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Failed handoffs in collaborative Wi-Fi networks

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ABSTRACT

Cognitive radio networks enable a more efficient use of the radioelectric spectrum through dynamic access. Decentralized cognitive radio networks have gained popularity due to their advantages over centralized networks. The purpose of this article is to propose the collaboration between secondary users for cognitive Wi-Fi networks, in the form of two multi-criteria decision-making algorithms known as TOPSIS and VIKOR and assess their performance in terms of the number of failed handoffs. The comparative analysis is established under four different scenarios, according to the service class and the traffic level, within the Wi-Fi frequency band. The results show the performance evaluation obtained through simulations and experimental measurements, where the VIKOR algorithm has a better performance in terms of failed handoffs under different scenarios and collaboration levels.

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1. INTRODUCTION

Currently, wireless communication systems exhibit certain defficiencies in voice and data services due to the saturation and scarcity in frequency bands within the spectrum. This can be explained by the considerable increase of mobile devices in the radiofrequency network [1]. According to some studies, it is expected that the IP traffic grows by 168 Exabytes in 2020 with the number of mobile devices equal to three times the worldwide population [2]. However, time-based and geographic studies carried out by the Federal Communications Commission of the United States [3] show that most of the radiofrequency spectrum is used inefficiently.

This has prompted the use of strategies seeking to mitigate the issue [4]. Cognitive Radio (CR) rises as a technology conceived to overcome this problem, through the dynamic access of the spectrum, and characterized to perceive, learn and plan (decision-making) according to the current conditions of the network [5–9]. This technology increases the bandwidth capacity and dynamic access to the spectrum guaranteeing that there are no interferences between licensed primary users [8, 10].

Centralized networks are architectures with an infrastructure that operates under the command of a central coordinator. The information from each SU feeds the central base, so that it can make decisions to maximize communication parameters. However, this is not the best option for large scale systems and applications in public security networks. The increase in measuring costs, system complexity and potential unbalance and chaos in case of failure (vulnerability) turns it into a non-feasible architecture for CRN [11]. The previous scenario can be solved if the responsibility of the information is split among different control points, serving as a baseline criterion for descentralized cognitive radio networks (DCRN).

The problem of the present research consists on carrying out the decision-making process for a DCRN, giving the nodes the capacity to learn from the environment and proposing strategies that allow the SU to exchange information collaboratively. The proposed solution is based on cooperative DCRN as this work proposes the collaboration between secondary users through the exchange of information between them [10, 12, 13].

This article presents a comparative assessment of the multi-criteria decision-making algorithms TOPSIS and VIKOR for a Wi-Fi DCRN. Both algorithms are assessed and compared in terms of the average number of failed handoffs over a 9-minute transmission for the same information size. The comparative analysis is carried out in four different scenarios based on the service class (real time and better effort) and the traffic level (high and low): real time (RT) with high traffic (HT), better effort (BE) with low traffic (LT), RT with LT and BE with HT. The main contribution of the proposed solution is to show the performance assessment obtained through simulations and experimental measurements, considering different collaboration levels within the analysis (10%, 20%, 50%, 80% and 100%) between secondary users, which share space-time information on spectral occupancy feeding the database of the decision-making algorithms.

2. RESEARCH METHOD

To determine the performance of each algorithm, a simulation tool was developed by the authors, in which the simulation environment progressively recreates the behavior of spectral occupancy based on real data captured in a metering campaign in the Wi-Fi frequency band. The spectral occupancy behavior corresponds to a metering campaign that lasted several weeks in the city of Bogotá, Colombia [14]. The energy detection technique was used to determine the availability matrix for each channel in the Wi-Fi frequency band. The decision threshold for the power variable was 5 dBm above noise floor.

One of the main contributions of this research is derived from handling experimental data of spectral occupancy which is the result of studying the collaborative activity between SU to determine the best spectral opportunities. The present research implemented and adapted a collaboration system combining TOPSIS and VIKOR algorithms, through a module for information exchange between secondary users. Initially, each secondary user stores the last k data in the radioelectric environment retrieved from information shared between SU. It is assumed that there are 100 SU with heterogeneous information of the spectrum for a given node of the descentralized network, and a percentage of that amount is used to gather the information used by the TOPSIS and VIKOR algorithms to sort out the spectral opportunities. The purpose of this process is to assess the influence of the cooperation between secondary users for a DCRN scenario.

2.1. Spectral allocation algorithms

The chosen alternatives for multi-criteria decision-making algorithms (MCDM) are the technique for order preference by similiarity to Ideal solution (TOPSIS) and the multi-criteria optimization and compromise solution (VIKOR).

2.1.1. TOPSIS

This algorithm has two sections: the unacceptable solution in any scenario and the ideal solution of the system. Initially, the decision matrix X is built and then normalized using the square root method (1) [15–19].

$$\tilde{X} = \begin{pmatrix} \tilde{\chi}_{11} & \cdots & \tilde{\chi}_{1M} \\ \vdots & \ddots & \vdots \\ \tilde{\chi}_{N1} & \cdots & \tilde{\chi}_{NM} \end{pmatrix} = \begin{pmatrix} \omega_1 \tilde{\chi}_{11} & \cdots & \omega_M \tilde{\chi}_{1M} \\ \vdots & \ddots & \vdots \\ \omega_1 \tilde{\chi}_{N1} & \cdots & \omega_M \tilde{\chi}_{NM} \end{pmatrix} \tag{1}$$

where ωi is the weight assigned to criterion i and the sum of weights must be equal to 1.

Afterwards, the ideal solution is determined as well as the worst solution, as described in (2) and (3).

$$\mathrm{A}^{+} = \left\{ \left(\max \tilde{\chi}_{\mathrm{ij}} | \mathrm{j} \in \mathrm{X}^{+} \right), \left(\min \tilde{\chi}_{\mathrm{ij}} | \mathrm{j} \in \mathrm{X}^{-} \right) \right\} = \left\{ \tilde{\chi}_{1}^{+}, \ldots, \tilde{\chi}_{\mathrm{M}}^{+} \right\} \tag{2}$$

$$\mathrm{A}^{-} = \left\{ \left(\min \tilde{\chi}_{\mathrm{ij}} | \mathrm{j} \in \mathrm{X}^{+} \right), \left(\max \tilde{\chi}_{\mathrm{ij}} | \mathrm{j} \in \mathrm{X}^{-} \right) \right\} = \left\{ \tilde{\chi}_{1}^{-}, \ldots, \tilde{\chi}_{\mathrm{M}}^{-} \right\} \tag{3}$$

where i = 1...M. X+ and X- are the set of benefits and costs, respectively.

Afterwards, the Euclidian distance *D* is calculated for each alternative as seen in (4) and (5).

$$D_i^+ = \sqrt{\sum_{j=1}^{M}\left(\tilde{\chi}_{ij} - \tilde{\chi}_j^+\right)^2} \qquad i = 1,\ldots,N \tag{4}$$

$$D_i^- = \sqrt{\sum_{j=1}^{M}\left(\tilde{\chi}_{ij} - \tilde{\chi}_j^-\right)^2} \qquad i = 1,\ldots,N \tag{5}$$

Finally, the alternatives are organized in descending order, according to the preference index given by (6).

$$C_i^+ = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i = 1,\ldots,N. \tag{6}$$

2.1.2. VIKOR

The VIKOR method assumes that each alternative is assessed based on each criterion function, and the classification can be established by comparing the measurements and choosing which are closest to the ideal alternative [20–22]. In [16, 23–25], the procedure of the VIKOR algorithm is described. For each parameter j = 1, 2, 3, …, N, the best and worst values are determined as shown in (7) and (8).

$$F_j^+ = \left\{\left(\max_{i\in M} x_{ij} | j \in N_b\right), \left(\min_{i\in M} x_{ij} | j \in N_c\right)\right\} \tag{7}$$

$$F_j^- = \left\{\left(\min_{i\in M} x_{ij} | j \in N_b\right), \left(\max_{i\in M} x_{ij} | j \in N_c\right)\right\} \tag{8}$$

where the benefit and cost parameters respectively named Nb and Nc belong to N.

Afterwards, the values of S_i and R_i for i= 1, 2, 3,…, M, are computed as described in (9) and (10).

$$S_i = \sum_{j\in N} w_j \frac{\left(F_j^+ - x_{ij}\right)}{\left(F_j^+ - F_j^-\right)} \tag{9}$$

$$R_i = \max_{i\in N}\left[w_j \frac{\left(F_j^+ - x_{ij}\right)}{\left(F_j^+ - F_j^-\right)}\right] \tag{10}$$

where W_j is the importance of the weight of parameter j.

Then, the values of Q_i are computed for i= 1, 2, 3,…, M, as shown in (11).

$$Q_i = \gamma\left(\frac{S_i - S^+}{S^- - S^+}\right) + (1-\gamma)\left(\frac{R_i - R^+}{R^- - R^+}\right) \tag{11}$$

where $S^+ = \min_{i\in M} S_i$, $S^- = \max_{i\in M} S_i$, $R^+ = \min_{i\in M} R_i$, $R^- = \max_{i\in M} R_i$, y $0 \le \gamma \le 1$.

Given the values of *Q* for all *i* belonging to *M*, the SO candidates are classifed from best to worst. Finally, the selected SO is given by the optimal value of *Q*, as seen in (12).

$$A^{*}_{\mathrm{VIK}} = \arg\min_{i \in M} Q^{*}_{i} \tag{12}$$

3. RESULTS AND DISCUSSION

In terms of performance assessment, two types of applications were considered: real time (RT) and better effort (BE) as well as two traffic levels: high traffic (HT) and low traffic (LT), leading to four different scenarios: GSM RT HT, GSM RT LT, GSM BE HT and GSM BE LT. The accumulative average failed handoffs (AAFH) is the metric used for assessment both for the TOPSIS as shown in Figure 1 and the VIKOR algorithms as shown in Figure 2. Ten simulations were performed for each experiment and then the average of each experiment was plotted.

Figure 1 shows that the number of failed handoffs is 24% lower for low traffic compared to high traffic since there are less spectral opportunities. Another interesting finding is that the number of failed handoffs is very similar between the BE and RT scenarios for the same level of traffic, which makes this variable less relevant within a spectrum allocation model and leading to reconsider the operation of the chosen algorithm. Finally, the collaboration percentage between secondary users is not significant for real time applications while better effort applications exhibit an improvement in performance by 11% as the collaboration percentage grows higher.

Figure 2 shows that the number of failed handoffs is 25% lower for low traffic compared to high traffic. As seen for the TOPSIS algorithm, the VIKOR algorithm reveals a similar number of failed handoffs between BE and RT, for the same traffic level. Finally, in terms of the collaboration percentage between secondary users, only the BE-LT scenario shows a significant improvement by 7%.

Table 1 shows the percentage-based relative values of the comparative performance assessment for each scenario among different levels of collaboration. It can be concluded that, although there is evidence of an improvement in performance for each algorithm when the level of collaboration rises, said improvement does not exceed 10% in most cases. Therefore, it could prove interesting to assess each algorithm comparatively in all scenarios, taking into account the highest and lowest collaboration levels of 10% and 100% respectively, as shown in Table 2. The scenario-based analysis does not reveal that an algorithm dominates over the other one in all scenarios or with common conditions.

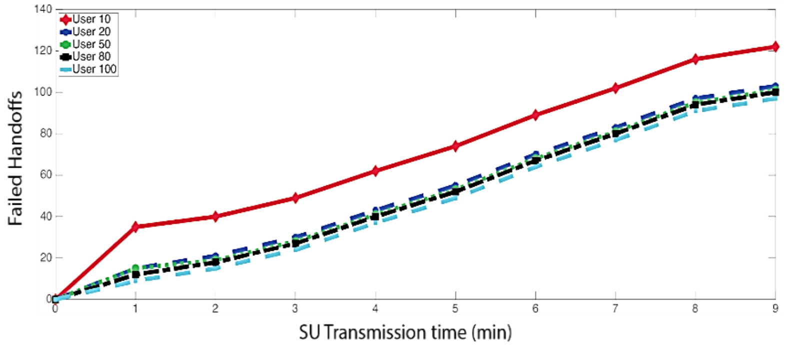
The significance of the results, regarding the collaboration module, shows that the level of collaboration between SU is directly proportional to the performance of the algorithm. However, the improvement rate is not significantly high. According to the results, an increase in the level of collaboration between SU by 1000% (from 10% to 100%) only improves the performance of the algorithm by approximately 10%.

Table 1. Benchmarking by level of collaboration for AAFH

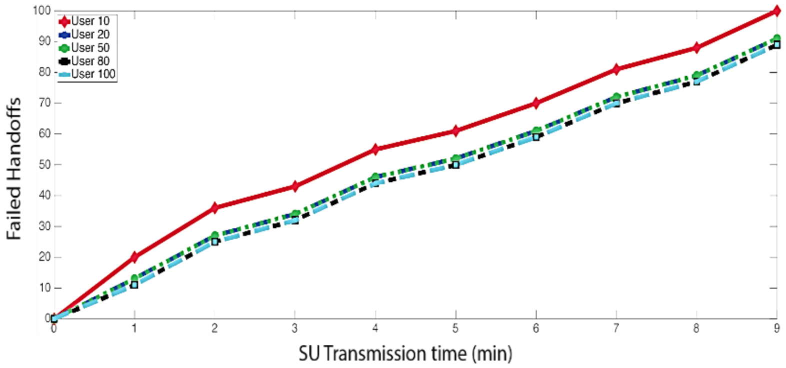
AAFH	Wi-Fi BE LT	Wi-Fi RT LT	Wi-Fi BE HT	Wi-Fi RT HT
TOPSIS SU10	26.83	72	42.22	71.31
VIKOR SU10	72.53	86.75	93.14	64.44
TOPSIS SU20	70.97	79.12	68084	84.47
VIKOR SU20	76.74	94,74	95	79.82
TOPSIS SU50	71.74	79.12	91.35	86.14
VIKOR SU50	78.57	98.63	95.96	83.65
TOPSIS SU80	74.16	80.9	94.06	87
VIKOR SU80	78.57	98.63	95.96	87.88
TOPSIS SU100	76.74	80.9	100	89.69
VIKOR SU100	81.48	100	97.94	87.88

Table 2. Benchmarking by scenario with 10% and 100% collaboration for AAFH

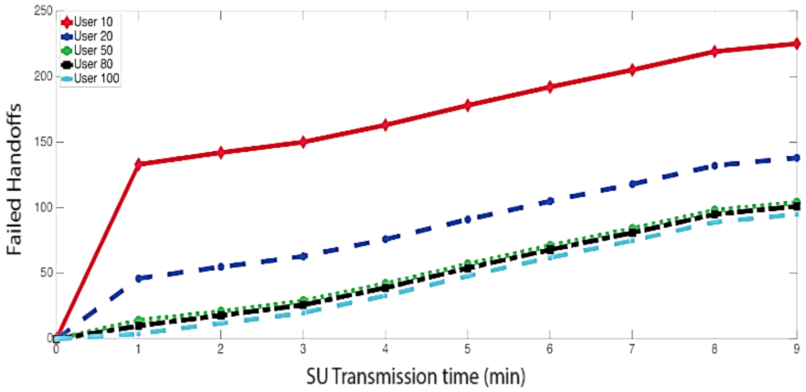
AAFH	TOPSIS SU10	VIKOR SU10	TOPSIS SU100	VIKOR SU100
Wi-Fi BE LT	26.83	72.53	76.74	81.48
Wi-Fi RT LT	72	86.75	80.9	100
Wi-Fi BE HT	42.22	93.14	100	97.94
Wi-Fi RT HT	71.31	64.44	89.69	87.88
Wi-Fi LT	49.415	79.64	78.82	90.74
Wi-Fi HT	56.765	78.79	94.845	92.91
Wi-Fi BE	34.525	82.835	88.37	89.71
Wi-Fi RT	71.655	75.595	85.295	93.94



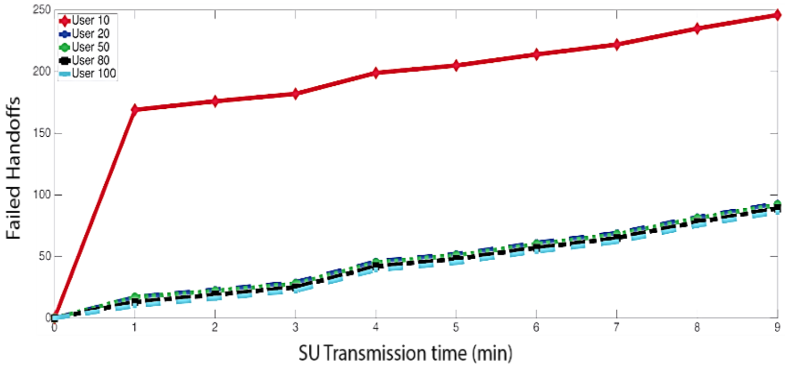
a. Wi-Fi RT HT



b. Wi-Fi RT LT

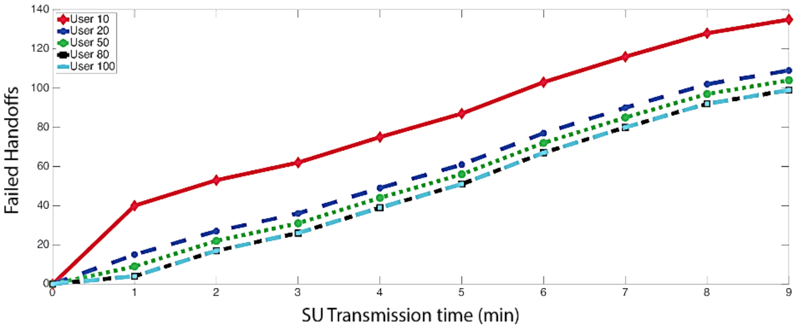


c. Wi-Fi BE HT

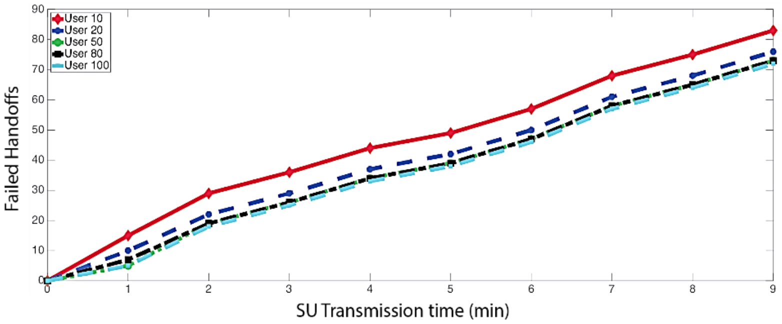


d. Wi-Fi BE LT

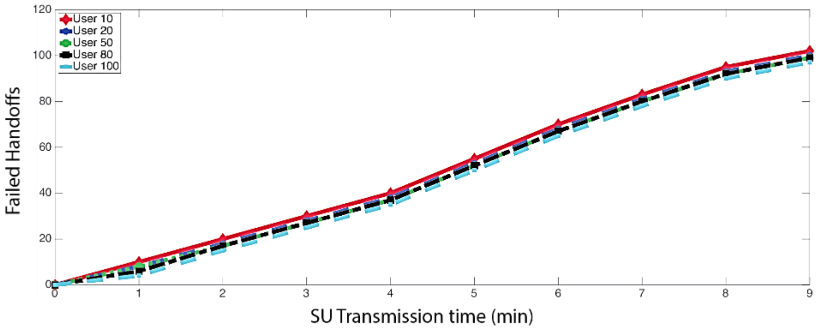
Figure 1. Failed Handoffs for TOPSIS algorithm in collaborative Wi-Fi networks



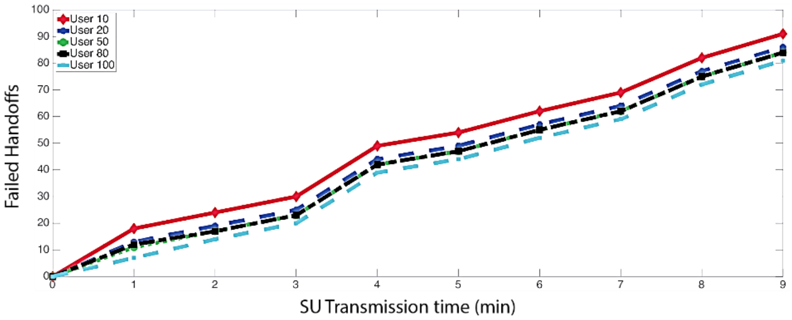
a. Wi-Fi RT HT



b. Wi-Fi RT LT



c. Wi-Fi BE HT



d. Wi-Fi BE LT

Figure 2. Failed handoffs for VIKOR algorithm in collaborative Wi-Fi networks

4. CONCLUSION

According to the results obtained, the level of collaboration between SU is directly proportional to the performance of the algorithm. However, the improvement rate is not significantly high. An increase in the collaboration level between SU by 1000% (going from 10% to 100%) only achieves an improvement in throughput between 5 and 7% approximately. The previous statement implies that a collaboration level of 10% is sufficient to deliver convenient results in terms of throughput.

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