

## AN IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM FOR SPECTRUM ALLOCATION IN COGNITIVE RADIO NETWORKS

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<https://doi.org/10.25271/sjuoz.2023.11.3.1083>**ABSTRACT**

The seriousness of the spectrum scarcity has increased dramatically due to the rapid increase of wireless services. The key enabling technology that can be viewed as a novel approach for utilizing the spectrum more efficiently is known as Cognitive Radio. Therefore, assigning the spectrum opportunistically to the unlicensed users without interfering with the licensed users, concurrently with maximizing the spectrum utilization is addressed as a major challenge problem in cognitive radio networks. In this paper, an improved metaheuristic optimization algorithm has been proposed to solve this problem that contingent on a graph coloring model. The proposed approach is a hybrid algorithm composed of a Particle Swarm Optimization algorithm with Random Neighborhood Search. The key objective function is maximizing the spectrum utilization in the cognitive radio networks with the subjected constraints. MATLAB R2021a was used for conducting the simulation. The proposed hybrid algorithm improved the system utilization by 1.23% compared to Particle Swarm Optimization algorithm, 5.57% compared to Random Neighborhood Search, 7.9% compared to Color Sensitive Graph Coloring algorithm, and 27.33% compared to Greedy algorithm. Moreover, the system performance was evaluated with various deployment scenarios of the primary users, secondary users, and channels for investigating the impact of varying these parameters on the system performance.

**KEYWORDS:** Cognitive Radio, Spectrum Allocation, Optimization Algorithms, Particle Swarm Optimization, Random Neighborhood Search.

**1. INTRODUCTION**

With the progressive development of wireless devices and gadgets, the traditional spectrum resource allocation scheme intensifies spectrum scarcity, which in turn reduces the utilization of the spectrum significantly (Feng & Weilian, 2018; M. G & V, 2021). The fixed channel allocation policy regulates the wireless networks, in other word, the governmental agencies regulate the spectrum for the authorize holders or services on a long-term basis for a large geographical region. Furthermore, referring to the Federal Communication Commission (FCC) report, temporal and geographical variation of the licensed spectrum exploitation varies from 15% to 85% (Liu, Wang, Chen, & Guo, 2018a, 2018b). Even though the traditional fixed spectrum allocation worked well in the past, however, the effectiveness of the traditional spectrum assignment policies in recent years reduced dramatically due to the significant access to limited spectrum resources in wireless mobile services (L. Zhang, Xie, & Chen, 2020).

Licensed users experience different needs for traffic and bandwidth for various amounts of time (Tarek, Benslimane, Darwish, & Kotb, 2020). Besides the new technologies, the bandwidth requirements for different types of applications keep on changing (Mishra, Sagnika, Singh, & Mishra, 2019). The inefficient spectrum utilization with the restricted spectrum availability necessitated a novel communication model for opportunistically exploiting the current wireless spectrum resources. Therefore, for solving these spectrum inefficiency problems, Cognitive Radio (CR) that is contingent on Dynamic Spectrum Access (DSA) was proposed (Singh & Dutta, 2020). The so-called NeXt Generation (xG) Networks, also called dynamic spectrum access networks (DSANs) are capable of

providing high bandwidth for their users in an opportunistic manner (Salehi & Solouk, 2022).

CR is the key enabling technology for the xG networks (Motta, Banerjee, & Sharma, 2023; Rajesh Babu, Garg, & Chakraborty, 2022). This technology was first introduced by Dr. Joseph Mitola in his PhD dissertation in 2000 (Salih & Shakir, 2022). CR is a Software Defined Radio (SDR) that can intelligently detect the spectrum bands (holes) for the secondary users (SUs) (also known as unlicensed users or cognitive users) and opportunistically utilizing the spectrum bands without interfering with the licensed users or so-called primary users (PUs) (Latif et al., 2021). A CR device can regulate its operating parameters for instance (power transmission, communication technology, operating frequency, modulation scheme, ... etc.). So it can adapt itself to the environment and achieve the desired objectives (Tarek et al., 2020). Spectrum allocation (also known as spectrum allotment or spectrum assignment) which is a part of the process of spectrum management is frequently addressed as a vital research challenge in the CRNs (Latif et al., 2021).

An efficient spectrum allocation system can determine the efficiency of the whole cognitive radio network along with maximizing the spectrum utilization (Feng & Weilian, 2018). Efficient allocation scheme that aims to maximize the spectrum utilization and minimize the interference is considered to be an optimization problem (Latif et al., 2021). Various traditional models have been utilized for modeling the spectrum resource allocation problem for instance graph model, game model, interference temperature model, auction model, and among other models. Graph-based models are the most commonly used methods for modeling the spectrum allocation problem (Feng & Weilian, 2018). Although the graph-based allocation optimization problem is a non-deterministic polynomial (NP)-

hard combinatorial optimization problem (Feng & Weilian, 2018; Liu et al., 2018b; Sehli & Babes, 2020). Therefore, inexact methods (also called approximate methods) are used to solve such problems, like heuristic and meta-heuristic optimization algorithms (Feng & Weilian, 2018).

In this paper, different optimization algorithms have been studied and has been applied for allocating the spectrum in CRNs. The algorithms were examined to show their capabilities for achieving the near optimal solution and to maximize the network utilization with interference-free allocation. Indeed, after studying each algorithm individually it was observed that there is a need to enhance the existing optimization algorithms as they tend to fall early into local optimum. Hence, an improved hybrid optimization algorithm is proposed. Therefore, the key contributions of this work can be listed as follows:

1. Modeling the problem of the spectrum allocation using graph coloring model.
2. Proposing an improved PSO algorithm that combines the Particle Swarm Optimization algorithm with Random Neighborhood Search. This algorithm improves the local search capabilities of the PSO, thus preventing the solution from falling early into local optimum.
3. Comparing the achievement validation of the anticipated hybrid (PSO-RNS) algorithm with other optimization algorithms such as: Greedy algorithm, RNS algorithm, CSGC algorithm, and classical PSO algorithm.

The rest of this paper is organized as follows: Section 2 presents the related studies that have been conducted in the research field of the spectrum allocation in CRNs. Section 3, presents the allocation system model and the utility function. Section 4, presents the proposed optimization algorithms for allocating the spectrum in CRNs. Section 5, presents the simulation results and analysis for the given optimization algorithms. Lastly, the conclusions are drawn in section 6.

## 2. LITERATURE REVIEW

Recently, the efficient spectrum allocation scheme has gained a huge attention in the research area of CRNs. A large number of works have been conducted by researchers for finding a near-optimal solution and proposing a new fast algorithm to solve this intractable problem in the research field. In this section various optimization algorithms that have been applied for spectrum allocation in the CRNs with the latest research conducted in this field has been reviewed.

Peng, Zheng, & Zhao (2006) proposed a Color Sensitive Graph Coloring (CSGC) technique to address the problem of the spectrum allocation. The system model was based on a graph coloring model. Three objective functions were presented and three policy labeling rules with both collaborative and non-collaborative rules each corresponds to a different objective function (Maximum Sum Reward (MSR), Maximum-Minimum Reward (MMR), and Maximum Proportional Fairness MPF). This algorithm has shown its capability not only in improving the spectrum performance, but also improved the utilization and fairness of the network.

Teng, Xie, Chen, & Zhang (2020) proposed an improved spectrum allocation scheme of a dynamic-time varying that based on chaotic binary particle swarm optimization. The chaotic map idea was introduced in the improved algorithm for optimizing the initial population and the optimal position for all particles in each generation. Moreover, the global ergodicity of the chaotic map was utilized to overcome the shortcomings of the PSO algorithm. The experimental results showed that a fast and efficient spectrum allocation can be realized for satisfying the demands of cognitive radio communication. While Yesaswini & Annapurna, (2021) in their study presented a comparison between the two optimization algorithms that is particle swarm optimization and genetic algorithm for assigning the spectrum in CRNs. The

results showed that PSO algorithm provided more spectrum utilization as compared to the GA based approach with less number of iterations to obtain the near optimal result.

Moreover, Satria, Mustika, & Widyawan (2018) presented a solution for spectrum allocation in CRN using Modified-ACO algorithm. The proposed solution depends on the intensity of the pheromone in the path used by the ants for making decision about the channel selection. The simulation results showed that the ants have improved the spectrum allocation and achieved fairness in the CR environment, as well as it increased the throughput of the system.

Mishra et al. (2019) proposed a PSO algorithm for allocating the spectrum for cognitive system. The author focused on maximizing the total transfer rate along with the subjected constraints such as individual transfer rate, total power usage, and bit error rate. The presented algorithm has shown its capability to increase the real-time total transfer rate and required less iterations to obtain the near optimum result as compared to GA based approach. Additionally, X. Zhang, Zhang, & Wu (2020) proposed an adaptive PSO algorithm based on sawtooth propagation technique (SA) for allocating the spectrum in the (OFDMA) cellular network system. They assessed the network utility performance with two forms, one with no fairness for the linked users and the other with considering the fairness with the linked users. The simulation results showed validation of the proposed algorithm in terms of utilization and fairness among the linked users in the cellular network system.

M. G & V (2021) studied and analysed the performance of the PSO algorithm taking into consideration several parameters such as individual power rate, entire power usage, and bit error rate (BER). These parameters were considered to confirm the fairness among the users along with the efficient energy with minimum BER. The simulation results showed the ability of the proposed algorithm to offer larger allocation rate instantaneously with less number of iterations.

Moreover, Tian, Deng, & Xu (2020) proposed an Immune Parallel Artificial Bee Colony Optimization (IPABCO) algorithm. The authors adopted the immune theory and the parallel theory for solving the problem of the spectrum allotment in the cognitive radio sensor networks. The proposed algorithm was based on the classical graph coloring model that aims at optimize the network efficiency. The anticipated algorithm showed its capabilities in terms of maximizing the total network benefits. In addition, it showed superiority in terms of having fast convergence speed and high optimization ability as compared to PSO and ACO algorithms.

However, an enhanced ABCO algorithm was presented in Agarwal, Vijay, & Bagwari (2021), for spectrum allocation in cognitive radio network. The proposed method first predicted the channel of the PUs, then it performed the spectrum sensing, thus the probability has been reduced, and the overall throughput of the network has increased. The simulation results showed that the proposed method had better efficiency by 11.48% in terms of spectrum usage compared to the binary artificial bee algorithm. While, Feng & Weilian (2018) pioneered the Fireworks Algorithm (FA) to address the spectrum allocation problem in the cognitive radio networks. The system was based on a graph coloring model with considering multiple objective functions. Two binary coding layers were considered for individual fireworks. The given algorithm has shown its capability in avoiding the local optimum and enhancing the system fairness, utilization, and convergence speed.

Moreover, Latif et al. (2021) proposed an improved evolutionary algorithm which is a differential evolution based particle swarm optimization algorithm with a repair process (DE-PSO-RP). Where the repair process is considered for excluding the interference among the secondary users, hence increasing the spectrum resources in the CRNs. The authors compared the

results obtained by the anticipated algorithm with that obtained by the other algorithms such as PSO with repair process (PSO-RP) and differential evolution with repair process (DE-RP). The simulation results showed that the proposed algorithm improved the spectrum utilization in the CRNs.

### 3. SYSTEM MODEL

In the conditions of the dynamic spectrum access like cognitive radio networks, the channel allocation problem is described by enabling unlicensed users (SUs) to access the spectrum with legacy users (PUs). Hence, dynamic spectrum systems increase the available spectrum's capacity and commercial value. Based on restrictions agreements upheld by PUs, secondary users are able to access the available spectrum in a non-interfering way. This section presents the system model aided by a sample model. The suggested model assumes that the environmental factors like user location and spectrum availability will not change during the period of spectrum allocation. This is because users quickly adapt to environmental changes despite the sluggish changes in the spectrum environment.

#### 3.1 System Sample Model

In this section a sample model describing the proposed system model is presented. Figure 1, illustrates the sample model deployment of a single cell with a base station to provide a wireless connection to a residential community. In this sample model there are four randomly distributed primary users (PU-I, PU-II, PU-III, PU-IV) and four randomly distributed secondary users (SU-I, SU-II, SU-III, SU-IV). Randomly every primary user  $k$  occupies a channel  $m$  with a protection area (radius) denoted as  $d_p(k, m)$ . It is assumed that the four secondary users opportunistically access the channels available in the network without affecting the transmission of the primary users only in two cases; either when PU is absent, or SU lies outside the protection area of the PU. Otherwise, there will be harmful interference. Accordingly, as demonstrated in Figure 1, SU-I cannot access the channel occupied by PU-I since the coverage area for both users are overlapped. However, SU-I can utilize the channel occupied by PU-I when it is absent (i.e., PU-I not transmitting data). On the other hand, SU-II can opportunistically access all the channels available in the network without affecting the PUs transmission as it allocates far away from all primary user's protection areas. As a result, a list of available channels will be attained for every secondary user, and each channel will provide a different reward for the secondary users which is the protection range that a user can get after utilizing that channel. Additionally, for preventing the interference among the secondary users, each channel will list a pair of secondary users that cannot utilize the same channel simultaneously. Therefore, (SU-III) and (SU-IV) cannot utilize channel  $m$  at the same time as their protection ranges overlapped. Hence, the system model output parameters are Availability matrix (L), Reward matrix (B), and interference matrix(C).

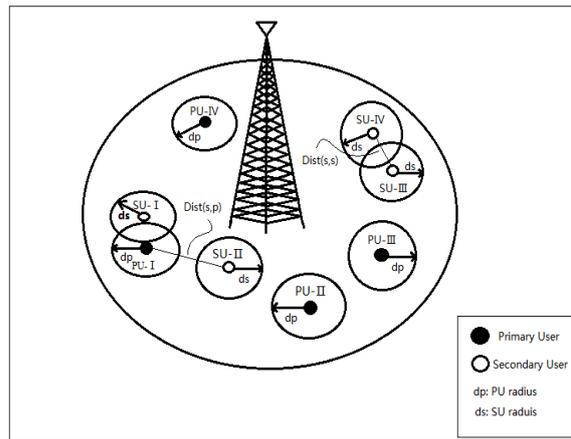


Figure 1: System Sample Model.

#### 3.2 Allocation Model and System Utility Function

Suppose a network of secondary users indexed from  $n=1$  to  $N$  and primary users indexed from  $k=1$  to  $K$  that are competing for a number of channels indexed from  $m=1$  to  $M$ . Furthermore, based on the location and usage of the channel by adjacent primary users, the channel availability and rewards of each secondary user can be determined. To adjust the interference range, each secondary user modifies the transmit power on channel  $m$  which is denoted as  $d_s(n, m)$  to avoid the interference constraints imposed by PUs. Thereby, the secondary user will regulate the interference range to the maximum permissible level using a fixed power control scheme. As a result, the transmission power of the SU will be bounded by two boundaries: the minimum transmit power  $P_{t_{min}}$  which corresponds to minimum interference range  $d_{min}$  and the maximum transmit power  $P_{t_{max}}$  which corresponds to maximum interference range  $d_{max}$  [ $d_{min}, d_{max}$ ]. Hence, it is assumed that channel  $m$  will be available for the secondary user  $n$  only if (Ghasemi & Ghasemi, 2020):

$$d_s(n, m) \leq Dist(n, k) - d_p(n, m) \quad (1)$$

Where  $d_s(n, m)$  is the protection range of the secondary user  $n$  on channel  $m$ ,  $d_p(k, m)$  is the protection range of the primary user  $k$  on channel  $m$ , and  $Dist(n, k)$  is the distance between secondary user  $n$  and primary user  $k$ . Furthermore, it is assumed that SUs uses the out of band mechanism to determine the primary users' location and power in order to correctly adjust their  $ds$  to avoid interference with the PU. If such power adjustment is utilized, the secondary user's interference ranges will be equal to the minimum value between the maximum permissible transmit power and the minimum distance from all the primary users which occupies that channel, according to Peng et al. (2006):

$$Dist_{SE}(n, m) = \min(d_{max}, \min_{k=1 \dots K, y_k=1 \dots m}(Dist(n, k) - D_{PR})) \quad (2)$$

[pWhere  $Dist_{SE}(n, m)$  represents the distance of secondary user  $n$  from channel  $m$  occupied by  $k$  number of PUs,  $d_{max}$  is the maximum permissible transmit power of SU,  $Dist(n, k)$  is the Euclidian distance between the  $n$ th secondary user and  $k$ th primary user, and  $D_{PR}$  is the primary user's coverage area (interference range). Additionally, after determining the availability of the channels for the secondary users based on interference ranges of the SUs with the PUs for a given topology, the interference among the secondary users will be determined. This can be implemented by measuring the distance from the centers of the protection range of secondary user  $n$  and  $i$  on channel  $m$  which is denoted as  $Dist(n, i, m)$ . This distance

indicates the position of the secondary users with respect to each other. If this distance was less or equal than the sum of radii of the protection ranges of  $SU_n$  and  $SU_i$ , that is:

$$Dist(n, i, m) \leq d_s(n, m) + d_s(i, m) \quad (3)$$

Then secondary users  $n$  and  $i$  cannot utilize channel  $m$  simultaneously because there will be interference due to overlapped regions of the protection area for both users. Where  $d_s(n, m)$  is the  $SU_n$  protection area and  $d_s(i, m)$  is the  $SU_i$  protection area. The key component of the proposed model is presented as follows (Ghasemi & Ghasemi, 2020):

**Channel availability matrix:**  $L = \{l_{n,m} | l_{n,m} \in \{0,1\}\}_{N \times M}$  is an N by M binary matrix that indicates whether channel  $m$  is available for secondary users  $n$  or not. Depending on the distance if  $d_s(n, m) \leq d_{min}$ , it means channel  $m$  is not available to  $SU_n$  ( $l_{n,m} = 0$ ), otherwise the channel is available ( $l_{n,m} = 1$ ).

**Channel reward matrix:**  $B = \{b_{n,m} | b_{n,m} > 0\}_{N \times M}$  is an N by M matrix that gives the reward matrix for each secondary user. In addition, this matrix signifies the bandwidth that a user  $n$  can attain after occupying channel  $m$  with the assumption that there is no interference from neighbors. Relying on the sample in Figure 1, the reward for each secondary user can be one of the following:

1. Coverage area of SU using channel  $m$ :  

$$b_{n,m} = d_s(n, m)^2, d_{min} \leq d_s(n, m) \leq d_{max} \quad (4)$$
2. The Capacity using channel  $m$  (with the assumption that the SNR is a function of  $d_s(n, m)$ ):  

$$b_{n,m} = \log(1 + f(d_s(n, m))) \quad (5)$$

where,  $d_{min} \leq d_s(n, m) \leq d_{max}$

Where  $b_{n,m}$  represents the reward of secondary user  $n$  after occupying channel  $m$ . It is worth noting that if  $l_{n,m} = 0$ , then  $b_{n,m} = 0$ . For the given problem, (Equation (4)) which represents the coverage area of the secondary users is considered as a reward for the secondary users).

**Interference constraint matrix:**  $C = \{c_{n,i,m} | c_{n,i,m} \in \{0,1\}\}_{N \times N \times M}$ , is an N by N by M matrix representing the interference constraints among the secondary users. In this matrix each channel will have a N-by-N matrix that represents the interference among users. Where  $c_{n,i,m}$  represents the interference of  $SU_n$  and  $SU_i$  occupying channel  $m$  simultaneously. If  $c_{n,i,m} = 1$ , it means that  $SU_n$  and  $SU_i$  cannot utilize channel  $m$  simultaneously. This matrix is a channel availability dependent matrix that is:  $c_{n,i,m} \leq l_{n,m} \times l_{i,m}$  and  $c_{n,i,m} = 1 - l_{n,m}$  if  $n = i$ . In this paper the geometry model has been used in which two users will conflict if there was no sufficient distance between them that is:  $Dist(n, i, m) \leq d_s(n, m) + d_s(i, m)$ . Moreover, this constraint is a channel specific in which two users might have conflict on one channel but not in another.

**Conflict-free channel allocation matrix:**  $A = \{a_{n,m} | a_{n,m} \in \{0,1\}\}_{N \times M}$ , is a N by M matrix representing the final channel allocation matrix. Where  $a_{n,m}$  represents the occupation of secondary users  $n$  to channel  $m$ . That is: if  $a_{n,m} = 1$ , it means that channel  $m$  is allocated to user  $n$ , otherwise channel  $m$  cannot be allocated to user  $n$ . This matrix necessitates to satisfy all the constraints imposed by the PUs.

**Radio interface limit  $C_{max}$ :** Represents the quantity of channels that the secondary user can allocate.

**User reward  $\mathfrak{R} = \{r_n = \sum_{m=0}^{M-1} a_{n,m} \cdot b_{n,m}\}_{N \times 1}$ ,** representing the reward vector that each secondary user can get after assigning the channels.

**Network utilization  $U(\mathfrak{R})$ :** This represents the objective, as the key objective of the spectrum assignment problem is to increase the utilization of the network.

### 3.3 Utility Function

After defining system model for the given network, the following utility function (i.e., objective function or fitness function) can define the spectrum allocation problem (Teng et al., 2020):

$$A^* = \arg \max_{A \in \Lambda(L, C)_{N \times M}} U(\mathfrak{R}) \quad (6)$$

The utility functions for a specific application type can be acquired based on extensive surveys. Alternatively, based on traffic pattern and fairness inside the network the utility functions can be designed. The single-hop-flows is considered for addressing the utility, as they are the simplest format of wireless transmission. In addition, in this work the utility function has been expressed as Maximum-Sum-Reward (MSR), the aim of this objective function is maximizing the network utilization without taking into consideration the fairness. The expression of this objective function is represented as follows (Peng et al., 2006):

$$U_{MSR} = \sum_{n=0}^{N-1} r_n = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} a_{n,m} b_{n,m} \quad (7)$$

To facilitate the simulation, the Mean Reward fitness function has been considered instead of the Maximum-Sum-Reward as follows:

$$U_{Mean} = \frac{1}{N} \sum_{n=0}^{N-1} r_n \quad (8)$$

The conflict-free assignment matrix requires to satisfy the subjected constraints below:

$$a_{n,m} = 1 \quad (9)$$

$$\sum_{m=0}^{M-1} a_{n,m} \leq C_{max} \quad (10)$$

$$a_{n,m} + a_{i,m} \leq 1 \text{ if } c_{n,i,m} = 1, \text{ Where } n \neq i, \quad (11)$$

$$\forall \begin{cases} n, i \in N \\ m \in M \end{cases}$$

The first constraint (Equation (9)) states that the channel has to be available in order to be allocated for the cognitive user. Otherwise, the user-channel pair will not be considered in the final solution. The second constraint (Equation (10)) shows that the highest quantity of channels that can be allocated to SU for the final conflict-free allocation matrix have to be less or equal than  $C_{max}$ . Meanwhile, the third constraint (Equation (11)) represents the incompatibility constraint, in other word, each channel might contain pairs of incompatible users that cannot utilize the same channel simultaneously to avoid interference. Therefore, for achieving a conflict-free assignment matrix, the proposed algorithms necessitate first to satisfy all the aforementioned constraints presented in this section.

#### 4. OPTIMIZATION ALGORITHMS FOR SPECTRUM ALLOCATION IN CRNS

##### 4.1 Spectrum Allocation using RNS Algorithm

Local search is based on the concept of the neighborhoods. This algorithm can be used for finding solutions for highly complex problems where their analytical model contains a huge number of variables and constraints or little theoretical knowledge is available. The neighborhoods require to be well defined for efficiently searching them. Thus, the local search can be implemented to find a good solution quickly for large scale instances of such problems. The local search is implemented with a number of iterations on the same problem instance using different (e.g. random generated) initial solutions. The size of the neighborhood can determine how the local search can effectively improve the solution in each iteration (Crama, Kolen, & Pesch, 1995).

The Random Neighborhood Search (RNS) algorithm is used for generating a population of candidate solutions for the given optimization problem (Saleh, Ahmed, & Nashat, 2020). Algorithm I illustrates the steps of the RNS method for allocating the spectrum in CRNs. This algorithm starts by initializing the number of iterations (Step2) in which it represents the population of candidate solutions. Step2 to Step7 defines the main steps for implementing this method which starts by randomly selecting a channel  $m$  and allocating it to a secondary user. After that checking the interference with other secondary users on channel  $m$ . If the selected user  $n$  has interference with user  $i$  on channel  $m$  ( $c_{n,i,m} = 1$ ), then allocate the channel to user  $n$  ( $a_{n,m} = 1$ ) and delete it from its channel list ( $l_{n,m} = 0$ ) and from user  $i$  channel list ( $l_{i,m} = 0$ ). Otherwise, if there was no interference with user  $i$  ( $c_{n,i,m} = 0$ ), then just allocate channel  $m$  to user  $n$  ( $a_{n,m} = 1$ ), and delete it from its channel list (Step 4). Repeat until the availability matrix is empty, then evaluate the fitness function using Equation (8) for evaluating the Mean Reward. After that update the iteration and repeat the previous steps (from 3 to 5). If maximum iteration is met, then select the best solution which represents the final conflict-free assignment matrix. Otherwise, repeat the procedure.

##### Algorithm I: RNS Algorithm

**Inputs:** Availability matrix(L), Reward matrix(B), and Interference matrix (C)

**Output:** Conflict-free allocation matrix (A)

**Let** N be the number of secondary users

**Let** M be the number of available channels

**Step1:** Initialize parameters set and simulation model

**Step2:** Set the value of maximum iteration.

**Step3:** For  $n = 1:N$ , randomly select channel  $m$  for  $SU_n$

**Step4:** For the selected channel  $m$ , check if  $SU_n$  and  $SU_i$  satisfy  $c_{n,i,m} = 1$ , then set  $a_{n,m} = 1$ ,  $l_{n,m} = 0$  and  $l_{i,m} = 0$ . Otherwise, if  $c_{n,i,m} = 0$ , then set  $a_{n,m} = 1$ ,  $l_{n,m} = 0$ .

**Step5:** Repeat Step2 for all  $SU_n$  until the availability (L) matrix is empty.

**Step6:** Evaluate the Fitness Function according to equation (8).

**Step7:** If a predefined maximum iteration is met, then select the best solution among all iterations, otherwise return to Step3.

**Step8:** End

##### 4.2 Spectrum Allocation using PSO Algorithm

Particle Swarm Optimization is a swarm intelligent optimization algorithm that was basically introduced for the first time in 1995

by Kennedy and Eberhart. This algorithm is utilized for solving the optimization problems as it imitates the attitude of the flock of birds and school of fishes as they continuously change their location to search for food relying on their current location. Recently, the researchers and scholars have adopted PSO algorithm for solving different problems in CRNs, although it has revealed a massive flexibility for solving the spectrum allocation problem and searching the near optimal solution (Mishra et al., 2019; Salih & Shakir, 2022). Since the spectrum allocation is a discrete space optimization problem, the binary PSO has been utilized with this problem. Therefore, for simulating the PSO behavior to solve the spectrum allocation problem and find near optimal solution, the birds will be represented by a population of particles. This algorithm starts by defining the number of particles or the population size denoted by P, and the length of particles is set to  $D = \sum_{n=1}^N \sum_{m=1}^M l_{n,m}$ , which counts the number of ones in the availability matrix. Binary coding mechanism is used to randomly generate particle  $i$  position at iteration  $t$  as  $x_{id}^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t]$ , where  $1 \leq d \leq D$  is the  $d$ th bit in the particle position vector, and  $x_{id}^t \in [0,1]$ . This mechanism is analogous to that used in Genetic Algorithm (GA), which is regarded as a possible solution in the optimization problem. Similarly, the velocity of particle  $i$  is implied by  $v_{id}^t = [v_{i1}^t, v_{i2}^t, \dots, v_{iD}^t]$ , where  $v_{id}^t \in [-V_{max}, V_{max}]$ , and  $V_{max}$  is a system parameter that prevent  $v_{id}^t$  from the continuous value. Additionally, this parameter has not been set to a small value to prevent high mutation rate. Then for each particle  $i$  map the  $j$ th element in  $x_{id}^t$  to  $a_{n,m}$  in the pre-conflict assignment matrix, according to the example in Figure 2 (Teng et al., 2020).

$$L = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 0 \end{bmatrix}, x_{id}^t = [0 \ 1 \ 0 \ 1 \ 1], A = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

Figure 2: Code Mapping Example

Then the interference is examined in each channel to achieve a conflict-free assignment matrix. After that the fitness function will be evaluated according to Equation (8). Then define  $p_{ibest}^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t]$  which is the local best solution that particle  $i$  has attained at iteration  $t$ , and  $g_b^t = [x_{b1}^t, x_{b2}^t, \dots, x_{bD}^t]$ , is the global best solution among all particles. At  $t + 1$ , all particle's velocities and positions will be updated using below expressions (Teng et al., 2020):

$$v_{id}^{t+1} = w * v_{id}^t + c_1 r_1 (p_{ibest}^t - x_{id}^t) + c_2 r_2 (g_b^t - x_{id}^t) \quad (12)$$

$$x_{id}^{t+1} = \begin{cases} 1, \eta < S(v_{id}^{t+1}) \\ 0, \eta \geq S(v_{id}^{t+1}) \end{cases} \quad (13)$$

Where  $v_{id}^{t+1}$  is the  $d$ -dimensional velocity of the particle  $i$  in the following generation, it is determined by the previous velocity value of particle  $i$ , the cognition part:  $c_1 r_1 (p_{ibest}^t - x_{id}^t)$  and the social part:  $c_2 r_2 (g_b^t - x_{id}^t)$ . Where  $w$  is the inertial weight,  $c_1$  and  $c_2$  are the acceleration coefficients,  $r_1$  and  $r_2$  are uniform random numbers generated in the interval of [0,1]. The value of  $v_{id}^{t+1}$  is limited to a value in the interval of [0,1] according to the following sigmoid function (Teng et al., 2020):

$$S(v_{id}^{t+1}) = \frac{1}{1 + \exp(-v_{id}^{t+1})} \quad (14)$$

Equation (13) defines that the probability of bit  $x_{id}^{t+1} = 1$ , if  $\eta < S(v_{id}^{t+1})$ . Otherwise,  $x_{id}^{t+1} = 0$ , where  $\eta$  is a uniform random number distributed in the interval of [0,1]. Additionally, to avoid  $S(v_{id}^{t+1})$  from approaching 0 or 1, the value of  $v_{id}^{t+1}$  is constrained in the limit of  $[-V_{max}, V_{max}]$ , that is (Zhao, Xu, Zheng, & Shang, 2009):

$$v_{id}^{t+1} = \begin{cases} V_{max}, & v_{id}^{t+1} > V_{max} \\ -V_{max}, & v_{id}^{t+1} < -V_{max} \end{cases} \quad (15)$$

Equation (15) defines that if the value of  $v_{id}^{t+1}$  is greater than  $V_{max}$  then set the value of  $v_{id}^{t+1} = V_{max}$ , or if the value of  $v_{id}^{t+1}$  is less than the  $-V_{max}$ , then set the value of  $v_{id}^{t+1} = -V_{max}$ .

### 4.3 Proposed Hybrid PSO-RNS Algorithm for Spectrum Allocation in CRNs

In this section a new algorithm is proposed which is hybrid PSO with the Random Neighborhood Search (PSO-RNS) algorithm. The performance of this algorithm has been compared with other optimization algorithms (such as: Greedy algorithm, RNS algorithm, CSGC algorithm, PSO algorithm) that have been examined individually to evaluate its capability to fit the given objective function and to validate the performance of the new proposed algorithm. As aforementioned, RNS is used to enhance the initial starting solution by providing a population of candidates to choose the best solution among all candidates with a predefined maximum iteration. While in PSO, particles can search globally and find the initial near optimal solution. As a result, in later algorithm, PSO tends to fall into the local optimum during the search process. Therefore, RNS is performed for each generation of particle velocity, allowing particles to achieve the near global optimum via evolution during the search iteration. Algorithm II illustrates the main steps for the proposed hybrid system. It starts by initializing all the parameters with defining the fitness function and the population size  $P$  (Step 1 to 3). At iteration  $t = 0$ , randomly generate particle  $i$  position vector  $x_{id}^t$  using a binary coding mechanism. Additionally, generate particle velocity vector  $v_{id}^t$ , where the bit values of this vector are randomly generated in the interval of  $[-V_{max}, V_{max}]$  (Step4). Then map the elements in the position vector to the pre-conflict assignment matrix then perform RNS algorithm utilizing Algorithm I (Step5). Where RNS algorithm provides additional search for finding the best position vector which is generated initially by the PSO algorithm. Hence, RNS with a predefined maximum iteration randomly selects the channels for the secondary users. The interference is checked among all the secondary users, so if two users interfere if they utilize the same channel, randomly allocate the channel to one of them and delete it from the other user channel's list. Thus, the free-assignment matrix will be generated for each particle. After a predefined maximum iteration is met for the RNS algorithm it will select the best solution for each particle among all iterations which in turn enhances the solution for all particles. Then evaluate the fitness function for all particles. Then it will search for the local best solution  $p_{ibest}^t$  and global best solution  $g_b^t$  (Step7). Update the iteration  $t$  and all particles' velocities and positions according to equation (12) and (13) respectively, then reassess the fitness function (Step8). If the current solution vector is superior to the previous best solution, then the particle position and global best position is updated (Step9). Finally (Step10), terminate the algorithm if a predefined maximum iteration is met and choose

the best solution among all iterations, otherwise repeat Step7. Figure 3 demonstrate the flow chart of hybrid PSA with RNS algorithm for spectrum allocation in CRNs.

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#### Algorithm II: Hybrid PSO with RNS Algorithm

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**Inputs:** Availability matrix(L), Reward matrix(R), and Interference matrix (C)

**Output:** Conflict-free allocation matrix (A)

**Let N** be the number of secondary users

**Let M** be the number of available channels

**Step1:** Initialize system parameters set, simulation model, and PSO parameter

**Step2:** Identify the Fitness Function  $U(\mathfrak{R})$ .

**Step3:** Set population size  $P$  and the length of particle  $i$  to:  $D = \sum_{n=1}^N \sum_{m=1}^M l_{n,m}$ .

**Step4:** Set iteration  $t = 0$ , and randomly generate the initial particle  $i$  position:  $x_{id}^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t]$  and particle  $i$  velocity:  $v_{id}^t = [v_{i1}^t, v_{i2}^t, \dots, v_{iD}^t]$ , where  $x_{id}^t \in \{0, 1\}$ , and  $v_{id}^t \in [-V_{max}, V_{max}]$ ,  $1 \leq i \leq P$ .

**Step5:** Map the  $j^{th}$  element in  $x_{id}^t$  to  $a_{n,m}$  for each particle. Then apply the RNS algorithm (refer to Algorithm I) which will return the Fitness Function  $U(\mathfrak{R})$  after a predefined maximum iteration.

**Step6:** Find the best position for each particle  $p_{ibest}^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t]$  and the global best position among all particles  $g_b^t = [x_{b1}^t, x_{b2}^t, \dots, x_{bD}^t]$ , where  $b$  is the index position of the particle that has the highest fitness value.

**Step7:** Set iteration  $t = t + 1$ , then update the velocity  $v_{id}^t$  and position  $x_{id}^t$  for all particles according to equation (12) and (13) respectively.

**Step8:** Update the particle position if the current particle's position is better than the previous best position. Then update the global best position.

**Step9:** Find the best solution if a predefined maximum iteration is met, otherwise return to Step7.

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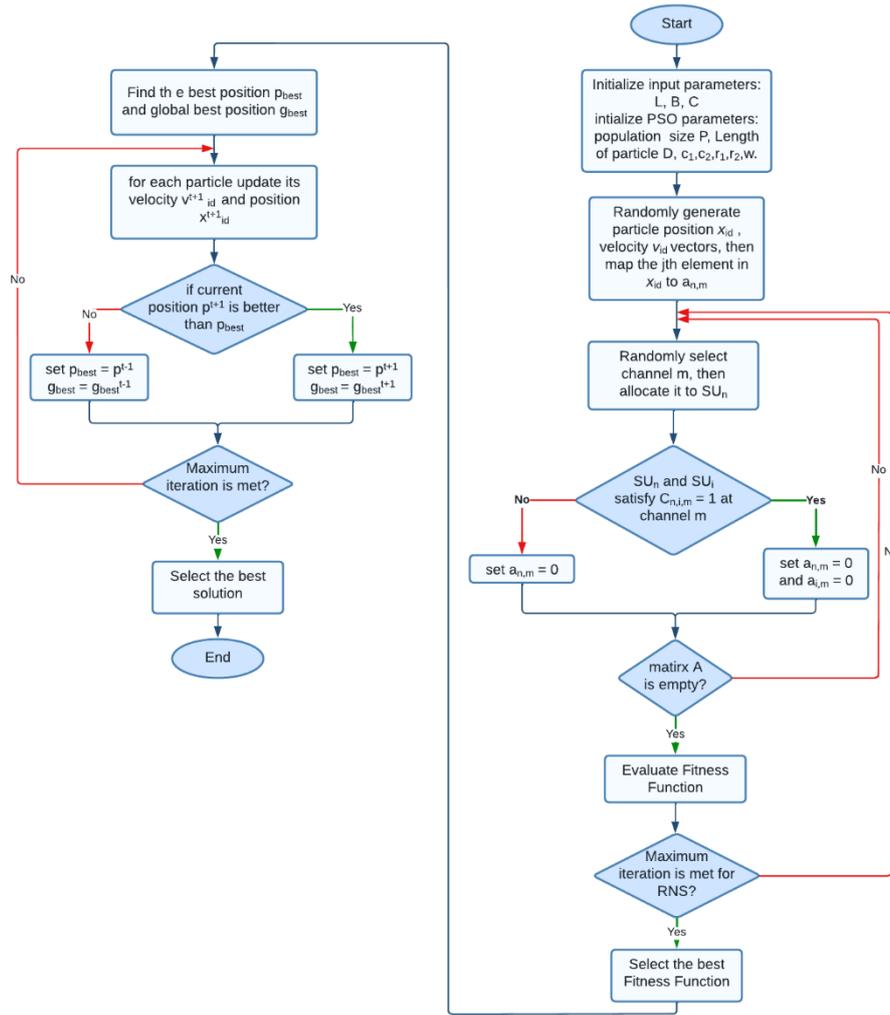


Figure 3: Flow Chart of the Hybrid PSO with RNS Algorithm for Spectrum Allocation in CRNs.

### 5. SIMULATION ENVIRONMENT AND PARAMETERS

The simulation has been conducted on a personal computer: Intel(R) Core (TM) i5-3230M CPU @ 2.60GHz and 8 GB RAM processor using MATLAB R2021a software. The simulation model area of the wireless network is taken to be (20km×20km). Where K primary users has been deployed randomly with a uniform coverage area of  $D_p = 2$ , and randomly each PU selects a random channel from the M number of channels. Additionally, randomly deploying N secondary users that regulates their transmit power on channel m  $ds(n, m)$  to prevent interfering with the primary users.  $C_{max}$  is assumed to be the same quantity as the available channels in the network (i.e.,  $C_{max} = M$ ). The minimum and maximum coverage area of SUs are equal to  $d_{min}$  and  $d_{max}$  respectively. It is assumed that all the secondary users use the Orthogonal Frequency Division Multiple Access (OFDMA) technique for simultaneously accessing multiple channels without interference. The maximum iteration = 100, for the proposed hybrid PSO-RNS algorithms. The standard parameter setting is used for the PSO algorithm were acceleration coefficient  $c_1, c_2 = 2$ ,  $r_1$  and  $r_2$  are random numbers in the interval of [0,1], and inertial weight  $w = 1$ . Where population

size  $P = 20$ ,  $V_{max} = 4$ , and  $V_{min} = -4$  for both PSO and PSO-RNS algorithms.

#### 5.1 Simulation Results and Analysis

In this section evaluation performance of the given optimization algorithms is presented. The same topological structure is used for the all algorithms and the initial parameter setting for simulation model is taken as:  $N=10$ ,  $K=10$ ,  $M=10$ ,  $d_{min} = 1$ ,  $d_{max} = 4$ , for the ten different topologies. Since the primary users and secondary users were distributed randomly, the configuration deployment of the PUs and SUs will be different which provides various numbers of topologies. Then the impact of varying the system parameters such as number of PUs, number of SUs, and number of channels on the Mean Reward system utility has also been examined.

Figure 4 shows the relationship between the Mean Reward utility function and various topologies deployments under the proposed optimization algorithms. Table 1 summarizes the simulation results obtained for the Mean Reward using the proposed hybrid (PSO-RNS) algorithm and other algorithms such as Greedy algorithm, Random Neighborhood Search, Color Sensitive Graph Coloring with non-collaborative sum labeling rule (CSGC-NSUM), Particle Swarm optimization algorithm under different topologies. Ten different topologies have been

considered. The average value is calculated for the results obtained from the ten different topologies by the given optimization algorithms. Hence, the results confirmed that the proposed hybrid (PSO-RNS) algorithm improved the system utilization by 1.23% compared to PSO algorithm, 5.57% compared to RNS, 7.9% compared to color sensitive graph coloring algorithm, and 27.33% compared to Greedy algorithm. The time execution for the five given algorithms are as follows: CSGC-NSUM is the fastest algorithm to give the solution with less time, it takes approximately (0.021831) second. While Greedy algorithm takes slightly more time than the CSGC-NSUM, it takes about (0.045582) second for the entire execution. The time execution for the RNS is (0.156339) second. While PSO algorithm takes much more time than the aforementioned algorithms, it takes approximately (7.564184) second. However, the execution time for the new proposed hybrid PSO-RNS algorithm is much heavier as compared to all other proposed algorithms, it approximately takes (35.271509) second.

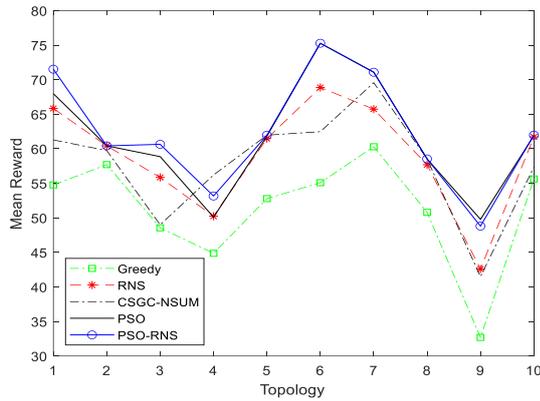


Figure 4: Mean Reward System Utility Under Different Optimization Algorithms for Various Topologies.

**5.2 Effect of Varying PUs Number on System Utility**

The performance of the five optimization algorithms were examined in this section under various deployment configurations of primary users. The primary users' deployment will determine the channel availability, reward, and interference constraints for secondary users. Increasing the number of primary users, on the other hand, will force secondary users to reduce their protection ranges. As a result, secondary users' chances for obtaining a channel will be reduced, and thus lowering the spectrum utilization. Figure 5, depicts the relationship between increasing the number of primary users and deterioration of the system utility. For the simulation, different numbers of primary users (ranging from 5 to 35), a fixed number of secondary users (N=10), and a fixed number of channels (M=10) is taken.

**5.3 Effect of Varying SUs Number on System Utility**

The performance of the five given optimization algorithms were examined in this section under various secondary user deployment configurations. The simulation began by changing user's density (i.e., the number of secondary users). Accordingly, increasing the secondary user's density degrades the system utility performance as it generates further interference constraints. Figure 6, depicts the relationship between an increase in the number of secondary users and a decrease in the system utility. For the simulation, different numbers of secondary users ranging from 10 to 40 are used, as well as a fixed number of primary users (K=10) and a fixed number of channels (M=10).

**5.4 Effect of Varying the Number of Channels on System Utility**

In this section, the performance of the five given optimization algorithms were examined with varying the number of channels and its effect on the system utility. Figure 7, shows how the system utility scale with increasing the number of available channels. This is because as the number of channels increases more spectrum will be available for the secondary users which significantly improves the system utilization. For conducting the simulation different numbers of channels are taken varied from 5 to 30, fixed number of SUs (N=10) and fixed number of PUs (K=10).

Table 1: Simulation Results for Mean Reward utility function with various topologies.

Mean Reward (System Utilization %)					
Top.	Greedy	RNS	CSGC	PSO	PSO-RNS
1	54.76	65.84	61.27	67.97	71.52
2	57.70	60.42	59.74	60.42	60.42
3	48.56	55.85	48.99	58.86	60.64
4	44.86	50.24	56.20	50.10	53.16
5	52.78	61.47	61.96	61.82	61.96
6	55.09	68.87	62.47	75.27	75.27
7	60.29	65.73	69.56	71.09	71.07
8	27.13	57.69	58.53	58.53	58.53
9	32.68	42.58	41.48	49.78	48.80
10	55.62	61.72	57.34	61.89	61.98
<b>Avg.</b>	<b>48.95</b>	<b>59.04</b>	<b>57.76</b>	<b>61.57</b>	<b>62.33</b>

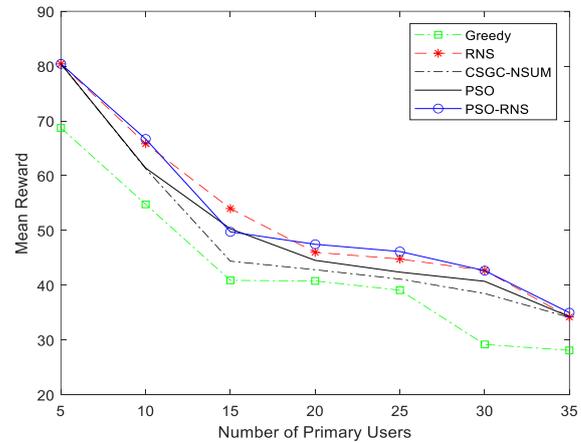


Figure 5: The Performance of Spectrum Allocation with Varying the Number of the Primary Users.

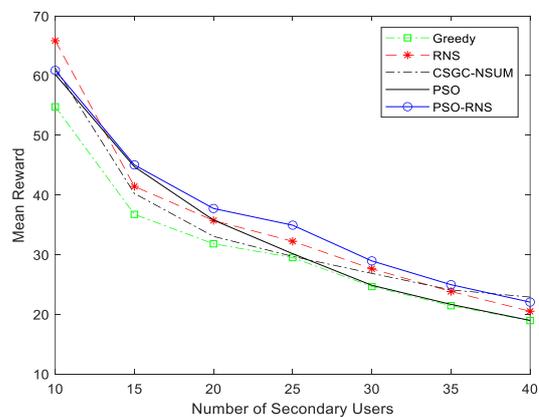


Figure 6: The Performance of Spectrum Allocation with Varying the Number of The Secondary Users.

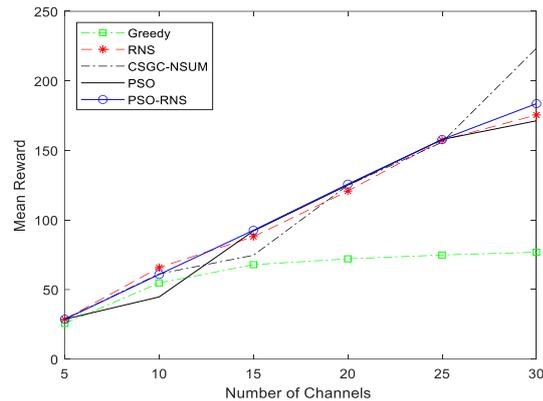


Figure 7: The Performance of Spectrum Allocation with Varying the Number of Channels.

## 6. CONCLUSIONS

In this study, an improved optimization algorithm was proposed that combines PSO algorithm with RNS for allocating the spectrum in the CRNs. The proposed algorithm was based on the graph coloring model. Therefore, based on the obtained simulation results the following points can be concluded:

1. The proposed PSO-RNS algorithm improved the system utilization by 1.23% compared to PSO algorithm, 5.57% compared to RNS, 7.9% compared to color sensitive graph coloring algorithm, and 27.33% compared to Greedy algorithm.
2. CSGC algorithm takes less execution time as compared to other algorithms (0.021831second), followed by Greedy algorithm (0.045582 second), RNS algorithm (0.156339 second), and PSO algorithm (7.564184 second). While the execution time of the proposed hybrid algorithm (PSO-RNS) was higher compared to the given optimization algorithms, it takes about (35.271509 second).
3. Increasing the quantity of primary users while fixing other parameters degraded the overall system performance for all optimization algorithms. Similarly, increasing the quantity of the secondary users also degraded the overall system performance for all algorithms. While it was noticed that the system performance was enhanced as the number of channels increases for all given optimization algorithms.

To sum it up, RNS has improved the exploitation and exploration capabilities of the PSO algorithm and prevent it from falling early into local optimum. Consequently, it improved the system utilization in the cognitive radio networks as compared to other given optimization algorithms. However, the execution time of the proposed algorithm was heavier than the other algorithms. Hence, this problem necessitates further investigation in the future study.

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