IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 26, 2016, accepted February 5, 2016, date of publication February 23, 2016, date of current version March 23, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2533394

Network Selection and Channel Allocation for Spectrum Sharing in 5G Heterogeneous Networks

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ABSTRACT The demand for spectrum resources has increased dramatically with the advent of modern wireless applications. Spectrum sharing, considered as a critical mechanism for 5G networks, is envisioned to address spectrum scarcity issue and achieve high data rate access, and guaranteed the quality of service (QoS). From the licensed network's perspective, the interference caused by all secondary users (SUs) should be minimized. From secondary networks point of view, there is a need to assign networks to SUs in such a way that overall interference is reduced, enabling the accommodation of a growing number of SUs. This paper presents a network selection and channel allocation mechanism in order to increase revenue by accommodating more SUs and catering to their preferences, while at the same time, respecting the primary network operator's policies. An optimization problem is formulated in order to minimize accumulated interference incurred to licensed users and the amount that SUs have to pay for using the primary network. The aim is to provide SUs with a specific QoS at a lower price, subject to the interference constraints of each available network with idle channels. Particle swarm optimization and a modified version of the genetic algorithm are used to solve the optimization problem. Finally, this paper is supported by extensive simulation results that illustrate the effectiveness of the proposed methods in finding a near-optimal solution.

INDEX TERMS Channel allocation, network selection, 5G heterogeneous networks, optimization.

I. INTRODUCTION

The last decade has seen the dramatic increase in the demand of mobile data due to the increase in mobile devices and versatile applications. It is forecast that the data traffic will increase 10-fold between 2014 and 2019 [1]. This explosive demand of mobile data results in several challenges which shifted the research directions to fifth generation (5G) networks [2]. 5G networks are intended to provide significantly high data rate access and guaranteed quality-of-service (QoS). Thus, the demand of spectrum resources is expected to increase significantly in 5G networks. This requires wireless system designers to propose efficient spectrum management schemes. Different views on 5G architecture are presented in [3]–[5] with key technologies such as massive MIMO, energy efficient communications, cognitive radios, visible light communication, small cells, etc. In nutshell, 5G is visualized as heterogeneous networks which can provide access to a range of wireless networks and access technologies [6]. The 5G heterogeneous networks will mainly consist of network densification, i.e., densification over space and frequency. The dense deployment of small cells is called the densification over space whereas utilizing radio spectrum in diverse bands is called densification over frequency. Network densification can meet the demand of high capacity in 5G networks [7]. However, opportunistic spectrum sharing is important in order to achieve stringent goals of 5G in heterogeneous environment.

Spectrum sharing ensures the coverage of 5G heterogeneous networks everywhere and all the time. It can support a large number of connected devices and diverse applications [8]. In addition, it is spectrum efficient as it can use all non-contiguous spectrum, can achieve better system capacity, reduce energy consumption, and increase cell throughput. Dynamic spectrum access (DSA) has emerged as key for spectrum sharing in an opportunistic way [9], [10]. A radio network employing DSA to coexist with a licensed network (primary network) is known as a cognitive radio network (CRN) [11]. The users who subscribe to any of these primary networks are known as primary users (PUs). On the other hand, users who do not belong to any of these primary networks and contend for the unused portion of the spectrum in these networks are known as secondary users (SUs). SUs may face a problem in choosing which primary network to join because a 5G heterogeneous network incorporates multiple primary networks with different characteristics in terms of bandwidth, price, and capacity; this is known as the network selection problem [12], [13].

Price is a key factor while leasing/selecting the network of a specific operator for spectrum access. In [14], a joint price-based spectrum sharing and power allocation scheme is proposed for interference management. Author in [15], presented a price based spectrum sharing algorithm. The optimization problem is formulated to minimize the price incurred by the SUs and solved using the particle swarm optimization (PSO). However, the algorithm is based on assumption that there exists an interaction between PU and SUs which is practically not a feasible option. A price-based spectrum sharing and rate allocation scheme is proposed to address the problem of sub-carrier sharing with discrete rate allocation in [16]. In [17], the PSO approach is used to solve the problem of network selection. However, due to the intractable nature of the network selection problem in 5G heterogeneous networks, it is desirable to explore other avenues to develop better algorithms for solving the network selection problem. Therefore, it is required to study network selection problem in order to enhance the previous work.

A. RELATED WORK

A media independent handover and software-defined network (SDN)-based framework for network selection in 5G heterogeneous network is proposed in [18]. The concept of SDN is used to propose a pre-selection mechanism and two-dimensional cost function in order to reduce the network selection latency. An effective network selection algorithm for 5G heterogeneous networks is proposed that can efficiently choose the network with guaranteed data rate and user performance [19]. The network is selected based on a parameter which considers various metrics associated with users, system, base station transmitted power, traffic load, and spectral efficiency. In [13], authors considered realistic approaches based on network-centric and user-centric for intelligent network selection. However, none of them considered price based network selection approach.

A uniform framework to investigate and evaluate network selection strategies is presented in [20]. Authors proposed a gradient-based optimal network selection strategy and discuss several existing strategies. In [12], authors studied a single network selection scheme to maximize the mutual information over all secondary networks while satisfying the constraint of availability of the primary service. Spectrum band selection scheme is presented in [21] while satisfying the constraint on delay. The aim is to select a band with highest secondary channel power gain and lowest interference channel power gain to PUs. Authors formulated a problem to maximize effective capacity by optimizing transmit power allocation with both band selection criteria. A game-theoretic framework for network selection is proposed in [22]. The network selection problem is formulated as a non-cooperative game (ordinal potential game) with SUs as players. To solve this problem, a decentralized stochastic learning-based algorithm was proposed in which Nash equilibrium is achieved without cooperation with other SUs. A cross-layer framework is designed in [23] while jointly considering spectrum sensing, access decision, physical-layer adaptive modulation and coding scheme, and frame size. The throughput of SUs is maximized for which problem is formulated as Markov decision process.

The genetic algorithm (GA) and the PSO are derived from natural phenomena and are commonly used for solving the optimization problem. They belong to the class of evolutionary algorithms. The GA is inspired from the concepts in evolutionary biology, such as inheritance, mutation, selection, and crossover. Whereas the PSO relies on the social behavior of the particles. In every generation, each particle adjusts its trajectory based on its own best position and the position of the best particle in the entire population. More specifically, regarding evolutionary computing in CRNs, a number of efforts have been reported so far, such as spectrum sensing using the PSO [24], [25], resource allocation using the PSO and the GA [26], [27], dynamic parameter adaptation using the GA [28], the GA aided transmit power control [29], energy efficient scheduling based on the PSO [30].

In summary, the above network selection schemes do not address more realistic case where both data rate and subscription fee are considered.

B. CONTRIBUTIONS

In this paper, we consider a 5G heterogeneous network that incorporates multiple primary networks. At any given instant, each primary network has a different number of channels available for the SUs, and each channel has a different capacity. Each network has some constraints in terms of interference, subscription fees, and capacity. SUs specify their requirements in terms of the minimum data rate and the maximum subscription fee that they are willing to pay. Based on SU requirements and primary network constraints, we employ the PSO and the modified GA algorithms to find a near-optimal solution. The goal of this paper is to find a solution such that the overall cost for all SUs is minimized and the overall interference incurred to the PUs of different primary networks is also reduced. Our work differs from previous efforts in the following ways:

- The proposed model respects the perspectives of the SUs as well as the PUs, and seeks to create a balance between SU requirements and constraints of primary networks.
- The metrics on which the proposed model is built are interference to PU and the price SU has to pay to achieve a desired quality of service.

- To solve the model, a modified version of the GA algorithm is proposed and compared with the PSO based network selection.

This paper is organized as follows: In Section II, the network selection problem for the 5G heterogeneous network is formalized. Sections III and IV focuses on the mapping of network selection problem in terms of PSO and GA, respectively. Section V presents the simulation results of of proposed work. Finally, the conclusion is drawn in Section VI.

II. PROBLEM FORMULATION

We consider a 5G heterogeneous network which is composed of N primary networks, where each primary network can have any number of subscribed users (PUs). Each primary network has maximum number of channels denoted by p_m, however, the number of channels available for SU communication depends on the PU behavior. For each particular primary network, the PU behavior is modeled using Poisson process with two states, i.e., ON-OFF state model. Most publications in this field modelled PU traffic as independent and identically distributed ON-OFF process [31]–[33]. For example, in [31], authors proposed a Super Wi-Fi using an ON-OFF model based PU activity. A Super WiFi uses spectrum holes and is operated by a wireless service provider which leases a licensed spectrum band.

The maximum possible rate of transmission on i^{th} channel of m^{th} network is C_{im}^{max}. The value of C_{im} depends on the i^{th} channel condition in network m. It is assumed that there is a cognitive network operator (CNO) that manages all the incoming SUs and collects the network status information of all the available primary networks, as shown in Fig. 1. This assumption depicts the practical scenario in which the 5G network has to implement authentication and an accounting mechanism. When j^{th} SU enters the system, it specifies its minimum data rate requirement γ_j and the maximum price p_j that it is willing to pay to the CNO. Let $U = \{u_1, u_2, \ldots, u_M\}$ denote the set of M SUs contending for access. When j^{th} SU is allocated a particular channel i in a network m, it is assumed that SU creates a unit interference denoted by h_{jm} with the PUs. The amount of interference depends on the channel condition. It is desired to limit the maximum interference to the PUs of m^{th} network below a specified threshold ϵ_m. Assume that a cost f_m is associated with every m^{th} network; this means if a j^{th} SU joins an m^{th} primary network the cost f_{jm} will be charged. The objective is to minimize the overall cost and the interference caused by assigning SUs to different networks, subject to the constraints of each network. Thus, the objective function for the optimization is expressed as:

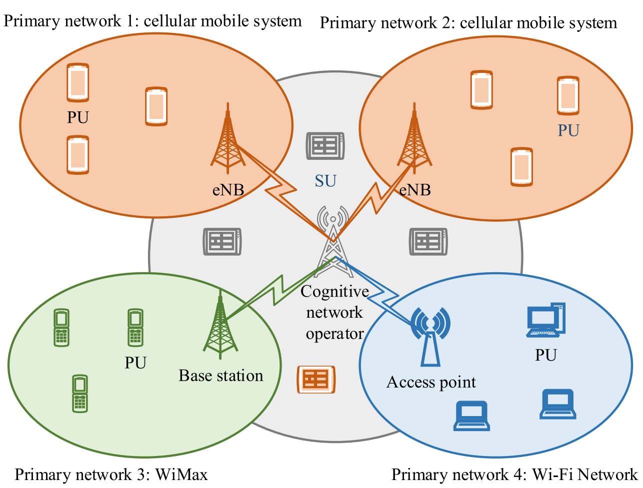


FIGURE 1. An illustration of cognitive network operator-based 5G heterogeneous network.

$$
\begin{aligned}
\text{Minimize} : Q(x) &= \sum_{j=1}^{M}\sum_{m=1}^{N}(h_{jm}+f_{jm})x_{jm},\\
\text{Subject to:} &\sum_{m=1}^{N} x_{jm} = 1, \quad \forall j = 1, 2, \ldots M,\\
&\sum_{j=1}^{M} h_{jm}x_{jm} \le \epsilon_m, \quad \forall j = 1, 2, \ldots N,\\
&\gamma_j x_{jm} \le C_{im}, \quad \forall\, i,\ j,\ \text{and } m,\\
&p_j x_{jm} \ge f_m, \quad \forall\, j \text{ and } m,\\
&x_{jm} \in \{0, 1\}, \qquad (1)
\end{aligned}
$$

where $Q(X)$ is the objective function that accumulates the interference incurred to PUs in the system and the amount that SUs have to pay for using primary networks. The first constraint states that each SU can be assigned only one channel among all the channels in networks at a given instant. If the binary decision variable x_{jm} is 1, the user is assigned to the m^{th} network and vice versa. Second, third and fourth constraints depend on the primary network resources available for SUs as well as the policy of the network. Second constraint ensures that the total interference caused by all SUs assigned to a particular network m will not exceed the maximum tolerable interference ϵ_m. Third and fourth constraints show that the assigned channel must be suitable for the SU in terms of bandwidth and cost requirements, respectively.

III. PARTICLE SWARM OPTIMIZATION (PSO) FOR NETWORK SELECTION IN 5G HETEROGENEOUS NETWORKS

PSO consists of a swarm of particles in which each particle resides at a position in the search space [34]. The position of each particle is represented by a vector that presents a solution. The algorithmic flow of PSO technique starts with an initial population of n random particles. Each particle is initialized with a random position and velocity in the search space. PSO is an evolutionary algorithm, so the position and velocity of each particle is updated in every iteration. After the update, the fitness value of each particle is computed using a fitness function. The fitness of each particle represents the quality of its position. The velocity of each particle is influenced by its own best previous position ($pbest$) found

Algorithm 1 Generale Description of PSO

1: Randomly initialize the position x_k and velocity v_k of each k^{th} particle
2: Calculate the fitness of k^{th} particle
3: Calculate $pbest_k$ for k^{th} particle
4: Calculate $nbest_k$ for the swarm
5: Update the velocity v_k of k^{th} particle using (2)
6: Update the position x_k of k^{th} particle using (3)
7: Calculate fitness of k^{th} particle
8: Update $pbest_k$ of k^{th} particle
9: Update $gbest_k$ of the swarm
10: Terminate the algorithm if the stopping condition is reached, otherwise go to step 5

by itself and the best previous position (*nbest*) found by its neighbors. If all the particles in a swarm are defined as neighbors of a particle, *nbest* is called global best (*gbest*), whereas if only some of the particles are declared neighbors of a particle, *nbest* is called local best (*lbest*).

Let v_k and x_k denote the velocity and position of the k^{th} particle, respectively. In [35], the author mentioned that they are updated as

$$v_k^{new} = w \times v_k + c_1 r_1 (pbest_k - x_k) + c_2 r_2 (nbest_k - x_k), \quad \forall\, k = 1, 2, \ldots n \tag{2}$$

$$x_k^{new} = x_k + v_k^{new}, \tag{3}$$

where w is the inertial weight and c_1 and c_2 are the acceleration constants of the particles. w, c_1, and c_2 represent the influence of their own previous velocities, personal best position, and its neighbor's best position on the new velocity, respectively. n is the number of particles in the swarm, and r_1 and r_2 are random numbers distributed in [0, 1]. The swarm will eventually converge to the optimal position, as it is driven by individual particle experience and global experience. The general description of PSO is given in Algorithm 1.

Now we discuss the PSO algorithm for network selection in 5G heterogeneous networks. The algorithm includes several features, such as associating a particle position into the different primary networks and channels (encoding of particles), computing fitness value of a particle, updating the particles position and velocity and employing a repair process for all infeasible allocations.

A. ENCODING OF PARTICLES

One of the key problems in applying PSO is the definition of an encoding scheme that describes one-to-one mapping between the solution and the particle. Each particle should consist of a complete solution for SUs, primary networks, and channels. This paper considers the k^{th} particle position in a search space of a vector for the problem of M SUs and N primary networks, each with p_m channels. To clarify, consider an example with parameters $N = 5$ and $M = 5$ which means that there are five primary networks with five SUs in a 5G heterogeneous network. It is assumed that each m^{th} network has the same channel denoted by p, i.e., $p_m = p = 7$. In this case, each group of 35 slots ($M \times p$) represents the network and channel allocation for one SU, as shown in Fig. 2. Slots 1-35 represent both the channel and network allocated for the first SU, slots 36-70 for the second SU and so on.

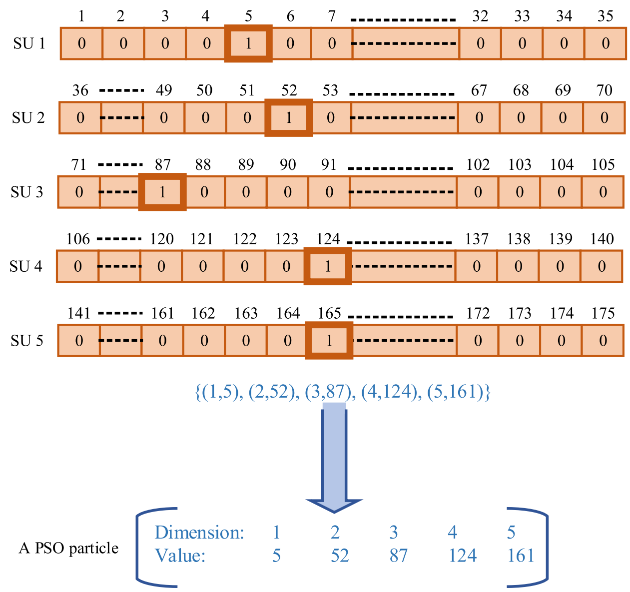


FIGURE 2. **Network selection to PSO particle mapping.**

The position of a particle can be represented by multi-dimensional vectors whose entries belong to a set of $\{1, 2, \ldots., M \times pN\}$. The M-dimensional position of the k^{th} particle is defined as $x_k = (x_{k1}, x_{k2}, \ldots., x_{kM})$, where x_{kj} represents the j^{th} dimension of the k^{th} particle, which indirectly provides the assigned network and channel for the j^{th} SU.

The above-mentioned encoding of the particles can be easily extended to a problem with m^{th} network having the different number of channels denoted by p_m. In this case, the value of p will be maximum of p_m, i.e., $p = \max\ p_m$. This means that it is supposed that each network has the same p channels. For any network m having the number of channels $p_m < p$, a value 1 is inserted in all the slots other than p_m, which indicates that $p - p_m$ slots of network m are already occupied. Mathematically, the network and channel corresponding to an element of a particle can be computed as follows:

$$\text{network} = \left\lceil \frac{x_{kj} - (j-1) \times N \times p}{p} \right\rceil \tag{4}$$

$$\text{channel} = x_{kj} - p \left\lfloor \frac{x_{kj}}{p} \right\rfloor. \tag{5}$$

Fig. 2 shows an example of a mapping between a network/channel selection and particle position. In this example, x_{kj} is $(x_{k1}, x_{k2}, x_{k3}, x_{k4}, x_{k5}) = (5, 52, 87, 124, 161)$. Out of 1-35 available slots, the first SU occupies slot number 5 ($x_{k1} = 5$), which means that the first SU is assigned to the fifth channel of the first network according to (4) and (5). Similarly, out of the 35 available slots for the second SU from 36-70, the second SU occupies the 17^{th} slot ($x_{k2} = 52$), which means the third channel of the third network according to (4) and (5).

B. FITNESS FUNCTION

The overall interference incurred by SUs and the overall cost SUs have to pay ($Q(x)$) as described in Section II are used to evaluate the performance of the algorithm. In our case, the fitness function is the inverse of $Q(X)$, which means a solution with higher accumulative interference and subscription charges will have a lower fitness value. The fitness value of each solution can be estimated using

$$\text{fitness}[k] = (Q(X))^{-1}. \tag{6}$$

C. UPDATE OF VELOCITY AND POSITION

The PSO algorithm uses the new velocity obtained from (2) to update the particle position to a new position according to (3). In this paper, we define the velocity vector of particle k as $v_k = (v_{k1}, v_{k2}, \ldots, v_{kM})$, $v_{kj} \in \mathbb{R}$ where v_{kj} is the real number pointing toward the movement of the SU for the k^{th} particle from the current slot to the next one. For example, the velocity vector $v_k = (1.2, -1.5, 2.3, -1.68, 1.87)$ in the next generation is added to the position vector $x_k = (5, 52, 87, 124, 161)$, and the new position vector equals $(6.2, 50.5, 89.3, 122.32, 162.87)$. Because the values in the particle are slot numbers, a non-integer value such as 6.2 cannot be a slot number. Therefore, elements of the position vector should be the integer slot numbers to which the non-integer numbers are rounded. Thus, the particle position $(6, 51, 89, 122, 163)$ is obtained in the next generation. Generally, the value of each component in v can be clamped to the range $[-v_{max}, +v_{max}]$ to prevent excessive roaming of particles outside the search area. If v_{kj} is smaller than $-v_{max}$, then set $v_{kj} = -v_{max}$; if v_{kj} is greater than $+v_{max}$, then set $v_{kj} = v_{max}$. We set $v_{max} = 7$, which limits the forward or backward movements of each SU to a maximum position of 7 slots. For example, if an SU is currently associated with network 3, in the next generation it can join network 2, network 4, or remain in network 3.

D. REPAIR PROCESS

The algorithm starts to randomly generate as many potential solutions for the problem as the size of the initial population of the PSO. Each dimension in the particle vector represents a channel as well as a network assigned to a SU. The allocation of a network and a channel to SUs is performed sequentially until all SUs are assigned to a network and channels. Each particle represents a complete solution that ensures that each allocation must satisfy the constraints mentioned in Section II.

The next stage is to use the proposed algorithm to adjust the position of the particles. This algorithm starts at the beginning of the first dimension and works through to the end of the

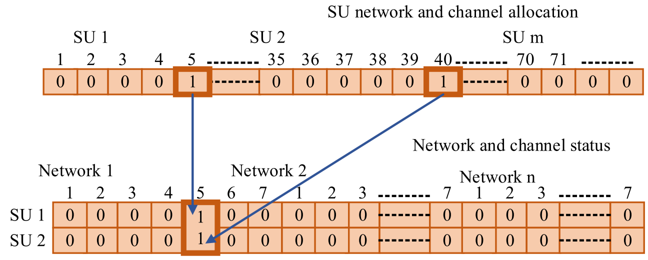


FIGURE 3. Repair process for an infeasible allocation of SU1 and SU2 to the same channel and network.

particle. As mentioned earlier, the algorithm uses the new velocity based on (2) to update the particle's current position to a new position according to (3). It is worth mentioning that the new position must be feasible, i.e., it must satisfy all the constraints, and the next step is to check whether the corresponding network and channel allocation satisfy all the constraints mentioned in Section II. Fig. 3 shows an example: the first SU occupies the fifth channel in the second network, and the second SU updates to the same slot in the second network. This means that the allocation of the fifth channel in the second network violates the constraint, i.e., a channel can be assigned to only one user at an instant, so it needs to be corrected. There are three approaches to deal with an infeasible allocation [36]: discarding it, applying a high penalty in the fitness function, and repairing it. The authors showed that discarding an infeasible solution or applying a high penalty is an option only when a large proportion of the population is feasible.

Here, we adopt a repair process where the position of SUs is adjusted to meet the constraints. The first step is to identify infeasibility. There are four types of infeasibility: 1) two SUs clash in terms of their allocation, 2) SU's demand is more than the capacity of the assigned channel, 3) a SU cannot be assigned to this network because it is not willing to pay the charges of this network, and 4) the network cannot accommodate any further assigned SUs because its interference tolerance limit has been reached. The second step is to regenerate the new velocity of the SU to identify a new position (slot) for reallocation. If the newly generated slot satisfies all the constraints, the SU's position is updated. Otherwise, the second step is repeated until a slot is obtained that satisfies all the constraints.

IV. GENETIC ALGORITHM (GA) FOR NETWORK SELECTION IN 5G HETEROGENEOUS NETWORKS

Normally GA starts by creating an initial population of chromosomes denoted by N_{pop}. Each chromosome encodes a solution of the problem, and its fitness value is related to the value of the objective function for that solution. Generic operations, such as crossover, mutation, and natural selection are applied during each iteration in order to search for potentially better solutions. The crossover operation combines two chromosomes to generate the next generation of chromosomes while preserving their characteristics. The mutation operation reorganizes the structure of genes in a chromosome randomly so that a new combination of genes may appear in the next generation. It serves the purpose of the search by jumping out of the local optimum solutions. Reproduction involves copying a chromosome to the next generation directly so that chromosomes from various generations can cooperate in the evolution. The quality of the population may be improved after each generation [36].

A. ENCODING OF CHROMOSOMES

Chromosomes are the basic building blocks of the GA. Each chromosome should be represented in such a way that it provides complete information about the solution of problem. A chromosome consists of genes that can be represented in the form of a binary or integer string. For the problem of N SUs and M primary networks, we represent each k^{th} chromosome (potential solution) as a binary string. Let us consider an example where there are 5 primary networks and 5 SUs ($N = 5$ and $M = 5$) and each primary network has 7 channels available for SUs. As there are 5 SUs, there are 5 genes in k^{th} chromosome. Once we have decided on the number of genes for the chromosome, the next step is the encoding of the chromosome. Each gene represents one SU, and each SU should be assigned to a network and a channel. Because there are 5 primary networks and 7 channels in each network, we need 3 bits for representing the network and 3 bits for representing the channel, i.e., each gene will have 6 bits. As a result, each chromosome will have 30 bits with 5 genes, as shown in Fig. 4.

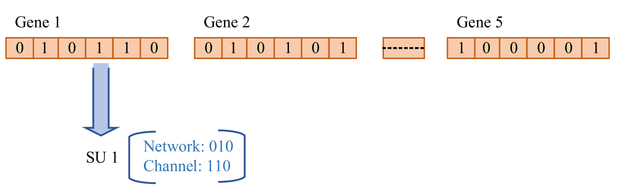


FIGURE 4. GA's chromosome mapping for network and channel selection.

The allocated network and channel for an SU are represented by the allocation bits of each gene in the chromosome. The first three bits represent the network id and last three bits are the channel id. For example, if the first gene representing the first SU has a value of 010110 as allocation bits, this means that the first SU is assigned to the second network and the sixth channel.

B. FITNESS MEASURE

The next step after construction of the chromosomes and generation of the initial population is to evaluate each chromosome by measuring its fitness. The fitness measure is also known as the survival measure that determines how well an individual (i.e., the chromosome) from a population solves the given problem. The fitness is generally a real number, the higher the value of its value, the closer the chromosome is to the optimal solution. We use the same fitness function as in (6) for the GA, as discussed in Section III-B.

C. SELECTION OF CHROMOSOMES

The process following the fitness measure is the construction of the next generation selection. The selection process is dependent on the fitness measure of the chromosomes. In the selection process, the population is first sorted by a comparison of fitness values. The top $N_{pop} \times R_{select}$ chromosomes are included in the selected/mating pool, where N_{pop} is the population size (total number of chromosomes) and R_{select} is the selection rate (which is chosen as 0.5 in this paper). A pair of parent chromosomes is selected from this pool and mated using the crossover procedure discussed in the next section.

D. CROSSOVER PROCESS

After the selection of chromosomes, the next step is to perform the crossover (also known as reproduction) on randomly selected chromosomes. Crossover is a process in which the characteristics of a pair of parent chromosomes are exchanged with each other to form a pair of child chromosomes. The crossover rate is taken as 0.5. There are several mechanisms for the crossover process, such as single point, 2-point, multi-point, and uniform crossovers. We have chosen the 2-point crossover process. As described in Section IV-A, a binary encoding is used for the chromosome structure, so we have to develop some crossover specifications. Two cross-points are set at the multiple of 3 bits, which means either the border between genes or the mid-point of a gene. Once two cross-points are chosen, every bit between the two cross-points is swapped between the parent chromosomes, rendering two child chromosomes. For example, as shown in Fig. 5, two parent chromosomes p_1 and p_2 crossover and produce two child chromosomes c_1 and c_2.

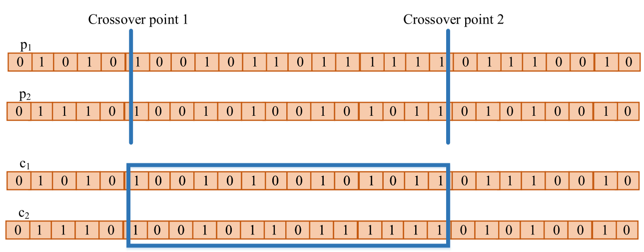


FIGURE 5. 2-point crossover procedure for generating child chromosomes.

Each crossover generates two child chromosomes that replace two chromosomes from the bottom of the population that are not in the mating pool. This replacement process continues until all the chromosomes that are not in the mating pool are replaced. In this manner, the chromosomes that have high fitness, i.e., the ones in the mating pool, survive in the subsequent generations. In contrast, the chromosomes that have low fitness, i.e., the ones that are not in the mating pool, do not survive and are replaced by the children of the chromosomes of the mating pool, which potentially have higher fitness.

Algorithm 2 Elitism Based Genetic Algorithm (GA)

1: Generate the initial population of chromosomes
2: Evaluate the fitness of each chromosome
3: Check for Termination if the stopping condition is reached goto step 4 otherwise step 5
4: Select the best chromosome and Stop
5: Elitist population to preserve the best individual of each generation using sorting mechanism
6: Apply crossover on selected chromosomes
7: Apply mutation on selected chromosomes
8: Goto step 3

E. MUTATION

After producing the new generation using the crossover process, another process, called mutation is performed. Mutation is applied to the child chromosomes, altering a binary bit of 0 to 1 or vice versa. The number of chromosomes undergoing the mutation process out of 100 chromosomes is specified by the mutation rate. Here, the mutation rate is chosen to be 0.03, which means that every chromosome is considered for mutation with a probability of 3%.

In the first generation, the population is randomly generated so there is a chance that certain constraints of primary networks are violated. For example, the channels and networks allocated for two SUs may be the same. Similarly, this can also happen after mutation. Whenever there is a violation of any constraint in a chromosome, including a clash between the positions of two SUs, data rate, cost violation, or violation of the second constraint, a repair process is triggered. In this repair process, the positions of the SUs are randomly adjusted so that violation of any constraint is eliminated. For example, if two genes in a chromosome are somehow assigned the same value, i.e., two SUs are assigned to the same channel in the same network. If such a situation occurs, the value of one of the two genes is randomly adjusted in such a way that the violation is eliminated.

F. ELITISM

We applied the concept of elitism in the GA. In this concept, unlike the standard GA, the excellent individual is reserved in each generation. As mentioned earlier in the selection process, the individuals are sorted according to their fitness value and the best individuals are preserved. The child chromosomes replace the parent chromosomes with lower fitness values. Together with the help of elitism, the best individual can be prevented from being lost during the process of selection, crossover, and mutation. This is clearly helpful in the global convergence property of the GA. The description of Elitism based GA for network selection is given in Algorithm 2.

V. SIMULATION RESULTS

A. PARAMETERS SETTINGS

Simulations are carried out for the network selection in 5G heterogeneous network in order to evaluate the quality of the solution and the convergence speed of both PSO and GA algorithms. The performance of both GA and PSO depends on the parameters chosen. After a preliminary set of experiments, the parameters chosen for the simulations of these algorithms are given in Table 1.

TABLE 1. Simulation parameters.

Parameters	Value
Number of iterations	3000
Number of SUs in CRN	12
Number of primary networks	7
Number of channels in each network (p)	7
PSO:	
Population Size	12
Acceleration constants c_1, c_2	2
Inertial weight (w)	0.6
V_{min}	-7
V_{max}	7
GA:	
Population Size	12
Crossover rate	0.5
Mutation rate	0.03

The simulations are performed under two scenarios using different data sets in order to compare the performance of GA and PSO. We performed 20 runs on each scenario to obtain the average performance of PSO and GA. The PU arrival process and channel availability for each primary network is modeled using Poisson process. A channel occupied by PU is considered to be unavailable for SUs, therefore, if an SU tries to access this particular channel, the repair process will be triggered. The information gathered about the primary networks for both scenarios 1 and 2 is given in Table 2. When a SU enters in the system, it specifies its requirements for data rate and the price it is willing to pay to the CNO. The information specified by the SU for both scenarios 1 and 2 is shown in Table 3.

TABLE 2. Primary networks for scenarios in CRN.

Network id	Cost to join (f_m)		Capacity per channel (C_m^{max} bps)		Target interference (ϵ_m)	
	1	2	1	2	1	2
1	90	80	80	80	5	7
2	50	60	100	70	10	6
3	70	65	70	70	7	7
4	95	60	100	90	8	10
5	95	70	80	100	9	9
6	40	40	80	70	7	5
7	60	50	80	60	9	9

When the j^{th} SU joins a network, it causes interference h_{jm} to the PUs of the m^{th} network. We assumed that the

TABLE 3. SU's requirements and preferences for scenarios.

SU	Scenario 1		Scenario 2	
j	Data rate (bps)	Price	Data rate (bps)	Price
1	50	100	50	80
2	70	100	70	75
3	70	100	70	70
4	20	100	20	90
5	60	100	60	60
6	40	100	40	50
7	50	100	50	60
8	40	100	40	75
9	50	100	50	55
10	60	100	60	95
11	40	100	40	100
12	40	100	40	70

interference created by the j^{th} SU is the same for all the channels of a particular network m. The interference caused by the SU when it joins a particular primary network m is given in Table 4 for both scenarios.

B. RESULTS FOR COMPARISON OF PSO AND MODIFIED GA

This section describes the results of the simulations performed to gain insight into the performance of PSO and GA implementations for the network selection problem in 5G heterogeneous networks. Two network selection scenarios with different network constraints, as well as the SUs' requirements and conditions described in Section V-A, were used to test the effectiveness of the proposed methods. Among the differences in both scenarios, the major difference is the price which SUs are willing to pay. In scenario 1, each SU can join any network because the price each SU is willing to pay is higher than the maximum cost of joining any primary network. In scenario 2, a SU may be unable to join a network owing to cost constraints. For example, in scenario 2, the 6^{th} SU can join only the 6^{th} and 7^{th} networks because the price it is willing to pay is less than the cost of joining the other networks. The objective function of the particle or chromosome that has the highest fitness value was

TABLE 4. SU's interference h_{jm} to PUs of a particular network m for scenarios 1 and 2.

SU	m=1		m=2		m=3		m=4		m=5		m=6		m=7	
j	1	2	1	2	1	2	1	2	1	2	1	2	1	2
1	2	2	1	1	3	3	1	1	2	2	1	1	2	2
2	1	2	2	1	1	2	4	4	3	2	1	2	1	1
3	4	4	1	1	1	1	3	3	1	1	1	1	2	3
4	1	3	2	2	1	2	2	2	2	2	1	1	1	1
5	1	1	2	2	3	3	2	2	1	1	1	1	1	1
6	1	2	2	3	1	1	3	3	1	2	1	2	1	1
7	1	1	2	2	1	1	3	1	1	1	2	2	2	2
8	4	4	1	1	2	2	1	1	2	2	1	1	3	1
9	1	3	2	3	2	1	1	1	3	3	1	1	4	3
10	1	1	1	1	2	2	2	2	1	1	1	1	3	3
11	3	3	1	1	2	1	1	1	1	1	1	2	3	3
12	1	2	2	2	1	1	1	1	2	2	1	1	2	2

TABLE 5. Objective values: GA versus PSO.

Iterations	Scenario 1		Scenario 2	
	GA	PSO	GA	PSO
100	0.001623	0.0014437	0.001646	0.001601
500	0.001769	0.0014736	0.001691	0.001626
1000	0.001783	0.0014968	0.001701	0.001634
1500	0.001795	0.0015050	0.001708	0.001642
2000	0.001800	0.0015180	0.001708	0.001652
2500	0.001806	0.0015230	0.001709	0.001656
3000	0.001813	0.0015290	0.001709	0.001660
Standard Deviation	5.386×10^{-5}	2.5727×10^{-5}	2.05×10^{-5}	1.353×10^{-5}

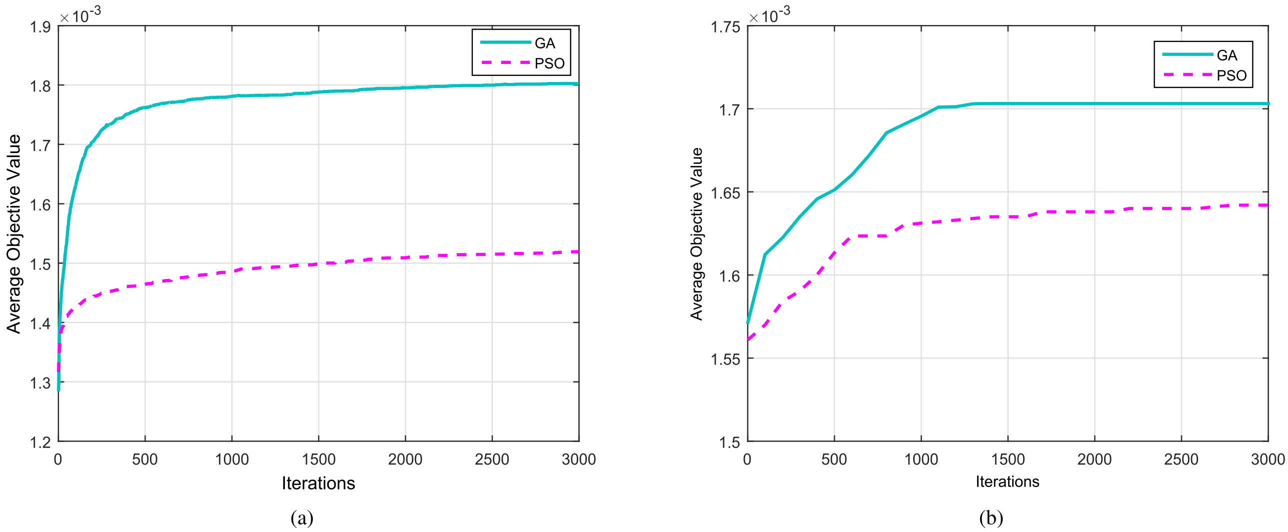


FIGURE 6. Performance comparison in terms of average objective value: GA versus PSO (a) scenario 1 and (b) scenario 2.

TABLE 6. Network allocations for SUs in scenario 1.

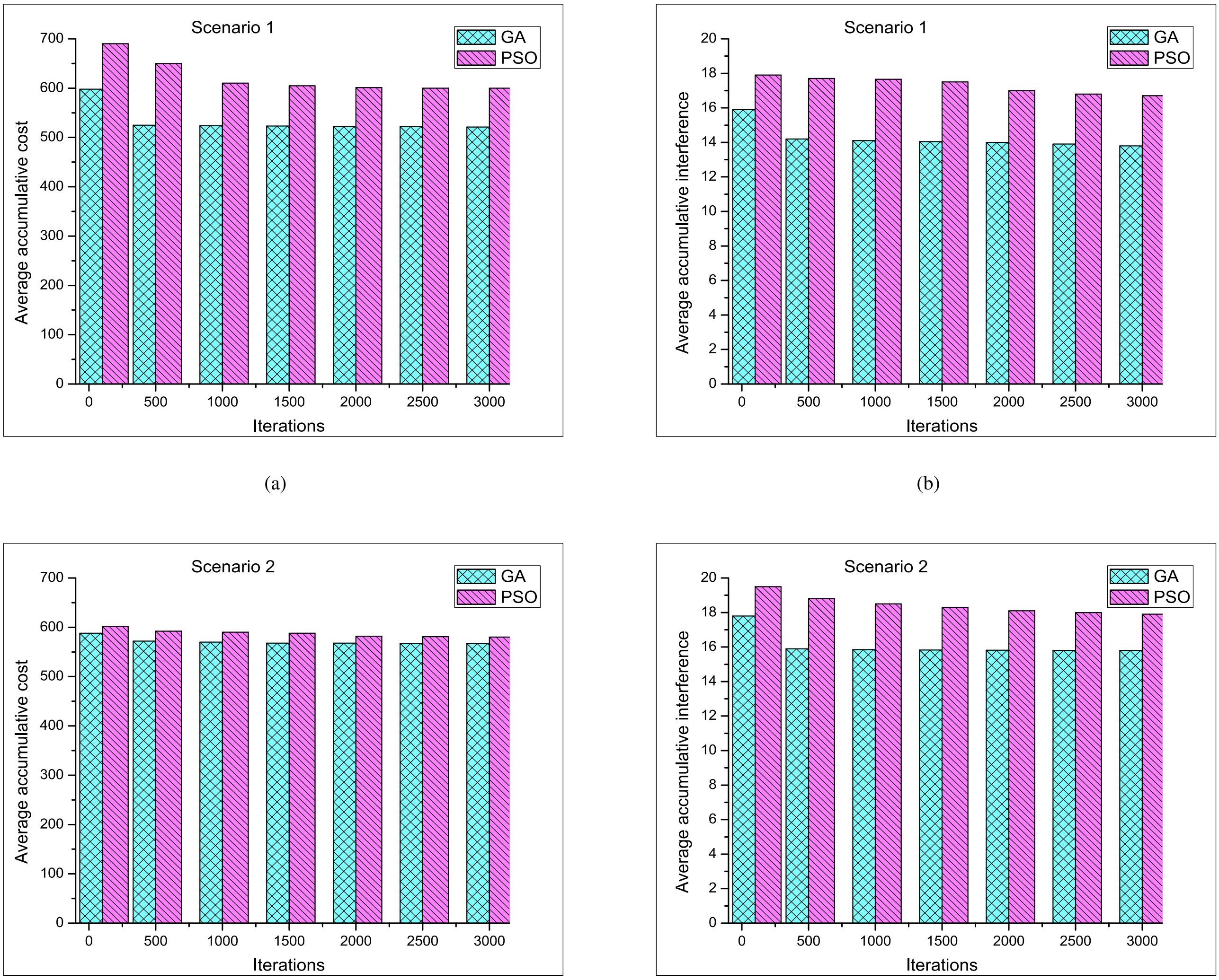
j	GA				PSO			
	m	I	f_{jm}	h_{jm}	m	I	f_{jm}	h_{jm}
1	6	4	40	1	7	7	60	2
2	2	1	50	2	6	3	40	1
3	2	4	50	1	1	1	90	4
4	6	5	40	2	6	5	40	1
5	6	6	40	1	2	1	50	2
6	6	7	40	1	2	1	50	2
7	7	6	60	2	4	7	95	3
8	2	5	50	1	6	1	40	1
9	6	3	10	1	6	7	40	1
10	6	1	40	1	3	1	70	2
11	2	6	50	1	4	5	95	1
12	6	2	40	1	6	2	40	1
	Accumulative Interference=15 Accumulative Cost =540				Accumulative Interference=20 Accumulative Cost =700			

TABLE 7. Network allocations for SUs in scenario 2.

j	GA				PSO			
	m	I	f_{jm}	h_{jm}	m	I	f_{jm}	h_{jm}
1	6	3	40	1	7	7	50	2
2	6	1	40	2	5	3	70	2
3	6	7	40	1	6	5	40	1
4	7	4	50	1	1	1	80	3
5	7	7	50	1	6	6	40	1
6	7	5	50	1	7	6	50	1
7	7	2	50	2	7	5	50	2
8	7	6	50	1	6	1	40	1
9	6	6	40	1	6	3	40	1
10	7	1	50	3	6	2	40	1
11	2	3	60	1	4	3	60	1
12	4	1	60	1	7	4	50	2
	Accumulative Interference=16 Accumulative Cost =580				Accumulative Interference=18 Accumulative Cost =610			

recorded in each iteration, and the resulting average objective function values over 20 simulation runs are shown in Fig. 6. The exact average objective function values after 100, 500, 1000, 1500, 2000, 2500, and 3000 iterations are shown in Table 5. Fig. 6 and Table 5 show that the PSO algorithm converges faster than the GA, however, the solution optimized by the GA has far higher fitness values than those optimized by the PSO. The standard deviations after 3000 iterations over 100 runs are also given in Table 5, indicating that the PSO algorithm is more stable than the GA.

Fig. 7 shows the impact of network selection for SUs on the overall interference incurred by the primary networks and the cost SUs have to pay in order to achieve their required QoS under both scenarios 1 and 2. It can be clearly seen that both GA and PSO significantly reduce both the average accumulative interference incurred by the PUs and the price a SU has to pay to join a different network. More SUs can be accommodated within the given PU interference limitations, and they can receive a better QoS for a lower price. Furthermore, it is also clear that the GA is more successful than PSO in minimizing both interference and cost for both scenarios. For example, in case of scenario 1, the average accumulative cost paid by SUs drops after 3000 iterations from almost 600 to 500 when the GA is used, whereas the cost paid by



(a) (b) (c) (d)

FIGURE 7. Performance comparison: GA versus PSO (a) scenario 1: average accumulative cost, (b) scenario 1: average accumulative interference, (c) scenario 2: average accumulative cost, and (d) scenario 1: average accumulative interference.

SUs when the PSO algorithm is used drops from 680 to 630 and decreases much more in scenario 2 than in scenario 1. In scenario 1, all SUs are able to pay; therefore every SU is willing to pay the price of joining any available network. In case of interference, the GA again performs remarkably better than PSO. The results indicate that the GA performs better as compared with the PSO in both scenarios, because GA uses the concept of elitism in which the best individual of each iteration is preserved during the selection process.

Tables 6 and 7 show the solutions obtained after 3000 iterations using GA and PSO for scenario 1 and 2, respectively. It can be seen that all the results shown in Tables 6 and 7 completely satisfy all the constraints mentioned in Section V-A. It also shows the exact value of interference caused by each SU and the cost each individual SU has to pay. To compute the convergence time of the PSO and the modified GA, we have done experiments when $N = 5$, $p = 7$, and $M = 12$. The experiment was conducted on a 2.93 GHz double processor PC with 4GB of memory. The result shows that average elapsed time after 100 iterations of the PSO and the modified GA is 0.25ms and 30ms, respectively. Hence, it is fairly available for real-time implementation to use evolutionary algorithms such as the PSO and the modified GA for a number of iterations.

C. EFFECT OF VARYING PU ACTIVITY

To demonstrate the effect of varying PU activity, we consider a PU associated with each available channel in the network. The probability of PU presence on a channel varies from 0.1 to 0.5 for each channel generated using Poisson process. Fig. 8 shows the effect of varying probability of PU appearance on accumulative cost for SU communication for scenario 1. The accumulative cost for SU increases with

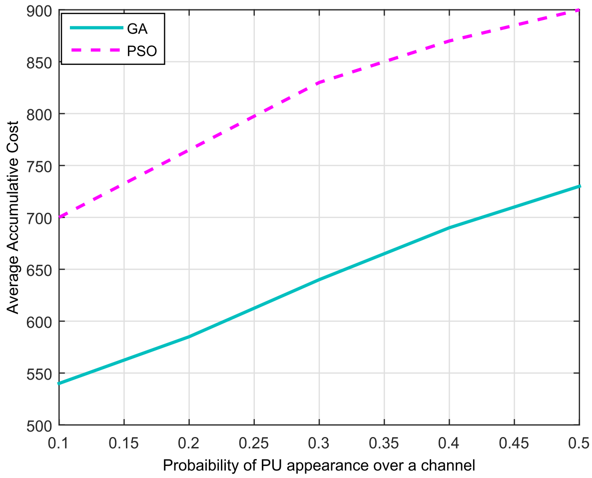


FIGURE 8. **Effect of PU activity on the accumulative cost for Scenario 1.**

increase PU activity because with more channel occupied we remained with less possibilities to select channel for fixed number of SUs.

VI. CONCLUSION

The emerging wireless applications with stringent QoS requirements continue to demand more spectrum resources. Spectrum sharing is the key solution to deal with the problem of spectrum scarcity. In this paper, we have studied the network selection problem in 5G heterogeneous networks. We have proposed a network selection mechanism and formulated an optimization problem for network selection to minimize the interference to primary networks and cost paid by SUs. We then solved the optimization problem with the PSO and modified GA in order to find near-optimal solution. We have also designed two scenarios for performance evaluation with different system settings, SU data rate demands, and price preferences. Then the performance of proposed mechanism for network selection was evaluated under these scenarios. The simulation results showed that the modified GA outperforms the PSO and achieves a higher fitness value with less iterations in terms of both interference reduction and SU price requirement.

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