

2022-11-11

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IEEE Access

<https://doi.org/10.1109/ACCESS.2022.3220628>

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Received 22 September 2022, accepted 25 October 2022, date of publication 11 November 2022,
date of current version 16 November 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3220628

RESEARCH ARTICLE

Improved Resource Allocation Model for Reducing Interference Among Secondary Users in TV White Space for Broadband Services

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ABSTRACT In recent years, the Television White Space has attracted the interest of many researchers due to its propagation characteristics obtainable between 470MHz and 790MHz spectrum bands. However, aggregate interference increase when secondary users in wireless network increase. Aggregate interference on the side of Primary Users has been extensively scrutinized. Therefore, resource allocation (power and spectrum) is crucial when designing the Television White Space network to avoid interferences from Secondary Users to Primary Users and among Secondary Users themselves. This study proposes a resource allocation model that uses joint power and spectrum hybrid Particle Swarm Optimization, Firefly, and Genetic algorithm for reducing the aggregate interference among Secondary Users. The algorithm is integrated with the admission control algorithm so that; there is a possibility of removing some of the Secondary Users in the network whenever the Signal to Noise Ratio threshold for Secondary and Primary Users is not met. We considered an infeasible system whereby all Secondary and Primary Users may not be supported simultaneously. Metrics such as Primary User Signal-to-noise ratio, sum throughput, and secondary user signal-to-noise ratio less than the threshold used to compare the performance of the proposed algorithm and the results show that PSOFAGA with effective link gain ratio admission control has the best performance compared to particle swarm optimization, genetic algorithm, firefly algorithm, and PSOFAGA algorithm.

INDEX TERMS Admission control algorithm, cognitive radio networks, effective link gain ratio algorithm, resource allocation, TV whitespace.

I. INTRODUCTION

Television White Space (TVWS) is the TV spectrum between 470MHz and 790MHz assigned for over-the-air TV channels that have been used as guard bands to mitigate interferences and that are not used by primary users (PUs) at a particular area in a specified time. Dynamic Spectrum Access (DSA) is the mechanism of improving spectrum effectiveness through a local spectrum sensing approach and self-establishment of wireless links midst of Cognitive radio networks (CRN). Cognitive Radio (CR) is the radio which detects automatically the usable channels in the wireless spectrum according

The associate editor coordinating the review of this manuscript and approving it for publication was Mauro Fadda¹.

to the change of its reception or transmission resources or parameters to permit more simultaneous wireless communications in a particular spectrum band. DSA with CRN allows Secondary Users (SUs) to use the unutilized spectrum as long as they do not cause any interferences to licensed users i.e. PUs.

TV frequencies have been one of the most promising frequencies for secondary sharing. The White Space signals can travel a long distance, penetrating human, and natural obstacles, and can be available in most places, can also use existing towers and infrastructures being used to transmit other wireless signals [1]. TVWS has the clear technical benefit of broad coverage up to 30 km which means less radio equipment is needed per unit area than in the case of

shorter-range devices, this makes TVWS specially fitted to rural backhaul applications [2].

The major issue in TVWS networks is interference control. Dynamic Spectrum Access with Cognitive Radio, is currently being used as a solution to spectrum underutilization and scarcity because it provides an efficient solution for spectrum sharing and management [3]. Resource allocation addresses the issues of interference to PUs and among SUs in TVWS networks so that TVWS can be efficiently utilized [3]. In a TVWS wireless network where there is a large number of secondary users, the optimization of power and spectrum allocation to SUs is very important to improve the quality of service (QoS). The main objective of resource allocation in cognitive access to TVWS is to efficiently allocate the available spectrum and power to SUs such that the interference limitations to primary users (PUs) and secondary users are met. Resource allocation addresses the issues of interference to PUs and among SUs in TVWS networks so that TVWS can be efficiently utilized [3].

Previous works in this area proposed methods for finding acceptable power requirements for SUs so that there is no deleterious interference from such unlicensed ones to the primary system. These current works either consider the co-channel (CH) or adjacent channel (AC) interferences constraints only while inventing the analytical methods:-The approaches consider only the interference constraints on one side of primary users and assume that the interference on SUs is negligible [3]. In the case of Co-channel Interference (CCI) the location of SU users is outside the TV footprint and transmitted on the matched channel used by TV broadcast systems [4]. Not only the CCI could affect the TV reception but also the Adjacent Channel Interference (ACI), thus even the SUs transmitting on different broadcasting channels may cause deleterious interference to the nearby TV receivers. Other researchers worked on the methods and algorithm of resource allocation to control the power of the SUs i.e. [4] did the study on optimization of power limits for TVWS.

In this study, the problem of finding upper limits in which the aggregate interference (AI) by SUs does not transcend the exact limit was considered. The AI is compelled in such a way that the probability of harmful interference is under a pre-set threshold. The researchers factored the log-normal fading into the model and considered both CCI and ACI. The authors used the Wilkinson approximation to find the summation of log-normal variables in calculating sum interference. The objective of this work was to increase the sum capacity by optimizing power limits for WSDs under a probability constraint on AI. The MATLAB *fmincon* function which uses an interior point algorithm was used in this model. The interior-point algorithm used is exact which makes it inefficient in computation and not suitable for resource allocation in a TVWS wireless network which is an NP-hard optimization problem. Also, this work does not explain how they can optimize the interferences which can be caused by improper spectrum allocation. This work also does not emphasize admission control.

The main contribution of this paper is to overcome the resource allocation-related issues, outlined in section II, by improving them by using the hybrid FA, GA, and PSO algorithms with admission control. Admission control has been currently considered in several works to maximize the number of admitted users in wireless networks [5]. The centralized admission control algorithm called Effective Link Gain Ratio Removal algorithm (ELGRA) has low computational complexity than the interference constraint-aware stepwise maximum interference removal algorithm (I-SMIRA), Effective Stepwise SU Removal with primary users' protection algorithm (ESRPA) is proposed in this work.

The proposed algorithm assumes that the communication is from the white space device (WSD) to the base station and does not include device-to-device communication. The algorithm considers both CCI and ACI interferences in GLDB-based wireless TVWS networks and includes the admission control algorithm so that some SUs can be removed from the network when the SU or PU signal-to-noise ratio (SINR) thresholds are not met. The admission control algorithm ensures all SUs meet the lowest required SINR threshold in the TVWS wireless network [6].

To the best of our knowledge, this hybrid of particle swarm optimization, firefly, and genetic algorithm (PSOFAGA) with Effective Link Gain Ratio admission control algorithm (ELGRA) has not been applied for joint spectrum and power allotment in the geolocation database (GLDB) based wireless TV white space network. FA has been chosen in this proposed work because the author in [7] and [8] found that, FA performs better than other metaheuristic algorithms like genetic algorithms and particle swarm optimization. The simulation results of the proposed algorithm will result in sum throughput and SINR at PU and SUs improvement. Apart from improving maximizing sum throughput and SINR at SUs, our work also overcome the problem of computational complexity and performance of the previous admission control algorithms proposed by other researchers.

The rest of this paper is organized as follows. We have shown the related literature review in section II. Section III shows the proposed system. Section IV shows the simulation setup. The simulation results of the proposed algorithm are discussed in section V. Finally, the paper's conclusion and recommendation are shown in section VI.

II. RELATED WORKS

In this section, we will provide a brief overview of the most important works that have proposed resource allocation with admission control in TVWS wireless network design. In this work, we based on centralized control algorithms which can be divided into the following groups; Random search algorithm (RSA), optimal searching algorithm (OSA), sequential searching algorithm (SSA), link gain ratio based algorithm (LGRA), and interference constraint-aware stepwise maximum interference removal algorithm (I-SMIRA). However, LGRA outperforms the mentioned algorithm.

In [7], the authors proposed the firefly power control algorithm for a Geolocation database (GLDB) based wireless TVWS network that considered both constraints; SUs and PUs constraints. The researchers considered both interferences which are CCI and ACI. This work aimed to protect PUs against harmful interference even if a high number of SUs are exposed in the TVWS network and also to improve the SINR for SUs by designing a fast heuristic algorithm. In their performance analysis to show the cumulative distribution of SINR for SUs, they used three scenarios; first, they placed 100 SUs, second 500 SUs, and finally 1000 SUs. For all three scenarios, the power algorithm was used to allocate the transmit power to each SU. However, the spectrum allocation and admission control were not scrutinized in this work.

In [6], the authors proposed joint power and spectrum hybrid FA, GA, and PSO algorithms for GLDB-based wireless TVWS. Their algorithm considers the communication from WSD to the base station and ignored the device-to-device communication. This PSOFAGA algorithm considered only the adjacent channel interference and ignored the CCI. Also, the algorithm for the TVWS network on this work considered only one cell, which means only one AP, and one PU, and didn't incorporate fading. Researchers ignored the admission control algorithm which ensures all SUs in TVWS wireless network meet the acceptable minimum SINR threshold. Therefore it is important to take into account admission control when optimizing resource allocation [9].

In [10], the authors proposed resource sharing with admission control for the D2D links scheme which comprises two stages to allow multiple links of D2D to access the TV spectrum. In the first stage, the algorithm allocates the spectrum to SUs, and finally, the power and admission control was done in the second stage. The authors in this work proposed the admission control with links removing whereby they used Single Removal Algorithm (SMIRA) which outperformed other removal algorithms such as multiple removals. Despite its better results based on its performance compared to other removal algorithms but SMIRA has high computational complexity. However the work doesn't talk about the communication from WSD to the base station, they only concentrate on the side of D2D communication.

In [11], the authors proposed a joint power and centralized admission control algorithm for CRN called joint power and admission control (JPAC). The authors proposed two algorithms; the Effective Link Gain ratio removal Algorithm (ELGRA) and the Effective stepwise SU Removal with Primary user's protection Algorithm (ES-RPA). The ELGRA outperforms the ES-RPA in terms of complexity with slightly low performance. In terms of complexity and performance, the two algorithms outperform all existing admission control algorithms i.e. Optimal Search Algorithm (OSA) and Interference constraints-aware Stepwise Maximum Interference Removal Algorithm (I-SMIRA). The overall complexity of ESRPA and ELGRA is $O(M_s^2)$ and $O(M_s \log M_s)$ respectively while the overall computational complexity of I-SMIRA, OSA, and LGRA is $O(M_s^3)$, $O(2^{M_s}, M_s^2)$ and $O(M_s^2 \log M_s)$

respectively. However, this work concentrated on power and admission control only and leave aside the part of spectrum allocation.

III. PROPOSED SYSTEM: SYSTEM MODEL, PROBLEM FORMULATION, ADMISSION CONTROL, AND RESOURCE (POWER AND SPECTRUM) ALLOCATION ALGORITHMS

The optimization of resource allocation (Power and spectrum) must be practiced in TVWS wireless network to improve the Quality of Services (QoS). Reference [12] in their scenario discussion admitted that; the vacant channels are inadequate, and it is tough to utilize the limited channel resources when there are numerous emerged D2D links in a cell, which normally cause interferences i.e. between themselves or incumbent service of TV receivers. The optimization of power and spectrum resources must be done to ensure that the secondary network is accessible by as many SUs as possible while making sure that the QoS requirements for SUs and interference constraints for PUs are met [6]. In our work, resource allocation refers to power and spectrum allocation.

A. SYSTEM MODEL

Figure 1 below shows the network scenario assumed in this work. Assume S is the number of SUs and C is the number of channels. Let B be the potential channel allocation matrix and represented as $B = \{b_{s,c}/b_{s,c} \in \{0, 1\}\}$. The dimension of B is $S \times C$ If the channel C is allocated to the user S then $b_{s,c} = 1$ and $b_{s,c} = 0$ if the channel C is not allocated to the user S . Since both power and spectrum are to be optimized then, assume that $\mathbf{P} = \{\mathbf{P}_c^1, \mathbf{P}_c^2, \dots, \mathbf{P}_c^s, \dots, \mathbf{P}_c^S\}$ is the power allocation vector, where P_c^s is the transmit power of secondary user S on the channel C . We assumed that the uplink transmission in a TVWS wireless network includes both PUs and SUs, hence $M = M_P + M_S$, whereby M_P and M_S are the primary and secondary users, $M = \{1, 2, 3, \dots, M\}$, $M_P = \{1, 2, 3, \dots, M_P\}$ and $M_S = \{M_P+1, M_P+2, \dots, M_P+M_S\}$. This interference scenario diagram is adopted from [13].

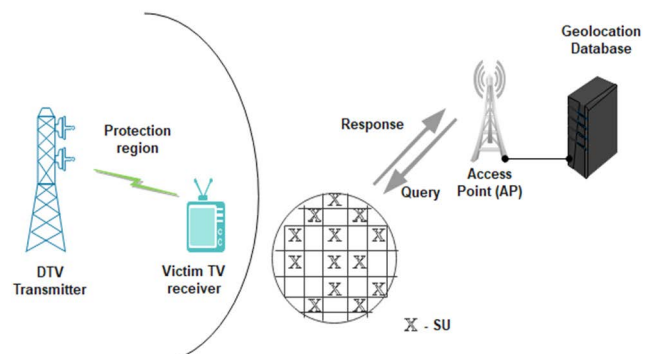


FIGURE 1. Interference scenario [7].

It is assumed that the TV receiver is operating using a channel b at a frequency f_b . The aggregate interference scenario is shown below. The single SU interference to the TV receiver

which is adopted from [7] is shown in (1).

$$I_{TVR,S} = \mu(b, c_s) P_s^{c_s} G_s^{SU \rightarrow PU} G_{SU} G_{PU}, \quad (1)$$

where the $P_s^{c_s}$ represent the SU S transmit power which operates on the channel C_s , the path loss from SU S to the victim TV receiver is denoted by $G_s^{SU \rightarrow PU}$, G_{PU} is the TV receiver antenna gain, G_{SU} is the secondary user antenna gain. Since we are considering both CCI and ACI hence we have to include CCI and ACI coefficients. $\mu(b, c_s)$ is the ACI coefficient. The formula of the ACI coefficient is shown in (2) and it is defined by [12].

$$\mu(b, c_s) = \begin{cases} 1 & b = c_s \\ \frac{\gamma(\Delta f)}{\gamma(0)} & b \neq c_s \end{cases} \quad (2)$$

where the term $\gamma(\Delta f)$ represents the minimum SINR with the offset frequency Δf at the receiver. Δf in (2) if the frequency offset between the two channels C and y is given by $\Delta f = |f_c f_y|$, for $\Delta f = 0$ implies the CCI. Hence the total interference to the primary users of the ACI is modeled the same as CCI is given as shown in (3) below:

$$I_{TVR} = \sum_{c=1}^M I_s = \sum_{c=1}^M \mu(b, c_s) P_s^{c_s} G_s^{SU \rightarrow PU} G_{SU} G_{PU}, \quad (3)$$

SINR at the receiver can be given as:

$$\beta_P = \frac{P_{TV}}{I_{TVR} + \sigma_{TVR}^2} \geq \beta_{PO}, \quad (4)$$

where β_{PO} is the required minimum SINR at the PU, σ_{TVR}^2 is the noise power, and the received power from the TV transmitter at the TV receiver is denoted by P_{TV} .

Despite the above scenario which shows the interference from SUs to PUs, each SU will receive interference from the neighbor SU. Assuming the SUs use the same channel n , hence the interference at SU S from other SUs will be written as in (5) below:

$$I_s = \sum_{\substack{r=1 \\ c_s=n, r \neq s}}^M I_{s,r} = \sum_{\substack{r=1 \\ c_s=n, r \neq s}}^M P_r^{c_r} G_r^s G_{SU}, \quad (5)$$

where the interference caused by SU S to SU r is denoted by $I_{s,r}$, G_{SU} is the antenna gain of SU, $P_r^{c_r}$ represent the SU r transmit power which operates on the channel c_r , G_r^s is the distance-based path loss from SU_r to SU_s.

Hence SINR at every secondary user is given by:

$$\beta_s = \frac{P^{AP} G_r^s G_{SU} G_{AP}}{I_s + \delta_s^2} \geq \beta_{so}, \quad (6)$$

where P^{AP} represent the Base Station (BS) transmit power, G_{AP} is the BS antenna gain and β_{so} is the minimum needed SINR at the secondary user.

B. PROBLEM FORMULATION

The goal of this work is to reduce the interference among SUs while maintaining the interference constraints to the PUs to not fall below the desired undesired threshold (D/U). Hence power and spectrum should be optimized and admission control should be included.

The aim is to find a power vector $P = \{P_c^1, P_c^2, \dots, P_c^S, \dots, P_c^S\}$ and channel allocation matrix B that performs the maximization of summation of downlink throughput while guaranteeing the minimization of interference constraint violations at the SUs and PUs. Each SU has its power which adjusted between the range of $[p_{min}, p_{max}]$ and channel matrix $b_{s,c} \in \{0, 1\}$

i.e. $b_{s,c} = 0$ or $b_{s,c} = 1$.

The optimization problem is adopted from () [6] and is shown in (7) below:

$$P, B = \operatorname{argmax}(V - c_n \sum_{i=0}^N \max[0, g_i^n]^2 - c_m [0, g_i^m]^2), \quad (7)$$

subject to:

$$p_{min} \leq P_i \leq p_{max} \\ b_{s,c} \in \{0, 1\}$$

From the above equation (7), the throughput summation of all SUs is denoted by V , and interference threshold violation for PU is represented by $c_m [0, g_i^m]$ while $(c_n \sum_{i=1}^N \max[0, g_i^n])^2$ represents the interference threshold violation for SUs. Where c_n and c_m are the penalty factors for SUs and PU interference threshold violations respectively.

Assume SINR vector is given by $\beta = [\beta_1, \beta_2, \dots, \beta_M]^T$, hence β is feasible if the current power vector $p_{min} \leq P_i \leq p_{max}$ satisfies the signal-to-noise ratio (SINR) vector β for all users $i \in M$. Similarly in a given effective SINR vector $\theta = [\theta_1, \theta_2, \dots, \theta_M]^T$ is feasible if its correlating SINR β is feasible. Furthermore, for the system to be feasible also if $\hat{\beta}$ or $\hat{\theta}$ is feasible, where $\hat{\beta} = [\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_M]^T$ and $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_M]^T$.

For the given power vector P , hence the set of SUs which achieve their desired target signal-to-noise ratio (SINR) is given as:

$$S(P) = \{i \in M_s \mid \beta_i(P) \geq \hat{\beta}_i\}, \quad (8)$$

Therefore the SINR allocation problem is given by:

$$\operatorname{maximize} |A_s(\theta)|, \quad \theta \in T_0 \\ \operatorname{Subject to} \theta \in F_0 \quad (9)$$

where F_0 is the user's feasible effective SINR vector space. For the case of an infeasible minimum/target SINR vector β doesn't grant how to set up a categorized list of candidate removal for secondary users to obtain the maximal number of admitted supported users. Therefore, the following is the easier mechanism for checking the feasibility of a specified effective signal-to-noise ratio (ESINR) vector θ .

Let $\theta = [\theta_{M_p}; \theta_{M_s}]$ be an identified effective SINR vector. Where θ_{M_p} and θ_{M_s} are the values of effective SINR for PU,

and SU respectively. Then, let θ_{A_s} indicate the ESINR for the admitted SUs. Therefore, θ holds if and only if the following conditions are met.

$$f_p(\theta_{A_s}) \leq K_p(\theta_{M_p}), \tag{10}$$

$$f_s(\theta_{A_s}) \leq K_s(\theta_{M_p}), \tag{11}$$

where;

$$f_p(\theta_{A_s}) = \sum_{j \in A_s} \left(\frac{h_j^{(p)}}{h_j^{(s)}} \theta_j \right) x \frac{1}{1 - \sum_{j \in A_s} \theta_j} \tag{12}$$

$$f_s(\theta_{A_s}) = \min_{i \in A_s} \left(\frac{P h_i^{(s)}}{\theta_i} \right) x \left(\sum_{j \in A_s} \frac{h_j^{(p)}}{h_j^{(s)}} \theta_j \right) - \alpha \left(1 - \sum_{j \in A_s} \theta_j \right) \tag{13}$$

where;

$$\alpha = \left(1 - \sum_{j \in M_p} \theta_j \right) x \frac{1}{\sum_{j \in M_p} \left(\frac{h_j^{(p)}}{h_j^{(s)}} \right) \theta_j}$$

$$K_p(\theta_{M_p}) = \frac{\min_{i \in M_p} \left(\frac{P_i h_i^{(p)}}{\theta_i} \right) x (1 - \sum_{j \in M_p} \theta_j) - \sigma_{TVR}^2}{\min_{i \in M_p} \left(\frac{P_i h_i^{(p)}}{\theta_i} \right) x \sum_{j \in M_p} \left(\frac{h_j^{(s)}}{h_j^{(p)}} \theta_j \right) + \delta_s^2} \tag{14}$$

$$K_s(\theta_{M_p}) = \frac{(\sum_{j \in M_p} \theta_j) - 1}{\sum_{j \in M_p} \left(\frac{h_j^{(s)}}{h_j^{(p)}} \theta_j \right)} \delta_s^2 - \sigma_{TVR}^2 \tag{15}$$

In (12) and (13), $(h_i^{(p)}/h_i^{(s)})\hat{\theta}_i$ indicates the effective link gain ratio (ELGR) for user i and $(h_j^{(p)}/h_j^{(s)})\hat{\theta}_j$ indicates the ELGR for user j . δ_s^2 and σ_{TVR}^2 are the noise power at secondary and primary BTS, $h_i^{(s)}$ and $h_i^{(p)}$ are the uplink gain user i and secondary and primary BTS respectively. The conditions from (10) and (11) enable the feasibility check of a given ESINR vector θ with a minimal complexity through the following conditions [5].

Condition 1 (Primary users protection):

If (10) holds, PUs are guaranteed to be protected against existing admitted SUs. Hence, the interference caused by admitted SUs does not affect PUs performance and cause an outage of any PUs.

Condition 2 (Supporting the admitted SUs):

If (11) holds, all SUs are guaranteed support with their allocated SINR. As long as the above two conditions hold, hence the feasibility of an effective SINR vector θ is also guaranteed, i.e. all PUs are guided against the existing admitted secondary users and all SUs are supported with their given SINR.

Now; the admission control problem can be given by;

$$\begin{aligned} & \max \theta \in T_0 | A_s(\theta) | \\ & \text{Subject to (10), (11).} \end{aligned} \tag{16}$$

Hence, a subgroup of secondary users $A_s \subset M_s$ is admitted and allotted with their target SINR in such a way that the given corresponding SINR vector is feasible and the admitted number of SUs is maximized. Once the A_s is obtained in (16), then the interrelated power vector and spectrum matrix can be computed.

C. FIREFLY ALGORITHM

Yang [14] introduced the FA which is a stochastic, meta-heuristic, and bio-inspired algorithm for solving the hardest optimization and NP-hard problems. The brighter male firefly flashes attract female fireflies [15]. The attractiveness is directly proportional to the brightness and the longer the distance they are apart the lower the attractiveness. The firefly will move randomly if there is no neighbor brighter firefly [15]. The flash intensity is usually inversely proportional to distance, that means as the distance increases the flash intensity decreases as per this formula: $I = \frac{1}{r^2}$. This phenomenon of flash intensity being reduced as the increase of square distance can be linked with the optimization of an objective function. In an optimized problem, the possible solution is represented by each firefly. Two issues are considered in designing FA; the flash intensity variation and attractiveness formulation. The following equation shows the variation of flash intensity $I(r)$.

$$I(r) = I_0 I^{-\gamma r^2}, \tag{17}$$

where I_0 represents the source flash intensity and γ is the fixed flash absorption coefficient. The fireflies' attractiveness β is directly proportional to their flash intensity $I(r)$ and it can be represented by the following equation:

$$\beta = \beta_0 I^{-\gamma r^2}, \tag{18}$$

where β is the flash intensity of the fireflies, r is the distance that separates two fireflies, and β_0 is the attractiveness at $r=0$.

If two fireflies x_i and y_j are separated by distance r_{ij} , the lesser bright fireflies will be forced to move in the direction of the brighter firefly according to the following equation below:

$$x_i^{t+1} = x_i^t + \beta_0 I^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha_t \epsilon_i^t, \tag{19}$$

where ϵ_i^t denotes a vector random number with Gaussian distribution and α is the parameter randomization. In (19), the first and second terms denote attractiveness and randomization respectively. The distance r_{ij} is calculated by the following equation:

$$r_{ij} = \sqrt{\sum_{k=1}^{k=n} (x_{ik} - x_{jk})^2}, \tag{20}$$

where n presents the problem dimensionality. FA has been used for spectrum allocation [16] and power allocation in CRNs [7].

In [7] and [16] FA performs better than other metaheuristic algorithms like GA and PSO. For our proposed work each firefly comprises of spectrum allocation matrix and power vector. Each firefly in this joint power and spectrum allotment stands for a possible solution for detecting resource allocation problems for all SUs in the TVWS wireless network. The best firefly is discovered at every iteration and the firefly movement is done according to the flash intensity and attractiveness of the firefly. After predetermined iteration numbers, the best firefly is chosen as the solution to the power and spectrum assignment problem.

D. GENETIC ALGORITHM

GA is a metaheuristic algorithm inspired by evolutionary biology which is used to solve search and combinational optimization problems which would be hard or take a long time to solve by using brute force methods [17]. An optimization problem of each candidate solution is represented by a string of genes called a chromosome. GA starts with a random choice of a variety of chromosomes which serves as the initial population [18]. Then each chromosome in the generation (population) is calculated by the fitness function to examine how well it fixes the problem. The exchange of information among each other of chromosomes will be done haphazardly. This process of exchanging information is called a crossover. The fitter a chromosome is, the more the chance of being selected. New offspring are created by two parents in the crossover process. Then the new offspring are mutated similar to the evolutionary biological structure. The next generation of parents is formed by the percentage of the best chromosomes. The GA has the characteristics of not being stuck or trapped in a local optimum (maximum) because of the mutation of offspring.

In [19] GA is used to solve a power problem in Cognitive Radio Networks (CRN). Also, GA was applied for spectrum allotment in CRN in [20], [21], and [22]. In our proposed work, the candidate solution of a joint spectrum and power network are represented by each chromosome. SUs are initially randomly allocated channels and power. The best chromosome is improved perpetually over several iterations through the crossover and mutation process. The value of power and spectrum allocations to SUs are exchanged by two randomly chosen power vectors and the channel allocation matrix is done by a cross-over process. After a settled number of iterations, the optimal solution to the problem of calculating an optimal power and spectrum allocation to SUs in CRN for minimization of sum power and interferences in the TVWS network will be represented by the best chromosome.

E. PARTICLE SWARM OPTIMIZATION ALGORITHM

PSO is an evolutionary metaheuristic algorithm that was first introduced by James Kennedy and Russell Eberhart [23]. PSO imitates the social habits of a bird's flock migration trying to get to an unspecified destination. The optimum solution is found based on population. Each solution in PSO is a bird in the flock. A bird is referred to as a particle. The particles that

existed are repetitively improved in PSO. When they move in the direction of the destination, the birds/particles modify their social behavior [24]. The bird's flocks communicate as they fly together. When they communicate together in a specific direction, the other birds determine the bird that is in the best position. Each bird from its position uses its velocity to reach the best bird location. PSO combines both global and local search. Local search means that the birds grasp their own experience while the global search, the birds learn from the other bird's experiences around them.

PSO starts by initializing a set of random particles with random solutions to the optimization problem, then the particle fitness is evaluated. All over the process, for every particle, I observe three parameters which are: particle current position (X_i), best particle position reached (P_i), and the particle flying velocity (V_i). Also, the best particle P_{best} is obtained at each iteration. And if the best particle P_{best} is better than the g_{best} at each iteration then the global best particle P_g and the related value of an objective function g_{best} is also updated. At each iteration, every particle flies in the direction of the current best position P_i and the best particle P_g at a determined velocity. The following equation number (12) is used for every particle to update its present velocity V_i .

$$\begin{aligned} \text{New}V_i &= \omega \times \text{current}V_i + c_1 \times \text{rand}() \times (P_i - X_i) \\ &+ c_2 \text{Rand}() (P_g - X_i), \end{aligned} \quad (21)$$

The updated position for the particle when using the new velocity is now given by the following equation below:

$$\begin{aligned} \text{NewPosition}X_i &= \text{currentposition}X_i + \text{New}V_i, \\ &\times V_{\min} \geq V_i \geq -V_{\max} \end{aligned} \quad (22)$$

whereby in the above equation. (21), the two positive constants are c_1 and c_2 , normally ($c_1 = c_2 = 2$), rand and Rand are the two random functions, ω is an inertia weight as proposed by Shi Y and Eberhart in [24] which take the path in the function of local balancing and global search. V_{\min} and V_{\max} are the particle's minimum and maximum velocities respectively.

PSO is used to optimize power in [25] and spectrum allocation in [26], [27], and [28]. Our proposed algorithm in this paper has the objective of maximizing the SINR for all secondary users (SUs). Several particles have been taken in this proposed algorithm. The possible result of the problem to obtain an optimum spectrum and power allotment to all SUs is represented by each particle position (X_i). The power is randomly assigned to all SUs at the beginning of the optimization process. If there is an improvement at every iteration, the global best power vector and the best power vector for every particle are updated. At a determined velocity, the particle (X_i) will move in the direction of the best particle position (P_i) and the global best particle (P_g) at each iteration. P_g will be chosen as an optimal result for the power assignment problem after a predefined number of iterations. Every particle will include a channel assignment matrix and

power vector in the case of the joint spectrum and power allotment.

F. ADMISSION CONTROL ALGORITHM

Admission control is a vital feature used in wireless networks for the optimization of radio resource usage to maintain the QoS of the existing users. Admission control is done when the load in TVWS wireless network is high, which means when the number of SUs requesting a link is too large. Admission control is used to maximize the number of admitted users and reduce interference [5].

G. JOINT SPECTRUM AND POWER ALLOCATION OPTIMIZATION USING HYBRID PSOFAGA ALGORITHM

When many SUs scramble for the channels in a TVWS wireless network may cause interference within themselves or to the PUs. According to [29] reducing interference can maximize the network throughput. Therefore, proper joint spectrum and power allocation with admission control are very important in TVWS networks. Due to its characteristics of faster convergency and multi-modality, the heuristic firefly algorithm can be hybridized with other algorithms [15]. The joint spectrum and power allotment using a hybrid PSOFAGA algorithm proposed are presented in this sub-section.

Steps on which the algorithm functions are shown in algorithm 1. PSO is first used to optimize the resource allocation in step 1 of algorithm 1. The reason for starting with PSO is that the FA final solution depends on the status of the initial solution. In the proposed algorithm each particle of PSO will consist of a channel allocation matrix and the power vector. The velocity computation and position update in step 1.3.4 will be separately done for the power allocation vector and channel allocation matrix. The velocity computation and position update are shown in (21) and (22) respectively.

Proceeding with step 2, the first solution of PSO created in step 1 will be the starting point of FA. The solutions developed in PSO particles at PSO termination in the first step will initiate all fireflies as shown in algorithm 1. In step 3, after the fitness ranking of the fireflies, the two best fireflies are crossed over to create four new offspring. Then the generated four offsprings are ranked as per their fitness. If the fitness of the best current firefly measured by the optimization problem (objective function) in (7) is better (higher) than the one of the best offspring then it will be replaced by that of the best offspring. Rather than the firefly to move according to (19), their movement will associate the local search in the direction of local personal best and the global search in the direction of the global best. This is essential because it will prevent PSO from the local optimum trapping. The new movement of the firefly will move according to (23) below and some of the PSO operators such as g_{best} , P_{best} , c_1 and c_2 are used in our proposed algorithm.

$$x_i^{t+1} = x_i^t + c_1 l^{-\gamma r_{ij}^2} (p_i - x_i^t) + c_2 l^{-\gamma r_{ij}^2} (p_g - x_i^t) + \alpha \epsilon_t^i, \quad (23)$$

H. JOINT SPECTRUM AND POWER ALLOCATION OPTIMIZATION USING HYBRID PSOFAGA WITH ADMISSION CONTROL ALGORITHM

This subsection illustrates the joint spectrum and power allocation optimization using hybrid PSOFAGA with an admission control algorithm to reduce interference among SUs and to PU to maximize throughput and SINR for all SUs in the TVWS network. In our work, we propose the ELGRA which has lower complexity and performance compared to other existing centralized admission control algorithms including ESRPA as mentioned in [5]. The joint spectrum and power allocation using PSOFAGA are integrated with ELGRA to maximize SINR and throughput for SUs in the network. Considering the ELGR of the user i as $\left(\frac{h_i^{(p)}}{h_i^{(s)}}\right) \theta_i$. As it is shown in (12) and (13) that, the values of $f_s(A_s)$ and $f_p(A_s)$ are related directly to the values of ELGR of admitted SUs.

Therefore, SU having a higher value of ELGR affects the other users and hence, it should be given less opportunity to access the TVWS network. At each iteration, the ELGRA algorithm instead of removing the user who has the lowest removal feasibility constraints for PUs or feasibility constraints for SUs ($f_p(A_s)$ or $f_s(A_s)$) respectively, we can just remove the user whose maximal ELGR to reduce the computational complexity of the algorithm. Algorithm 2 below shows the illustration of the proposed joint power and spectrum allotment using hybrid PSOFAGA with the ELGR algorithm.

Algorithm 1: Joint Spectrum and power Allocation optimization using PSOFAGA Algorithm.

Step 1:

- 1.1 Initialization of the number of particles, c_1 , c_2 , ω , v_{min} , v_{max} .
- 1.2 For every particle
 - Within the allowed range initialize the Power vector with random power values.
 - With one channel allocated to every user, initialize the channel matrix.
- End
- 1.3 Do
 - 1.3.1 For every particle
 - Compute fitness value.
 - Set the recent value as new P_i , if the fitness value is better than the best fitness value (P_i)
 - End
 - 1.3.2 Select P_{best} as the particle whose best fitness value.
 - 1.3.3 If current P_{best} with its related best position x_{best} is better than the g_{best} then set the current P_{best} as g_{best} .
 - 1.3.4 For every particle
 - Compute the velocity of a particle as per (19)
 - Update position of a particle for both channel matrix and power vector as per (20)
 - Look over the power vector to see whether all values of power are in range or not. Generate in-range random values if any values are out of range.

- If there is an allocation of more than one channel to SU, then select randomly a single channel for each SU.

End

While maximal iterations have not been held out.

1.4 Set g_{best} as the final solution of PSO.

Step 2:

- 2.1 Initialize the control parameters of the algorithm α, β, γ , firefly number NP and the maximum number of iterations t_{max} .
- 2.2 Set D as the dimension of the firefly.
- 2.3 Set the first position of the fireflies as those of solution for the problem in (7) generated by PSO in step 1.

Step 3:

- 3.1 Using (7) compute the fitness value of the firefly and rank the firefly according to their fitness values.
- 3.2 Calculate the current best solution.
- 3.3 Apply crossover mechanism separately for the power vector and spectrum channel matrix on the top to best solutions.
- 3.4 Out of the four offspring formulated through crossover, choose the best offspring and utilize it as the latest best solution of the FA, if its fitness is better than that of the current best.

Step 4:

- 4.1 For each firefly, move it to the better solution according to (7).
- 4.2 Check firefly y_i to see if every single power values in the power vector are in-range. If any values are out of range then generate random values that are in range to replace them.

Step 5:

- 5.1 If it reaches the predefined maximum number of iterations, then the power vector and channel allocation matrix of the current best solution mentioned in step 3 is derived and stop the progress else go to step 3 and continue.

Algorithm 2: The proposed Joint Spectrum and power Allocation optimization using PSOFAGA with Admission Control Algorithm

Step 1: Initialization:

- 1.1 Initialize all parameters as per algorithm 1 i.e. $c_1, c_2, \omega, v_{min}, v_{max}$.
- 1.2 Assuming all SUs are allocated with their required minimum/target- SINR (i.e., $A_s \leftarrow M_s$ and $\theta_i = \hat{\theta}_i$ for all $i \in M_s$ or $\theta_{M_s} \leftarrow \hat{\theta}_{M_s}$ equivalently).
- 1.3 Assume all PUs is allocated with their target/required minimum SINR (i.e., $\theta_i = \hat{\theta}_i$ for all $i \in M_p$ or $\theta_{M_p} \leftarrow \hat{\theta}_{M_p}$ equivalently).
- 1.4 Compute $K_s(\theta_{M_p})$ and $K_p(\theta_{M_p})$ as per equations (14) and (15).

Step 2: Admission Control

- 2.1 If $|A_s| > 0$ and (10) and (11) do not hold then, do the following or otherwise go to step 3.

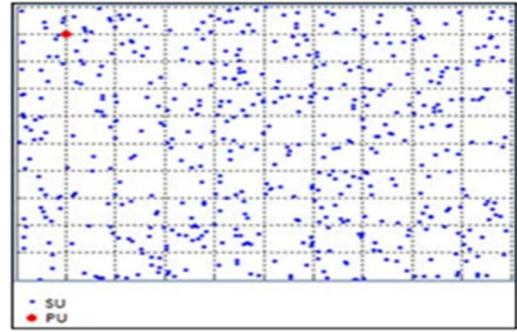


FIGURE 2. Network diagram.

$$2.2 A_s \leftarrow A_s \left\{ \begin{matrix} * \\ i \end{matrix} \right\}, \text{ where}$$

$$* = \text{Argmax}_{i \in A_s} \left\{ \frac{h_i^{(p)}}{h_i^{(s)}} \hat{\theta}_i \right\}.$$

Step 3: Spectrum and Power Allocation

- 3.1 Allocate joint power and spectrum as per the algorithm

IV. SIMULATION SETUP

Simulation results for the joint spectrum and power allocation optimization using PSOFAGA with ELGRA are presented in this section. The proposed PSOFAGA with admission control algorithm is compared with PSO, FA, GA, and PSOFAGA algorithms [6]. The following metrics were used to compare the performance of the algorithm: sum throughput, SU SINR, PU SINR, objective function values, and running time of the algorithm. Considered $P_{max} 20\text{dBm}$ for mobile WSDs only.

Matlab R2020a is used in simulation because it is rich in built-in functions. The simulation parameters are listed in Table 1. Secondary users $S = 500$ are dispersed over an area of 1km^2 . The network diagram generated by Matlab is shown in figure 3. Initial power and spectrum allocation are done randomly. SUs are initially randomly dispersed across 16 channels. The path loss was modeled by the free-space path loss model shown in equation (24) below:

$$PL(d) = 20 \log(d) + 20 \log(f) - 147.55, \quad (24)$$

where f is the operation frequency, and the distance measured in meters is denoted by d . The FA parameters used are: $\beta_0 = 1, \alpha = 30, \gamma = 10$, firefly numbers $NP = 50$. The Genetic algorithm parameters are as follows: mutation rate = 0.8, chromosome = 50, and selection rate = 0.5. PSO used the following parameters, inertia weight $\omega_{min} = 2$ and $\omega_{max} = 4$, number of particles = 50, cognitive parameters $c_2 = 2$, and social parameters $c_1 = 2$. The number of iterations used for PSO, FA, and GA is 50. For PSOFAGA, the number of iterations used for FA and PSO used is 25 which is half of the pure FA and PSO.

V. SIMULATION RESULTS

Simulation results for the joint spectrum and power allocation optimization using PSOFAGA with admission control are presented in this section. The proposed PSOFAGA with ELGRA algorithm is compared with PSO, FA, GA, and PSOFAGA algorithms. The following metrics were used to

TABLE 1. Simulation parameters.

Parameter	Value	Description
B.W	8MHz	TV channel bandwidth
f_b	474MHz	Center frequency of DTT signal
P_{TV}	-70.6dBm	Received power from TV transmitter at the TV receiver
σ_{TVR}	-102dBm	Noise power
η_0	23dB	SINR threshold required at PU
β_0	7dB	SINR threshold needed at SU
p^{AP}	36dBm(4W)	Access point (AP)/base station (BS) transmit power
P_{max}	200dBm	Maximum SU transmit power
$\mu(b, c_s)$	(0,-28dBm)	ACI coefficient
G_{PU}	10dB	TV receiver (PU) antenna gain
G_{SU}	10dB	SU antenna gain
G_{AP}	10dB	AP antenna gain

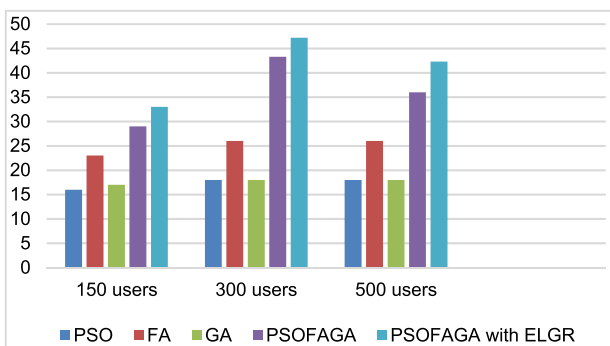


FIGURE 3. Sum throughput for all algorithm.

compare the performance of the algorithm: sum throughput, SU-SINR, PU-SINR, and percentage of SU less than SU-SINR threshold. Considered P_{max} 20dBm for mobile WSDs only.

A. SUM THROUGHPUT

For all values of S , the output results indicate that the PSOFAGA with the ELGRA admission control algorithm attains the highest sum throughput of all compared algorithms. This is because the SU with a higher value of ELGRA is given less opportunity to access the TVWS network hence reduction of interference and maximization of the network sum throughput. Shannon channel capacity theorem reveals the fact that when you reduce interference you also improve the throughput. Table 2 and figure 3 show the performance of PSOFAGA with ELGRA admission control algorithm with the other existing algorithms in TVWS wireless networks for the variety of users S with C equal to 10.

B. SU SIGNAL TO NOISE RATIO (SU SINR)

As S increases in the TVWS wireless network, the sum of interference power to SUs is also increasing hence SU-SINR decreases. PSOFAGA with ELGR admission algorithm achieves the biggest average SU-SINR for all S values.

TABLE 2. Sum throughput comparison for S=150,300 and 500.

Algorithm	$P_{max}=20dBm$					
	Sum throughput(Mbps)			Improvement Percentage of Sum throughput for PSOFAGA with ELGR		
	S=150	S=300	S=500	S=150	S=300	S=500
PSO	16	18	18	107.5%	162.2%	13.5%
FA	23	26	26	44.34%	66.04%	62.7%
GA	17	18	18	95.29%	162.2%	135%
PSOFAGA	29	43.3	36	14.48%	9%	17.5%
PSOFAGA with ELGR	33	47.2	42.3			

TABLE 3. Average SU SINR comparison for S=150,300 and 500.

Algorithm	$P_{max}=20dBm$		
	S=150	S=300	S=500
PSO	17.04	15.03	14.04
FA	17.26	15.46	14.39
GA	17.03	15.02	14.01
PSOFAGA	22.3	21.2	20.1
PSOFAGA with ELGR	26.20	25.15	23.12

TABLE 4. PU SINR comparison for S=500.

Algorithm	$P_{max}=20dBm$	
	Average PU SINR (dB)	S=500
PSO	56.271	
FA	56.012	
GA	49.0101	
PSOFAGA	57.313	
PSOFAGA with ELGR	57.512	

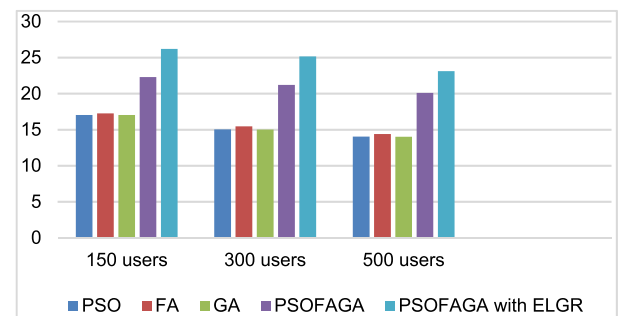


FIGURE 4. Average SU SINR comparison for S=150,300 and 500.

This is because PSOFAGA with the ELGR admission control algorithm assigns both spectrum and power and the ELGR algorithm uses equation 13 to support all SUs with their given SINR.

C. PU SIGNAL TO NOISE RATIO (PU SINR)

As S increases, the signal-to-noise ratio (SINR) for PU also decreases due to the increase of interference caused by the massive number of secondary users in the TVWS wireless network. Compared with the other algorithms, PSOFAGA with ELGR admission control attains the biggest PU-SINR

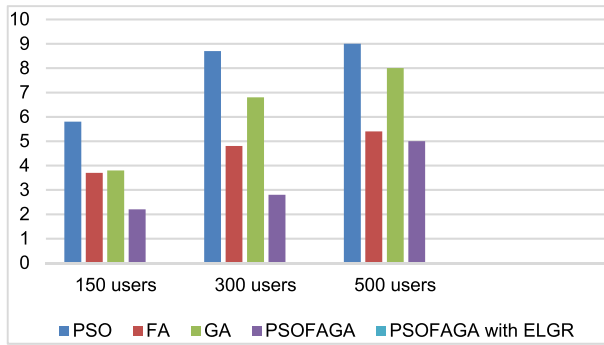


FIGURE 5. SUs less than SINR threshold percentage for various algorithms and values of S .

TABLE 5. Percentage of SU less than SU SINR threshold comparison for $S=150, 300$, and 500 .

Algorithm	$P_{\max}=20\text{dBm}$			Improvement Percentage of SU less than SU SINR for PSOFAGA with ELGR			
	Percentage of SU less than SU SINR(dB) threshold	S=150	S=300	S=500	S=150	S=300	S=500
PSO	S=150	5.8	9	9	62%	67.8%	44.4%
FA	S=150	3.7	5.4	5.4	40.5%	66.04%	7.4%
GA	S=150	3.8	8	8	42.1%	58.8%	37.5%
PSOFAGA	S=150	2.5	5.3	5.3	12%	12.5%	6.1%
PSOFAGA with ELGR	S=150	2.2	5	5			

for all S values. Because PSOFAGA with ELGR admission control algorithm assigns both spectrum and power and ELGR uses equation 16 to protect PU against admitted SUs. Therefore, the interference caused by admitted SUs does not affect PU performance and cause an outage of any PU.

D. PERCENTAGE OF SU LESS THAN SU SINR THRESHOLD

The SINR threshold in the TVWS network is 13dB. Compared with the other algorithms, PSOFAGA with ELGR admission control algorithm performs better and attains the smallest percentage of SU-SINR lower than the threshold for the values of the number of users S . Table 5 and figure 5 show the performance of PSOFAGA with ELGRA admission control algorithm with the other existing algorithms in TVWS wireless networks for the variety of users S with C equal to 10. PSOFAGA with ELGR admission control performs better since; it allocates joint spectrum and power and restricts/removes the SUs with the highest effective link gain ratio, therefore, reducing interference in the TVWS network.

VI. CONCLUSION AND RECOMMENDATIONS

The efficiency of hybrid PSOFAGA with ELGR admission control algorithm for joint spectrum and power assignment in TVWS wireless network is evaluated using MATLAB2020a and compared with the algorithms such as PSO, FA, GA, and FAGAPSO. The performance of the proposed algorithm is compared using the metrics such as sum throughput, PU-SINR, and SU-SINR threshold. The results show that the PSOFAGA with ELGR admission control algorithm has the best performance in PU signal-to-noise ratio (SINR),

SU SINR threshold, and sum throughput compared to other algorithms.

Also, the admission control method used in this research uses an effective link gain ratio to remove users, therefore, effective stepwise SU removal with the primary users, protection algorithm (ESRPA) can also be integrated with the joint power and spectrum PSOFAGA algorithm and the results can be compared with our proposed work.

This work can be further extended for better results. Firstly, the developed model in this research does not involve fading, hence it can be further extended by including fading. Secondly, the joint power and spectrum assignment using hybrid PSOFAGA with ELGR admission control algorithm uses a TVWS wireless network whose only one cell which means it uses only one base station (BS), therefore, the extension of this work can be the addition of more than one cell in TVWS wireless network.

Thirdly, the simulation environment we used in our work used only FDMA as a MAC protocol, therefore, other MAC protocols such as CSMA/CA or CSMA/CD, TDMA, and CDMA.

REFERENCES

- [1] M. Rahman and A. Saifullah, "A comprehensive survey on networking over TV white spaces," *Pervasive Mobile Comput.*, vol. 59, Oct. 2019, Art. no. 101072.
- [2] D. Johnson, N. Zlobinsky, A. Lysko, M. Lamola, S. Hadzic, R. Maliwatu, and M. Densmore, "Head to head battle of TV white space and WiFi for connecting developing regions," in *Proc. Int. Conf. e-Infrastruct. e-Services Developing Countries*. Ouagadougou, Burkina Faso: Springer, Dec. 2017, pp. 186–195.
- [3] K. K. Ronoh, G. Kamucha, T. Olwal, and T. Omwansa, "A survey of resource allocation in TV white space networks," *J. Commun.*, vol. 14, no. 12, pp. 1180–1190, 2019.
- [4] Y. Selén and J. Kronander, "Optimizing power limits for white space devices under a probability constraint on aggregated interference," in *Proc. IEEE Int. Symp. Dyn. Spectr. Access Netw.*, Oct. 2012, pp. 201–211.
- [5] X. Gong, S. A. Vorobyov, and C. Tellambura, "Joint bandwidth and power allocation with admission control in wireless multi-user networks with and without relaying," *IEEE Trans. Signal Process.*, vol. 59, no. 4, pp. 1801–1813, Apr. 2011.
- [6] R. Kennedy and O. K. T. George, "Novel resource allocation algorithm for TV white space networks using hybrid firefly algorithm," *Int. J. Comput.*, vol. 32, no. 1 pp. 34–53, 2019.
- [7] R. Kennedy, K. George, O. O. William, O. Thomas, and O. Tonny, "Firefly algorithm based power control in wireless TV white space network," in *Proc. IEEE AFRICON*, Sep. 2017, pp. 155–160.
- [8] S. Arora and S. Singh, "The firefly optimization algorithm: Convergence analysis and parameter selection," *Int. J. Comput. Appl.*, vol. 69, no. 3, pp. 48–52, May 2013.
- [9] Y. Li, T. Jiang, M. Sheng, and Y. Zhu, "QoS-aware admission control and resource allocation in underlay device-to-device spectrum-sharing networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 11, pp. 2874–2886, Nov. 2016.
- [10] Z. Xue and L. Wang, "Geolocation database based resource sharing among multiple device-to-device links in TV white space," in *Proc. Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2015, pp. 1–6.
- [11] H. Y. Gu, C. Y. Yang, and B. Fong, "Low-complexity centralized joint power and admission control in cognitive radio networks," *IEEE Commun. Lett.*, vol. 13, no. 6, pp. 420–422, Jun. 2009.
- [12] Z. Xue, L. Shen, G. Ding, Q. Wu, L. Zhang, and Q. Wang, "Coexistence among device-to-device communications in TV white space based on geolocation database," in *Proc. Int. Workshop High Mobility Wireless Commun.*, Nov. 2014, pp. 17–22.

- [13] K. K. Ronoh and G. T. K. K. Omwansa, "Comparison of hybrid firefly algorithms for power allocation in a TV white space network," *Int. J. Comput. Appl.*, vol. 975, p. 8887, Aug. 2019.
- [14] X.-S. Yang, *Nature-Inspired Metaheuristic Algorithms*. Luniver Press, 2010.
- [15] I. Fister, X. S. Yang, and J. Brest, "A comprehensive review of firefly algorithms," *Swarm Evol. Comput.*, vol. 13, pp. 34–46, Dec. 2013.
- [16] K. K. Anumandla, S. Kudikala, B. A. Venkata, and S. L. Sabat, "Spectrum allocation in cognitive radio networks using firefly algorithm," in *Proc. Int. Conf. Swarm, Evol., Memetic Comput.* Cham, Switzerland: Springer, 2013, pp. 366–376.
- [17] A. Shrestha and A. Mahmood, "Improving genetic algorithm with fine-tuned crossover and scaled architecture," *J. Math.*, vol. 2016, pp. 1–10, Mar. 2016.
- [18] J. Carr, "An introduction to genetic algorithms," *Senior Project*, vol. 1, no. 40, p. 7, 2014.
- [19] R. Lopez, S. Sanchez, E. Fernandez, R. Souza, and H. Alves, "Genetic algorithm aided transmit power control in cognitive radio networks," in *Proc. 9th Int. Conf. Cognit. Radio Oriented Wireless Netw.*, 2014, pp. 61–66.
- [20] P. S. Varade and Y. Ravinder, "Optimal spectrum allocation in cognitive radio using genetic algorithm," in *Proc. Annu. IEEE India Conf. (INDICON)*, Dec. 2014, pp. 1–5.
- [21] S. Chen, T. R. Newman, J. B. Evans, and A. M. Wyglinski, "Genetic algorithm-based optimization for cognitive radio networks," in *Proc. IEEE Sarnoff Symp.*, Apr. 2010, pp. 1–6.
- [22] P. Supraja, V. M. Gayathri, and R. Pitchai, "Optimized neural network for spectrum prediction using genetic algorithm in cognitive radio networks," *Cluster Comput.*, vol. 22, no. S1, pp. 157–163, Jan. 2019.
- [23] R. Eberhart and J. Kennedy, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, 1995, pp. 1942–1948.
- [24] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Proc. IEEE Int. Conf. Evol. Comput. IEEE World Congr. Comput. Intell.*, 1998, pp. 69–73.
- [25] S. Motian, M. Aghababae, and H. Soltanian-Zadeh, "Particle swarm optimization (PSO) of power allocation in cognitive radio systems with interference constraints," in *Proc. 4th IEEE Int. Conf. Broadband Netw. Multimedia Technol.*, Oct. 2011, pp. 558–562.
- [26] S. B. Behera and D. D. Seth, "Resource allocation for cognitive radio network using particle swarm optimization," in *Proc. 2nd Int. Conf. Electron. Commun. Syst. (ICECS)*, Feb. 2015, pp. 665–667.
- [27] Z. Jie and L. Tiejun, "Spectrum allocation in cognitive radio with particle swarm optimization algorithm," *Chin. Sci. Papers Online*, 2012.
- [28] S. Mishra, S. Sagnika, S. S. Singh, and B. S. P. Mishra, "Spectrum allocation in cognitive radio: A PSO-based approach," *Periodica Polytechnica Electr. Eng. Comput. Sci.*, vol. 63, no. 1, pp. 23–29, Jan. 2019.
- [29] N. Nie and C. Comaniciu, "Adaptive channel allocation spectrum etiquette for cognitive radio networks," *Mobile Netw. Appl.*, vol. 11, no. 6, pp. 779–797, 2006.



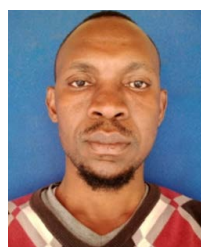
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