An Evolutionary Scheme for Secondary Virtual Networks Mapping onto Cognitive Radio Substrate

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Abstract

The Fifth Generation (5G) of wireless communication is envisioned to comprise heterogeneous applications, different radio access technologies (RATs) and a large demand for mobile traffic. In this respect, Wireless Virtualization (WV) and Cognitive Radio (CR) are put forward as 5G enablers for providing additional spectrum resources through dynamic spectrum access (DSA) techniques, besides dealing with heterogeneity with no hardware modification. By empowering the synergy between CR and WV, we visualize an environment denoted as Cognitive Radio Virtual Networks Environment (CRVNE) that encompasses VWNs with different access priorities, called Primary Virtual Networks (PVNs) and Secondary Virtual Networks (SVNs)that may be deployed in an overlay manner. In this scenario, the SVNs users (SUs) access the resources opportunistically, which naturally raises challenges towards the SVN mapping. In this paper, we revisit our previous letter that models the interactions between PUs and SUs in a CRVNE and analyzes a proposed formulation for collision probability during the SVN mapping process. The current work is pioneer as it presents a comprehensive approach to the SVNs mapping problem; models, validates and analyzes additional performance metrics such as SU blocking and SU dropping probabilities, and joint utilization; formulates the SVNs mapping as a multiobjective problem and proposes an evolutionary scheme based on Genetic Algorithms (GAs) to solve it. The results show that the proposed scheme outperforms the alternative method in terms of collision, SU dropping, SU blocking probabilities and joint utilization under different primary and secondary loads.

Keywords:
Cognitive Radio Virtual Networks Environment, Secondary Virtual Networks Mapping, Cognitive Radio, Wireless Virtualization, Genetic Algorithms

1. Introduction

The Fifth Generation (5G) of wireless communication is envisioned to comprise three service categories - enhanced mobile broadband (eMBB), massive machine-type communication(mMTC) and ultra-reliable and low latency communication(URLLC) - that have different requirements in terms of Quality of Service (QoS), Quality of Experience (QoE) and security [1]. To tackle this heterogeneity, Wireless virtualization (WV) is put forward as a key technology [2], since virtual wireless networks (VWNs) with different services may share the same wireless infrastructure.

Wireless virtualization comprises both spectrum and infrastructure sharing (e.g. base stations and access points). Spectrum sharing focuses on the air interface virtualization, i.e., how to schedule the spectral resources for VWNs. Some works such as [5][6] address spectrum sharing, but consider a strict resource allocation, i.e., the resources allocated to a VWN are not shared with another during operation, which may cause resource underutilization and revenue losses for the Mobile Network Operator (MNO), the owner of the physical resources. In this respect, opportunistic resource sharing has been raised in [7][8] as an alternative for solving such problem as it enables multiple flows from different VWNs to share common resources. However, little flexibility at the PHY and MAC layers have been achieved, since the VWNs mapping is tied to specific radio access technologies (RATs) [5], that is, the RAT adopted by VWNs is limited to that employed by the wireless infrastructure. In addition, there is no difference among VWNs in terms of access level to the resources (e.g. high and low priority VWNs). Therefore, these approaches do not address VWNs with different access priorities or RATs on the same wireless infrastructure.

Due to the mobile traffic increase, by 2020 it is expected that the demand should be two hundred times greater than the current moment [3]. Hence, the scarce electromagnetic spectrum must be made available and used efficiently to allow attending our future needs. Cognitive Radio (CR) has been envisioned as an enabler for the deployment of 5G systems as it focuses on the smart use of the spectrum through the dynamic spectrum access (DSA) techniques [4].

By combining wireless virtualization and CR, the deepest level of wireless virtualization can be achieved (spectrum based virtualization [9]). This combination provides isolation among VWNs at a low level [10], better resource utilization through DSA and grants VWNs with different RATs coexisting on same wireless infrastructure with no hardware modification. By empowering the synergy between CR and WV, we visualize an environment denoted as Cognitive Radio Virtual Networks Environment (CRVNE), in which VWNs with different access priorities to the resources, called Primary Virtual Networks (PVNs) and Secondary Virtual Networks (SVNs), may be deployed in an overlay manner, and share the same cognitive radio substrate. The SVNs users known as secondary users (SUs) only have access to the resources when the PVNs users, i.e., primary users (PUs), are not using them, avoiding to cause harmful interference to the PVN communication.

The PVNs are managed by Primary Service Providers (PSPs) and could offer any application type supported by wireless substrate such as multimedia and real time applications. Since the SVNs, which are managed by Secondary Service Providers (SSPs), may suffer preemption, they show some limitations on the supported types of application. In this respect, delay sensitive (e.g. URLLC services) or real time services might not work as expected on this type of network. On the other hand, best-effort services such as P2P downloading and web browsing could be offered. This scenario raises new challenges, ranging from mapping to operation, being this paper focused on the first (SVNs mapping).

Mapping VWNs onto wireless substrate (i.e., reservating/allocating physical resources from MNO to the VWNs) is a NP-hard problem [12] and current approaches only consider VWNs with homogeneous access priorities to the resources [5][6][7] or do not take into account opportunistic resource sharing [5][6]. Our problem is more challenging as it involves an environment composed of PVNs and SVNs that share common resources. In order to provide reasonable Quality of Service (QoS) to the SUs and avoid interference to the PVN transmission, the SVN mapping must not only consider the SVNs demand (e.g. bandwidth) but also the PVN activity. Differently from non-virtualized scenarios in which the resources are shared among individual users[9] and focus on channel selection/channel-user assignment in the network operation phase, the current environment addresses the resource allocation to multiple virtual wireless networks (group of users) during the dimensioning stage.

This paper deals with the SVN mapping problem. It revisits our previous letter [13] that models the interactions between PUs and SUs in a CRVNE and analyzes the proposed formulation for collision probability during the SVN mapping process. However, the current work is pioneer as it (1) presents a comprehensive approach to the SVNs mapping problem; (2) formulates, validates and analyzes additional performance metrics such as SU blocking and SU dropping probabilities, and joint utilization (to be used in the SVNs mapping); (3) formulates the SVNs mapping as a multi-objective problem; (4) proposes an evolutionary scheme based on Genetic Algorithm (GA) to solve this problem and evaluates it in terms of collision, SU dropping, SU blocking probabilities and joint utilization. Due to its versatility, scalability and computational simplicity, GA has been widely adopted for solving optimization problems in wireless networks[14][15][16][17][18] and solutions to reduce its convergence time have been proposed [19]. In this work, we assume that the GA is adopted for mapping SVNs, during the CRVNE dimensioning, before the network becomes fully operational. The results show that our scheme outperforms the alternative method based on the First-Fit strategy.

This paper is organized as follows. Related works are discussed in Section 2. Section 3 presents the Cognitive Radio Virtual Network Environment and the challenges that emerge in the SVNs mapping, highlighting the events/situations that impair the primary and secondary communications and that must be taken into account in the mapping process. CRVNE modeling and formulations for the SU blocking, SU dropping and collision probabilities, as well as, joint utilization are presented in Section 4. The model validation and analysis on the SVN mapping are conducted in Section 5. The formulation of the SVN mapping as a multi-objective problem and a scheme based on GA to solve it are presented in Section 6. The performance results are discussed in Section 7. Section 8 concludes this paper and highlights the future works.

2. Related Works

Studies have been proposed for wireless virtualization in homogeneous [5] and heterogeneous wireless networks [6] or without specifying any network technology [10][11], but assuming that the resources allocated to a VWN cannot be shared during operation. This restriction may cause resource underutilization when the VWNs experience low traffic load periods, hindering new VWN deployments. Opportunistic resource sharing has been raised in [7][8] to solve the problem as it considers the workload in a VWN to be the combination of a permanent and a variable sub-workload (following a given probability). Thus, multiple flows from different VWNs may share common resources, which my cause collision and should be managed. Unlike our proposal combines CR and WV, previous works only reckon homogeneous access priority VWNs (e.g. no high and low priority VWNs) besides providing little flexibility at the PHY and MAC layers, since the VWNs mapping is tied to specific RAT.

Proposals for opportunistic sharing in non-virtualized Cognitive Radio Networks (CRNs) have been widely presented in literature; each CRN usually has its own physical infrastructure and it is generally employed over a primary network in a one-to-one relationship, such as [20] and [21]. In terms of resource allocation in non-virtualized CRNs, the focus is on channel selection/channel-user assignment; The resources are shared among multiple parties that are individual users [9] and this process takes place during the network operation. By applying virtualization to CRNs, VWNs with different services/RATs/priorities can be mapped onto the same substrate network and easing the no one-to-one mapping restriction. Thus, channels that are allocated to different PVNs can be used by the same SVN, providing better resource utilization. In this environment, the resources are also shared among multiple parties, but unlike non-virtualized scenarios, these are virtual wireless networks (groups of users).

The work developed in [7] is based on opportunistic resource sharing. However, it does not include PUs or SUs. In addition, there are other factors in CRVNE (apart from the collision probability) that must be considered during the SVN mapping process, such as the SU blocking and SU dropping probabilities, both neglected in [7].

Moreover, platforms for end-to-end network virtualization that consider cognitive radio as a component have been proposed in [22] and [23]. Yet, the authors only provide a schematic illustration of the interaction between the elements. In [24], a hypervisor-based architecture for intra and inter-node resource scheduling in virtualization-based CR networks is presented. Similarly to [22][23], neither the VWN mapping nor the evaluation in terms of SU blocking, SU dropping and collision probabilities and joint utilization is addressed. Differently, this work focuses on the multiobjective formulation for the SVNs mapping problem and the design of an evolutionary scheme to solve it. In addition, our scheme is envisioned to act on the dimensioning stage, i.e., resource allocation from infrastructure provider to VWNs.

An approach denoted as spectrum demand access as a service is proposed in [25]. It dynamically offers spectrum services to users and enables these to set up dynamic virtual topologies to meet the needs of a specific application. The authors adopt the dynamic spectrum allocation approach for DSA, which does not distinguish between PUs and SUs. Thus, each user has an exclusive spectrum band within a certain time period, e.g. in the order of minutes. In addition, besides considering only homogeneous requests, i.e., all virtual topologies request the same spectrum amount (not always the case in real scenarios), they fail to draw on any proposal in the literature to make a comparative evaluation. Unlike [25], our study adopts the opportunistic spectrum access (OSA) approach for DSA, which differentiates PU and SU. In OSA, the SUs dynamically search and access idle PUs spectrum bands through spectrum sensing or databases. In view of this, we take into account the existence of the PVNs and the heterogeneous requests on the SVN mapping process.

As it can be seen, works have proposed mechanisms for wireless network virtualization by using strict resource allocation, opportunistic resource sharing or spectrum demand as a service. But, they fail with regard to flexibility at MAC/PHY layer, resource efficiency or support to the users/networks with heterogeneous priorities. Although other studies have adopted cognitive radio in the wireless part for providing end-to-end network slicing, they do not address the virtual network mapping or schemes to map virtual networks. Differently, we combine CR and WV to tackle these and define a new virtual environment, in which the SVN mapping is addressed and a GA-based scheme is proposed. Next section describes this new environment and the challenges that emerge in the SVNs networks mapping.

3. Cognitive Radio Virtual Network Environment (CRVNE)

The cognitive radio virtual network environment(CRVNE) is made up of three wireless networks types: substrate network, PVNs, and SVNs. The substrate networks are managed by the MNO and consist of channels, spectrum bands, base stations, and other features that compose wireless environment [22]. The PVNs have higher access priority to the resources than SVN and are usually mapped without taking into account the SVNs existence [5][6], hence, not supporting the concept of opportunistic sharing.

Owing to the existence of low traffic periods in the PVNs, SVNs can be embedded through the opportunistic access to the resources. These networks have lower access priority to the resources and will only use them when the PVNs are idle. The adoption of SVNs can provide better resource utilization (e.g. spectrum) and increase revenue for the provider infrastructure, as more VWNs can be admitted.

The introduction of cognitive radio in wireless virtualization allows new players to emerge in the business model. Without CR, game is basically composed of two players: the service provider (SP), which leases the virtual wireless networks, programs them and offers end-to-end services to users, and the Mobile Network Operator (MNO), which owns the network infrastructure (e.g. radio access networks, backhaul, transmission networks, and licensed spectrum and core networks) [9]. When CR is considered, the SP is split into two players: Primary Service Provider (PSP) and Secondary Service Provider (SSP) [26]. The former offers its services via PVNs, which have higher access priority. Hence, they could offer any type of application supported by wireless substrate such as voice service, multimedia and real time applications. The second manages SVNs that could offer best-effort services such as P2P download and web browsing. Fig.1 illustrates the CRVNE.

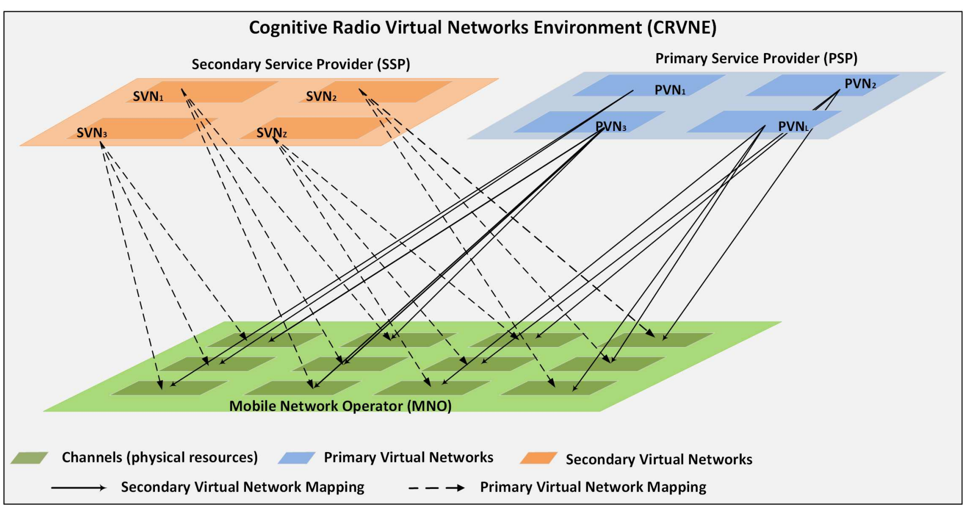

Figure 1: Cognitive radio virtual networks environment (CRVNE).

The resources allocation in CRVNE raises several challenges, for instance, since the SVNs perform opportunistic access, their mapping must take into account both the demand requested by the SVN (e.g. the number of users/requested bandwidth), and the primary activity. In this respect, both protecting the primary communication from the SU interference and meeting the SVN requirements are relevant, requiring resources usage pattern awareness by the PVNs and which situations/events could impair the primary and/or secondary communications in the CRVNE.

The collision between PU and SU is one of these events. It happens when a PU returns to a channel that is being used by a SU. PU collides with SU and both communications suffer degradation. Moreover, as PU has higher priority of access to the resources than SU, so the SU has to vacate the channel and find another available channel to resume its communication. A collision between PU and SU is shown in Fig. 2. In this example, a PVN was mapped onto channels (Ch) 1, 2 and 3 and shares these channels with the SVN. Ch 2 is occupied by PU2 (i.e., the channel is in ON state). Thus, the channel 2 cannot be used by users from the SVN at this moment. SU1 is performing its communication in the channel Ch1, which is denoted as OFF state due to the PU not using it. At this moment, when PU1 arrives at PVN and accesses Ch 1, which is occupied by SU1, a collision occurs and the primary communication suffers interference from the secondary one and vice-versa. Consequently, SU has to vacate channel 1 and find another available channel to resume its communication (e.g. Ch 3). Avoiding or keeping this interference below a threshold is a feature that must be taken into account in the SVNs mapping.

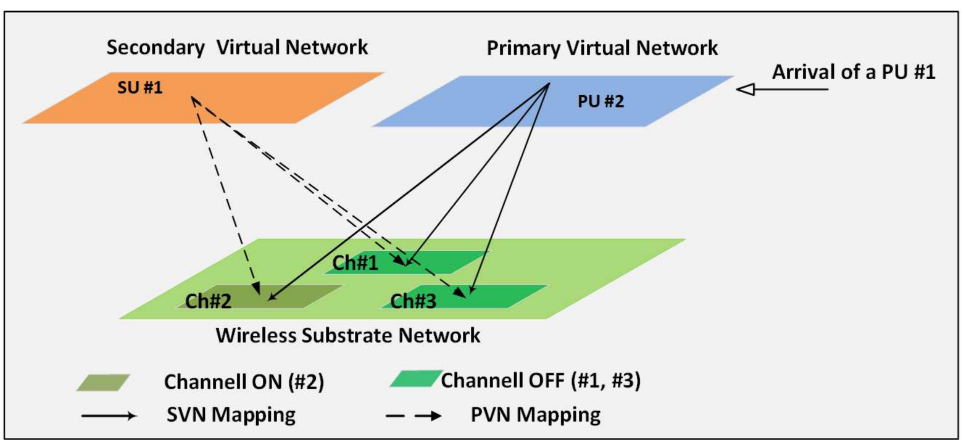

Figure 2: An example of collision when the PU arrives in a channel occupied by SU.

When a SU tries to access the SVN and there are not enough resources to its communication, it is blocked/rejected, which damages the secondary communication. Thus, admitting as many SU as possible dimensioned for each SVN, i.e., reducing the SUs blocking probability is an important goal in the SVNs mapping. A situation in which a SU is blocked due to resource scarcity is shown in Fig. 3. PVN shares channels 1 and 2 with the SVN. Users PU2 and PU3 are occupying channels 2 and 3, respectively. Here, there are two secondary users (SU1 and SU2) arriving at SVN, but there is only one channel available (Ch1) to be used for communication. Thus, only one SU can be admitted while other is rejected.

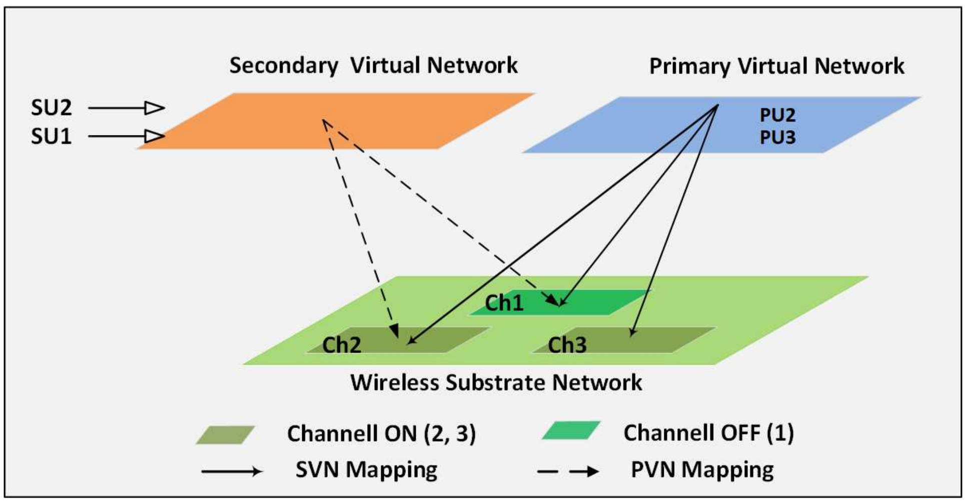

Figure 3: An example of SU blocking when there is no enough available resource in the SVN to admit a new secondary user.

A third situation that can affect the quality of service of the secondary communication is when the SU is dropped from SVN, due to a returned PU to the channel occupied by an SU while an extra channel is not available in its current SVN. An example where the SU dropping happens is depicted in Fig. 4. There are two primary users (PU2 and PU3) in the PVN, which are using channels 2 and 3, represented as channels ON (in ON state). Ch 1 is not being used by PVN, which is represented as a channel OFF (in OFF state), but the SU 1 is using it in an opportunistic way. When a new PU arrives at PVN, SU1 is preempted from channel 1 and it searches for another one to resume its communication. However, as there is no available channel in its SVN, SU1 is dropped from the SVN. This event forces the termination of the secondary communication prematurely.

In the next section, we model the interactions between PUs and SUs in CRVNE by using queueing theory and formulate the probabilities for the collision (Subsection 4.1), SU blocking (Subsection 4.2) and SU dropping (Subsection4.4) events, as well as, the resource joint utilization (Subsection 4.3), which are considered in the SVNs mapping problem.

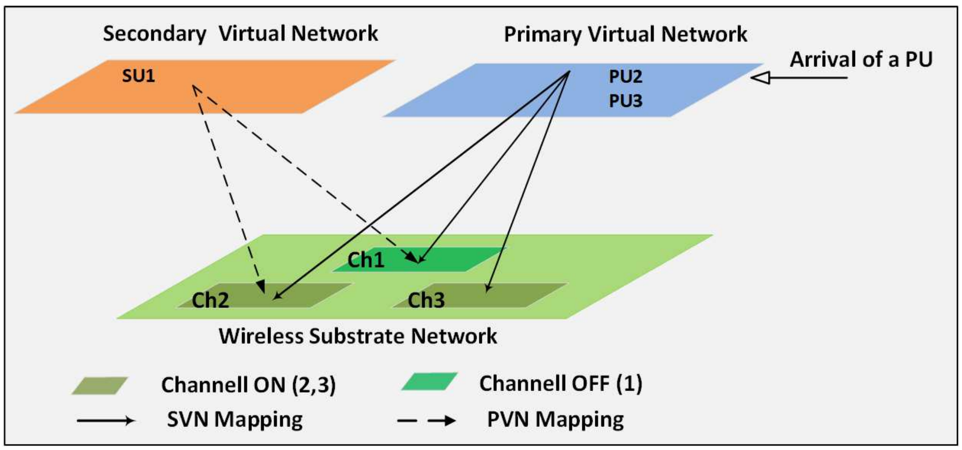

Figure 4: An example of SU dropping when the PU returns and there is no available resource in the SVN for resuming the SU communication.

4. CRVNE Model

In a CRVNE, the PSP requests the creation of and manages L primary virtual networks (PVNs). Given that the substrate network is composed of M channels and that the mapping algorithm divides the resources between the PVNs according to percentage q_j, with $j = 1, 2, 3, ..., L$, $0 \leq q_j \leq 1$ and $\sum_{j=1}^{L} q_j = 1$, then for each PVN j is allocated $|Q_j| = \lfloor M * q_j \rfloor$ or $\lceil M * q_j \rceil$ channels, where Q_j means the set of channels allocated to PVN j, $\lfloor x \rfloor$ and $\lceil x \rceil$ are the ceil and floor functions, respectively.

We assume that the PUs arrive at channel i (C_i) of virtual network j, with $C_i \in Q_j$, following a Poisson process with arrival rate $\lambda_{PU,i,j}$, and the user holding time is given by an exponential distribution with mean $1/\mu_{PU,i,j}$. In addition, we consider each channel has capacity to satisfy one PU.

Given that N channels were allocated to the PVN j, i.e. $|Q_j| = N$, the total PU arrival rate may be obtained by (1).

$$\lambda_{PU,j} = \sum_{C_i \in Q_j} \lambda_{PU,i,j} \tag{1}$$

The SVNs provide their services by opportunistically using the resources. In CRVNE, there is no one-to-one mapping between PVNs and SVNs as in non-virtualized CRN [20][21]. Thus, channels allocated to different PVNs can be allocated to the same SVN.

We consider that the SSPs requests Z SVNs to be mapped onto cognitive radio substrate. In each SVN l (SVN_l), with $l = 1, 2, ..., Z$, the SUs arrival follows a Poisson distribution with rate $\lambda_{SU,l}$ users per second (users/s) and the SU holding time is exponentially distributed with mean $1/\mu_{SU,l}$ seconds [27]. Similarly to PVN, we consider that the bandwidth requested by each SU can be satisfied by one channel. Hence, the average number of SUs in the SVN_l and the amount of resources requested by SUs considering each channel with bandwidth w bps are calculated by (2) and (3), respectively.

$$\overline{NSU_l} = \lambda_{SU,l} * \frac{1}{\mu_{SU,l}} \tag{2}$$

$$\overline{Bw_{req,l}} = \lambda_{SU,l} * \frac{1}{\mu_{SU,l}} * w = \overline{NSU_l} * w \tag{3}$$

Given that the mapping of the SVN l onto CR substrate adopted a set of N channels, $SC_l = \{C_1, C_2, ..., C_N\}$, with $SC_l \subset \bigcup_j Q_j$, and $SC_l \cap SC_u = \oslash$, for all $l \neq u$, where $l, u = 1, 2, ..., Z$ are SVN identifiers, and that the PU service rate is homogeneous and denoted as $\mu_{PU,l}$, i.e. $\mu_{PU,l} = \mu_{PU,i,l} = \mu_{PU,d,l}$, $\forall C_i, C_d \in SC_l$, the interaction between PVN and SVN may be modeled as an M/M/N/N queue with preemptive-priority service, where PUs and SUs compete for N channels [13]. In this system, resources are limited and no queue is allowed to form. Moreover, a SU can be forcibly terminated if a PU arrival occurs when there is no other available channel in the SVN_l.

In our model, each state (i, j), with $0 \leq i, j \leq N$ and $0 \leq i + j \leq N$, means that there are i PUs and j SUs in the system (SVN_l). The states $(i, N - i)$ denote a full system, where all resources are being used by PUs or SUs. Specifically, when $N - i \geq 1$, these states model situations where the SU is dropped from SVN due to PU arrival and there is no available channel to resume its communication. Fig. 5 presents the state transition diagram of our CRVNE model. Horizontal flows to right (left) mean PU arrival (departure) and vertical flows to top (down) represent SU arrival (departure).

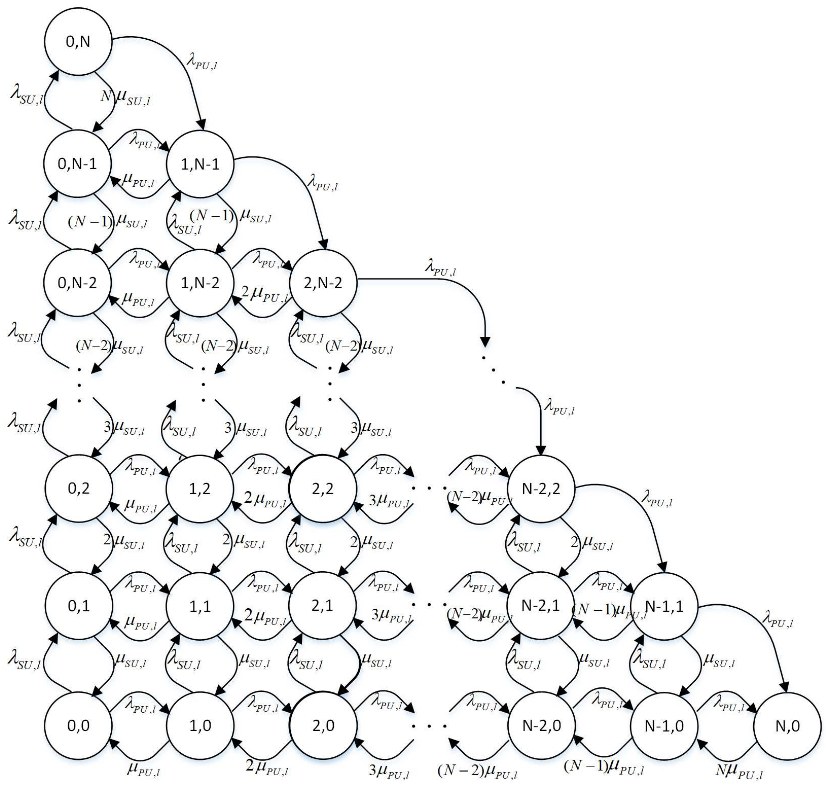

Figure 5: State transition diagram of the CRVNE model.

4.1. Formulation for Collision Probability

In the SVNs mapping, it is important to consider other factors apart from the demand for these networks. As the channels adopted by the SVNs are shared with the PVNs, it is necessary to ensure minimum interference to PVNs, which can be defined as a threshold, based on the service level agreement (SLA) from the PVNs, for example. A collision (between PU and SU) happens when a PU returns to a channel that is being used by SU, damaging both primary and secondary communications. It is noted that the PU arrival in the SVN_l certainly leads to a collision with SU when the SVN_l is full and there is at least one SU active, i.e., for states $(N-j, j)$, with $j > 0$.Thus, the probability sum of these states (see (4))bounds the collision probability.

$$Pc_{inf,l} = \sum_{j=1}^{N} P(N-j, j) \tag{4}$$

When the SVN_l is not full and at least one active SU is present, the PU arrival does not necessarily lead to a collision, since the PU may have returned to a channel that is not being occupied by SU. States (i, j), with $j > 0$ and $(i+j) < N$ model this situation and the probabilities sum of these states (Δcol_j, in (5)) denotes the probability of such event taking place.

$$\Delta col_l = \sum_{i=0,j=1}^{(i+j)<N} P(i, j) \tag{5}$$

In order to calculate the collision probability, it is necessary to know which channels the PUs and SUs are using. However, this specific information is not available in the mapping process, since it just deals with the allocation of a set of channels to each VWN. Generally, this kind of information may be obtained during the network operation, because it involves channel-user allocation, which is not represented by this model.

For states $(i, 0)$, with $i \geq 0$, the PU arrival does not trigger a collision because there are no SUs in the SVN_l. In this respect, a collision might only take place in the previous two cases and we may use (6) to estimate its probability. It uses (4) as an inferior bound and (5) multiplied by a β factor as an increment. The β factor expresses how likely a collision may occur when the SVN_l is in the states (i, j), with $j > 0$, and $(i + j) < N$.

$$Pc_l = Pc_{inf,l} + \beta * \Delta col_l \tag{6}$$

The β factor is given by (7), which represents the average probability that the PU returns to the channel while the SU is using it. So, for each channel i allocated to SVN_l, the probability that a PU returns to the channel during the SU communication ($Pback, i$) is computed, i.e., the probability of the OFF time (time in which the PU is absent) being lower than the SU service time.

$$\beta = \frac{\sum_{i=1}^{N} P_{back,i}}{N} \tag{7}$$

Given that the PU arrival rate in a channel i is modeled as a Poisson process with rate $\lambda_{PU,i}$ and that the PU service time follows an exponential distribution with rate $\mu_{PU,i}$, the channel's mean OFF period is given by (8).

$$\overline{T_{OFFi}} = \frac{1}{\lambda_{PU,i}} - \frac{1}{\mu_{PU,i}} \tag{8}$$

Assuming that the SU service time is exponentially distributed with rate μ_{SU}, the $Pback,i$ is given by (9), where $\lambda_{OFFi} = 1/\ \overline{T_{OFFi}}$. The proof for (9) is given in [13].

$$P_{back,i} = \frac{\lambda_{OFFi}}{\lambda_{OFFi} + \mu_{SU}} \tag{9}$$

4.2. Formulation for SU Blocking Probability

As well as protecting the PUs, the SVNs mapping process must provide reasonable quality of service for the SUs. Thus, it must provide high level of SU admission, i.e, low SU blocking probability. As stated in Section 3, the SU blocking occurs in the SVN when all channels are busy during a SU arrival. Hence, the SU blocking probability on the SVN_l is given by (10), which is the probability sum of the states that represent the full system.

$$Pb_{SU,l} = \sum_{i=0}^{N} P(N-i, i) \tag{10}$$

4.3. Formulation for Joint Utilization

As well as seeking to admit as many users as possible, providing better resource utilization is also a goal of both SVN mapping and cognitive radio technology through opportunistic access to the resources, besides increasing the revenue for the MNO. Given the set of N channels $SC_l = C_1, C_2, ..., C_N$ used in the SVN_l mapping, the joint utilization (primary and secondary usage) of these channels is given by (11), which is the ratio of the average number of channels occupied by PUs or SUs to the number of channels allocated to SVN_l.

$$util_l = \frac{\overline{NPU_l} + \overline{NSU_l}}{N} \tag{11}$$

Where $\overline{NPU_l}$ is the average number of PU in channels shared with SVN_l, calculated by (12), and $\overline{NSU_l}$ is the average number of SUs, which can be obtained by (13).

$$\overline{NPU_l} = \sum_{i=0}^{N} \sum_{j=0}^{N-i} i * P(i,j) \tag{12}$$

$$\overline{NSU_l} = \sum_{j=0}^{N} \sum_{i=0}^{N-j} j * P(i,j) \tag{13}$$

4.4. Formulation for SU Dropping Probability

The SU blocking probability is the rejection level of new SUs in the SVN. Once the SUs are admitted, some events triggered by PU activity can affect their QoS. Among these events, the SU dropping happens as a result of the PU return to the channel occupied by SU and inexistence of available channel in its SVN. The SU dropping causes great degradation to secondary communication, as the SU has its communication abruptly terminated. With a full network, each collision between PU and SU leads to a SU preemption. Thus, the SU preemption rate from SVN_l is numerically equal to the rate of PUs that suffered collision, which is given by (14). Where the summation considers the states that represent the full network and there is at least one active SU.

$$Rd_{SU,l} = \lambda_{PU,l} * \sum_{j=1}^{N} P(N-j, j) \tag{14}$$

By dividing the rate of SU preempted from SVN_l by the rate of admitted SUs, the SU dropping probability is given by (15).

$$Pd_{SU,l} = \frac{Rd_{SU,l}}{(1 - Pb_{SU,l}) * \lambda_{SU,l}} \tag{15}$$

Next section presents the model validation and analyzes the behavior of the collision, SU blocking, SU dropping probabilities and the joint utilization regarding a mapping scenario with different PU and SU loads.

5. Model Validation

A Matlab simulation model was used to validate the work presented in Section 4. We considered a scenario with two channels, which were shared by a SVN and PUs (from PVNs). The PU and SU service rates were defined as 1 and 0.1 (users/s), respectively. PU arrival rate (in users/s) in each channel was varied (from 0.1 to 0.9) in order to analyze the model behavior when in different PU loads. Similarly, the model was evaluated considering different SU arrival rates (ranging from 0.2 to 2.5 users/s), i.e., under different SU loads.

We performed 10 simulation instances for each evaluated point. The simulation time was 10,000 seconds and the average results are presented considering a 95% confidence level, which were obtained by the Bootstrap method [28], with ‘resample’ size and number of (re)sam-plings equal to 10 and 1000, respectively. In the following figures, 'Model' and 'Sim' mean results obtained through the analytical model and simulation, respectively.

The results for the SU blocking probability are presented in Fig. 6, where the analytical model followed the simulation. It is noted that initially the SU blocking probability tends to decrease when the PU arrival rate increases. This behavior occurs until a certain PU arrival rate value. Beyond this, the PU arrival rates increase enables more SU blocking events. Considering an SU arrival rate equals 0.2, we note that the SU blocking probability changes its behavior (decreasing to increasing) when PU arrival rate is about 0.2. Similarly, when we consider SU arrival rates equal to 0.4 and 0.6, the change happens in the points where the PU arrival rate is about 0.4 and 0.6, respectively. In these points, we observe that there is a range where the PU arrival rate increase does not necessarily lead to a SU blocking probability boost. This initial decrease occurs due to cases where the SU is dropped from the SVN, and the PU only uses the channels for a short time, releasing it afterwards. Therefore, a new SU can be accepted in the SVN, which might experience the same situation.

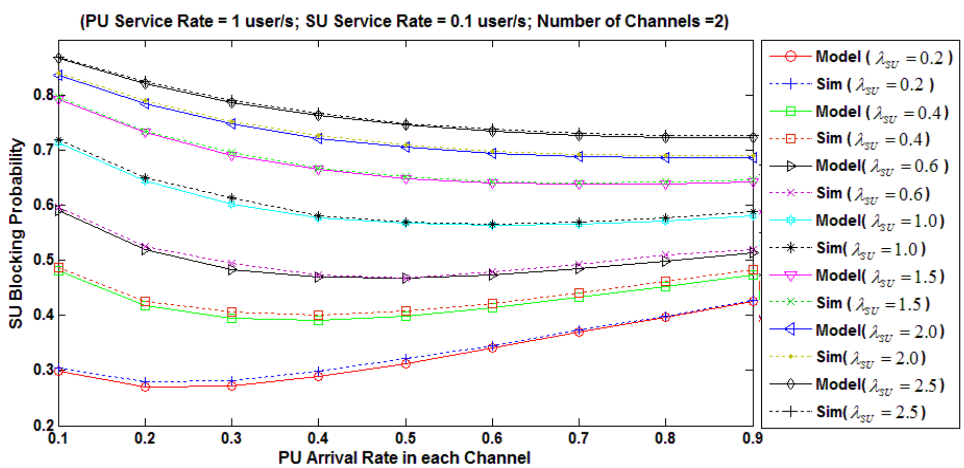

Figure 6: Results obtained by model and simulation in terms of SU blocking probability.

For the cases where the SU arrival rate is equal to 1.0, 1.5, 2.0 or 2.5, it was observed that the SU blocking probability decreases when the PU arrival rate increases in the interval [0.1, 0.9]. For this region, as the SU arrival rate is higher than PU arrival, i.e., the SU inter-arrival time is shorter than the PU inter-arrival time, the SU can access the channel when it is idle (in OFF state). But, as its service time is larger (on average) than the channel's OFF period, it is preempted due to the PU return.

In turn, a PU arrival raise causes the SU blocking increase and the consequent opportunistic access reduction. This is observed when SU arrival rate is equal to 0.2, 0.4 or 0.6. Moreover, it is shown in Fig. 6 that when SU arrival rate increases, the SU blocking increases as well, because the same resource amount is considered to satisfy an increasing SU demand.

Fig. 7 depicts the joint utilization results for both the model and simulation, which present the same behavior. The joint utilization is similar to the SU blocking probability. Initially, it decreases and later it starts to increase when the PU arrival rate escalation. In order to analyze such behavior, it is highlighted that the joint utilization is obtained by taking into account the primary and secondary utilization. As the primary user has higher access priority to the channels, the resource utilization provided by the primary communication is not influenced from the secondary communication. Therefore, it increases when the PU arrival rate increases, as shown in Fig. 7. On the contrary, the secondary utilization is impacted by the PU communication, hence, when the PU arrival rate increases, the secondary utilization decreases once there are fewer chances for opportunistic access to the channels.

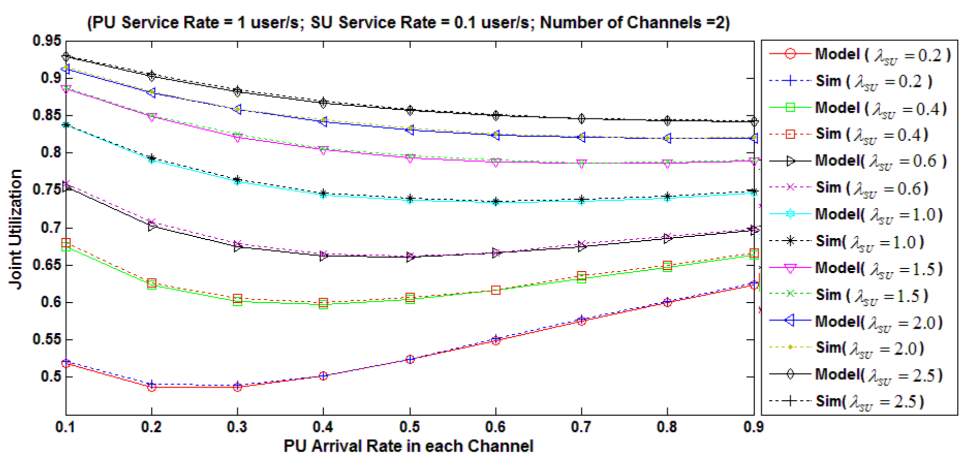

Figure 7: Results obtained by model and simulation in terms of joint utilization.

According to Fig. 8, the secondary utilization is dependent of the PU arrival rate. In some cases, the secondary utilization reduction is compensated by the primary utilization, leading to a joint utilization increase. This can

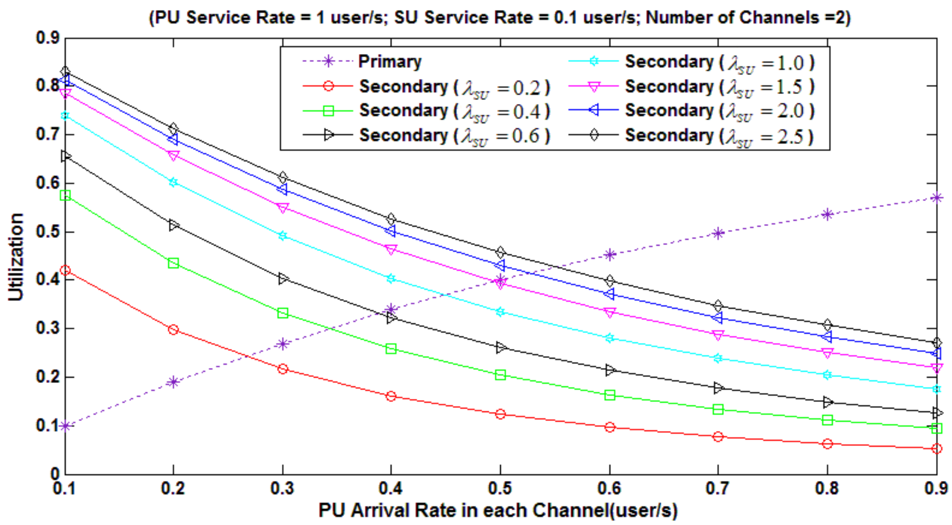

Figure 8: Primary and secondary utilization obtained by model under different loads of PU and SU.

be noted in the cases where the SU arrival rate is equal to 0.2, 0.4 or 0.6, for example (see Fig. 7), whereas in other cases, the primary utilization cannot compensate the secondary utilization reduction. Hence, the joint utilization tends to decrease, which is noted in the cases where the SU arrival rate is higher than 0.6 as shown in Fig. 7. Moreover, in Fig. 7, the joint utilization increases together with the SU arrival rate, which is expected since the SU load is higher, leading to a secondary utilization increase (see Fig. 8).

The SU dropping probability results are depicted in Fig. 9, which illustrates that both model and simulation present a similar behavior. We note that the SU dropping increases when the PU arrival rate increases. This is expected, since a higher PU arrival rate implies a shorter PU inter-arrival time, which boosts the chances of an admitted SU to be preempted. Moreover, it is observed that the SU dropping probability also increases due to the SU arrival rate raise (see Fig. 9), while resource amount is kept the same.

The results for the collision probability are presented in Fig. 10, and although (6) expresses an approximation for such metric, the results obtained are similar to those ones from our simulation. In addition, the figure shows that, when the PU arrival rate increases, the collision probability decreases. At first, it seems as an odd conclusion, once when the PU arrival rate increases, the PU load also increases and therefore we would expect that the

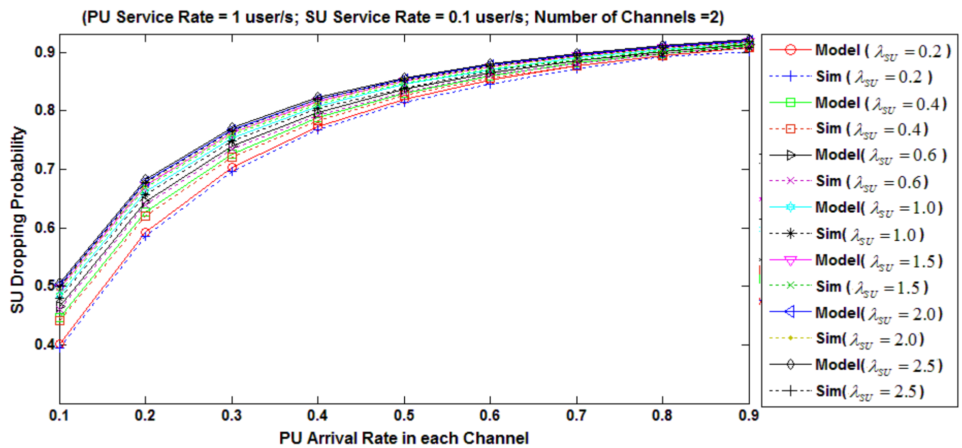

Figure 9: Results obtained by model and simulation in terms of SU dropping probability.

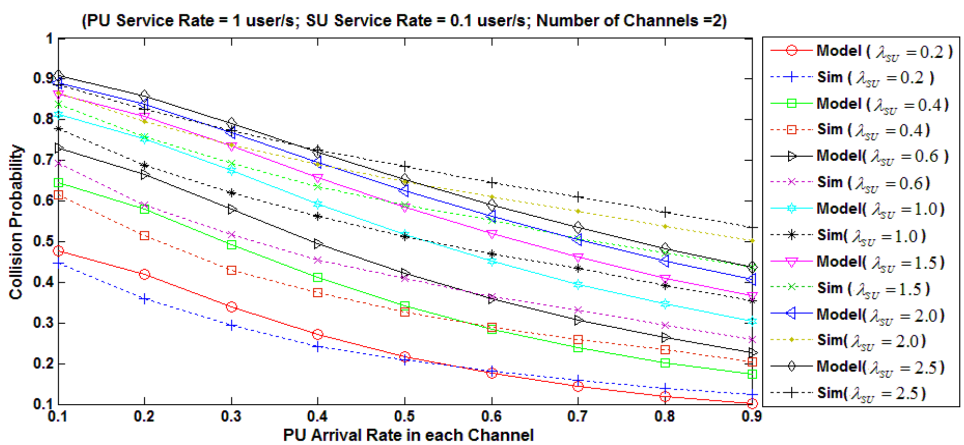

Figure 10: Results obtained by model and simulation in terms of collision probability.

collision probability would also increase. This is true when we are addressing collision in a media access control situation, where the users compete for channel access, and a higher user arrival rate leads to a greater collision amount. However, for a collision between PU and SU to occur in a CRVNE (Section 3), the following condition has to be satisfied: the SU is using the channel to which the PU will return during this period. From this condition, we note that SU needs access opportunities for a collision to happen. If these are reduced, the collision number also tends to be reduced. Therefore, in Fig. 10, when the PU arrival rate increases, implying less opportunity for the SUs, the collision probability decreases. Moreover, as the SU service time is higher (on average) than the channels OFF time (the PU is not currently using it), when the SU gets the access to the channel, it is very likely that the SU will still be using the channel when the PU returns.

6. Formulation Problem and Proposed Scheme

This section presents he formulation of the SVN mapping as a multi-objective problem, which takes into account the objectives discussed in the previous section. Moreover, it proposes a scheme based on genetic algorithms to solve the problem, detailing its structure, parameters values and operation.

6.1. Formulation of the SVN Mapping Optimization Problem

As shown in previous sections, several objectives must be considered in the SVN mapping process. The following optimization problem (see (16))as formuated as: given a set of Z SVN requests and the channel usage pattern for the primary networks, to perform the SVNs mapping, i.e., to determine the set of channels to be allocated to each SVN, in order to minimize the average collision ($\overline{Pc}$), SU blocking ($\overline{Pb_{SU}}$), and SU dropping($\overline{Pd_{SU}}$) probabilities and maximize the average joint utilization ($\overline{util}$). Two constraints must be satisfied: the resource amount allocated to each SVN cannot be less than the requested demand, and a common channel cannot be allocated to different SVNs. This last constraint aims to provide inter-slice isolation among SVNs [10]. Formally:

$$
\begin{aligned}
&Minimize \quad \overline{Pc},\ \overline{Pb_{SU}},\ \overline{Pd_{SU}}\ and\ Maximize \quad \overline{util}\\
&Subject\ to:\\
&\qquad\qquad \begin{cases} Ralloc_l \geq \overline{Bw_{req,l}},\ l = 1, 2, ..., Z \\ SC_l \cap SC_u = \oslash,\ l \neq u, l, u = 1, 2, ..., Z \end{cases}
\end{aligned}
\tag{16}
$$

Where $Ralloc_l$ and SC_l are the amount of resources and the set of channels allocated to SVN_l, respectively. A challenging problem arises if the SVN mapping is focused on a specific objective: it may deteriorate other SVN's performance goals. To mitigate such effect, our evolutionary scheme (based on genetic algorithms) is proposed in the next subsections.

6.2. Chromosome Structure and Fitness Function

GA is a search algorithm based on the principles of natural selection. It relies upon evolving a set of solutions, represented by the so-called chromosomes. Eventually, through the GA operators (selection, crossover and mutation) a good solution will be found by combining different solutions [14].

Some GA characteristics such as versatility, scalability and computational simplicity are suitable for the SVN mapping problem. GA handles many solutions simultaneously at each interaction and evolves them to achieve better solutions. Thus, many possible mappings are evaluated at each interaction. In general, GA is flexible enough to tackle many objectives or constraints, and can be combined with classical approaches [29] to deal with this kind of problem. In addition, GA has been widely adopted for solving optimization problems in wireless networks [14][15][16][17][18] and solutions to reduce its convergence time have been proposed [19]. In this work, it is assumed that the GA is adopted for the CRVNE dimensioning phase,i.e., before the network becomes fully operational.

In our GA-based the proposed scheme, the individual or chromosome X_l^j is represented by a sequence of K bits (see Fig. 11), where K is the number of available channels that can be used to meet the requested SVN_l, and $j = 1, 2, 3, ..., S$, where S is the population size. Each gene (bit) in the chromosome refers to an available channel for allocation. If the gene value is equal to 1, then the respective channel is selected for the SVN mapping. Otherwise, the channel is not selected. In the individual shown in Fig. 11, channels 1 and k are selected for mapping the requested SVN. Our proposal considers the intrinsic parallelism of the GA when seeking to find an optimal or sub-optimal mapping for each SVN.

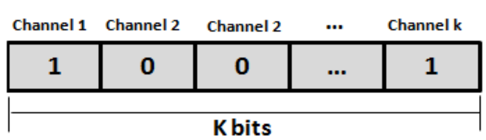

Figure 11: Chromosome Structure.

It should be noted that there is an equivalence between an individual in the GA and a set of channels. Thus, given an individual X_l^j, it is possible to know the set of channels represented by it (SC_l^j), and vice-versa. (17) describes how to obtain the set of channels represented by an individual X_l^j

in the GA, where AC_l is the set of available channels for mapping the SVN l, C_i is the channel associated with the gene x_i. The gene (bit) x_i composes the chromosome X_l^j.

$$SC_l^j = \{C_i \in AC_l |\ x_i \in X_l^j \text{ and } x_i = 1\} \tag{17}$$

In our scheme, the SVNs are mapped sequentially, so a population is created for each SVN and evolves to obtain a final solution represented by a set of channels that can be allocated to the respective SVN.

To evaluate the individuals (solutions), we defined the fitness function given in 18. In order to handle the multi-objective problem of SVNs mapping and reduce its complexity, we adopted the classical approaches such as weighted sum, ϵ-constraint and programming method [29]. In this respect, two expressions defined our fitness function. The weighted sum method was adopted to compose the first part of the fitness function, where the collision and SU dropping probabilities were taken into account, which are mainly related to primary and secondary communications, respectively. In addition, the ϵ-constraint method was also used in this part, where T_{block} and T_{util} were the constraints defined to SU blocking probability and joint utilization, respectively. Thus, the first part of our fitness function aims to reduce the collision and SU dropping probabilities while keeping the joint utilization and SU blocking within certain limits. The ϵ-constraint method should have constraints defined in a feasible region, otherwise no solution will be found. However, it is hard to do so for all possible SVN mapping scenarios, since the constraint values may or may not be in a feasible region. Therefore, the second part of our fitness function adopts the goal programming method along with the expression given by weighted sum (f_{main}).

Thus, target values were defined for SU blocking probability and joint utilization, which are also represented by T_{block} and T_{util}, respectively. The second expression (in (18)) adopts the average between Δ_{block} and Δ_{util} as a penalization factor for f_{main}. Δ_{block} is the relative difference between the SU blocking probability and its target value. Similarly, the relative difference between the joint utilization and its target value is Δ_{util}. They are expressed in (20) and (21), respectively. In our approach, T_{block} and T_{util} were set up as 0.1 and 0.8, respectively.

$$fitness(X_l^j) = \begin{cases} f_{main}, \ if \ Pb_{SU,l} \leq T_{block} \ and \\ \qquad\qquad\qquad util_l \geq T_{util} \\ \left(1 - \frac{(\Delta_{block} + \Delta_{util})}{2}\right) * f_{main}, \\ \qquad\qquad\qquad otherwise \end{cases} \tag{18}$$

Where f_{main} is defined in (19).

$$f_{main} = 100 * [(1 - Pc_l(X_l^j)) + (1 - Pd_{SU,l}(X_l^j))] \tag{19}$$

$$\Delta_{block}(X_l^j) = \begin{cases} \frac{(Pb_{SU,l} - T_{block})}{(1 - T_{block})}, \ if \ Pb_{SU_l} > T_{block} \\ 0, \ otherwise \end{cases} \tag{20}$$

$$\Delta_{util}(X_l^j) = \begin{cases} \frac{(Tutil - util_l)}{T_{util}}, \ if \ util_l < T_{util} \\ 0, \ otherwise \end{cases} \tag{21}$$

It is noted that 20 and 21 have values different from zero when the collision probability or joint utilization values provided by a given mapping (individual) are worse than the targets. In addition, the greater the collision and utilization are from the target values, the greater the penalty in the individual's fitness of the individual will be. Both expressions in 18 aim to achieve a good tradeoff between the objectives of the optimization problem presented in Section 6.1.

Although there are GA approaches for solving multi-objective problems such as Multi-Objective Generic Algorithms (MOGA) and Non-dominated Sorting Genetic Algorithm (NSGA) [31], for instance, in our scheme, (as shown in 18), the classical methods were used to deal with multiple objectives. With this approach, the complexity of the multi-objective problem is reduced and just handled in the fitness function. Moreover, it does not require any changes to the basic GA mechanism. In addition, the literature includes studies that have successfully used this approach in a multi-objective optimization [14][30]. Next section presents the GA operators and parameters adopted in our evolutionary scheme.

6.3. Genetic Operators and Parameters

We adopted the roulette wheel as the selection operator, which involves selecting individuals for the crossover process based on their fitness values. It simulates the natural selection mechanism, which acts on biological species [32]. Hence, individuals with the highest fitness values are best suited for the next generation.

A uniform operator was employed for the crossover operation, which selects genes (bits) from parents chromosomes and creates a new offspring. A bit mutation was used as the mutation operator, i.e., it randomly changes the new offspring [32].

Two key parameters are the crossover (pc) and mutation (pm) probabilities since they express the frequency with which the crossover and mutation operations are carried out, which have great impact on the GA performance [14].

In this way, multiple tests were conducted to define the probability values (pc and pm) that could be used in our GA-based scheme. We have employed 8 test values within the interval [0.1 0.8] for the crossover probability (pc) and 8 test values within the interval [0.01 0.8] for the mutation probability (pm), as shown in Table 1. Combined, these meant 64 test cases. For each test case, 5 simulation instances were performed. The test scenario was composed of 40 channels, PU service rate equals 1 for all channels and PU arrival rate in each channel defined within the interval [0 1]. Moreover, the SU arrival rate and average SU service time were uniformly distributed in [1 3] and [1 4], respectively.

Table 1: Test case values

Pc	0.1/0.2/0.3/0.4/0.5/0.6/0.7/0.8
Pm	0.01/0.03/0.05/0.1/0.3/0.5/0.7/0.8

We have selected the highest average fitness value for the last generation's population, as highlighted in Fig. 12. Test case 49 displayed the best performance for the GA, having crossover and mutation probabilities equal to 0.7 and 0.01, respectively. In addition to crossover and mutation probabilities, the population size (S) and number of generations (G) were defined as being equal to 100 and 200, respectively; all GA parameter values are summarized in Table 2.

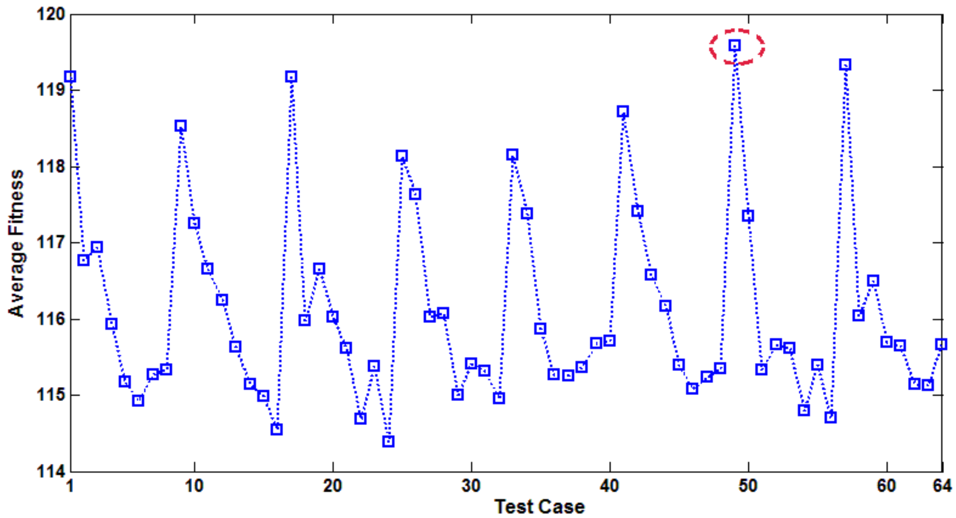

Figure 12: Test case results for GA.

Table 2: Ga parameters

Parameter	**Value**
Number of generations(G)	200
Population size (L)	100
Crossover rate (Pc)	0.7
Mutation rate (Pm)	0.01

6.4. Execution Flow of the Scheme

The execution flow of our SVN mapping GA-based scheme is as follows (see Fig. 13). Given a SVN request, the population (which might be used for mapping the SVN) is randomly generated so as to provide candidate solutions. The information about channel availability is considered to create feasible solutions. Then, the individuals are evaluated in accordance with the adopted fitness function that takes into account the SU blocking probability, joint utilization, SU dropping probability, and collision probability for computing each individual's fitness value. Thereupon, the individuals are submitted for selection, together with the crossover and mutation operators, and moreover, an elitist strategy is employed to ensure the best fitness individuals will not be lost during the selection process. Finally, a new generation of candidate mappings will be created and the stop criterion, which is determined by the number of generations (G), is evaluated. If the stop criterion is not satisfied, the process is repeated in the fitness evaluation stage. Otherwise, the best individual is chosen as the final solution. This represents the set of channels that will be allocated to the requested SVN. In this way, the pool of available channels is updated.

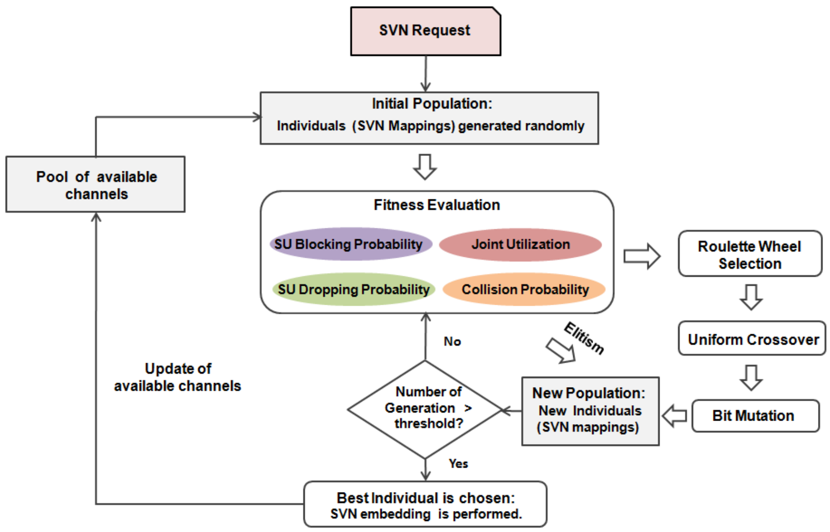

Figure 13: Execution flow of the scheme based on GA.

7. Scheme Evaluation

This section presents the scenarios and metrics adopted in the performance evaluation of the proposed scheme. It analyzes the results achieved in comparison to those of the first-fit strategy,as well as, the GA convergence.

7.1. Evaluated Metrics

For evaluation purposes, four metrics were employed: collision probability, SU blocking probability, SU dropping probability, and joint utilization (see Section 3). They aim to show the mapping impact that was carried out, on both primary and secondary communications and on the resource utilization.

7.2. Evaluation Scenarios

Three evaluation scenarios were defined to analyze the proposed scheme. Each scenario has a evaluation focus, which are presented in Table 3. In the first scenario, the SU arrival rate varied from 4 to 16 with a step of 4, which shows the behavior of the proposed scheme under different SU loads. The $\lambda_{PU,min}$ and $\lambda_{PU,max}$ were defined as 0 and 1, respectively and the substrate network was composed of 50 channels.

To evaluate the performance the scheme in cases where the environment has different PU loads and, hence, distinct possibilities of opportunistic use, in the second scenario, two cases (intervals for $\lambda_{PU,i}$) were defined. In the first, $\lambda_{PU,min}$ and $\lambda_{PU,max}$ were set as 0 and 0.5, respectively. Thereupon, the channels that compose this scenario are more susceptible to opportunistic use because of the low primary activity. In the second case, a new the PU rate interval of [0.5 1] was specified. It represents scenarios with high PU load, which reduces the possibility of opportunistic use. Additionally, the SU arrival rate was changed to 5 users/s. The channel number and SVN requests were the same as the previous case and the remaining parameters are as described in the first paragraph of this section.

The goal in the two first scenarios was to analyze the proposed scheme under different PU and SU loads. Thus, the number of SVNs to be mapped was one SVN in both cases. On the contrary, the third scenario evaluated the scheme's performance when more than one SVN had to be mapped. Hence, the number of SVN requests was set up to 4. For this experiment, the SU arrival rate was uniformly distributed between 2 and 4 users/s, the substrate network was composed of 80 channels and similarly to the first scenario, the PU arrival rates were uniformly distributed within [0 1].

In all scenarios, the primary (for all channels) and secondary service rates were defined as 1 user/s, along with the PU arrival rate of each channel i ($\lambda_{PU,i}$) that was set within the interval [$\lambda_{PU,min}$, $\lambda_{PU,max}$], with $\lambda_{PU,min} \leq \lambda_{PU,max}$. Table4 shows the chosen parameter values

Table 3: Evaluation Scenarios

Scenario	**Focus**
1	To evaluate the schemes considering different SU loads
2	To evaluate the schemes considering different PU load
3	To evaluate the schemes considering more than one SVN requests

A first-fit strategy (similar to that used in [8]) was also built for further comparison. It maps the SVNs sequentially, in the same way as the GA scheme does. First, all the SVN requests are sorted in a descending order

Table 4: Parameter values adopted in the scenarios

All Scenarios			
Parameter	**Value**		
$\lambda_{PU,i}$	U $\left[\lambda_{PUmin,}\lambda_{PUmax}\right]$		
$\mu_{PU,i}$	1 user/s		
$\lambda_{SU,l}$	1 user/s		
	Scenario 1	**Scenario 2**	**Scenario 3**
$\left[\lambda_{PUmin,}\lambda_{PUmax}\right]$	[0 1]	[0 0.5] and [0.5 1]	[0 1]
$\lambda_{SU,l}$	4/8/12/16	5	U[2 4]
#Channels	50	50	80
#SVN	1	1	4

in terms of requested demand and are placed in a queue. Next, the first-fit strategy is employed to sequentially allocate channels for each SVN in the sorted queue. It takes the next available channel (not being used by other SVNs) to map the current SVN, aiming to achieve the lowest collision probability. Similarly to the GA scheme, the First-Fit strategy encompasses the restrictions defined in (16).

Next, the GA convergence and a comparison between the GA-based and the First-Fit are drawn. For each evaluated point, 30 instances were performed and the average results are presented considering a 95% confidence level, which were obtained by using the Bootstrap method [28], with 'resample' size and number of (re)samplings equal to 30 and 1000, respectively. No bars were drawn due to a small difference between upper and lower bounds.

7.3. GA Convergence

Before evaluating the GA considering all the scenarios and metrics defined in previous subsections, its convergence was examined with regards to the population average fitness. To this end, the scenario 1 with $\lambda_{SU,l}$ equals 4 was taken into account. Moreover, we extended the GA's evolution process by adopting 250 generations to verify whether the average fitness would change significantly after the number of generations defined in Table 2.

Fig. 14 shows the evolution of the population's average fitness. It can be noted that in the first 100 generations the average fitness increases sharply as consequence of the GA's exploration process in which it searches for new solutions and explores the search space. In the next 50 generations, the population fitness rises softly, indicating that the GA is refining already

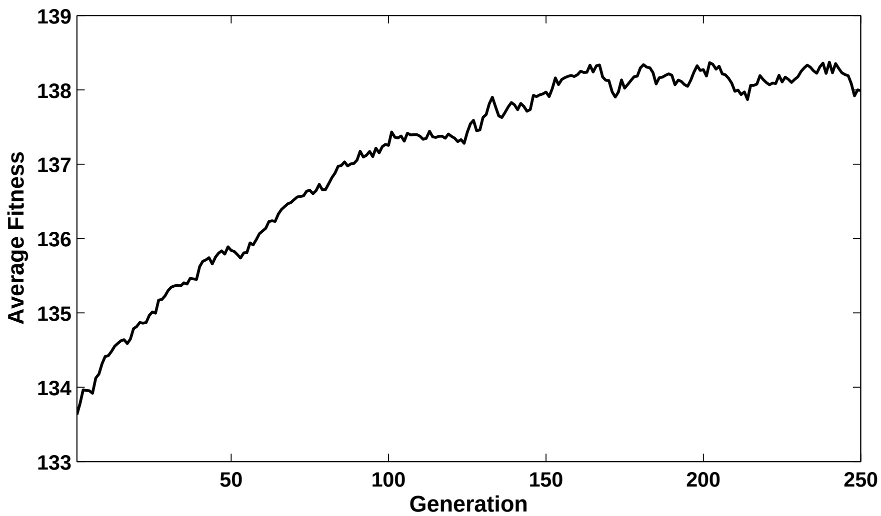

Figure 14: Average Fitness of the Population over the Generations.

existing solutions to improve their fitness (explotation). About generation 150, the average fitness of the population becomes stable and no significant changes take places, denoting that the individuals have similar fitness values. It is worth observing that other GA-based works such as [15], which performs resource allocation during network operation and, thus, has a critical time scale, converge significantly later than our GA-based scheme.

7.4. Results for Scenario 1

This section presents the results obtained by the schemes when the SVN experiences different SU loads. In terms of SU blocking probability, they achieved similar performance (there are intersections between the confidence intervals), with slight superiority for the First-Fit, when SU arrival rate is 8, 12, or 16 (see Fig. 15). On the other hand, the GA-based scheme showed a stable performance under different SU loads in the SVN. Besides, it selected the appropriate channels to meet each demand, which allowed the SU blocking probability to be lower than 0.1.

As shown in Fig. 15, both approaches presented similar SU admission levels, however, the First-Fit adopted more channels than our GA-based scheme (see Table 5). This shows that the proper selection of channels is more important than the number of channels to be allocated, since they have

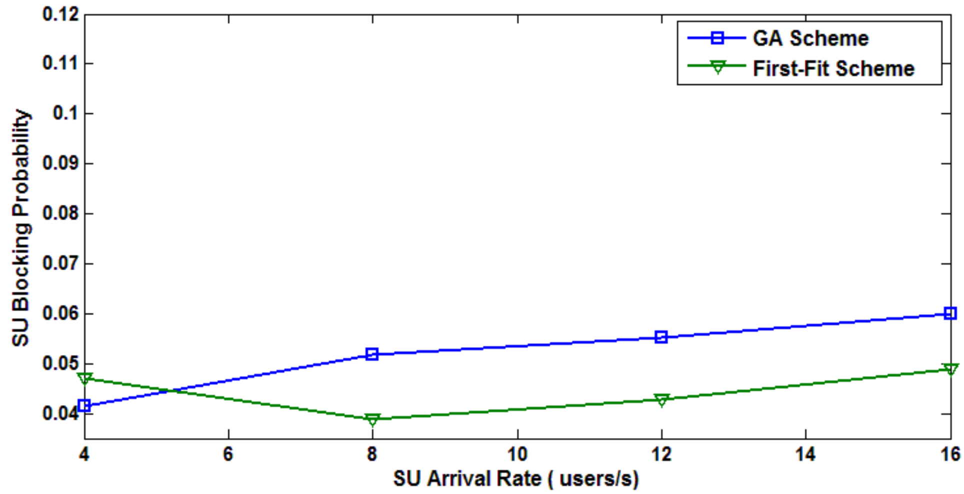

Figure 15: Average blocking probability when the SU arrival rate varies.

different primary usage patterns. Likewise, it was observed an intersection between the two schemes when the SU arrival rate varies from 4 to 6 (see Fig. 15). For the first value, the First-Fit adopts channels that provide a higher user per channel density, which leads to a higher SU blocking probability than our GA-based scheme. When the SU arrival is 6, the First-Fit allocates much more channels (sequentially) in order to reduce the collision probability. With more channels, the possibility of opportunistic access by SU increases and, consequently, the SU blocking probability reduces.

Table 5: Average number of channels adopted by the schemes to map the SVN considering the scenario 1

$\lambda_{SU,l}$	**First-Fit**	**GA**
4	17.9	11.5
8	26.7	16.8
12	34.9	22.9
16	40.8	30

For collision probability, the GA-based scheme outperformed the First-Fit for all SU arrival rates (see Fig. 16). In the first three cases ($\lambda_{SU,l}$ equals 4, 8 or 12), the average reduction in the collision probability was 38.57% (on average) and even when in a high SU load ($\lambda_{SU,l}$ equals 16), our GA-based scheme obtained a performance gain of 24.01%. In brief, the GA approach was superior to the First-Fit for various SU loads in up to 39.08%, i.e., it largely reduced the interference caused to PU communication, providing better protection to the PU.

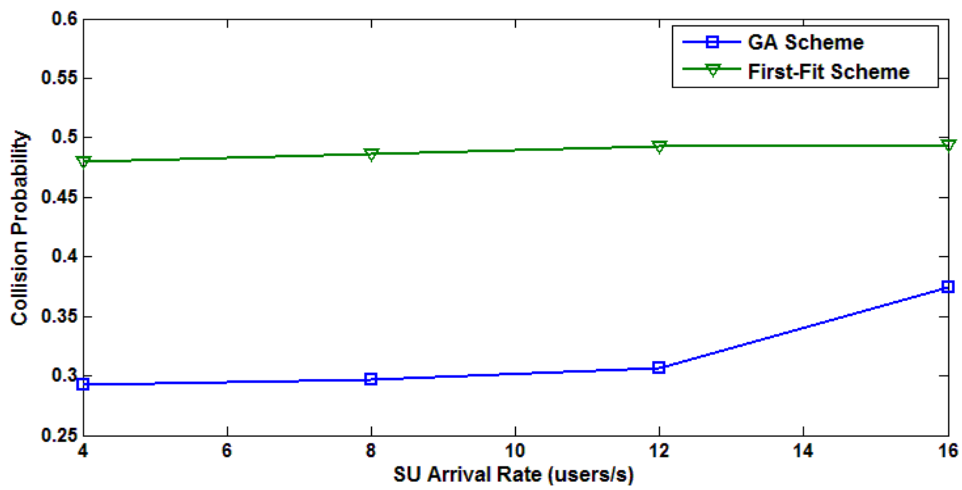

Figure 16: Average collision probability when SU arrival rate varies.

In order to achieve a low collision probability in this scenario, the First-Fit scheme allocated more channels to the SVN than the GA scheme (see Table 5). However, this did not ensure a low collision probability. The PU load of the selected channels must be observed to properly select the channels that will provide less interference. As the GA evaluates multiple solutions in each generation and composes the final solution by using building blocks, it provided a lower collision probability even adopting fewer channels.

The average SU dropping probability got by the schemes is illustrated in Fig. 17. Similarly to the previous metric, our GA-based scheme also outperformed First-Fit. It significantly reduced the SU dropping probability in up to 62.13% compared to the First-Fit. These results were achieved when $\lambda_{SU,l}$ was 4 but even in the worst case, when $\lambda_{SU,l}$ was 16, it reduced the SU dropping probability by 32.46%. On average, the GA-based scheme reduced the SU dropping probability by 48.90% compared to the First-Fit. Therefore, a reasonable QoS could be achieved by enabling the admitted SUs a better chance to finish their communications.

Results for the channel's joint utilization are shown in Fig. 18. As opposed to previous evaluations, the First-Fit had a slightly better performance than the GA scheme, mainly where the SU arrival rate is considered low, such as for 4 and 8 users/s. In these cases, it achieved a performance gain of 13.65% and 6.71%, respectively. On the other hand, both behaved similarly when there was a high load of SUs, such as with $\lambda_{SU,l}$ equal to 12 or 16, where the absolute difference between them was 3.44% and 1.85%, respectively.

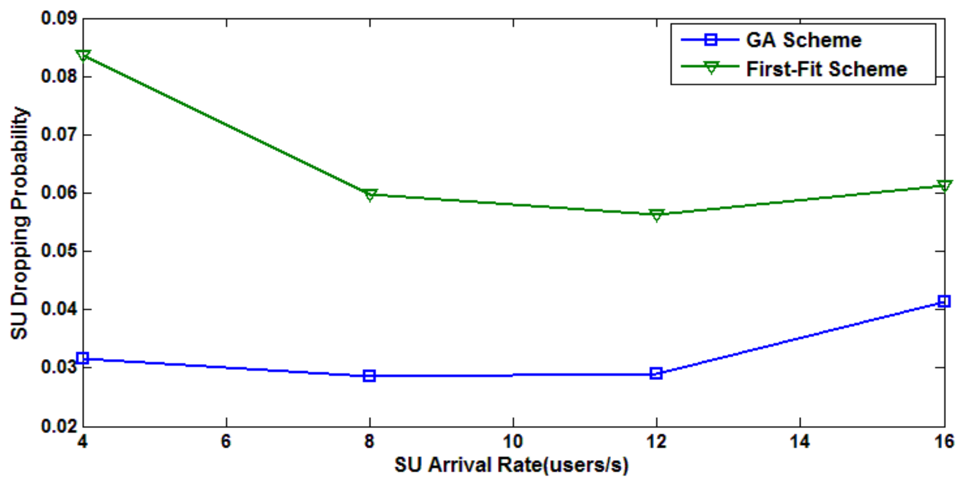

Figure 17: Average SU dropping probability when SU arrival rate varies.

Although First-Fit achieves better joint utilization, this does not imply that the secondary utilization is higher than that provided by the GA-based scheme. Since both approaches are similar in terms of SU blocking, and our scheme is better than First-Fit (when the SU dropping is considered), the secondary utilization achieved by GA strategy is probably higher than that obtained by the competitor. In this scenario, the First-Fit achieves a high joint utilization by selecting high PU load channels, which reduces the possibility of opportunistic access and, consequently, highly impacts on the secondary utilization.

7.5. Results for Scenario 2

This section analyzes the results obtained by the schemes when the substrate networks is composed of channels with high or low PU load, leading to different opportunistic access possibilities.

Fig. 19 presents our findings considering a low PU load. The First-Fit scheme achieved approximately zero blocking and dropping probabilities for the SUs, by allocating more channels than the GA scheme (see Table 6). As the channels have low PU load (PU arrival rate defined between 0 and 0.5),

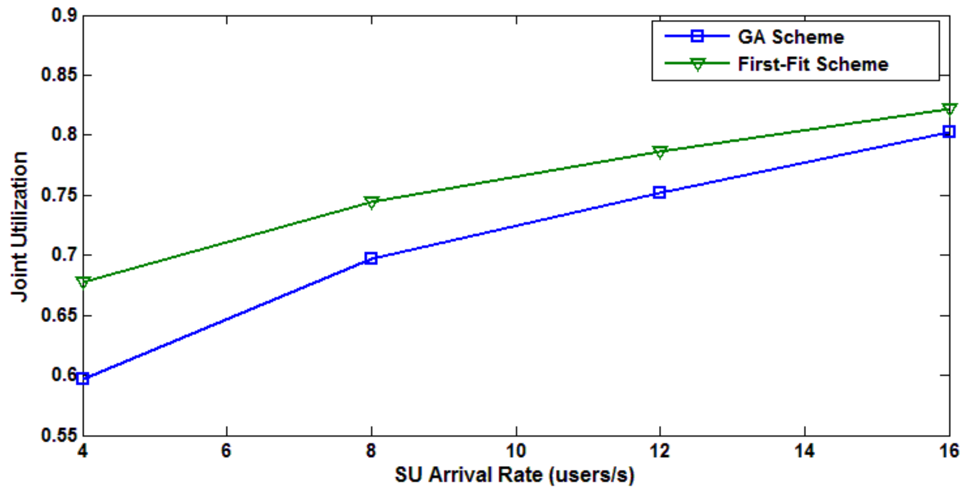

Figure 18: Average joint utilization when SU arrival rate varies.

the opportunistic access possibilities increased and, as a consequence, the SU blocking and SU dropping probabilities were greatly reduced. On the other hand, although the Fist-Fit scheme had achieved a low collision probability, our GA scheme has outperformed it, by reducing the collision probability by 24.32%.

The probability of having active SUs increases when the First-Fit is adopted as more SUs are admitted in the SVN. Also, when more channels are allocated and each one has a PU load, the total PU arrival rate increases. However, as noted, lower collision probability cannot be achieved by simply allocating more channels to SVN. Moreover, the way of mapping used by the First-Fit significantly impairs the joint utilization, as shown in Fig. 19, where it had 38.79%. Contrarily, the GA-based scheme provided a reasonable tradeoff between the adopted metrics. It has selected the most appropriate channels to map the SVN and although both SU blocking and SU dropping probabilities are higher than those offered by the First-Fit, the values obtained by GA-based scheme were also low and it achieved a higher joint utilization, with a gain of 51.40%.

The GA-based scheme also presented better results towards the blocking probability, considering the PU arrival rate defined between 0.5 and 1.0 (high PU load), as shown in Fig. 20. With GA, the blocking probability was reduced by 88.55% compared to the First-Fit scheme, which has a high blocking probability under heavy PU load. Such behavior occurs because the

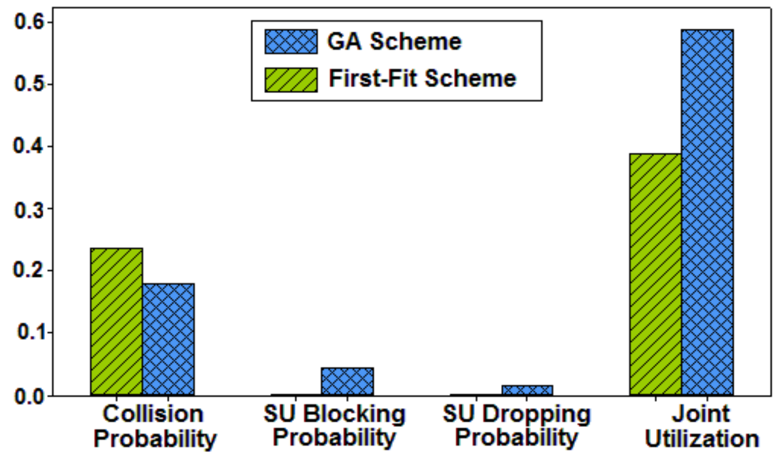

Figure 19: Results obtained by schemes when the PU arrival rates are within the [0.0 0.5].

Table 6: Average number of channels adopted by the schemes to map the SVN considering the scenario 2

PU Arrival Rate	First-Fit	GA
[0 0.5]	35.6	10.6
[0 5 1]	5	27.3

First-Fit scheme allocates fewer channels for the SVNs in order to achieve lower collision probability, thus reducing the SU access to the SVN. On other hand, it increases the user per channel density, which impacts on the blocking probability and, consequently, on the SU admission. This shows that the First-Fit scheme is not able to provide a reasonable service to the SUs when the channels are submitted to high primary loads.

In terms of collision probability, Fig. 20 shows that the First-Fit had a slightly superior performance in comparison to our scheme. The absolute difference between their performances was 3.79%, which means a reduction of 6.17% in the collision probability. Although this may suggest the First-Fit scheme's superiority, it achieved a lower collision probability because it allocated fewer channels to SVN (see Table 6) and its SU blocking probability was high (see Fig. 20), similar to what was described in the previous paragraph. With fewer admitted SUs, the collision probability tends to be lower. Hence, the result obtained by the First-Fit scheme was masked by its high blocking probability and this way of providing protection to PU communication significantly impairs the secondary network. The GA-based scheme, in turn, provided a similar protection to PU and a reasonable service to SVN.

The results for the SU dropping probability are also shown in Fig. 20, where the GA scheme surpassed the First-Fit, with gain of 64.47%, on average. Hence, our scheme provided better service to the secondary communication, by admitting more SUs and by reducing the chances of communication flaws due to the forced termination process.

In terms of joint utilization, the First-Fit strategy outperformed the GA by 6.68% (in absolute value). It has selected fewer channels to map the SVN (see Table 6), and, therefore, presented higher user per channel density. However, this caused an adverse effect in the secondary communication, since more SUs were rejected or dropped. Briefly, the joint utilization achieved by the First-Fit does not mean a higher secondary usage. On the contrary, our scheme achieved a similar joint utilization but provided more secondary opportunities. In addition, it reached the goal defined for SU blocking probability and a close result to that defined for joint utilization (see Section 6.2).

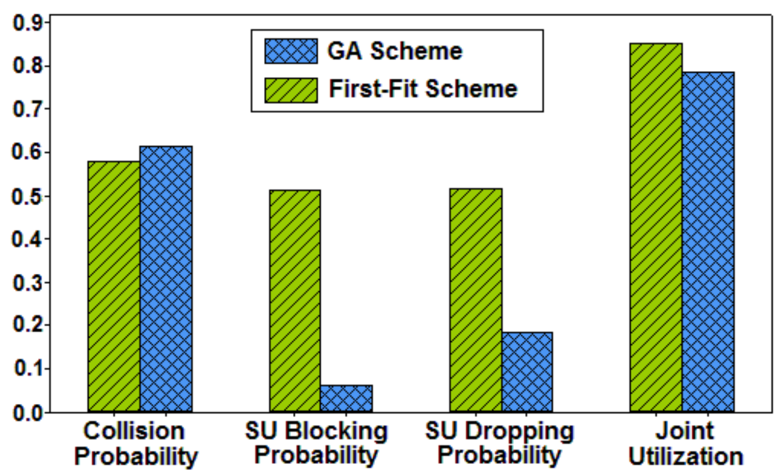

Figure 20: Results obtained by schemes when the PU arrival rates are within the [0.5 1.0].

7.6. Results for Scenario 3

The third scenario's challenge was map multiple SVNs with maximum efficiency. As shown in Fig. 21, the GA-based scheme had better lower blocking probability value, ensuring the secondary access to the SVNs. In brief, when 4 SVNs were mapped, the First-Fit achieved an average blocking probability of 0.4783 while the GA had 0.0693. In other words, the GA approach reduced blocking probability by 85.51%.

In terms of collision probability, the GA-based scheme also outperformed First-Fit (see Fig. 21). It has been found that the GA reduced the collision probability by 10.85% when compared to the First-Fit scheme, i.e., the GA-based scheme provides more protection for PU communication. Furthermore, it should be stressed that our scheme can provide a higher protection degree for the PU and ensure a low SU rejection rate for the SVN simultaneously, which is not the case for the First-Fit.

The SU dropping probability results are also drawn in Fig. 21. For such metric, our scheme outplayed the First-Fit with an impressive reduction of 77.95%. Thus, our scheme does not only admit more secondary users in the SVN, but also provides better quality for secondary communication, as the possibility of the secondary communication dropping is largely mitigated.

For the joint utilization (see Fig. 21), it was noted that the First-Fit had the best value, with performances gap of 13.53% (absolute value). However, this does not necessarily mean higher secondary utilization or QoS. Again, it is possible to infer that our scheme in fact provides higher secondary utilization, as the achieved SU blocking and SU dropping probabilities were lower than the First-Fit. Therefore, as in the first scenario, in order to achieve a higher joint utilization, the First-Fit selected channels with higher primary load to map the SVNs, meaning that the primary utilization was dominant on the joint utilization result.

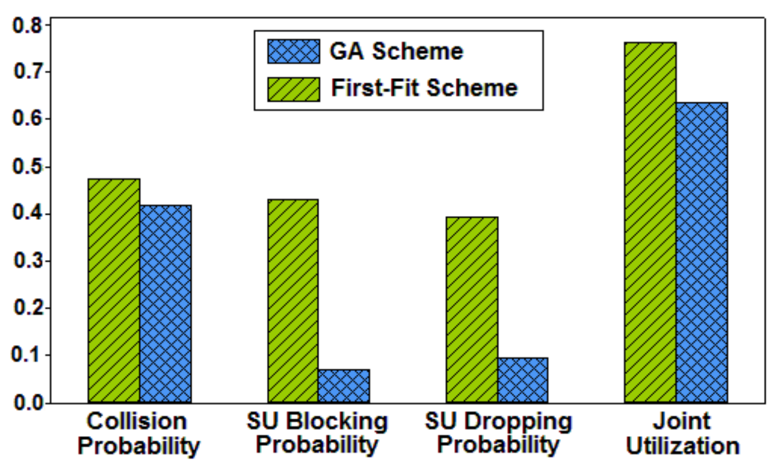

Figure 21: Results obtained by schemes when 4 SVNs are mapped.

8. Conclusion

We have combined two key technologies for 5G networks (Cognitive Radio and Wireless Virtualization) in order to provide enhanced resource utilization besides dealing with heterogeneous applications and wireless technologies with no hardware modification. By empowering the synergy between them, a new scenario, denoted as CRVNE, has been presented and modeled to address the SVNs mapping onto cognitive radio substrate as a multi-objective problem. A GA-based scheme was suggested as an alternative to a known solution named First-Fit strategy. It was found that our approach provided reasonable protection to the primary communication and an efficient tradeoff between the SU blocking, dropping, and joint resource utilization. Besides, we have also few situations where the First-Fit had apparently beaten our scheme, such as for the joint utilization metric.

The GA's intrinsic parallelism and the use of fitness functions that encompass multiple objectives enable many solutions to be handled, improved and evaluated simultaneously. During the mapping process, the proposed scheme not only deals with the collision probability, SU dropping probability and SVN demands, but also takes a broad view of the SU blocking probability and joint utilization, which also composes the defined objectives for the mapping problem.

Several practical implications emerge from our results, for instance, it was found that it is possible to share spectrum resources (e.g. channels) between different access priority users while meeting individual demands. Thus, a business model that offers a layered service type (e.g. primary and secondary) can be deployed, for example, by assigning a price menu to virtual network communications depending on their access level, being managed by different service providers: PSPs and SSPs.

When sharing resources between virtual networks (PVNs and SVNs) with different access levels, it is important to ensure that their demands and restrictions are met, for example, a PVN that imposes inflexible restrictions regarding interference to its communication. This condition must be satisfied during the mapping process and in a similar way, during the SVN mapping, so that the SVN can opportunistically access the resources, preventing starvation, despite the PU load. In brief, we have sought to show that our GA-based scheme can simultaneously meet the restrictions and demands from PVNs and SVNs.

Regarding the future development of this work, some possibilities may be explored. The first involves designing other bio-inspired approaches to the same problem while the second relates to the model extension through the support for heterogeneous secondary user scenarios (e.g. SVNs with different QoS requirements), considering SU handover and channel aggregation technology, and the combination of spectrum access approaches such as opportunistic spectrum access (OSA) and spectrum leasing.

Data Availability

The data used to support the fndings of this study are available from the corresponding author upon request.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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