A Fuzzy-Genetic Approach for 5G/6G Opportunistic Slicing

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***Abstract*—Network Slicing (NS) and Dynamic Spectrum Access are two key-technologies for 5G/6G networks since they enable a myriad of services coexisting on the same wireless infrastructure through different virtual networks (slices) and deal with the spectrum needs to support the expected amount of mobile traffic. When combined, they allow Opportunistic Slices (OSs) and Primary Slices (PSs) to share resources in such a way that the former only accesses resources when the latter are not occupying them. Defining which physical resources will be allocated is a NP-hard problem. This work addresses the Opportunistic Slicing Mapping Problem and proposes a Fuzzy-Genetic solution in which GA individuals are evaluated by a fuzzy system. In addition, a metric denoted as Effective opportunistic Use is defined to capture the exploration degree of transmission opportunities by the OSs. Our scheme is analyzed in terms of interference, blocking, and dropping probabilities and effective opportunistic use and compared to our previous GA approach.**

***Keywords*—5G and 6G Networks, Network Slicing, Cognitive Radio, Genetic Algorithms, Fuzzy System**

I. Introduction

The Fifth Generation (5G) of Mobile Networks aims at supporting a plurality of services such as autonomous vehicles, ultra-high definition video streaming and Internet of Things (IoT), which are categorized into Ultra-reliable and Low Latency Communication (URLLC), enhanced Mobile Broadband (eMBB) and massive Machine Type Communication (mMTC) [1]. In consonance with the 5G deployment, studies on the sixth generation (6G) have already been issued, where new verticals (e.g. holographic communications) and key-technologies (e.g. terahertz communication) are put in perspective [2]. To deal with this diversity, the 5G/6G network architectures are evolving from the current “one-fits-all” design model to a more customized and dynamically scaling one that enables the deployment of parallel systems, tailored to the service requirements on top of a shared infrastructure and network slicing is seen as an enabler since different virtual networks (slices) can run on the same wireless infrastructure [3]

Moreover, 5G/6G networks are expected to face a great amount of mobile traffic and connections (e.g. 14.7 billion M2M connections by 2023 [4]), which requires that network operators increase their system capacity, demanding for spectrum resources. Millimeter wave (mWave) [1] and Terahertz communications [2] have been considered in 5G and 6G to address this issue, but due to high path loss, signal strength can be severely reduced in non-line-of-sight scenarios [6]. Another solution is to apply the dynamic spectrum access policy to the sub 6 GHz underutilized (e.g. TV bands) in a non-interference base, being cognitive radio (CR) an enabler.

Combining CR and network slicing allows extending virtualization from the higher layer (e.g. enabled by Software Defined Networking and Network Function Virtualization technologies) to the lower one (e.g. MAC/PHY) and enables the opportunistic use of radio resources, allowing Opportunistic Slices (OSs) and Primary Slices (PS) to share resources in such way that the former only access the resources when the latter are not occupying them. In this respect, OSs may support non delay-critical applications or be used to boost the throughput of eMBB users anchored in cell networks. Defining which physical resources will be allocated to the slice, denoted as slice mapping onto physical substrate, is a NP-hard problem [7]. When it involves opportunistic radio resource sharing, the embedding process becomes more challenging because it must not only consider the service requirements to be placed in the OS but also the resource usage pattern by the PS in order to provide Quality of Service (QoS) to the opportunistic users (OUs) and avoid harmfull interference to the PS communication.

In our previous paper [8], we presented the Opportunistic Slice Mapping Problem (OSMP) and a GA-based solution in which classical techniques were adopted to handle multiple goals. This current work revisits the OSMP and proposes a Fuzzy-Genetic solution, where GA individuals are evaluated via fuzzy system. Our scheme eases to get the problem solution since it eliminates the need for the user to choose a final solution from a large number of possibilities [9], unlike Pareto sets-based approaches. Differently from [8] that evaluates the resource utilization level achieved by a given slice mapping via joint utilization metric, we define the effective opportunistic use one to clearly capture the exploration degree of the transmission opportunities by the OSs, which overcomes the problem of assigning a high value of utilization to a mapping that does not provide a reasonable opportunistic use. The remainder of this paper is organized as follows. Section II

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discusses some related works. The OSMP and fuzzy-genetic solution are defined in Section III. Results and Analysis are presented in Section IV. Section V concludes this work.

II. Related Work

Network slicing allows resource sharing among heterogeneous services in 5G/6G networks and has received great attention from industry and academia. For instance, [10] addresses the network slicing in the radio access network (RAN) by proposing a two-level hierarchical approach with network and gNodeB slicing. The former pre-allocates radio resources to each gNodeB in a large time scale, while in the latter, the pre-allocated resources are dynamically scheduled to services in response to the small time scale resource request variations. In [11], a RAN slicing strategy for a heterogeneous network with eMBB and vehicular services was investigated. The authors propose an off-line reinforcement learning scheme for allocating radio resources to the eMBB and V2X users, which aims at maximizing the network resource utilization. Although [10] [11] deal with resource provisioning in RAN slices under different time-scales, they do not consider opportunistic slices. Our previous work [8] addresses this lack and present the OSMP and a GA-based solution that evaluates the GA individual via classical techniques. The current work differs from [8] as it adopts a fuzzy system to evaluate the GA individuals and also defines the effective opportunistic use metric to capture the exploration degree of transmission opportunities by the OSs, overcoming the problem of assigning a high utilization value to a mapping that does not provide reasonable opportunistic use, which may happen in [8].

By using a hybrid Fuzzy-Genetic approach, the authors in [12] address the resource allocation for VANETs in 5G networks. They use the Fuzzy system to optimize the weights of the multi-objective function. To do so, the type of service (expressed in terms of delay, throughput, and cost) and a binary value are taken as inputs by the fuzzy system, which outputs the weights to be used in the multi-objective function. Similar to our proposal, the author in [9] adopts a fuzzy system to evaluate the GA individuals but addressing the single machine scheduling problem and focus on showing the fuzzy system feasibility to determine the fitness of GA individuals.

III. Proposal

A. The Wireless Environment

We consider a wireless environment made up of PSs and OSs that share resources from substrate networks (SNs). The SNs consist of spectrum bands, base stations (gNBs), core and backhaul facilities, and other features that compose the end to end networks [13]. In this work, we focus on the RAN, addressing the radio resource slicing. The PSs have higher priority to access the resources and are mapped without considering the OSs, which makes them able to support all 5G services categories. On the other hand, the OSs are mapped to operate via opportunistic resource sharing, with a lower access priority to the radio resource. In this respect, their users access the spectral resources opportunistically, when the PS users (PUs) are not using them. As consequence, the OSs are limited in terms of supported services, where offering delay-tolerant ones (e.g. some mMTC applications) or boosting the throughput of eMBB users anchored in 5G networks are options.

Network slicing resource provisioning may be seen as a two-stage process, mapping and operation. The former defines the amount of resources to be allocated to each slice, i.e., maps a set of resources to a set of users. It has a soft time-scale, defines which and how many slices are supported, and assists the SN provider in the infrastructure planning (e.g., expansion, prices, etc). The operation stage takes place when the slice is mapped and comprises resource allocation to the individual users in a hard time-scale, considering the resources defined in the mapping process. In this stage, each slice may apply its own allocation mechanism and policies to serve its users. This paper focuses on the first stage, dealing with the OS mapping.

The OS mapping is a NP-problem [8] and involves meeting the OS requirements but without causing excessive interference to the PSs. So, the opportunistic communication quality, the amount of interference to the PUs, and the effectiveness of the resource opportunistic use must be analyzed to properly select the resources to map each OS. Since the OSs are employed under an opportunistic usage-base, two events negatively affect their communications, the opportunistic user blocking and dropping. The first takes place when there is no available resource to meet an arriving OU, i.e., all OS resources are being used by PUs or other OUs. The second is caused when the PU accesses the resource that is being used by the OU with no more available resources in the OS. So, the OU releases the resource but does not find another one to resume its communication, being evicted from the OS.

The interference is caused when the PU and OU uses the same resource simultaneously, even in a short duration (e.g. within a transmission time interval in 5G networks), which occurs when the PU returns to a channel that is being used by the OU. So, the PU collides with the OU and both communications are degraded, being the latter more impacted due to the time spent in the spectrum handoff, i.e., vacating the current resource, finding another idle one and accessing it .

B. System Model

The system comprises a substrate network that has N radio channels to support PSs and OSs. The resources are allocated to the PSs according their demands, characterized by their PU arrival and service rates, with each channel capable of meeting a single user. To characterize the radio channel usage pattern by the PUs, we consider that the PU arrival at channel C_i follows a Poisson process with rate $\lambda_{PU,i}$ and that the service time is exponentially distributed with mean $1/\mu_{PU,i}$.

Given that the set of N radio channels $SC_l = \{c_1, c_2, ..., c_3\}$ be used to map an opportunistic slice l in with the user arrival follows a Poisson process with rate $\lambda_{OU,l}$ and the user holding time is exponentially distributed with rate $\mu_{OU,l}$ and that the PU service rate be homogeneous at the channels in SC_l, i.e., $\mu_{PU,l} = \mu_{PU,i}$, $\forall C_i \in SC_l$, the total PU arrival rate in the channels used by the slice l ($\lambda_{PU,l}$) is obtained by summing the individual rates $\lambda_{PU,i}$, $\forall C_i \in SC_l$, and the interaction between PSs and OSs may be represented by an M/M/N/N queue with preemptive-priority service, where PUs and OUs compete for channels [12], with the latter having lower access priority.

In our model, each state (i,j) denotes the number of PUs (i) and OUs (j) in the system. Furthermore, to derive useful metrics for the OS mapping analysis, the steady-state probabilities $\pi(i,j)$ are extracted solving the linear system formed by the normalization condition (1) and balance equations (2-8) depicted in Table I.

$$\sum_{i=0}^{N}\sum_{j=0}^{N-i}\pi(i,j) \tag{1}$$

C. Analysis Metrics

a) Interference Probability: The interference probability (Eq. 9) is the chance of a PU arrives/returns to a radio channel that is occupied by an opportunistic user [8], which degrades both communications and requires that the OU finds another channel to resume its communication. The first part (Eq.9) is the probability of PU arrival triggering a collision for sure (system is full with at least one OS present). The second one is the possibility of interference occurrence during the PU arrival even when the system is not full. Details about Eq. 9 are given in [8].

$$Ip_l = \sum_{j=1}^{N}\pi(N-j,j) + P_{back,l}\sum_{i=0,j=1}^{(i+j)<N}\pi(i,j) \tag{9}$$

$$P_{back,l} = \frac{1}{N}\sum_{i=1}^{N}\frac{\frac{\mu_{PU,i}-\lambda_{PU,i}}{\lambda_{PU,i}\mu_{PU,i}}}{\frac{\mu_{PU,i}-\lambda_{PU,i}}{\lambda_{PU,i}\mu_{PU,i}}+\mu_{SU,l}} \tag{10}$$

b) Blocking Probability: An opportunistic user is not admitted in the opportunistic slice l when all resources (SC_l) are busy, whose possibility of occurrence is given by Eq. 11.

c) Dropping Probability: When an PU arrives to a resource occupied by an OU, the OU has to leave the resource and find another one to resume its communication. However, if there is no another available resource in the OS l, the OU is evicted from the OS l. Eq. 12 describes the dropping probability as the ratio between the collision rate of PUs and OUs in a full system and the admitted opportunistic user rate.

d) Effective Opportunistic Use: The OS mapping must also achieve an effective use of the opportunities that emerge when the PU is not using the channel. To capture the level of effective use by the OS, we define the Eq. 13 that relates the overall opportunistic utilization to the level of opportunities available in the channels SC_l.

$$Bp_l = \sum_{i=0}^{N}\pi(N-i,i) \tag{11}$$

$$Dp_l = \frac{\lambda_{PU,l}\sum_{j=1}^{N}\pi(N-j,j)}{(1-Pb_l)\lambda_{SU,l}} \tag{12}$$

$$Ef_l = \frac{\frac{1}{N}\sum_{j=0}^{N}\sum_{i=0}^{N-j}j\pi(i,j)}{1-\frac{1}{N}\sum_{i=0}^{N}\sum_{j=0}^{N-i}i\pi(i,j)} \tag{13}$$

D. Formulation Problem

The OS mapping involves goals related to the opportunistic (blocking and dropping) and primary (interference) communications as well as to the infrastructure provider (effective use of resources). So, it may be formulated as a multi-objective problem as follows (Eq. 14). Given an OS request l with demand defined in terms of user arrival and service rates ($\lambda_{OU,l}$ users/s, $\mu_{OU,l}$ users/s) and the primary usage pattern of each resource (channel) C_i denoted by the PU arrival and service rates ($\lambda_{PU,i}$ and μ_{PU}), define the set of channels to map the OS l (SC_l) in order to minimize the blocking, dropping and interference probabilities and maximize the effective opportunistic use. In addition, two constraints must be satisfied: the resource amount allocated to the OS l cannot be less than the requested demand (product $\lambda_{OS,l} * \mu_{OS,l}$) and a common channel cannot be allocated to different OSs (inter-slice isolation constraint).

$$\begin{aligned}&Minimize\ Bp_l,\ Dp_l,\ Ip_l,\ and\ Maximize\ Ef_l\\&Subject\ to:\\&\qquad |SC_l| \geq \lambda_{OS,l} * \mu_{OS,l}\\&\qquad SC_l \cap SC_k = \oslash,\ with\ k \neq l\end{aligned} \tag{14}$$

E. The Fuzzy-Genetic Solution

A Fuzzy-Genetic solution is proposed for Eq. 14. The genetic algorithm (GA) is a search heuristic based on the Darwin's natural evolution theory of species, which applies genetic operators such as selection, mutation and crossover to evolve candidate solutions toward optimal or sub-optimal points [14]. Fuzzy logic is a technique that transforms the expert knowledge into a mathematical model via IF-THEN rules, which encompass linguistic variables defined by continuous membership functions [15]. Both techniques have been used to solve problems in 5G networks such as admission control [16] and service function chain placement [17].

a) GA Individual: Each individual x (candidate solution) in the GA is coded with a sequence of M bits, with M being the number of available channels. If the bit i, with $i = 1, 2, ..., M$, is set, then the channel c_i is allocated to the OS_l, i.e., $c_i \in SC_l$.

b) Fuzzy System - based Fitness Function : The individuals are evaluated via fuzzy system that takes the interference, blocking and dropping probabilities, and effective opportunistic use (defined in Section III-C) to compute their fitness values, as shown in Fig. 1. The designed fuzzy system consists of four components, Fuzzifier, Rule Base, Inference Engine, and Deffuzifier, which are described as follows.

1) **Fuzzifier**: performs the mapping of input variable values (given in the real/crisp domain) into fuzzy sets. These sets denote the linguist values assumed by the variables and are given by membership functions [15]. We defined

TABLE I
BALANCE EQUATION DESCRIPTION

Eq. Number	Equation	State(s) (i,j)	Condition	Meaning
(2)	$N\mu_{PU,l}\ \pi_{(N,0)} = \lambda_{PU,l}\ \pi_{N-1,0} +_{PU,l}\ \pi_{N-1,1}$	$(N,0)$	n/a	*All resources are occupied by PUs*
(3)	$(\lambda_{PU,l}+\lambda_{OU,l})\pi_{0,0} = \mu_{PU,l}\pi_{1,0}+\mu_{OU,l}\pi_{0,1}$	$(0,0)$	n/a	*The system is empty*
(4)	$(N\mu_{OU,l}+\lambda_{PU,l})\pi_{0,N} = \lambda_{OU,l}\pi_{0,N-1}$	$(0,N)$	n/a	*All resources are occupied by OUs*
(5)	$(i\mu_{PU,l}+\lambda_{OU,l}+\lambda_{PU,l})\pi_{i,0} = \lambda_{PU,l}\pi_{i-1,0} +(i+1)\mu_{PU,l}\pi_{i+1,0} +\mu_{OU,l}\pi_{i,1}$	$(i,0)$	$1 \leq i \leq N-1)$ *and* $N > 1$	*Only PUs are using some resources*
(6)	$(j\mu_{OU,l}+\lambda_{PU,l}+\lambda_{OU,l})\pi_{0,j} = \lambda_{OU,l}\pi_{0,j-1} +\mu_{PU,l}\pi_{1,j} +(j+1)\mu_{OU,l}\pi_{0,j+1}$	$(0,j)$	$(1 \leq j \leq N-1)$ *and* $N > 1$	*Only OUs are using some resources*
(7)	$((N-j)\mu_{PU,l}+j\lambda_{OU,l}+\lambda_{PU,l})\pi_{N-j,j} = \lambda_{PU,l}\pi_{N-j-1,j} +\lambda_{PU,l}\pi_{N-j-1,j+1} +\lambda_{OU,l}\pi_{N-j,j-1}$	$(N-j,j)$	$(1 \leq j \leq N-1)$ *and* $N > 1$	All resources are occupied by PUs and OUs
(8)	$(j\mu_{OU,l}+\lambda_{PU,l}+\lambda_{OU,l}+i\mu_{PU,l})\pi_{i,j} = (j+1)\mu_{OU,l}\pi_{i,j+1}+\lambda_{PU,l}\pi_{i-1,j}+\lambda_{OU,l}\pi_{i,j-1}+(i+1)\mu_{PU,l}\pi_{i+1,j}$	(i,j)	$(1 \leq j \leq N-2)$, $1 \leq i \leq N-j-1$ *and* $N > 2$	*The system is not full but there are at least one PU and one OU*

the fuzzy sets "Low","Medium" and "High" for each input variable, whose membership functions are given in Table II. They assign a degree of membership (between 0 and 1) to a given crisp value y in each set. We adopted the singleton fuzzifier in our system [15].

2) **Rule Base**: comprises if-then rules that embody the knowledge about the OS mapping problem. They involve the input and output variables and their linguist values (fuzzy sets) and are handled by the inference engine to define the fuzzy output. The rules of our our fuzzy system are shown in Fig. 2 and have the format " ***IF** Ip is ip and DPL is dpl and BPL is bpl and EF is* ***THEN*** *Fitness is fitness*", with *ip, dpl, bpl* and *ef* being the linguist values *Low (L), Medium (M)* or *High (H)* and *fitness* meaning *Very Low (VL), Low, Medium, High* or *Very High (VH)*. The rules were obtained by combining all linguist values of the input variables in the antecedent part and assigning the proper output fuzzy set in the consequent one, resulting in 81 rules.
3) **Inference Engine**: combines the fuzzy rules into a mapping from input fuzzy values into output one. We adopted the mandani inference engine [15], which uses the minimum implication operator in the antecedent-consequent relationship. Moreover, the outputs from different rules are aggregated via maximum operator [15].
4) **Defuzzifier**: translates the fuzzy output set from the inference engine into real values via membership functions. We used the centroid defuzzifier in our system, which determines the output crisp value (fitness) based on the center of the area a covered by the output fuzzy set [15]. In our system fuzzy, the output variable (fitness) may assume four different linguist values (fuzzy sets) with membership functions defined in Table III.

c) The Genetic Operators: similar to our previous work [8], we adopted the roulette wheel to select the individuals for the crossover process, which assigns more chances of selection to individuals that have higher fitness values [14]. Moreover, the uniform crossover and bit mutation also were considered to combine the characteristics of two solutions (parents) to generate a new solution (offspring) and maintain the genetic diversity throughout the generations, respectively, with crossover and mutation probabilities of 0.7 and 0.01 [8].

d) Workflow: our fuzzy-genetic scheme works as follows. Given an OS mapping request, an initial population of candidate solutions is generated randomly. After that, the individuals are evaluated via fuzzy system that takes into account their values of blocking, dropping and interference probabilities and effective opportunistic to define their fitness ones. Then, the selection, crossover and mutation take place to evolve the individuals and an elitist strategy is employed to ensure that the best fitness individual will survive throughout evolution process. Finally, a new population is formed and the stopping criterion is checked. If it is not satisfied, then the process repeats from the fitness evaluation stage. Otherwise, the best individual is chosen as solution to the OS problem, i.e., the set of radio resources to be used to map the target OS. Here, we used the number of generations as stopping criterion.

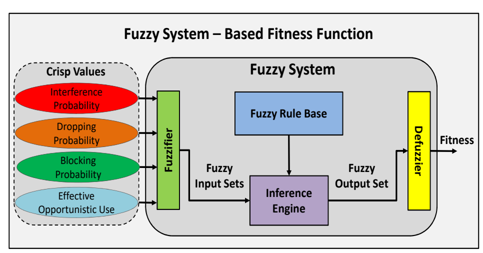


Fig. 1. Fuzzy System-based Fitness Function

IV. RESULTS

To evaluate the proposed scheme (Fuzzy-AG) in comparison to our previous work [8], called GA, two scenarios were considered. The first one considers an environment with different PU loads and, consequently, distinct opportunistic use levels. To do so, the channel primary use (via PU arrival rate, λ_{PU}) was set for two ranges ([0 0.5] and [0.5 1.0]), resulting in two

TABLE II
MEMBERSHIP FUNCTIONS OF THE FUZZY SETS FOR INPUT VARIABLES

Set / Variable	Low	Medium	High
Interference probability	$Ip_L(y) = \begin{cases} 0, y < 0 \\ -5y + 1, 0 \leq y \leq 0.2 \\ 0, y > 0.2 \end{cases}$	$Ip_M(y) = \begin{cases} 0, y < 0 \\ 5y, 0 \leq y \leq 0.2 \\ -5y + 2, 0.2 \leq y \leq 0.4 \\ 0, y > 0.4 \end{cases}$	$Ip_H(y) = \begin{cases} 0, y < 0 \\ -5y + 1, 0.2 \leq y \leq 0.5 \\ 1, 0.5 \leq y \leq 1 \\ 0, y > 1; \end{cases}$
Dropping Probability	$Dp_L(y) = \begin{cases} 0, y < 0 \\ 1, 0 \leq y \leq 0.05 \\ (-y + 0.2)/0.15, 0.05 \leq y \leq 0.2 \\ 0, y > 0.2 \end{cases}$	$Dp_M(y) = \begin{cases} 0, y < 0.05 \\ (y - 0.05)/0.15, 0.05 \leq y \leq 0.2 \\ (-y + 0.35)/0.15, 0.2 \leq y \leq 0.35 \\ y > 0.2 \end{cases}$	$Dp_H(y) = \begin{cases} 0, y < 0.2 \\ 2y - 0.4, 0.2 \leq y \leq 0.7 \\ 1, 0.7 \leq \ y \leq 10, y > 1 \end{cases}$
Blocking Probability	$Bp_L(y) = \begin{cases} 0, y < 0 \\ -5y/0.15 + 1, 0 \leq y \leq 0.15 \\ 0, y > 0.15 \end{cases}$	$Bp_M(y) = \begin{cases} 0, y < 0.05 \\ 10y - 0.5, 0.05 \leq y \leq 0.15 \\ -y/0.15 + 2, 0.15 \leq y \leq 0.3 \\ 0, y > 0.3 \end{cases}$	$Bp_H(y) = \begin{cases} 0, y < 0.15 \\ (y - 0.15)/0.35, 0.15 \leq y \leq 0.5 \\ 1, 0.5 \leq y \leq 1 \\ 0, y > 1 \end{cases}$
Effective Oppor-tunistic Use	$Ef_L(y) = \begin{cases} 0, y < 0 \\ 1, 0 \leq y \leq 0.15 \\ -4y + 1.6, 0.15 \leq y \leq 0.4 \\ 0, y > 0.4 \end{cases}$	$Ef_M(y) = \begin{cases} 0, y < 0.15 \\ (y - 0.15)/0.25, 0.15 \leq y \leq 0.4 \\ -4y + 1.6, 0.4 \leq y \leq 0.65 \\ 0, y > 0.65 \end{cases}$	$Ef_H(y) = \begin{cases} 0, y < 0.4 \\ (y0.45)/0.45, 0.15 \leq y \leq 0.4 \\ 1, 0.85 \leq y \leq 1 \\ 0, y > 1 \end{cases}$

TABLE III
MEMBERSHIP FUNCTIONS OF THE FUZZY SETS FOR THE OUTPUT VARIABLE (FITNESS)

Set	Membership Function
Very Low	$F_{VL}(y) = \begin{cases} 0, y < 0 \\ 1, 0 \leq y \leq 0.1 \\ -10y + 2, 0.1 \leq y \leq 0.2 \\ 0, y > 0.2 \end{cases}$
Low	$F_L(y) = \begin{cases} 0, y < 0.1 \\ 10y - 1, 0.1 \leq y \leq 0.2 \\ -10y + 3, 0.2 \leq y \leq 0.3 \\ 0, y > 0.3 \end{cases}$
Medium	$F_M(y) = \begin{cases} 0, y < 0.2 \\ 5y - 1, 0.2 \leq y \leq 0.4 \\ 1, 0.4 \leq y \leq 0.45 \\ -4y + 2.8, 0.45 \leq y \leq 0.7 \\ 0, y > 0.7 \end{cases}$
High	$F_H(y) = \begin{cases} 0, y < 0.55 \\ (y - 0.55)/0.15, 0.55 \leq y \leq 0.7 \\ -5y + 4, 5, 0.7 \leq y \leq 0.9 \\ 0, y > 0.9 \end{cases}$
Very High	$F_{VH}(y) = \begin{cases} 0, y < 0.7 \\ 5y - 0.35, 0.7 \leq y \leq 0.9 \\ 1, 0.9 \leq y \leq 1 \\ 0, y > 1 \end{cases}$

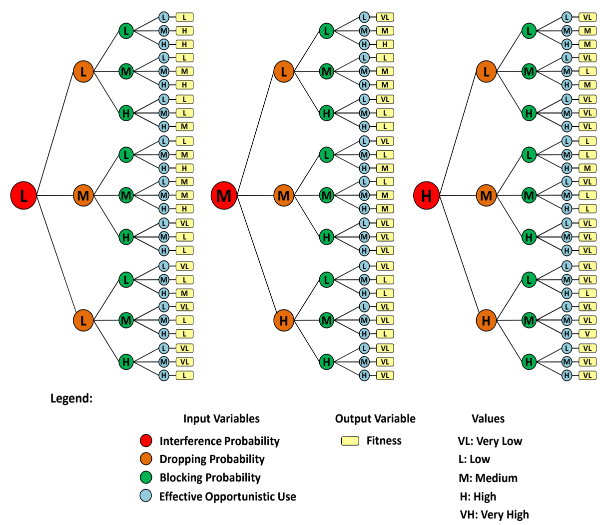
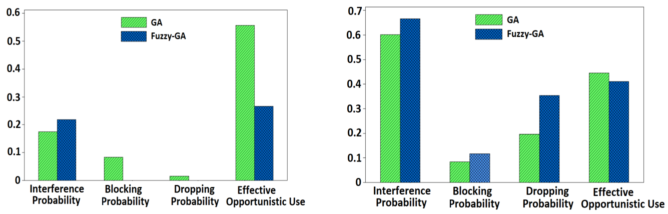


Fig. 2. Fuzzy Rule Base

cases. The former presents channels with low primary activity and more chances to be opportunistically used by the OS users. The latter is composed of channel with high PU activity.

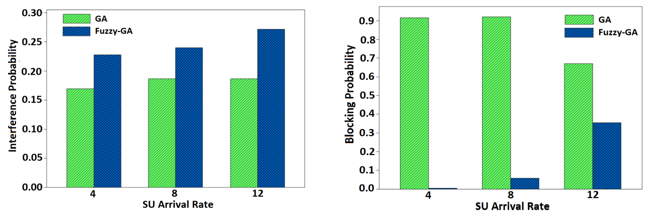
The second scenario analyzes the OS mapping schemes under different OS loads, with the OU arrival rate (λ_{OU}) assuming the values 4, 8 and 12. For all scenarios, unless otherwise stated, the PU arrival rate is uniformly distributed within [0 1], PU and OS service rates are set in 1, the OS user arrival rate is defined as 5, and the total number of radio resources/channels (N) was defined as 50. The average interference, blocking and dropping probabilities and effective opportunistic are given with a 95% confidence level. In both approaches, the number of generations, population size and crossover and mutation probabilities were set as 15, 100, 0.7 and 0.01, respectively.

Fig. 3a presents the scheme results when the PU load is low, i.e., defined in [0 0.5]. We note that the Fuzzy-GA gets better results in terms of blocking and dropping probabilities, achieving values about $2.8x10^{-4}$ and $2.6x10^{-4}$, while the GA approach results in 0.0839 and 0.016, respectively. So, the Fuzzy-GA provides better quality of service to the opportunistic user. However, to achieve this great performance it got a slightly higher interference probability (about 0.04 higher) and a lower EOU when compared to the GA scheme. These different behaviors in terms of objectives favored by the schemes may be used to reflect the operator preferences during the mapping process, i.e., the focus to be considered (e.g. on OS quality of service or protection to the PU or better use of resources) and define the most suitable scheme to be adopted. For the high PU load (Fig.3b), the Fuzzy-GA scheme



(a) When the PU load is low (b) when the PU load is high.

Fig. 3. Scheme Results under Different PU Loads.



(a) Interference Probability (b) Blocking probability.

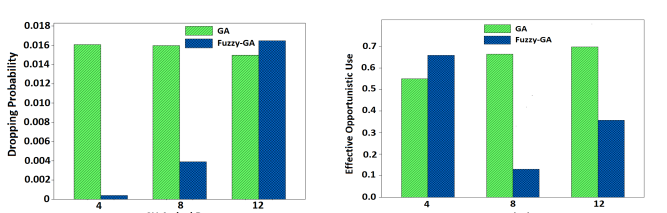
Fig. 4. Results in terms of Interference and Blocking Probability when the OS load varies.

had similar blocking probability and effective opportunistic use (difference less than 0.03) compared to the GA scheme. But when the interference and dropping probabilities are put in perspective, we note that the GA is the most effective.

Figs. 4 and 5 present the results achieved by the approaches under different SU loads. In general, Fuzzy-GA provides better quality of service to the opportunistic user since it achieves the lowest values for blocking and dropping probabilities, with an expressive difference when the SU load is 4 or 8. On the other hand, the GA approach achieves higher EOU and lower interference probability, which implies more protection to the PU and better use of radio resource, respectively.

V. Conclusion

This work addressed the OSMP and presented a Fuzzy-Genetic solution in which GA individuals were evaluated via fuzzy system. It also proposed the Effective Opportunistic Use metric to capture the exploration degree of transmission opportunities by the OSs. Our scheme was analyzed in terms of interference, blocking and dropping probabilities besides the effective opportunistic use and compared to our previous approach. Results showed that both GA and Fuzzy-GA schemes may be adopted to address the OSMP problem, being selected according to the operator preferences. Future directions include analyzing the performance of different 5G services categories when deployed onto OS and PS slices and incorporating hybrid slices, composed of resources that have opportunistic and non-opportunistic uses, in the slice mapping problem.



(a) Dropping Probability (b) Effective Opportunistic Use.

Fig. 5. Results in terms of Dropping Probability and Effective Opportunistic Use when the OS load varies.

References

[1] I. Parvez, A. Rahmati, I. Guvenc, A. I. Sarwat, and H. DaiJ, "A Survey on Low Latency Towards 5G: RAN, Core Network and Caching Solutions," IEEE Communications Surveys & Tutorials, vol. 20, 2018, pp.3098–3130.

[2] M. Giordani, M. Polese, M. Mezzavilla, S. Rangan and M. Zorzi, "Toward 6G Networks: Use Cases and Technologies," IEEE Communications Magazine, vol. 58, no. 3, pp. 55-61, 2020, doi: 10.1109/MCOM.001.1900411.

[3] I. Afolabi, A. Ksentini, Miloud Bagaa, T. Taleb, M. Corici, and A. Naka, " Towards 5G Network Slicing over Multiple-Domains," IEICE Transactions on Communications, vol. 100-B,pp. 1992-2006, 2017, doi: https://doi.org/10.1587/transcom.2016NNI0002.

[4] Cisco, "Cisco Annual Internet Report (2018-2023)", white paper available at https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.pdf, 2020.

[5] W. Khawaja, O. Ozdemir, Y. Yapici, F. Erden and I. Guvenc, "Coverage Enhancement for NLOS mmWave Links Using Passive Reflectors," IEEE Open Journal of the Communications Society, vol. 1, pp. 263-281, 2020, doi: 10.1109/OJCOMS.2020.2969751.

[6] S. Sirotkin,"5G Radio Access Network Architecture: The Dark Side of 5G", Wiley, 2020.

[7] A. Belbekkouche, M. M. Hasan, and A. Karmouch, "Resource discovery and allocation in network virtualization," IEEE Communications Surveys & Tutorials, vol. 14, no. 4, pp. 1114–1128, 2012.

[8] A. Balieiro, M. Falcão, K. Dias, "An Evolutionary Scheme for Secondary Virtual Networks Mapping onto Cognitive Radio Substrate", Wireless Communications and Mobile Computing, vol. 2019, doi: 10.1155/2019/1872765.

[9] D.M. Allard, "A Multi-Objective Genetic Algorithm To Solve Single Machine Scheduling Problems Using A Fuzzy Fitness Function", College of Engineering and Technology of Ohio University, Master Thesis, June 2007

[10] J. Li, W. Shi, P. Yang, Q. Ye, X. S. Shen, X. Li, J. Rao, "A Hierarchical Soft RAN Slicing Framework for Differentiated Service Provisioning," IEEE Wireless Communications, vol. 27, no. 6, pp. 90-97, 2020, doi: 10.1109/MWC.001.2000010.

[11] H. D. R. Albonda and J. Perez-Romero, "An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services", IEEE Access, vol. 7, pp. 44771-44782, 2019.

[12] A. A. Khan, M. Abolhasan, W. Ni, J. Lipman and A. Jamalipour, "A Hybrid-Fuzzy Logic Guided Gnenetic Algotithms (H-FLGA) Approach for Resource Optimization in 5G VANETs", IEEE Transactions on Vehicular Technology, vol 68, pp. 6964 - 6974, 2019, doi: 10.1109/TVT.2019.2915194

[13] M. Chahbar, G. Diaz, A. Dandoush, C. Cérin and K. Ghoumid, " Comprehensive Survey on the E2E 5G Network Slicing Model," IEEE Transactions on Network and Service Management, vol. 18, no. 1, pp. 49-62, 2021, doi: 10.1109/TNSM.2020.3044626.

[14] D.E. Goldberg, "Genetic Algorithms in Search, Optimization, and Machine Learning,", Addison-Wesley Publishing Company, 1953.

[15] L-X. Wang, "A Course in Fuzzy System and Control" Prentice-Hall International, 1996.

[16] T. Sigwele, P. Pillai, A. S. Alam, Y. F. Hu, "Fuzzy logic-based call admission control in 5G cloud radio access networks with preemption", Journal on Wireless Communications Network, 2017, doi: 10.1186/s13638-017-0944-x.

[17] B. Pradhan, V. Vijayakumar, S. Pratihar, D. Kumar, K. H. K. Reddy, D. S. Roy, "A genetic algorithm based energy efficient group paging approach for IoT over 5G ", Journal of Systems Architecture, vol. 113, 2021, doi: 10.1016/j.sysarc.2020.101878.