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COMPARATIVE EVALUATION OF SPECTRAL HANDOFF MODELS

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Abstract

Currently there are several proposals for spectral handoff models for cognitive radio networks, each useful within the scenario for which it was designed. The present work presents a comparative evaluation of five spectral handoff models: Deep Learning, FFAHP, SAW, TOPSIS and VIKOR, which are validated based on five evaluation criteria: total handoffs, failed handoffs, bandwidth, delay and throughput, under two high and low traffic scenarios. The results show a variable performance in the evaluation criteria by each of the handoff models, suggesting an adaptive multi-model as a proposal.

Keywords: Handoff, Spectrum, MCDM, Cognitive radio, Evaluation metrics.

I. INTRODUCTION

The growth of wireless applications poses new challenges in future communication systems, according to Cisco, mobile data traffic has grown 18 times in the last 5 years and total mobile data traffic is expected to grow to 49 exabytes per month by in 2021 [1]–[6]. This, together with the fact that the current allocation policies are fixed and regulated by the state [7], have caused the radioelectric spectrum to present shortage problems.

However, temporal and geographical studies carried out by the Federal Communications Commission of the United States [8] show that much of the radio frequency spectrum is being used inefficiently. Additionally, measurements made in recent research [1], [2] show that more than 70% of the spectrum is available [8], [9].As a result of the inefficient use of the radioelectric spectrum, there are saturated bands and others little used.

The inefficient use of the spectrum has promoted the use of strategies to mitigate this problem [10]. Cognitive Radio (CR) arises as a technology to overcome the problem, through dynamic access to the spectrum and is characterized by perceiving, learning, planning (decision-making) and acting in accordance with current network conditions.

The National Information and Communications Administration defines CR as a radio or system that detects its electromagnetic operating environment and dynamically and autonomously adjusts its radio operating parameters to modify the operation of the system, to maximize performance, reduce interference and facilitate interoperability. Unlike traditional networks, in CR there are two types of users, the user who accesses the frequency bands in a licensed manner, called licensed or Primary User (PU), and the unlicensed user or Secondary User (SU) who uses the spectrum opportunistically [11], [12].

This work presents a comparative evaluation of five validated spectral handoff models based on five evaluation metrics: total handoff, missed handoff, bandwidth, delay and throughput, for both high and low spectral traffic.

II. HANDOFF MODELS

The analysis and comparative evaluation were carried out with five different spectral handoff models: VIKOR, TOPSIS, SAW, FFAHP and DEEP LEARNING; which are described below.

II.I Multi-Criteria Optimization and Compromise Solution - VIKOR

"The VIKOR method assumes that each alternative is evaluated according to each criterion function, and the classification can be developed by comparing the measures that are closest to the ideal alternative" [13]–[15]. VIKOR was developed to achieve the optimization of complex systems with multiple criteria, therefore, it is able to determine the commitment in a ranking list, even in the presence of conflicting criteria, which makes it a suitable algorithm for decision making in the SA [16].

The VIKOR algorithm follows the steps described in [13], [17]–[19]. For each decision criterion, the best and worst value is determined taking into account whether they are benefits or costs. Then the values of Q_i for i= 1, 2, 3, …, M, given by equation (1).

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

Given the values of Q for all the i belonging to M, the SO candidates are classified from highest to lowest. Finally, the selected SO is given by the optimal Q.

In [13] VIKOR is used to select the best OS in the uplink of the GSM frequency band, evaluating the level of handoff blocks, and comparing the results with two other SA algorithms.

II.II Technique for Order Preference by Similarity to Ideal Solution – TOPSIS

The development of this algorithm is based on the determination of two components: the ideal solution of the system, and the solution that cannot be accepted in any situation. To achieve this, it is necessary to compare the results obtained to determine which solution is the closest possible to the ideal, and which is the furthest (which will not be accepted). This metric is obtained from the Euclidean distance [19], [20].

The procedure of the TOPSIS algorithm is described in [19]–[21]. Initially the decision matrix X is constructed and normalized using the square root method, then the ideal solution and the worst solution are determined. Subsequently, for each alternative the Euclidean distance D is calculated, and finally, the alternatives are organized in descending order according to the preference index given by equation (2).

$$C_i^+ = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i = 1, \ldots, N. \tag{2}$$

In [14] TOPSIS is used to select the best SO by evaluating the level of interference per adjacent channel and the average number of handoffs performed, the results are compared with another algorithm and its respective versions when combined with three prediction algorithms based on series of weather.

II.III Simple Additive Weighting – SAW

This algorithm develops a decision matrix made up of attributes and alternatives, for each intersection of the matrix the algorithm assigns a weight according to the designer's criteria. This makes it possible to establish a rating for each of the SO evaluated, and thus obtain a ranking of all the alternatives. The OS with the highest score will be the one selected [19], [20] The alternative Ai is defined by equation (3) [21].

$$u_i = \sum_{j=1}^{M} \omega_i r_{i,j} \quad \forall i \in 1, \ldots, N \tag{3}$$

Where ri, j belongs to the matrix and the sum of the weights is 1.

The steps to develop this algorithm are: (1) identify the objectives and alternatives; (2) evaluate the alternatives; (3) determine the weights of each combination; (4) add the added values according to preferences; and (5) analyze the sensitivity [19]–[22].

In [23] SAW is used to select the best OS in a GSM frequency band, evaluating the amount of handoff performed and comparing the results with two other SA algorithms.

II.IV Feedback Fuzzy Analytic Hierarchical Process - FFAHP

FFAHP is based in FAHP [24] and is described in detail in [25]. “FFAHP aims to increase the accuracy in the selection of the spectral opportunity by feeding back the information from past evaluations. The selection of the spectral opportunity is made based on the evaluation of the current spectrum information plus past evaluations. FFAHP evaluates each available spectral opportunity using the equation (4).

$$Score_i = AP \times 0.3593 + ETA \times 0.2966 + SINR \times 0.1970 + BW \times 0.1471 \tag{4}$$

Where Scorei is the score assigned to the spectral opportunity i. The evaluation score range is between 0 and 100, with 100 being the best possible score. AP is the probability of availability, ETA is the estimated time of availability, SINR is the signal-to-noise ratio plus interference and BW is the bandwidth.

In this stage of the process, it is obtained a ranking of each of the spectral opportunities available based only on the current information regarding the decision criteria. However, the opportunity with the best assessment at this moment may not be the final selection, because this evaluation is weighted with evaluations in the past. The feedback process receives current assessments (CA) of each spectral opportunity and it weighs them up with the last evaluation (LE) and with the average evaluations (AE) which are carried out in the last minute. This weighting results in the final ranking of spectral opportunities as expressed in Equation 5.

$$Final\_Score_i = \alpha \times CA + \beta \times LE + (1 - \alpha - \beta) \times AE \tag{5}$$

Where α and β ϵ [0,1] characterize the weighting of CA, LE, and AE, and then, the Final_Scorei is the result of the final evaluation of the spectral opportunity i. " [25].

II.V Deep Learning

The Deep Learning algorithm used in this research is described in detail in [26].

III. RESULTS

The Fig. 1 to Fig. 5 describe the AAH, AAFH, ABW, AAD and AAT evaluation metrics for the non-predictive models: FFAHP, VIKOR, TOPSIS, SAW and Deep Learning, during a 9-minute transmission, with a HT trace. and LT, in a GSM network. Tables 1 and 2 show the comparative percentages of the evaluation metrics for each non-predictive model, with a trace of HT and LT, in a GSM network.

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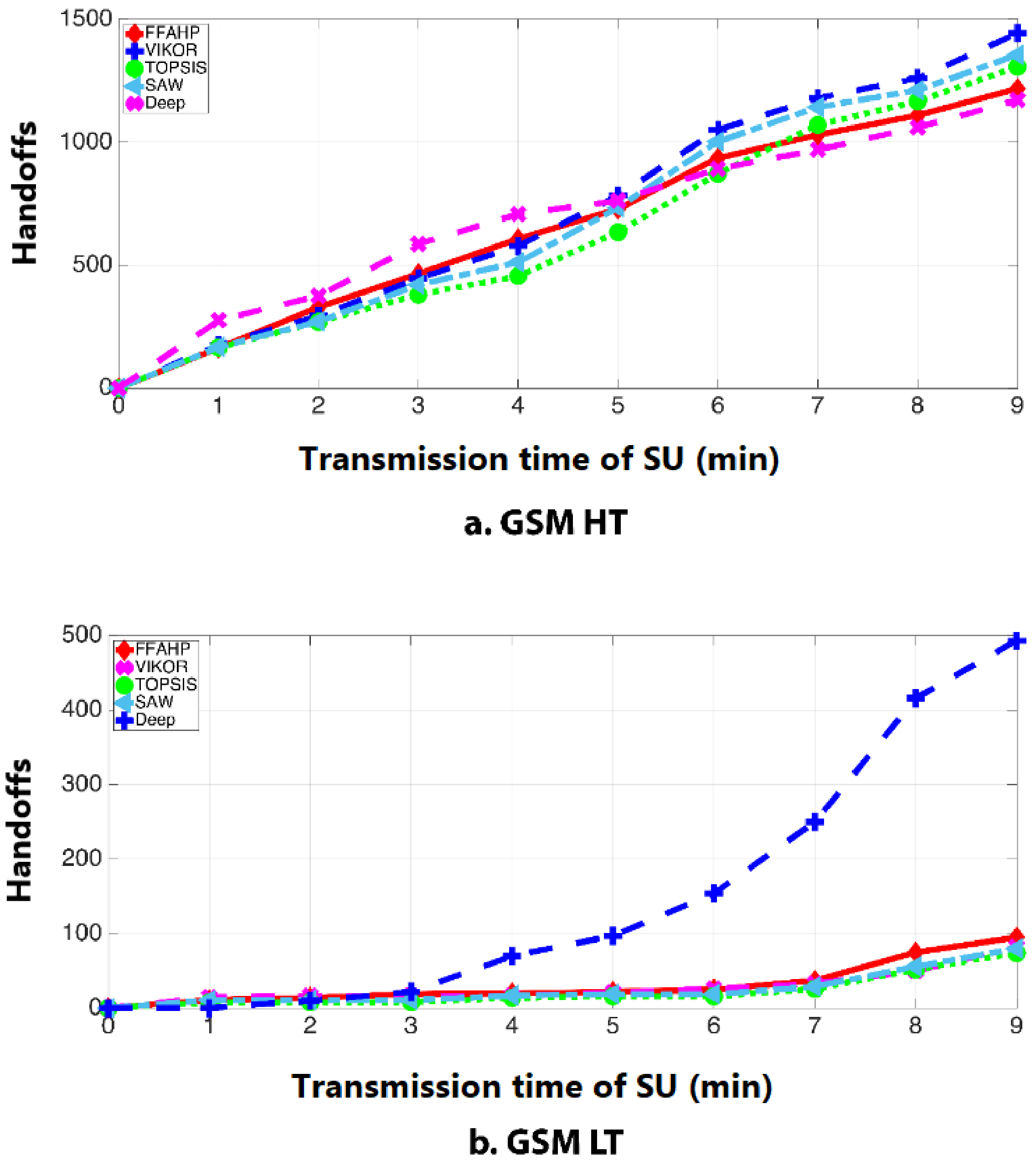


Fig. 1. AAH of Non-Predictive Models in GSM for HT and LT

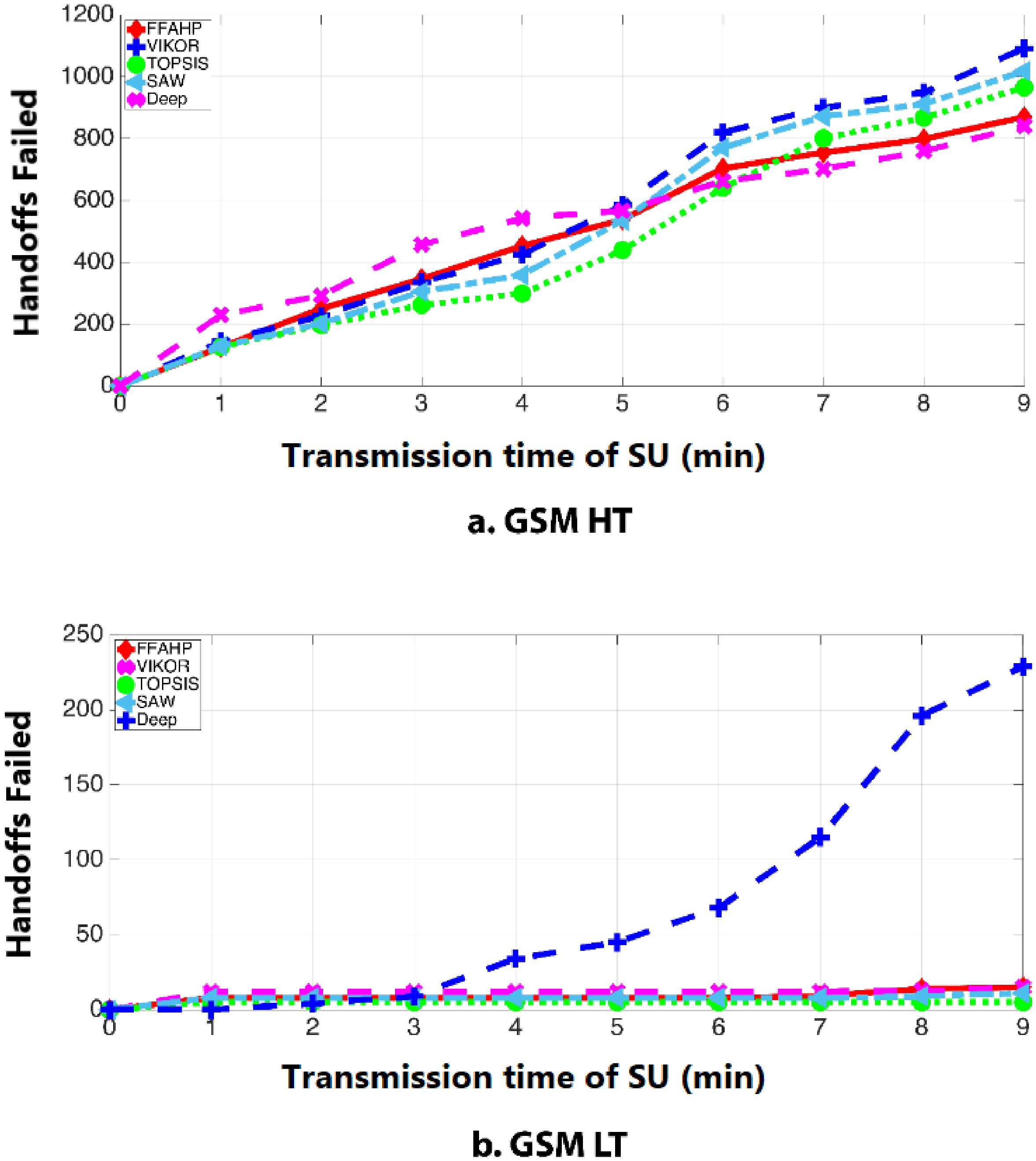
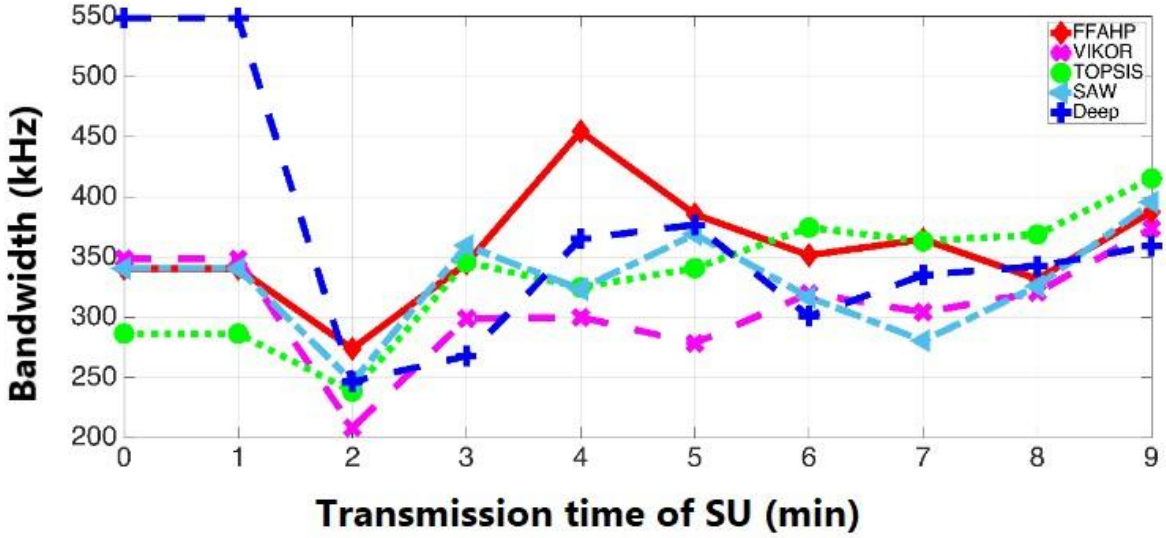
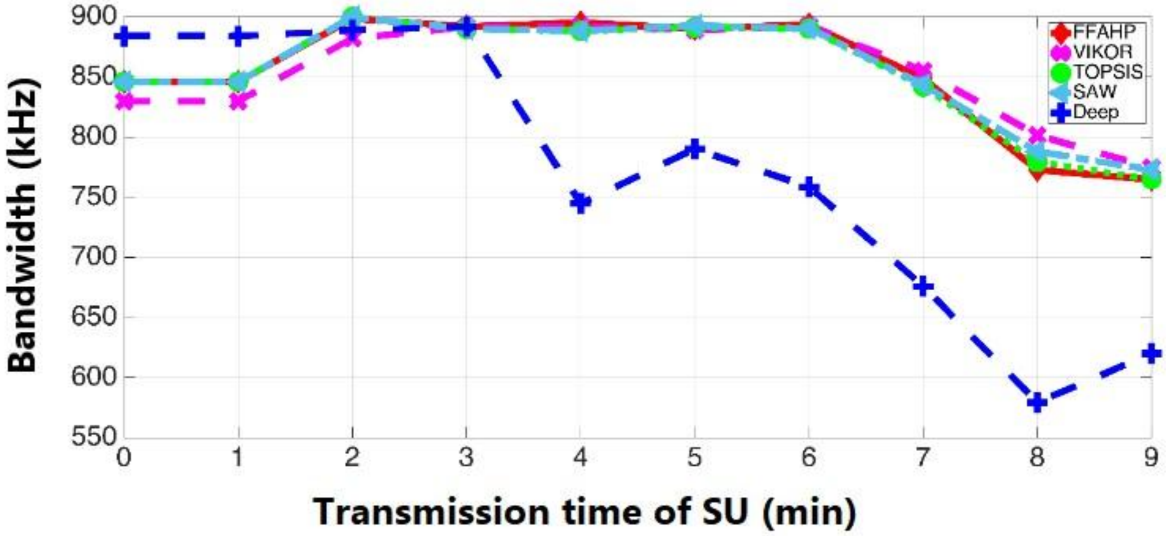


Fig. 2. AAFH of Non-Predictive Models in GSM for HT and LT



a. GSM HT



b. GSM LT

Fig. 3. ABW of Non-Predictive Models in GSM for HT and LT

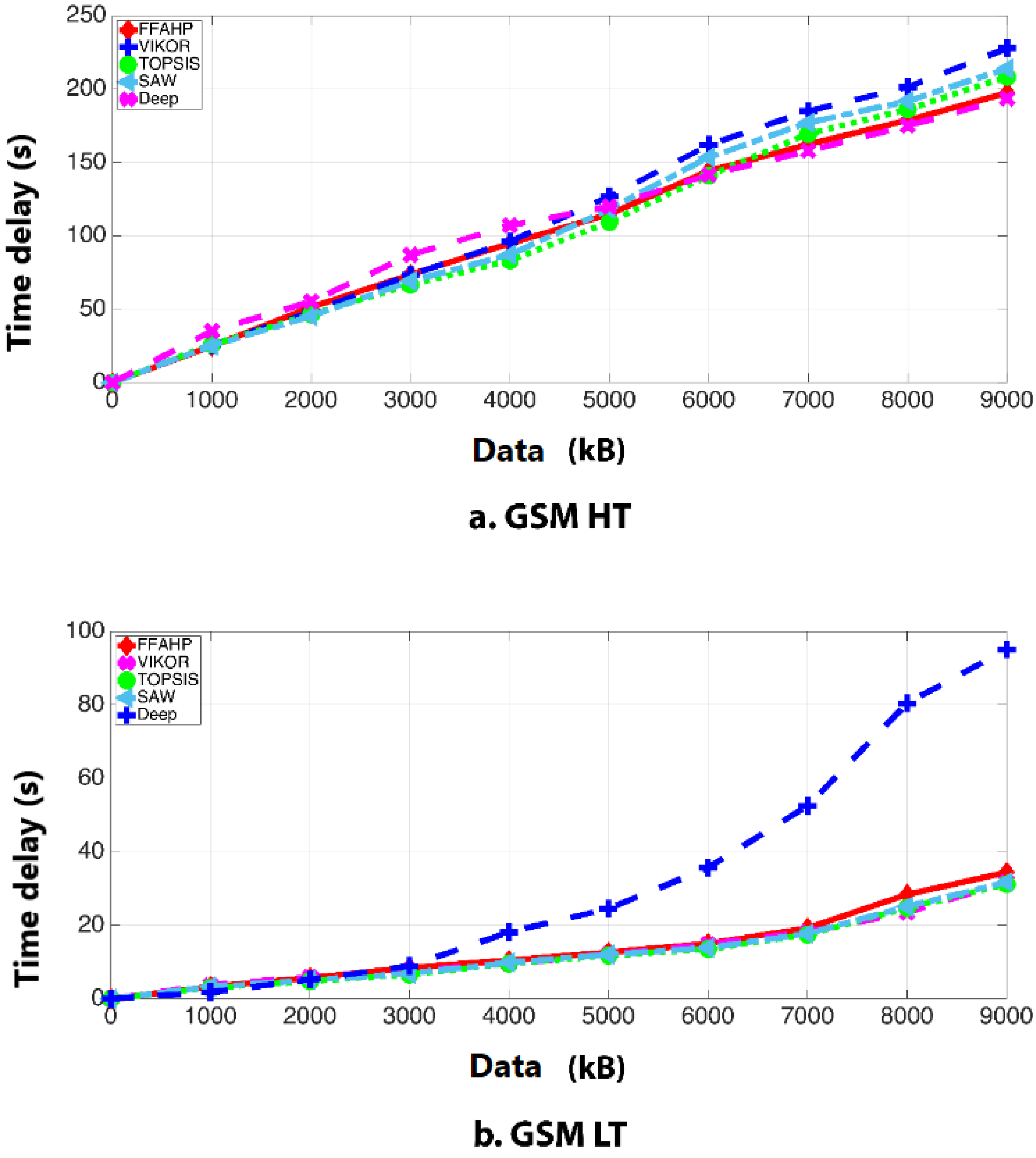
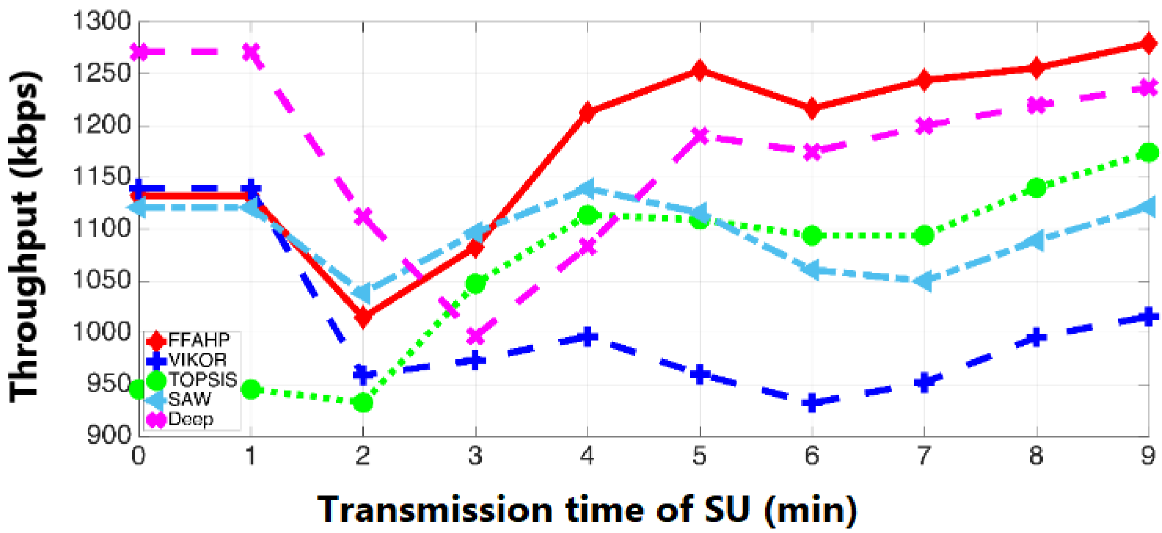
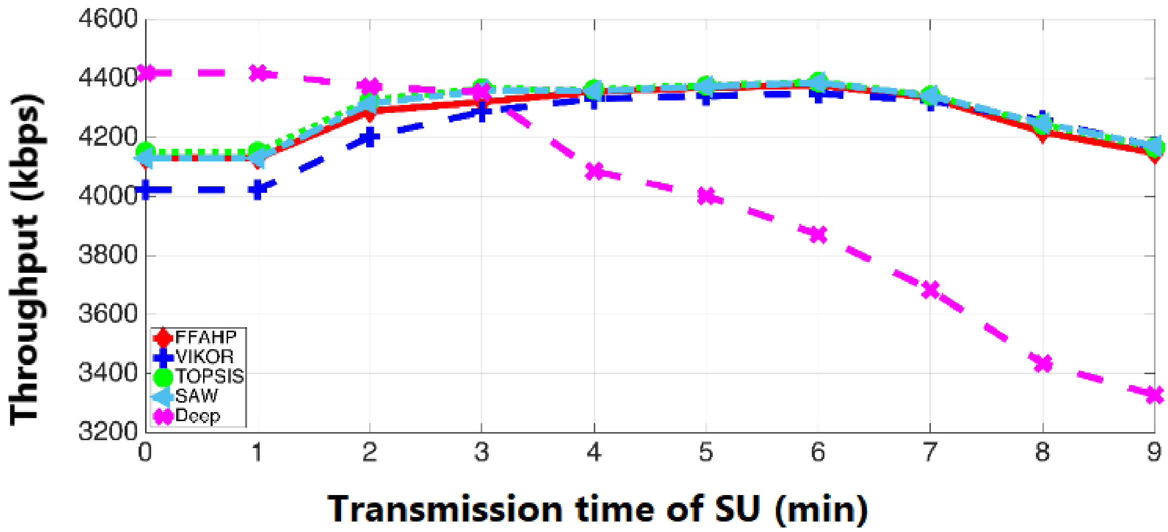


Fig. 4. AAD of Non-Predictive Models in GSM for HT and LT



a. GSM HT



b. GSM LT

Fig. 5. AAT of Non-Predictive Models in GSM for HT and LT

Table 1. Relative values of the metrics for Non-Predictive Models in GSM with HT

Métrica de Evaluación	FFAHP	SAW	TOPSIS	VIKOR	Deep Learning
AAH	96,22	86,43	89,67	81,16	100
AAFH	96,67	82,53	87,06	77,01	100
ABW	96,86	89,34	90,56	84,01	100
AAD	98,07	100	92,94	90,46	84,94
AAT	100	87,72	91,79	79,44	96,72
Score	**97,56**	**89,2**	**90,4**	**82,42**	**96,33**

Table 2. Relative values of the Non-Predictive Models metrics in GSM with LT

Métrica de Evaluación	FFAHP	SAW	TOPSIS	VIKOR	Deep Learning
AAH	77,89	92,5	100	90,24	15,01
AAFH	33,33	45,45	100	33,33	2,18
ABW	99,88	100	39,07	99,78	90,18
AAD	90,75	98,27	100	98,27	32,82
AAT	99,4	100	99,86	99,93	79,75
Score	**80,25**	**87,24**	**87,79**	**84,31**	**43,99**

IV. DISCUSSION

For the evaluation of the non-predictive models, four multi-criteria techniques (FFAHP, VIKOR, TOPSIS, SAW) and Deep Learning were implemented. For the level of HT traffic, the results are presented in Table 2, according to the cost and benefit criteria of each of the metrics, Deep Learning obtains the best performance with respect to multi-criteria techniques with a score of 96.33%, FFAHP obtains the second best performance, TOPSIS, VIKOR and SAW the third, fourth and fifth performance respectively. Regarding the individual evaluation metrics, for the two models with the highest scores (Deep Learning and FFAHP), the average difference between metrics is 3.38%, except AAD, where Deep Learning obtains the poorest performance, for this metric, the difference is 13.13%. Between the model with the highest score (Deep Learning) and the lowest score (VIKOR), the average difference between metrics is 18.76%, except AAD, for this metric, the difference is 5.52%.

For the LT traffic level, the results are presented in Table 2, unlike HT and according to the cost and benefit criteria of each of the metrics, Deep Learning and FFAHP obtain the lowest performance compared to TOPSIS, VIKOR and SAW. TOPSIS obtains the highest score with 87.29%, SAW the second with 87.24%, finally VIKOR with 84.31%. Regarding the individual evaluation metrics, for the three models with the highest scores (TOPSIS, VIKOR and SAW), it is not feasible to obtain an average difference between metrics because there are no variations over the same range.

V. CONCLUSIONS

According to the results obtained in the spectral allocation model, it can be concluded that there is no algorithm that performs excellently in all evaluation metrics and for all simulation scenarios (traffic level, type of application, type network). According to the results in scenarios with high traffic, the models with the best performance are Deep Learning and FFAHP, since Deep Learning requires a higher computational cost, the best option for high traffic would be FFAHP. In the case of scenarios with low traffic, the models with the best performance are SAW, TOPSIS and VIKOR, of which SAW has the lowest computational cost, being the best option for low traffic. The performance validation of the compared models was carried out through real spectral occupation data captured in experiments carried out in the GSM frequency band.

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