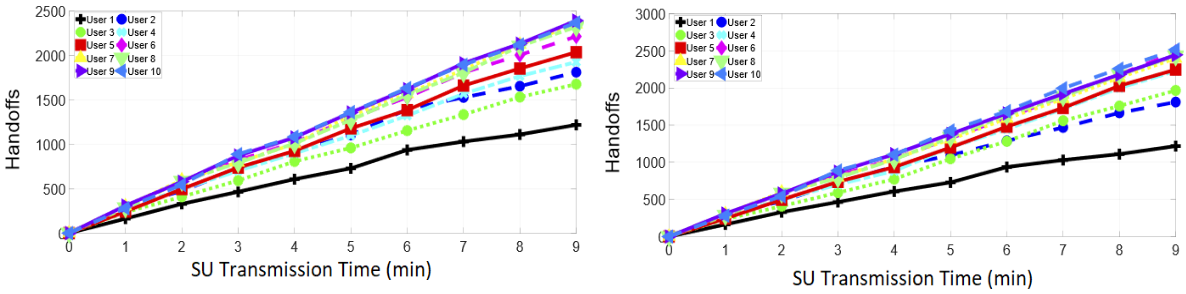
(a) (b)

Figure 2. Deep learning with 10 SUs in HT with and without additional random SUs
(a) conventional mode in HT and (b) real mode in HT



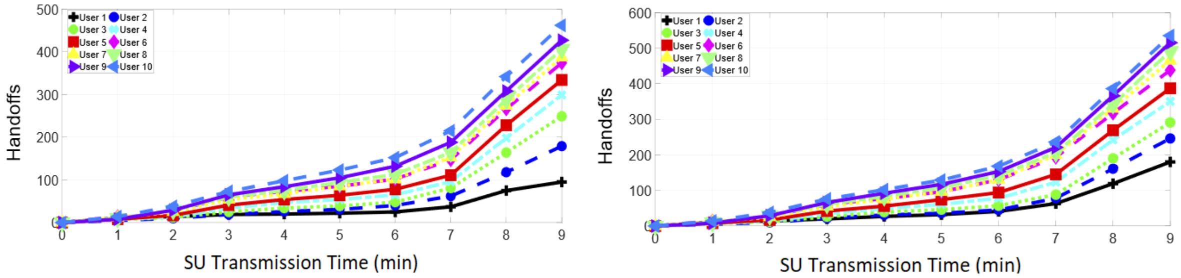
(a) (b)

Figure 3. Deep learning with 10 SUs in LT with and without additional random SUs
(a) conventional mode in LT and (b) real mode in LT



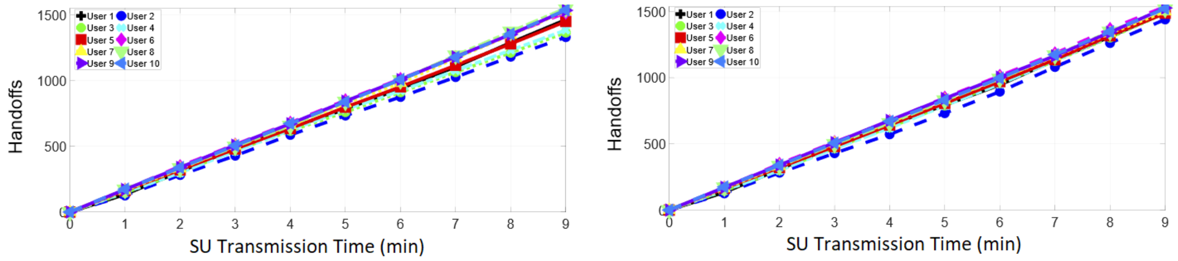
(a) (b)

Figure 4. FFAHP with 10 SUs in HT with and without additional random SUs
(a) conventional mode in HT and (b) real mode in HT



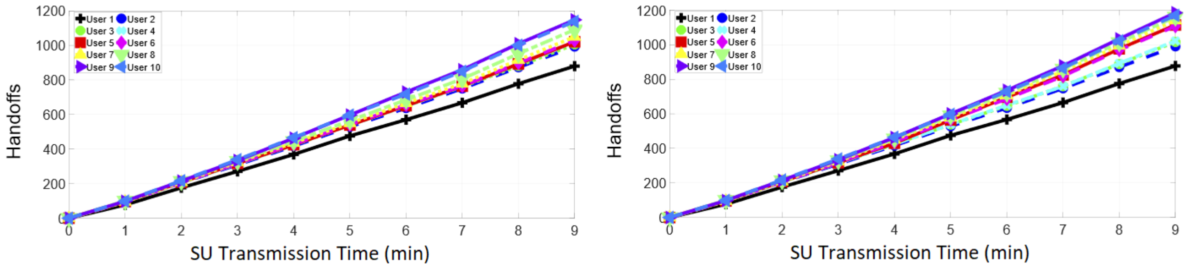
(a) (b)

Figure 5. FFAHP with 10 SUs in LT with and without additional random SUs
(a) conventional mode in LT and (b) real mode in LT



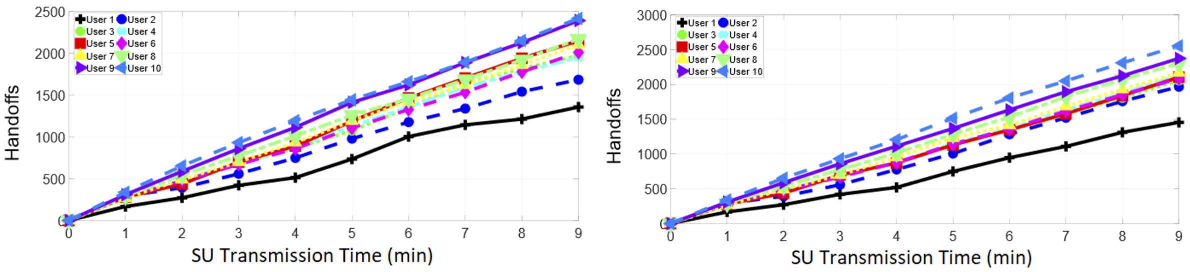
(a) (b)

Figure 6. Naïve Bayes AAH with 10 SUs in HT with and without additional random SUs
(a) conventional mode in HT and (b) real mode in HT



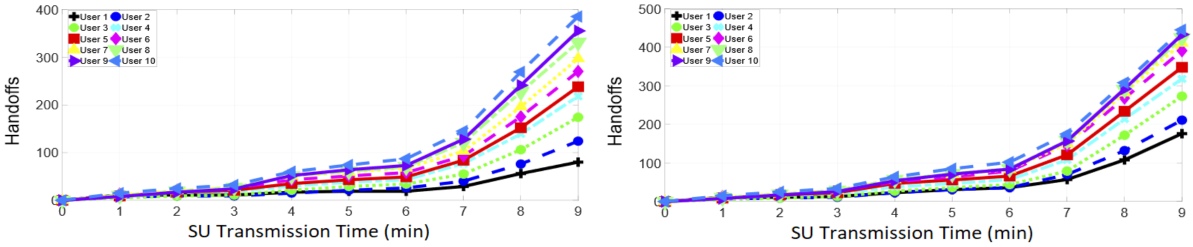
(a) (b)

Figure 7. Naïve Bayes AAH with 10 SUs in LT with and without additional random SUs
(a) conventional mode in LT and (b) real mode in LT



(a) (b)

Figure 8. SAW AAH with 10 SUs in HT with and without additional random SUs
(a) conventional mode in HT and (b) real mode in HT



(a) (b)

Figure 9. SAW AAH with 10 SUs in LT with and without additional random SUs
(a) conventional mode in LT and (b) real mode in LT

3.1. Multi-user benchmarking

Tables 2-5 present the comparative percentages of the performance of each algorithm for the multi-user environment in conventional mode and the real mode for 1, 2, 4, 6, 8, and 10 users. The above aims to analyze each model's behavior as the number of simultaneous accesses of the ED increases. Table 2 and Table 3 present the multi-user benchmarking for HT and LT in conventional and real modes. Table 4 presents the overall benchmarking by traffic type for HT and LT in conventional and real modes. Finally, Table 5 presents the multi-user benchmarking for the prediction metrics for NB.

Table 2. Multi-user benchmarking for HT

Multi-user features	Deep learning	Armed forces	Naïve Bayes	SAW
MSU1 - Conventional	100	96,22	80,05	86,43
MSU2 – Conventional	100	89,9	97,42	89,6
MSU4 – Conventional	84,65	83,65	100	79,71
MSU6 – Conventional	77,6	78,26	100	76,59
MSU8 – Conventional	74,79	74,57	100	75,36
MSU10 – Conventional	71,87	72,22	100	72,61
Conventional Score	84,82	82,47	96,25	80,05
MSU1 – Real	85,29	100	83.2	89,82
MSU2 – Real	80,94	80,7	100	83,77
MSU4 – Real	78,3	75,12	100	75,64
MSU6 – Real	78,58	77,49	100	77,7
MSU8 – Real	71,94	71,41	100	73,33
MSU10 – Real	66,12	68,97	100	70,75
Score Real	76,86	78,95	97,2	78,5

Table 3. Multi-user benchmarking for LT

Multi-user features	Deep learning	FFAHP	Naïve Bayes	SAW
MSU1 - Conventional	16,23	77,89	8,41	92,5
MSU2 – Conventional	18,36	74,45	10,89	100
MSU4 – Conventional	13,52	72,51	15,29	100
MSU6 – Conventional	13,12	77,2	18,56	100
MSU8 – Conventional	13,66	77,91	21,41	100
MSU10 – Conventional	14,4	79,43	23,83	100
Conventional Score	14,88	76,57	16,4	98,75
MSU1 – Real	17,54	84,21	9,1	100
MSU2 – Real	13,92	73,29	13,21	100
MSU4 – Real	12,24	54,26	15,37	100
MSU6 – Real	12,61	64,6	19,96	100
MSU8 – Real	13,77	63,87	21,39	74,52
MSU10 – Real	14,89	73,86	26,7	83,94
Score Real	14,16	69,02	17,62	93,08

Table 4. Global benchmarking by traffic type

Scenario	Deep learning	FFAHP	Naïve Bayes	SAW
AAH HT Conventional	84,82	82,47	96,25	80,05
AAH HT Real	76,86	78,95	97,2	78,5
AAH LT Conventional	14,88	76,57	16,4	98,75
AAH LT Real	14,16	69,02	17,62	93,08
Score HT Global	80,84	80,71	96,73	79,28
Score LT Global	14,52	72,8	17,01	95,92

Table 5. Multi-User benchmarking for Naïve Bayes interference

Multi-user features	AAIH-HT	AAIH-LT	AAUH-HT	AAUH-LT	AAPH-HT	AAPH-LT	Score
MSU1 - Conventional	52,6	75	100	100	100	44,67	78,71
MSU2 – Conventional	68,18	100	65,66	47,17	98,65	52,63	72,05
MSU4 – Conventional	86,89	82,76	52,01	26,77	91,26	79,57	69,88
MSU6 – Conventional	92,19	60	50,33	23,24	85,42	97,34	68,09
MSU8 – Conventional	95,65	50,51	47,08	22,34	82,89	100	66,41
MSU10 – Conventional	100	40,27	43,65	22,04	81,79	96,26	64
Conventional Score	82,59	68,09	59,79	40,26	90	78,41	69,86
MSU1 – Real	47,35	62,5	100	100	100	45,93	75,96
MSU2 – Real	79,89	100	49,67	40,98	97,51	58,41	71,08
MSU4 – Real	76,27	58,82	53,43	23,73	89,84	94,02	66,02
MSU6 – Real	80,54	50	49,06	23,27	83,49	100	64,39
MSU8 – Real	87,73	28,99	45,24	21,3	82,51	97,76	60,59
MSU10 – Real	100	31,65	37,35	21,26	81,01	94,98	61,04
Score Real	78,63	55,33	55,79	38,42	89,06	81,85	66,51
Score Global HT	80,61	ON	57,79	ON	89,53	ON	75,98
Score Global LT	ON	61,71	ON	39,34	ON	80,13	60,39

4. DISCUSSION

In the multi-user evaluation, both predictive and non-predictive models were employed. For scenarios involving HT, the models used include DL, the NB predictive model, and the MCDM techniques of FFAHP and SAW. These models were implemented under both conventional and real modes, with evaluations conducted for various user counts, specifically for 1, 2, 4, 6, 8, and 10 users. The primary metric used for this evaluation was the cumulative average handoff (AAH). The comparative results, based on the type of simulation (either real or conventional) and the number of users, are presented in Table 2. The findings indicate that as the number of simultaneous users increases, the performance of each model tends to decline, as the available SOs become more limited and challenging to identify.

According to the score obtained in Table 2 for HT, in conventional mode, the best performance is NB, with a score of 96.25%, followed by DL, FFAHP and SAW, on average; the average difference of each model compared to NB is 13.65%. For the real mode, Naive Bayas continues to be the model with the best performance, however, there is variation with respect to the score of the other techniques, DL drops in position and is located in the fourth score, FFAHP and SAW increase in position maintaining the order of the classification; the average difference of each model with respect to NB is 17.48%.

According to the score obtained in Table 3 for LT, in conventional mode, the best performance is obtained by multi-criteria techniques, unlike HT, DL, and the NB predictive model are not located in the first places, in the same way. Regarding the multi-criteria technique, SAW obtains the highest score, while FFAHP is in second position. The best performer is SAW, with a score of 98.75% followed by FFAHP with 76.57%; the lowest scores are for NB and DL below 17%; the difference of each model with respect to SAW is below 22.18% for FFAHP, for NB 75.46%, and for DL 78.92%. For the real mode the behavior is proportional, the best performance is SAW, with a score of 93.08% followed by FFAHP with 69.02%, the lowest scores are for NB and DL with scores below 20%; the difference of each model with respect to SAW is below 20% for multi-criteria techniques and 75.46% and 78.92% for predictive model and DL respectively.

Table 4 presents the comparative evaluation according to the number of Handoffs for HT and LT, in conventional and real modes. For HT the highest score is NB, additionally, this prediction technique has another relevant characteristic compared to the others, performance increases for a realistic model, as expected in a realistic scenario, with users entering and leaving in random time, the profit metrics should decrease, however, although there is an increase in performance, it is only 0.95%, which allows us to establish that this strategy is not affected by the incorporation of random users. For the rest of the strategies, the variation of the realistic scenario with respect to the conventional one is less than 2% for SAW and for FFAHP it is 3.52%, and finally, the greatest variation is DL with 7.96%.

In LT the best scores are for the multi-criteria techniques SAW and FFAHP with 95.92% and 72.8% respectively, DL and NB obtain scores below 20%, with respect to the variations of the realistic scenario versus the conventional one, the greatest variation is presented in the multi-criteria techniques, 7.55% for FFAHP and 5.67% for SAW, the variations of DL and NB are below 1%, although as in HT, NB presents an increase in performance.

Based on the cumulative cost metric analyzed across various decision-making models during the nine-minute transmission period, both in conventional and real modes, there is a notable decline in the performance of the multi-criteria techniques as the number of users increases. The scenario with a single SU demonstrates the best performance, with the fewest accumulated handoffs, while the scenario with ten SUs shows the poorest performance, with the highest number of accumulated handoffs. For scenarios with intermediate numbers of users, the order of performance fluctuates during the first three minutes; however, beyond this point, scenarios involving 2 to 5 SUs experience the most significant average increase in handoffs.

Performance in real mode is consistently lower than in conventional mode, primarily due to the introduction of random users, which diminishes the number of available SOs, making them more challenging to identify. It is clear from the results that as the number of users rises, the effectiveness of the MCDM models decreases, underscoring the limitations of these techniques in environments with higher user densities.

5. CONCLUSION

With respect to the multi-user environment, it was evident that as the number of users increases, the performance of each of the models decreases. NB responds very well to multi-user traffic, DL is not affected by realistic scenarios and the multi-criteria FFAHP and SAW techniques perform well for scenarios with low traffic. It is also interesting to note how at HT levels the performance of the evaluated strategies is reduced by around 25% when incorporating random users, while for low traffic performance is only affected by about 12% in the same scenario of random users. This shows the importance of carrying out simulations in environments closer to reality, since the results can be affected by significant magnitudes. Now, taking into account only the number of simultaneous users, it is evident that in effect the greater the number of users, the lower the level of performance, however, the reduction in this case is better than that observed in the case of random users, for HT it is only 10% and for low traffic there is no evidence of any affectation. In general, each strategy performs satisfactorily in certain scenarios, to improve performance in multi-user access, an interesting proposal would be to hybridize the implemented strategies or develop a multi-model with an adaptive module that selects the best strategy based on the scenario and application that is being executed at that time.

For future research, two main directions are suggested. The first involves developing an adaptive module capable of dynamically choosing the most suitable spectral selection model based on the specific requirements of the active application. The second direction focuses on conducting evaluations and validations using actual CR equipment that can mimic the behavior of a CRN, rather than relying solely on simulations. This approach would incorporate real spectral occupancy data to provide more realistic and reliable assessments.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Cesar Hernandez	✓	✓		✓	✓	✓			✓	✓		✓	✓	✓
Diego Giral		✓	✓	✓		✓	✓		✓	✓	✓			
Fredy Martinez			✓	✓	✓	✓		✓		✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [CH]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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