Benchmarking between 2 Proactive Handoff Models

C. Hernández *, D. Giral , and F. Martínez

Electrical Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia
Email: cahernandezs@udistrital.edu.co (C.H.); fhmartinezs@udistrital.edu.co (D.G.), dagiralr@udistrital.edu.co (F.M.)
*Corresponding author

***Abstract*—Cognitive radio is a technology that allows a more efficient spectrum use. Currently, there are several proposals for the spectral mobility of secondary users. However, very few of them are proactive. The advantage of proactive models is that they allow a reduction in the level of interference between primary and secondary users due to the prediction of the arrival of the primary. This work presents the comparative evaluation of two predictive spectral decision models, Naïve Bayes, and Logistic Regression, analyzing the level of interference they generate and the level of quality in the prediction. The evaluation is done through five metrics in low and high traffic scenarios: failed handoffs, interference handoffs, bandwidth, delay and throughput; in two types of scenarios: low traffic and high traffic. The main contributions of this work are the use of real spectral occupancy data captured in previous measurement campaigns and the robust evaluation carried out through five metrics, among which the interference measured from the moment in which the primary and secondary users coexist in the same channel, and the analysis under a radio environment with many and few primary users. The results show that the Naïve Bayes model has a 20% better performance than the logistic regression model; this together with its low processing level makes it an excellent candidate for the selection of selecting opportunities in cognitive radio networks.**

***Keywords*—benchmarking, cognitive radio networks, Multiple Criteria Decision Making (MCDM), spectrum decision, spectrum handoff, spectrum mobility**

I. Introduction

Cognitive radio Networks (CRN) are one of the most promising innovations in the telecommunications field [1]. This concept is based on the ability of communication devices to "learn" and adapt to the radio environment, optimizing the use of the spectrum and improving the efficiency of data transmission [2, 3]. A cognitive radio network is an intelligent communication system that can perceive the radio environment, understand the channel conditions and adjust its operating parameters in real-time [4, 5]. Its main objective is to improve the radio spectrum's use a limited and scarce resource, often underutilized due to the lack of flexibility in traditional networks [6, 7].

Manuscript received February 5, 2025; revised March 11, 2025, accepted March 28, 2025; published May 23, 2025.

The spectrum decision is the core of a Cognitive Radio Networks (CRN); efficiently and without causing any type of interference, it establishes through a set of techniques the process to select the most appropriate spectral opportunity according to the requirements of the Secondary User (SU) and the conditions of the radio environment [8, 9]. An incorrect decision-making process affects network parameters such as the Handoffs; however, despite its relevance it is not as explored a function as spectrum detection [10, 11]. Currently, the research that has been developed focuses more on reactive spectral decision models (non-predictive) even though proactive (predictive) models allow for a reduction in the level of interference between Primary User (PU) and Secondary User (SU) [12]. In addition, the research works with random spectral information data, presents only one or two evaluation metrics, and does not analyze how the level of spectral traffic can affect the decision-making of the proposed models [13].

Predictive spectral mobility models are crucial in cognitive radio networks, as they allow them efficiently predict and manage how the spectrum moves over time and space, ensuring that secondary users access frequencies without interfering with primary users [14]. Since spectrum is a limited and dynamic resource, these models allow for an intelligent and adaptive allocation of available frequencies, optimizing spectrum utilization and improving network efficiency [15]. Furthermore, spectral mobility models anticipate traffic patterns and congestion, facilitating more effective network management, especially in high-demand environments with constantly changing channel conditions. Thus, spectral mobility models are essential to ensure harmonious and efficient coexistence between different types of users in a cognitive environment [16].

By predicting spectrum usage patterns and the presence of primary users at different times and locations, these models help secondary devices to proactively adapt, avoiding interference and maximizing network performance [17]. Furthermore, the ability to predict spectral mobility optimizes the use of limited resources, improves the quality of service for users, and reduces channel congestion, which is crucial in highly dynamic environments with variable demand. Ultimately, predictive spectral mobility models enable smarter and

doi:10.12720/jcm.20.3.282-290

more efficient spectrum management, which is key to the success of cognitive radio networks [18].

In Ref. [19], a Multi-User Proactive application was proposed as proactive optimal resource allocation framework for spectrum management in cognitive radio networks, was proposed. A machine learning and mathematical optimization-based approach was used to predict spectrum availability and dynamically allocate it to secondary users compared to traditional approaches, PORA improved spectrum usage efficiency, reducing interference and improving network performance.

In Ref. [20], a deep learning-based approach was proposed for proactive beam handoff in multi-user 6G networks. A deep neural network was trained to predict connectivity changes and optimize beam handoff, improving link continuity in dynamic environments. The model was able to reduce latency and improve handoff efficiency compared to conventional methods, optimizing stability and quality of service in 6G networks.

In Ref. [21], a hybrid spectrum-handoff mechanism was presented for cognitive radio ad hoc networks, allowing better spectrum management in dynamic environments. A reactive and proactive approach for spectrum handoff was combined using machine learning-based prediction and optimization models. The hybrid method reduced spectrum handoff latency and improved communication continuity compared to traditional techniques.

In Ref. [22], a proactive scheme based on fuzzy logic was proposed for backup channel selection in spectrum handoff in cognitive radio networks. A fuzzy inference system was employed to evaluate metrics such as channel quality and interference, optimizing the assignment of backup channels before an interruption occurs. The approach improved the efficiency of spectrum handoff, reducing the communication failure rate and improving the quality of service compared to conventional methods.

In Ref. [23], an efficient proactive handoff scheme based on Artificial Neural Networks (ANN) was proposed for cognitive radio networks. An ANN was trained to predict spectrum availability and perform channel handoff in advance, optimizing service continuity. The ANN-based approach reduced handoff time, minimized interference, and improved communication stability compared to traditional methods.

Current proposals mostly focus on reactive models evaluated from random data with a single metric, which are easier to develop than predictive models. This generates a higher level of interference and does not allow their performance to be measured reliably.

The objective of this research is to comparatively evaluate the performance of two predictive spectral decision models: Naïve Bayes and Logistic Regression, which were selected for having a low level of processing and a high performance in terms of prediction. The validation of the two models was carried out quantitatively through a simulation tool developed with real spectral occupancy data captured in a previous measurement campaign; based on five evaluation metrics: (1) Failed Handoff (FH), (2) Interference Handoff (IH), (3) Bandwidth (BW), (4) Delay (D) and (5) throughput (T); for a low-traffic scenario and a high-traffic scenario.

II. Methodology

In the evaluation of the performance of the Naive Bayes and Logistic Regression algorithms, five evaluation metrics were measured: (1) Failed Handoff (FH), (2) Interference Handoff (IH), (3) Bandwidth (BW), (4) Delay (D) and (5) Throughput (T), for two levels of traffic: High (HT) and Low (LT). The results were obtained using a previously developed simulation tool, which utilizes experimental spectral occupancy data collected during a measurement campaign conducted earlier in Bogotá. This simulation tool progressively reconstructs the spectrum occupancy behavior using experimental data traces captured in the Global System for Mobile communications (GSM) band. This allows the simulation to incorporate an approximation of the real behavior of the Primary User (PU), enabling a more accurate validation of the actual performance of each algorithm. The spectral occupancy data corresponds to two months of observations gathered in Bogotá D.C., Colombia [24–27].

The developed simulation tool follows this procedure if an SU intends to transmit for φ minutes. First, it updates the value of the DCs based on information from the previous Instant of Time (TS), referred to as $\tau 0$, when the SU requests the spectral resource. Second, it ranks the spectral opportunities based on the score each opportunity receives, according to the decision-making algorithm being evaluated. Third, it selects the spectral opportunity ranked first and assigns it to the SU to begin transmission. Fourth, at this moment, $\tau 1$, it checks the database (trace of captured and processed data) to verify whether the selected spectral opportunity is available. (It should be noted that decision-making algorithms only know APs, not real-time availability of spectral opportunities.) If available, the handoff metric is incremented by one, and the fifth step is carried out. If unavailable, the FH evaluation metric is increased by one, the next spectral opportunity in the ranking is selected, and the fourth step is repeated. Fifth, at each TS, the simulation tool checks the database to ensure that the spectral opportunity currently used by the ED is still available. Sixth, when τk, the moment the selected spectral opportunity is needed by a PU (i.e., when it is no longer available according to the database), if $\Delta\tau = \tau k - \tau 1$ is less than 60 seconds, the next spectral opportunity in the ranking is selected, and the fourth step is repeated. If $\Delta\tau$ is greater than 60 seconds, $\tau 0$ is updated with the current time, and the process returns to the first step. Seventh, the communication is considered lost if no channel is available for ζ seconds.

One of the key factors in choosing a prediction model is the potential to incorporate multiple features or criteria that could enhance the accuracy of the prediction. This is because during the training of the prediction model, factors such as the Probability of Availability (PA) and the average Time of Availability (TA), among other metrics, can be considered, which can help improve the accuracy of the forecast. In the current literature, it is possible to find works related to predicting spectral occupancy in cognitive radio networks, through prediction models such as artificial neural networks, autoregressive time series, decision trees, hidden Markov models and deep learning, among the most prominent. However, the computational load is high compared to other models offering similar performance with lower computational cost, which is why Naïve Bayes and Logistic Regression were selected.

A. Naïve Bayes

Referencing the Naive Bayes theorem, it can be deduced that the independent variables or predictors in this specific case would be the Probability of Availability (PA) and the mean Time of Availability (TA), while the dependent variable, or class, would be channel availability. Based on this, the Naive Bayes prediction model effectively predicts multiple classes and assumes independence between them.

In simpler terms, a Naive Bayes classifier assumes that the presence of a particular feature is unrelated to the presence of any other feature. Even if these features are dependent on each other or influenced by the presence of other features, each property is treated independently. One of the main advantages of this model is its ability to perform effectively on very large datasets.

Bayes' theorem provides a way to calculate the posterior probability P (c | x) of P (c), P (x), and P (x | c) ((see Eq. (1)).

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

where:

$P(c|x)$ is the subsequent probability of the class (c, objective) given predictor (x, attributes).

$P(c)$ It is the previous probability of class.

$P(x|c)$ The probability of the predictor given the class

$P(x)$ is the predictor's prior probability.

Based on Eq. (1) and considering the independent variables PA and TA, as explained in the previous sections, along with the dependent variable or class, which in this case is channel availability (denoted as either occupied or available), Eq. (1–3) are provided.

$$\begin{aligned}&Posterior(occupied)\\&= \frac{P(occupied)p(TA|ocuppied)p(PA|occupied)}{evidence}\end{aligned} \tag{2}$$

$$\begin{aligned}&posterior(available)\\&= \frac{P(available)p(TA|available)p(PA|available)}{evidence}\end{aligned} \tag{3}$$

where "evidence" would be given by Eq (4).

$$\begin{aligned}&evidence\\&= P(occupied)p(TA \mid ocuppied)p(PA \mid occupied)\\&+ P(available)p(TA|available)p(PA|available)\end{aligned} \tag{4}$$

B. Logistic Regression

The primary benefit of logistic regression is its ability to simultaneously incorporate multiple explanatory variables. While this may appear straightforward, it is crucial because understanding the effect of these explanatory variables on the response variable is highly valuable. Examining the explanatory variables individually, without considering the covariance between them, could lead to misleading conclusions.

Logistic regression models the probability of an outcome based on individual characteristics, as represented by Eq. (5).

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_m x_m \tag{5}$$

In this context, π represents the probability of an event, βi are the regression coefficients corresponding to the reference group, and xi are the explanatory variables. At this point, it's essential to highlight an important concept: the reference group, denoted by β0, consists of individuals exhibiting the reference level for each variable x1... m.

For this specific study, the signal-to-noise plus Interference Ratio (SINR), availability, and mean Availability Time (TA) were defined as explanatory variables, as they are interrelated and must be used together in the prediction of channel availability. As a result, Eq. (5) is modified into Eq. (6).

$$\begin{aligned}\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 PD_1 + \beta_2 TED\\ + \beta_3 PSINR\end{aligned} \tag{6}$$

C. Traffic Scenarios

An analysis is carried out prior to the power matrix captured in the GSM band based on the probability of availability; from this analysis, a frequency range is determined where the availability of the power matrix is high, for the analysis of the models to be equitable, a previous adjustment to this frequency range is required. To adjust the frequency range, a strategy is implemented that involves all the channels of the power matrix; it consists of generating a set of matrices for different levels of probability of availability, to generate the two traffic scenarios, high and low.

The methodology takes the measured power matrix, and, several availability matrices are obtained by modifying the threshold level. For a threshold value of −80dBm the availability increased to 70% and it was considered as a low traffic scenario, i.e. when the number of spectral opportunities is much higher than the number of PUs in the network. On the contrary, when the threshold value was set to −105dBm, the availability was reduced to 30%. It was considered as a high traffic scenario, i.e. when the number of spectral opportunities is much lower than the number of PUs in the network.

D. Evaluation Metrics

The performance evaluation of the prediction algorithms was conducted using five metrics, as outlined in Table I. This table includes the acronym, definition, description, and type of evaluation metrics. The type of evaluation refers to whether the metric is a benefit (the higher, the better) or a cost (the lower, the better). The term "average" in the evaluation metrics indicates that the results represent the average values obtained from multiple experiments.

In order to facilitate the comparative analysis of each algorithm, the relative values (in percentage) of each evaluation metric were calculated.

TABLE I. ADDITIONAL METRICS FOR PREDICTIVE MODEL EVALUATION

Acronym	Name	Description	Evaluation metric type
FH	Failed handoff	It refers to the number of handoffs the SU could not execute because the corresponding target spectral opportunities were occupied.	Cost
IH	Interference handoff	It represents the total number of reactive handoffs made once the PU arrives, during the SU's transmission period.	Cost
BW	Bandwidth	It indicates the average bandwidth the SU uses during the 9 minutes of its transmission.	Benefit
D	Delay	It refers to the average time the SU experiences transmitting a specific amount of information.	Cost
T	Throughput	It represents the effective data rate transmitted by the SU during the 9 minutes of communication.	Benefit

III. RESULTS

Figs 1–5 illustrate the results for each of the evaluation metrics FH, IH, BW, D, and T. Each figure displays the outcomes of the two predictive spectral decision models, Naive Bayes and Logistic Regression, over a 9-minute transmission, with HT and LT traces, in a GSM network. Additionally, Tables II and III present the comparative percentage values of the evaluation metrics for each predictive model, using HT and LT traces, in a GSM network.

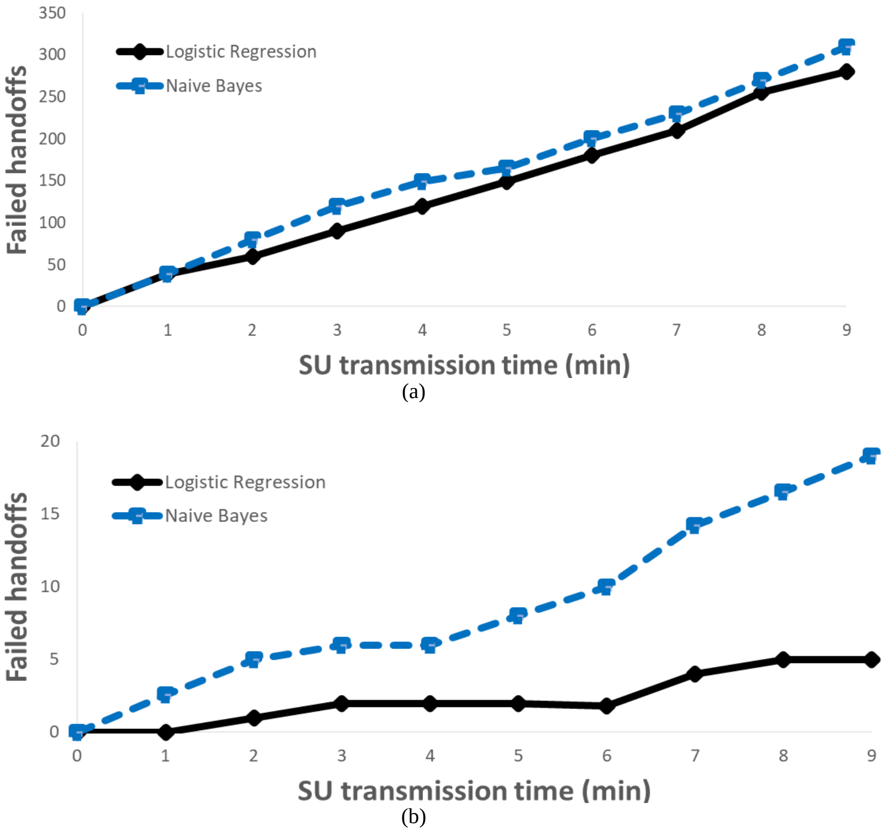

Fig. 1. FH of Predictive Models in GSM for HT and LT, (a). GSM HT, (b). GSM LT.

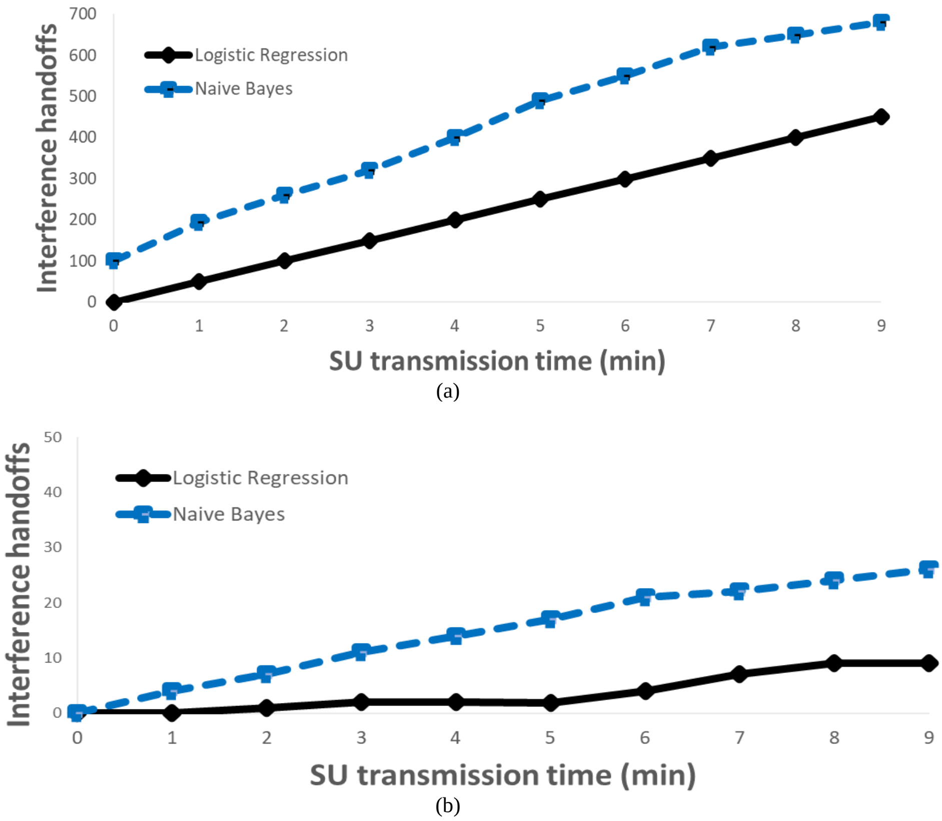

Fig. 2. IH of predictive models in GSM for HT and LT, (a). GSM HT, (b). GSM LT.

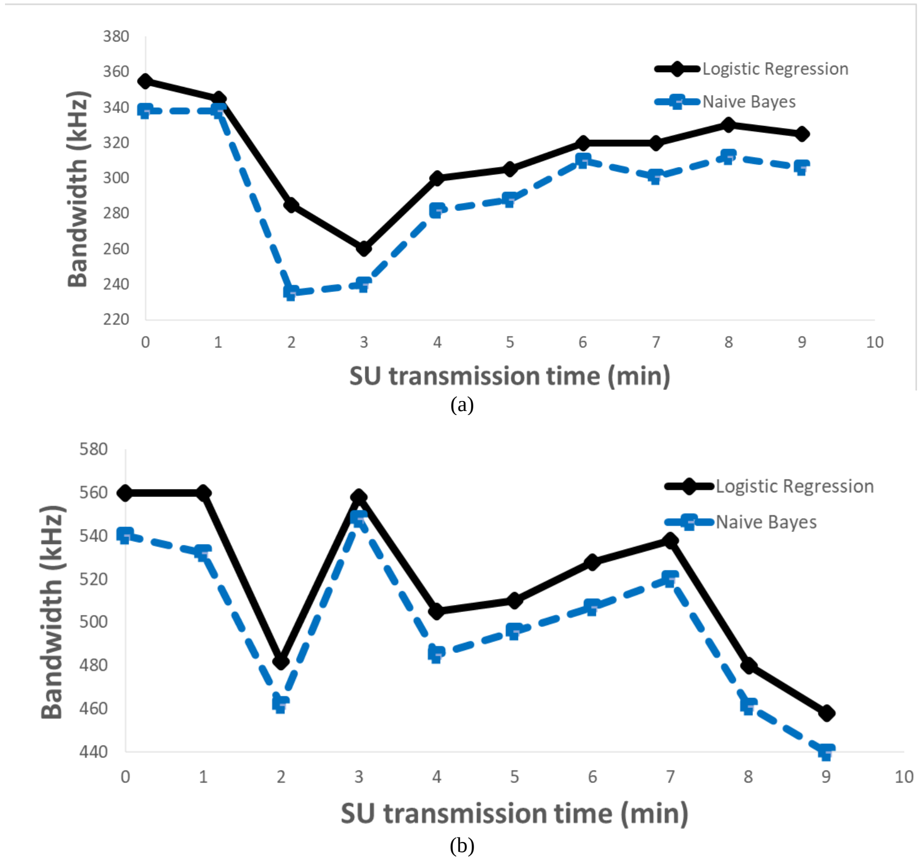

Fig. 3. BW of predictive models in GSM for HT and LT, (a). GSM HT, (b). GSM LT.

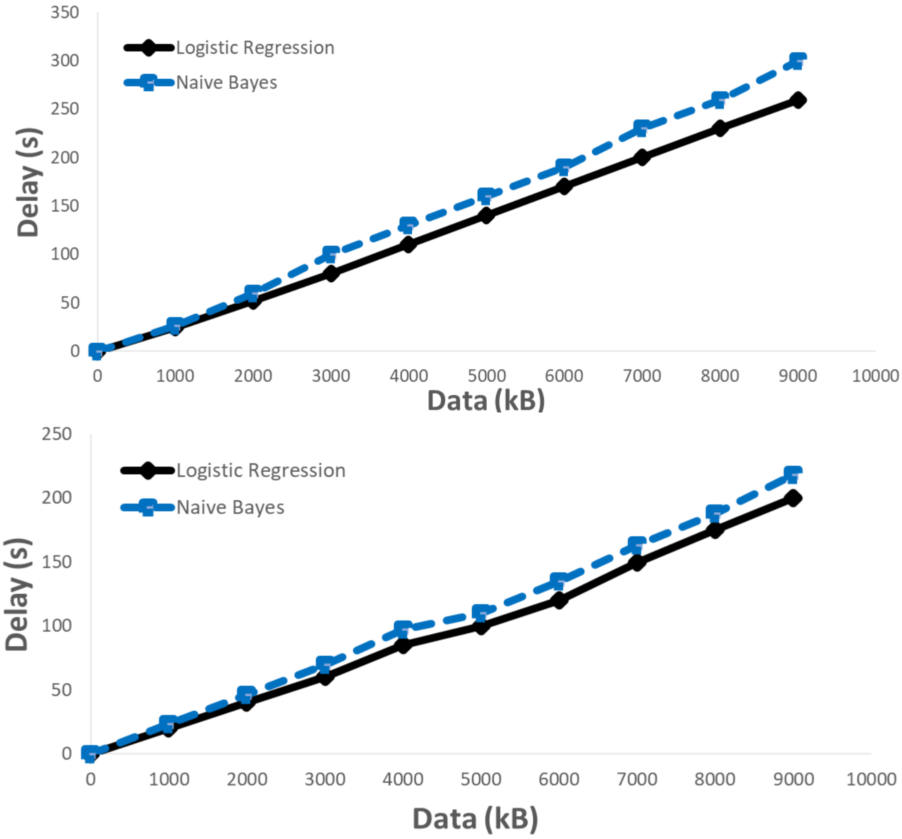

Fig. 4. D of predictive models in GSM for HT and LT, (a). GSM HT, (b). GSM LT.

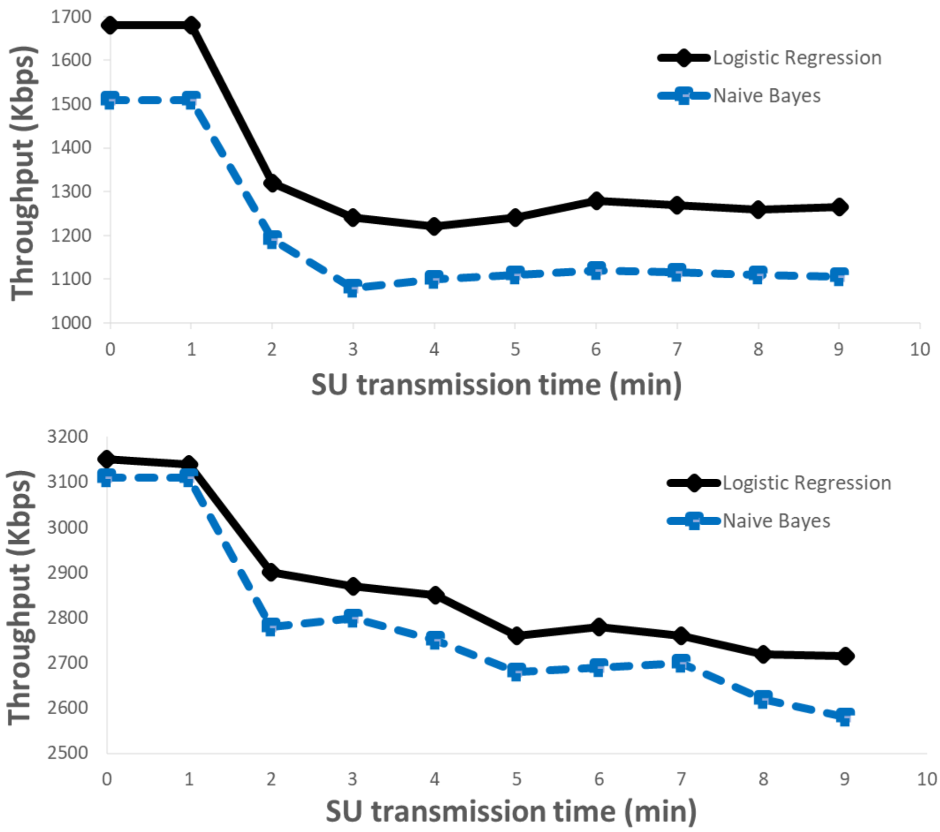

Fig. 5. T of predictive models in GSM for HT and LT, (a). GSM HT, (b). GSM LT.

TABLE II. RELATIVE VALUES OF THE METRICS FOR PREDICTIVE MODELS IN GSM WITH HT

Evaluation Metrics	Logistic Regression	Naïve Bayes
FH	100%	88%
IF	100%	53%
BW	100%	94%
D	100%	87%
T	100%	89%
Score	100%	88%

TABLE III. RELATIVE VALUES OF THE METRICS FOR PREDICTIVE MODELS IN GSM WITH LT

Evaluation Metrics	Logistic Regression	Naïve Bayes
FH	100%	32%
IH	100%	25%
BW	100%	96%
D	100%	90%
T	100%	97%
Score	100%	32%

Finally, to determine whether the results are statistically significant, a t-student test was performed, which yielded a *P*-value of 0.04621, thus rejecting the null hypothesis. Because the *P*-value is less than 0.05, it can be said that the results are statistically significant and not a result of chance.

IV. DISCUSSION

The main results achieved in the research project are the design and development of a predictive module that reduces the level of interference between SUs and PUs; (2) the determination of four carefully selected decision criteria to choose the best spectral opportunity; (3) all the algorithms developed worked with the same four criteria, and each decision criterion is calculated from the occupancy data.

Two techniques were implemented evaluate the predictive models, logistic regression and naive Bayes. The results for the HT traffic level, are presented in Table I. As they are prediction techniques, one additional metric is included: IH. For the Naive score analysis, Bayes presents the highest score, 94.9%, with a difference of less than 1% compared to Logistic Regression. For the metrics associated with the prediction, Logistic Regression presents the highest relative values for perfect handoffs and anticipated handoffs, with a difference of 10.95 % and 1.04 % concerning Naive Bayes, for handoffs with Naive Bayes interference presents the highest relative values with a difference of 31.88 %. For the other metrics, the average difference is 9.72%, except for D, where the difference is 0.02%.

The results of the level of LT traffic, are presented in Table II. As they are prediction techniques, one additional metric is is included: IH. For the score analysis, Naive Bayes presents the highest score with 99.0%, with a difference of 18.61% compared to Logistic Regression. For the metrics associated with the prediction, Logistic Regression presents the highest relative values for perfect handoffs and anticipated handoffs, with a difference of 3.33 % and 4.6 % concerning Naive Bayes, for handoffs with Interference. Naive Bayes presents the highest relative values with a difference of 81.4 %. For the other metrics, the average difference is 0.46%, except for FH, where the difference is 73.68%.

From the diversity of results obtained, it is possible to determine some interesting relationships between them. For example, the total handoffs are equal to the failed handoffs (those that could not be made), plus perfect handoffs (those that were made at the exact moment before the primary user arrived), plus anticipated handoffs (those that were made long before the primary user arrived), plus interference handoffs (those made after the primary user arrived). Although the ideal is to have as many perfect handoffs as possible, the two most relevant metrics are the total handoffs, since the greater the handoffs, the lower the quality of communication, and the handoffs with interference, since they more directly affect the quality of service of communication between users.

The present research presents results achieved with real spectral occupancy data, based on five evaluation metrics: failed handoffs, interference handoffs, bandwidth, delay and throughput, in low and high traffic scenarios. This represents a significant contribution because in the current literature, most related works present results based on random spectral occupancy data, for a single evaluation metric and for a single type of traffic, which is generally not characterized. Due to the above, it is difficult to perform fair comparative evaluations, firstly, by the use of real spectral occupancy data captured in measurement campaigns; secondly, because they do not generate the diversity of evaluation metrics presented in this work, generally, they are restricted to bit error rates or probability of error, and not applied to communications systems as in this case; thirdly, because the type of traffic or the frequency band, which for this work is GSM, is not characterized; and finally, because the level of traffic or spectral occupancy is not characterized to analyze the behavior in high or low traffic as if it is done in this work, focused on cognitive radio networks.

In the current literature, it is possible to find works related to predicting spectral occupancy in cognitive radio networks through prediction models such as artificial neural networks, autoregressive time series, Bayesian models, hidden Markov models, and deep learning, among the most prominent. In the case of artificial neural networks, the performance evaluation is carried out through the prediction of spectral occupancy directly, obtaining a 10% error, which in the case of this work is below 10%, as can be seen from Tables II and III, where the only values with an average error greater than 10% are IH and FH. Autoregressive models evaluate performance based on the probability of error, and similarly, hidden Markov models are based on the probability of error as a function of the useful cycle. One of the works found presents a Bayesian model that calculates the performance of the prediction in terms of the bit error rate, and finally, within the most recent works, a model based on deep learning is presented, which uses cooperation between users to raise the level of accuracy in prediction. Based on the probability of error as a function of the range of cooperation [22].

V. Conclusions

This study compared the performance of two predictive spectral decision models, Naïve Bayes and Logistic Regression, using real spectral occupancy data from the GSM band. The evaluation was based on five metrics: failed handoffs, interference handoffs, bandwidth, delay, and throughput, in both low-traffic and high-traffic scenarios.

The performance in low-traffic scenarios is notably better than in high-traffic situations. This is because, in low-traffic environments, there is a broader range of spectral opportunities, which enables predictive spectral decision models to select different frequency channels, often with similar qualities. This helps prevent any degradation in communication quality due to interference or unnecessary handoffs.

While both models show similar performance in high-traffic scenarios, Naïve Bayes offers a notable advantage over Logistic Regression in low-traffic situations, with an approximate 20% improvement. Its lower processing demands make Naïve Bayes an excellent choice for spectral opportunity selection in cognitive radio networks.

The results achieved in the development of this work describe an excellent predictive behavior of the Logistic Regression algorithm, which would allow the development of an effective proactive strategy to carry out the spectral mobility of secondary users, allowing a better level of quality of service in the communications of secondary users, in cognitive radio networks.

VI. Future Work

As future work, it is proposed to create a pilot network that implements the two models analyzed in this research and compare them with seasonal time series such as SARIMA and deep learning models, currently widely used, such as long short-term Memory (LSTM).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

C.H. conceptualized and conducted the research; D.G. and C.H. developed the methodology; D.G. developed the software; F.M. analyzed the data; D.G. and F.M. validated the results; C.H. and F.M. performed the formal analysis; D.G., C.H. and F.M. wrote, reviewed, and edited the manuscript; All authors approved the final version of the manuscript and agree to publish it.

Funding

This research was funded by Universidad Distrital Francisco José de Caldas under the framework of contract 06-2019.

Acknowledgment

The authors thank the Research Office (ODI) of the Universidad Distrital Francisco José de Caldas.

References

[1] C. Hernández, L. F. Pedraza, I. Páez, and Y. E. R. Colina, "Analysis of spectral mobility in cognitive radio networks," *Información Tecnológica*, vol. 26, no. 6, pp. 169–186, 2015. doi: 10.4067/S0718-07642015000600018

[2] C. Hernandez, H. Marquez, and D. Giral, "Comparative evaluation of prediction models for forecasting spectral opportunities," *International Journal of Engineering and Technology*, vol. 9, no. 5, pp. 3775–3782, 2017. doi: 10.21817/ijet/2017/v9i5/170905055

[3] K. Kumar, A. Prakash, R. Tripathi, "Spectrum handoff in cognitive radio networks: A classification and comprehensive survey," *Journal of Network and Computer Applications*, vol. 61, pp. 161–188, 2016. doi: 10.1016/j.jnca.2015.10.008

[4] M. Tahir, M. H. Habaebi, and M. R. Islam, "Novel distributed algorithm for coalition formation for enhanced spectrum sensing in cognitive radio networks," *International Journal of Electronics and Communications*, vol. 77, pp. 139–148, 2017. doi: 10.1016/j.aeue.2017.04.033

[5] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, 2006. doi: 10.1016/j.comnet.2006.05.001

[6] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40–48, 2008. doi: 10.1109/MCOM.2008.4481339

[7] Y. C. Cheng, E. H. Wu, and G. H. Chen, "A decentralized MAC protocol for unfairness problems in coexistent heterogeneous cognitive radio networks scenarios with collision-based primary users," *IEEE Systems Journal*, vol. 10, no. 1, pp. 346–357, 2016. doi: 10.1109/JSYST.2015.2431715

[8] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, 2005. doi: 10.1109/JSAC.2004.839380

[9] D. Giral, C. Hernández, and E. R. Colina, "Spectrum decision-making in collaborative cognitive radio networks," *Applied Sciences*, vol. 10, no. 19, art. no. 6786, 2020. doi: 10.3390/app10196786

[10] C. Hernandez, D. Giral, and C. Salgado, "Failed handoffs in collaborative wi-fi networks," *Telkomnika*, vol. 18, no. 2, pp. 669–675, 2020. doi: 10.12928/telkomnika. v18i2.14894

[11] C. Hernandez, D. Lopez, and D. Giral, *Collaborative Spectral Decision Model to Improve the Performance of Cognitive Radio Networks*, 1st ed., pp. 35–280, Editorial UD, Bogotá, Colombia, 2020.

[12] D. Giral, C. Salgado, and C. Hernandez, "Spectral decision in cognitive radio networks based on deep learning," *Expert Systems with Applications*, vol. 180, pp. 1–16, 2021. doi: 10.1016/j.eswa.2021.115080

[13] C. Hernandez, D. Giral, and C. Salgado, *Multi-User Spectral Allocation Model for Decentralized Cognitive Radio Networks*, 1st ed., pp. 17–99, Editorial UD, Bogotá, Colombia, 2021.

[14] Y. Rizk, M. Awad, and E. W. Tunstel, "Decision making in multi-agent systems: a survey," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 10, no. 3, pp. 514–529, 2018. doi: 10.1109/TCDS.2018.2840971

[15] L. T. David, H. López, and C. Hernández, *A Multifractal Model for Cognitive Radio Networks*, 1st ed., pp. 35–120, Editorial UD, Bogotá, Colombia, 2019.

[16] P. S. Yawada and M. T. Dong, "Intelligent process of spectrum handoff/mobility in cognitive radio networks," *Journal of Electrical and Computer Engineering*, vol. 2019, 7692630, pp. 1–12, 2019. doi: 10.1155/2019/7692630

[17] C. Hernández, I. Páez, and D. Giral, *Multivariate Adaptive Spectral Handoff Model to Increase Performance in Mobile Cognitive Radio Networks*, 1st ed., pp. 35–191, Editorial UD, Bogotá, Colombia, 2017.

[18] D. A. López, N. Y. García, and J. F. Herrera, "Development of a predictive model for the estimation of the behavior of variables in a network infrastructure," *Informacion Tecnologica*, vol. 26, no. 5, pp. 143–154, 2015. doi: 10.4067/S0718-07642015000500018

[19] M. S. Gupta, A. Srivastava, and K. Kumar, "PORA: A proactive optimal resource allocation framework for spectrum management in cognitive radio networks," *IEEE Transactions on Network and Service Management*, 2025. doi: 10.1109/TNSM.2025.3540717

[20] F. B. Mismar, A. Gündoğan, A. Ö. Kaya, and O. Chistyakov, "Deep learning for multi-user proactive beam handoff: A 6G application," *IEEE Access*, vol. 11, pp. 46271−46282, 2023. doi: 10.1109/ACCESS.2023.3274810

[21] M. Uprit and R. N. Raj, "Hybrid spectrum-handoff in cognitive radio ad hoc networks," in *Proc. 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, Bengaluru, India, 2023, pp. 719−725. doi: 10.1109/IITCEE57236.2023.10090925

[22] E. Alozie, N. Faruk, A. A. Oloyede, O. A. Sowande, A. L. Imoize, and A. Abdulkarim, "Proactive fuzzy-based backup channel selection scheme for spectrum handoff in cognitive radio networks," in *Proc. 2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON)*, Lagos, Nigeria, 2022, pp. 1−4. doi: 10.1109/NIGERCON54645.2022.9803179

[23] V. Agarwal, A. Kumar, D. Kumar, P. Tripathi, V. Rajpoot and V. S. Tripathi, "A novel ANN based efficient proactive handoff scheme for cognitive radio network," in *Proc. 2019 International Conference on Computing, Power and Communication Technologies (GUCON)*, New Delhi, India, 2019, pp. 400−404

[24] A. Roy and S. Midya, "Optimized secondary user selection for quality-of-service enhancement of two-tier multi-user cognitive radio network: A game theoretic approach," *Computer Networks*, vol. 123, pp. 1–18, 2017. doi: 10.1016/j.comnet.2017.05.002

[25] L. F. Pedraza, A. Molina, and I. Paez, "Spectrum occupancy statistics in bogota-colombia," in *Proc. IEEE Colombian Conference on Communications and Computing*, 2013, pp. 1–6. doi: 10.1109/ColComCon.2013.6564815

[26] L. F. Pedraza, C. Hernández, K. Galeano, E. Rodríguez-Colina, and I. P. Páez, *Spectral Occupation and Cognitive Radio Model for Bogotá*, 1st ed., pp. 89–101, Editorial UD, Bogotá, Colombia, 2016.

[27] E. Hamid, K. Sithamparanathan, R. J. E. Robin, C. L. Ying, and B. Ristic, "Statistical spectrum occupancy prediction for dynamic spectrum access: A classification," *Eurasip Journal on Wireless Communications and Networking*, vol. 29, pp. 1–17, 2018. doi: 10.1186/s13638-017-1019-8