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Novel Resource Allocation Algorithm for TV White Space Networks Using Hybrid Firefly Algorithm

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Abstract

There is continued increased demand for dynamic spectrum access of TV White Spaces (TVWS) due to growing need for wireless broadband. Some of the use cases such as cellular (2G/3G/4G/5G) access to TVWS may have a high density of users that want to make use of TVWS. When there is a high of density secondary users (SUs) in a TVWS network, there is possibility of high interference among SUs that exceeds the desired threshold and also harmful interference to primary users (PUs). Optimization of resource allocation (power and spectrum allocation) is therefore necessary so as to protect the PUs against the harmful interference and to reduce the level of interference among SUs. In this paper, a novel and improved resource allocation algorithm based on hybrid firefly algorithm, genetic algorithm and particle swarm optimization (FAGAPSO) has been designed and applied for joint power and spectrum allocation. Computer simulations have been done using Matlab to validate the performance of the proposed algorithm. Simulation results show that compared to firefly algorithm (FA), particle swarm optimization (PSO) and genetic algorithm (GA), the algorithm improves the PU SINR, SU sum throughput and SU signal to interference noise (SINR) ratio in a TVWS network. Only one algorithm considered (SAP) has better PU SINR, SU sum throughput and SU signal to interference noise (SINR) ratio in a TVWS network but it has poor running time.

Keywords: Dymamic spectrum access; cognitive radio; TV white spaces; spectrum allocation; power control;, resource allocation; firefly algorithm, hybrid firefly algorithm genetic algorithm, particle swarm optimization.

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1. Introduction

Spectrum occupancy assessments done in USA, Spain, Singapore, New Zealand and Germany [1] and UK [2], indicate that a large portion of spectrum assigned to primary users (PUs) is underutilized. Spectrum is considered a scarce resource. More and more devices want a pie of the spectrum and yet the useful spectrum is limited. Dynamic spectrum access (DSA), through the use of cognitive radio (CR) techniques is currently being embraced as a solution to spectrum underutilization and spectrum scarcity. This is because DSA, together with CR, provides an efficient way for spectrum management and spectrum sharing. DSA allows the existence of both primary and secondary users in a non-interfering basis. With DSA, spectrum allocated for exclusive use to a primary user (PU) but being not used by the PU (incumbent), or any other idle frequency bands (such as guard bands) can be shared by different secondary users (SUs) as long as the interference to the incumbent by the secondary users to the PU is kept to an acceptable level [3,4]. The spectrum band which has attracted a lot interest in the DSA community is the TV White Spaces (TVWS). TVWS is the spectrum band not being utilized efficiently by TV transmitters in the UHF band. The main reason for this increased interest is the good propagation characteristics of the sub-1GHz spectrum.

Regulatory authorities worldwide have mandated the use of geo-location database (GLDB) for protection of PUs. Geo-location database is used by a SU or white space device (WSD) to find the set of frequency channels that can be used on a secondary basis at a given area and at any given time [5]. GLDB is populated through the use of a propagation model. The database contains estimated power levels of incumbents (PUs) for any point in a particular region of interest. The WSD, which has a cognitive radio system (CRS), queries a central database. The WSD provides the database with parameters such as its location, device type and antenna height. The GLDB will then use this information along with the parameters of all surrounding TV transmitters such as antenna height, transmit power and frequency of operation in order to come up with the list of available TVWS channels that can be used by the WSD on secondary basis without causing harmful interference to the primary users. The GLDB will also give the WSD limits on the transmit power and also the time period in which each channel can be used.

It is expected there will be continued demand for dynamic spectrum access (DSA). There is increased demand for DSA to TVWS from internet of things (IoT) [6], machine to machine communications, vehicle to vehicle (V2V) communications [7,8], cellular networks (3G , 4G, 5G) [9,10,11]. This will result in secondary networks with a high density of users. Problem of interference will arise in a TVWS network with a high density of users. Some SUs also may not be admitted into the secondary network due to interference constraints at PUs and SUs. TVWS can be used as long as the interference to the PU do not fall below a certain threshold. This threshold is commonly referred to as protection ratio or desired to undesired (D/U) ratio. In a network where there is high number of devices seeking access to a secondary network allocation of two resources, power and spectrum, needs to be optimized to ensure that as many SUs as possible access the secondary network while ensuring that interference constraints for PUs and QoS requirements for SUs are met. In this paper, resource allocation refers to joint allocation of power and spectrum to SUs.

The aim of this paper is to design a novel and improved algorithm for resource allocation based on hybrid firefly algorithm (FA), genetic algorithm (GA) and particle swarm optimization (PSO) for a TVWS network that considers adjacent channel interference as well as interference constraints at both PUs and SUs. The algorithm is referred to as FAGAPSO. The contribution of this paper is the design of an improved algorithm based on hybrid FA, GA and PSO (FAGAPSO) for joint power and spectrum allocation in a GLDB based wireless TVWS network where devices communicate via a base station. Among other evolutionary algorithms, FA is chosen because it has been found to perform better than other algorithms in terms of solution quality and convergence time [12,13]. Despite its superior performance over other algorithms, FA can get trapped in local optimum. Crossover feature of GA and the features of $\mathrm{P_{best}}$ and $\mathrm{g_{best}}$ PSO are incorporated into FA so as to diversify the search of solution space so that FA can avoid being trapped in the local optimum. In addition to incorporating the features of PSO and GA, the initial solution of FA is derived from final solution of PSO. To the best of our knowledge, FAGAPSO has not been used for joint power and spectrum allocation in a TVWS network that makes use of a GLDB. Simulation results show that the use of FAGAPSO results in improvement in sum throughput and SU SINR in a TVWS network.

The rest of the paper is organized as follows. Section 2 provides a review of related work on resource allocation in a TVWS network. In Section 3 FA, GA, PSO and related hybrid algorithms are discussed. Section 4 presents problem formulation for the optimization problem under consideration. In Section 5, the proposed algorithm based on FAGAPSO has been presented. Simulation set up has been presented in Section 6. Simulation results have been discussed in Section 7. The paper is concluded in Section 8.

2. Related Work

A resource allocation method has been proposed for IEEE 802.11af [14]. In an IEEE 802.11af network, a device sends a channel availability query (CAQ) to registered location secure server (RLSS). RLSS operates as a GLDB. Once a CAQ is received by the RLSS, it will respond with a white space map (WSM). The WSM contains the list of available channels and their respective effective isotropic radiated power (EIRP). IEEE 802.11af allows for both closed loop power control and open loop power control. With open loop power limitation the WSD has rigid power limitation similar to those provided by FCC regulations [3,15] whereby fixed power values are used are assigned to SUs. In closed loop power control, the WSD has more flexible power limits that depends on location, time of use and the channel. The technique proposed in IEEE 802.11af is not designed to optimize resource allocation as it seeks to ensure that specific users that request channel are allocated one with an associated power level. In our proposed algorithm, resource allocation is done for all users that already exist in the network.

IEEE 802.22 makes use of a spectrum manager (SM) to allocate spectrum [16]. IEEE 802.22 allows the use of both GLDB and spectrum sensing for incumbent protection. The SM makes use of spectrum sensing function and GLDB to find out the channels available for secondary use and their respective effective isotropic radiated power (EIRP) limits. Just like IEEE 802.11af, the technique proposed in IEEE 802.22 is not designed to optimize resource allocation as it seeks to ensure that specific users that request channel are allocated one with an associated power level. Power and spectrum allocation is done in an arbitrary manner with no use of an objective function. It will not be applicable in a high density network where there is need to optimize resource allocation so as admit as many users as possible into the network.

GLDB based spectrum allocation with power control, co-channel interference and adjacent channel interference considerations has been proposed by [17]. Co-existence (mutual interference) among SUs is also considered. Channel allocation and power control is then done in such a manner that the TV receiver and SUs SINR constraints are met. A greedy algorithm is used for power control and spectrum allocation. Each SU is allocated a channel and a power level when it makes a channel request to the GLDB. The major disadvantage of the proposed algorithm is that, being a greedy algorithm, it may get trapped in a local optimum. Being trapped in local optimum will result in sub-optimal resource allocation.

GLDB based spectrum allocation with power control and admission control for TVWS multiple device-to-device links has been proposed by [18]. Only co-channel interference has been considered. Spectrum allocation is done using a game theory algorithm called spatial adaptive play (SAP). The disadvantage of this algorithm is that it will have a high running time because of the high number of iterations required for the iterative power allocation algorithm.

In our previous publication [19], we presented a resource allocation algorithm based on modified firefly algorithm. The algorithm considers SUs operating in both co-channel and adjacent channels to PUs in a GLDB based wireless TVWS network where devices communicate via a base station. We proposed a hybrid continuous-binary FA since the optimization involves both continuous values (power allocation) and binary values (spectrum allocation). In the current proposed algorithm FA is hybridized with both GA and PSO. The The hybrid FA, GA and PSO is used for resource allocation because two reasons. Firstly, features of PSO and GA incorporated into FA enables FA to diversify the search of solution space so as avoid being trapped at the local optimum. Secondly, by using the PSO solution as initial solution of FA, the final solution of FA is improved since final solution of FA depends on the initial solution [20].

3. Firefly Algorithm, Particle Swarm Optimization, Genetic Algorithm and Related Hybrid Algorithms

This section presents FA, PSO and GA as well as a review of hybrid FA and PSO and hybrid FA and GA in literature.

3.1. Firefly Algorithm

FA mimics the behaviour of fireflies. Firefly is an insect that flash to either attract a mate or potential prey [21]. Flashing may also serve as a warning mechanism. The flashing of a firefly is rhythmic. For female fireflies, the attractiveness of male fireflies depends on its brightness. The light intensity has an inverse relationship with distance. Light intensity reduces as distance increases according to this formula: $I \; \alpha \; \frac{1}{r^2}$. Fireflies, therefore, are visible within a limited distance. FA steps are presented in Algorithm 1. The objective function of an optimization problem can be associated with the flashing. The light intensity is determined by brightness I which is associated with an objective function value.

Table 3.1

Algorithm 1: Pseudocode for Firefly Algorithm[19]

Step 1: Initialize the control parameter values for the FA: light absorption coefficient γ, attractiveness β, randomization parameter α, maximum number of iterations t_{max}, number of fireflies NP, domain space D.
Step 2: Define objective function $f \underset{x}{\rightarrow}, \underset{x}{\rightarrow} = x_1, x_2, x_3, \ldots, x_n$. Generate the initial location of fireflies x_i $(i = 1,2, \ldots, NP)$ and set the iteration number $t = 0$.
Step 3:

```
while t ≤ t_max do
    for i = 1 to NP (do for each individual sequentially) do
        for j = 1 to NP (do for each individual sequentially) do
            Compute light intensity β_i as x_i is determined by f(x_i)
            if β_i < β_j, then
                Move firefly i towards j as described by Equation 2.2
            End if
            Attractiveness varies with distance r via e^{-γr}
            Evaluate new solutions and update light intensity
            Check updated solutions are within limits
        end for
    end for
    Step 3.1
    Rank the fireflies and find the current best;
    Increase the iteration count
end while
```

In an optimization problem, each firefly represents a potential solution to the optimization problem. In the FA, variation of attractiveness with distance is given by:

$$\beta = \beta_o e^{-\gamma r^2}, \tag{2.1}$$

where the term β refers to light intensity of the firefly, r is the distance between two fireflies and γ is the light absorption co-efficient. For any two flashing fireflies, the less bright one will move towards the brighter one according to equation (2.2):

$$x_i^{t+1} = x_i^t + \beta_o e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_t^i, \tag{2.2}$$

where the terms x_i and x_j are the locations of firefly i and firefly j, the symbol α is randomization parameter and the term ϵ_t^i is a vector of random numbers with uniform distribution. The first term represents attractiveness while the second term represents randomization. The symbol t is the iteration number. The distance between fireflies, r_{ij}, is computed according to equation (2.3):

$$r_{ij} = \sqrt{(x_{i,t} - x_{j,t})^2}\,. \tag{2.3}$$

FA has been found to perform better than PSO and genetic algorithm (GA) [22][23]. FA has also been used for spectrum allocation in a cognitive radio network (CRN) in [22]. As discussed in section 2, we proposed a resource allocation algorithm based on modified FA in [19]. For joint power and spectrum allocation, each firefly represents a potential solution to the problem of finding optimal resource allocation to all SUs in the TVWS network. Each firefly will consist of a power vector and channel allocation matrix. The objective function of the optimization problem is to maximize sum throughput in the network and also minimize violation minimum SINR at SUs and PU. At every iteration, the best firefly is determined and each firefly movement is done according to step 3 in Algorithm 1. After a fixed number of iterations, the best firefly is selected as the solution to the resource allocation problem.

3.2. Genetic Algorithm

Genetic algorithm (GA) mimics evolution of biological systems [24]. Each candidate solution to an optimization problem is represented by a string called a chromosome. Random solutions that represent initial chromosomes are first generated. The fitness of each of chromosome is then measured by using the objective function. In order to imitate survival of the fittest in a biological system, chromosomes will exchange information amongst each other in a random manner. The process of exchange of information is referred to as crossover. Two parents that are randomly selected exchange information in the cross over process to create new offsprings. Just like the evolution of biological systems, the new offsprings are then mutated. The mutation can prevent the GA from getting stuck in a local maximum by randomly introducing little modifications in the chromosomes. The new offsprings and previous parents are then evaluated using the objective function and ranked. Only a percentage of the best chromosomes form the next generation of parents. The process of crossover and mutation is then repeated again until maximum number of iterations is reached.

GA has been applied for spectrum allocation in a CRN in [25,26]. GA has been applied for transmit power control in a CRN in [27]. For the problem under consideration in the paper, each chromosome represents a candidate solution of joint power and spectrum allocation to all SUs in a CRN network. Initially SUs are assigned power and channels randomly. Through the process of crossover and mutation, the best chromosome is continuously improved over a number of iterations. The process of cross over involves two randomly chosen power vectors exchanging the values of power assignment to SUs. After a fixed number of iterations, the best chromosome will represent the optimal solution to the problem of finding optimal power allocation to SUs in the CRN that minimizes sum power in the network as well as interference.

3.3. Particle Swarm Optimization Algorithm

PSO is inspired by a flock of birds flying towards a destination. Each candidate solution is referred to as a particle. Each particle represents a bird in the flock. Unlike GA, now new birds/particles are generated. The existing particles are improved iteratively. The birds adjust their social behaviour as they move towards the destination. Birds communicate as they fly. As they communicate they identify the bird which is in the best position and then they move towards it at a certain velocity. PSO combines both local search and global search. Local search is represented by each bird learning from their own experience. Global search is represented by each bird learning from the experience of others.

PSO starts by generating a set of particles with a random solutions in the to the optimization problem. The fitness of each particle is then evaluated. Each particle looks at three parameters: its current position X_i, its current best position P_i and associated objective function value P_i, and its flying velocity V_i. At every iteration X_i and associated objective function value P_i is updated if there is an improvement in P_i. The best particle, P_{best}, is also determined at every iteration. The global best particle P_g and associated objective function value g_{best} is also updated if the current P_{best} is better than g_{best} at every iteration. At every iteration also, each particle flies towards P_i and P_g at a certain velocity. Each particle updates its current velocity, V_i, according to the equation (3.4):

$$New\ V_i = \omega \times current\ V_i + c_1 \times rand() \times (P_i - X_i) + c_1 \times rand() \times (P_g - X_i), \qquad (3.4)$$

where c_1 and c_2 are two positive constants and rand() is a random function. The term ω plays the role of balancing local search and global search. With the new current velocity, the position of the particle is then updated according to the equation (3.5):

$$New\ position\ X_i = current\ position\ X_i + New\ V_i, \qquad (3.5)$$

$$V_{min} \geq V_i \geq -V_{max}$$

where V_{max} is the maximum particle velocity and V_{min} is the minimum particle velocity.

PSO has been applied for spectrum allocation in a CRN in [28,29]. In both papers, a binary version of PSO is used. PSO has been applied for power allocation in a CRN in [30] . In the proposed algorithm, the objective is to maximize signal to interference noise ratio (SINR) for all SUs. Each particle (X_i), represents a potential solution to the problem of finding optimal power and spectrum allocation to all SUs. Initially SUs are assigned power randomly. The objective function used is minimization of minimum SINR violation. At each iteration the best power vector for each particle (P_i) and global best power vector (P_g) are updated if there is an improvement. At every iteration, X_i will then moves towards (P_i) and (P_g) at a certain velocity. After a fixed number of iterations, P_g will be selected as the optimal solution to the problem of power assignment. For joint power and spectrum allocation, each particle will consist of power vector and channel allocation matrix.

3.4. Hybrid Firefly and Particle Swarm Optimization Algorithms

Arunacham et. al. [30] proposed a hybrid FA and PSO for problem of combined economic and emission dispatch including valve point effect. In the proposed algorithm, there is no modification to firefly algorithm but the initial solution is obtained from PSO. The authors argue that quality of the final solution of FA depends on the initial solution. Simulation results show that hybrid the algorithm performs better than both PSO and FA.

Kora P. and Krishna K. [31] also proposed a hybrid FA and PSO algorithm for detection of bundle branch block. The hybrid algorithm makes use of PSO concepts and parameters. The concepts of personal best and global best which are absent in FA are introduced. All the steps in FA remain the same with that of the proposed algorithm except that equation (2.2) of the FA that represents firefly movement is changed to incorporate the idea of personal best and global best. In the proposed algorithm, each firefly movement involves a move towards the local best (P_i) and global best (P_g).

3.5. Hybrid Firefly and Genetic Algorithm

Rahmani A. and Mirhassani S.A. [21] proposed a hybrid FA and GA. All the steps in the FA remain the same except that for every iteration, the two current best solutions are crossed over. Two fittest offsprings out of the four offsprings are then selected. For mutation, one of the two offsprings is randomly selected. If the selected offspring has a better solution compared to the current best solution, it replaces the current best solution in step 3.1 of Algorithm 1.

Luthra J. and Pal Saibal K. [32] also proposed a hybrid FA and GA for the solution of the monoalphabetic substitution cipher. In the proposed algorithm, movement of fireflies in space is done using genetic operators and the concept of dominant gene cross over. With dominant gene cross over, an offspring takes more from one parent than the other during cross over.

4. Problem Formulation

The optimization problem to be considered is about resource allocation optimization described in our paper in [19]. We consider a network illustrated by Figure 1. In the figure there a single TV receiver placed at the edge of the protection region. Among all the TV receivers in the protection region, a TV receiver at this location is the one which is most vulnerable to interference since it is very close to the secondary network. GLDB regulations require that the protection ratio be measured at the edge of protection region [33]. Aggregate interference at the TV receiver, both co-channel and adjacent channel should not make the protection ratio fall below the required protection ratio threshold. We assume that the network consist of M SUs.

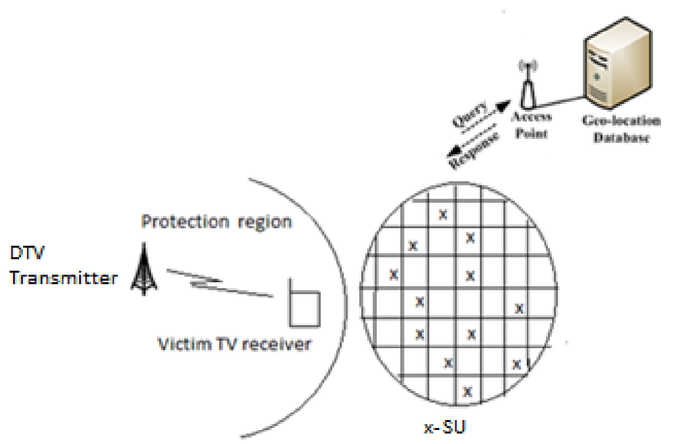

Figure 1: Interference scenario

The optimization goal is to find a power vector ($P^* = \{P_m^{n_i}, P_m^{n_i}, \dots P_m^{n_i}\}$) and channel allocation matrix A^* that maximizes sum downlink throughput while ensuring that interference constraints violations at the PU and SUs are minimized. The optimization problem is defined as follows [19]:

Problem 1

$$p^*,\ A^* = \arg max\ (U - c_s \sum_{i=1}^{N} \max[0, g_i^s]^2 - c_p \max[0, g_i^p])^2 \qquad (4.1)$$

subject to $C: p_{min} \leq p_i \leq p_{max}$

$a_{n,m} \in \{0,1\}$

The first of equation (4.1), U, represents the sum throughput of all SUs, the second term $(c_s \sum_{i=1}^{N} max[0, g_i^s]^2)$ represents interference threshold violation for SUs while the third term represents interference threshold violation for PU. The terms c_s and c_p are penalty factors for SU interference threshold violation and PU interference threshold violation.

5. Optimal Resource Allocation Using Hybrid Particle Swarm Optimization and Firefly Algorithm with Genetic Operators

This section presents the proposed joint power and spectrum allocation optimization using FAGAPSO. The algorithm steps are outlined in Algorithm 2. In step 1 of Algorithm 2, optimization of resource allocation is first done using PSO. This is necessary because the final solution of FA depends on the quality of initial solution. Each particle will consist of power vector and channel allocation matrix. All particles will be initialized with random valid power and channel assignment for all SUs. In step 1.3.4, computation of velocity (equation (3.4)) and position update (equation (3.5)) will be done separately for channel allocation matrix and power allocation vector. Here, PSO is used to solve a continuous-binary problem. This is because spectrum allocation is a binary optimization problem while power allocation is a continuous optimization problem.In step 2, FA starts with initial solution of PSO generated in Step 1. All fireflies will be initiated with solutions found in PSO particles at the end of PSO in Step 1. In step 3, after ranking fireflies according to their fitness, the best two fireflies are crossed over to generate four new offsprings. The four new offsprings are then ranked according to their fitness. The current best firefly will then be replaced by the best offspring if its fitness as measured by objective function value in equation 4.1 is higher (better) than that of the best offspring. Instead of firefly movement being that described by equation (3.3), firefly movement will involve local search towards local personal best and global search towards the global best according to equation (5.1). This is necessary so as to prevent PSO from getting trapped in local optimum. The proposed algorithm therefore makes use some PSO operators including P_{best}, g_{best}, c_1 and c_2.

$$x_i^{t+1} = x_i^t + c_1 e^{-\gamma r_{ij}^2}(p_i - x_i^t) + c_2 e^{-\gamma r_{ij}^2}(p_g - x_i^t) + \alpha_t \epsilon_t^i, \qquad (5.1)$$

Table 5.1

Algorithm 2: Joint Power and Spectrum Allocation Optimization Using Hybrid Firefly and Particle Swarm Optimization with Genetic Operators

Step 1:

- 1.1 Initialize number of particles, c_1, $c_{2,}$ ω, v_{min}, v_{max}
- 1.2 For each particle
  Initialize power vector with random power values that are within allowed range.
  Initialize channel allocation matrix, with one channel assigned to each SU.
  End
- 1.3
  Do
  1.3.1 For each particle
  Calculate fitness value
  If the fitness value is better than the best fitness value (p_i) in history
  set current value as the new p_i
  End
  1.3.2 Choose the particle with the best fitness value of all the particles as the p_{best}
  1.3.3 If current $\mathrm{p_{best}}$ and its associated x_{best} is better than g_{best} set current p_{best} as g_{best}
  1.3.4 For each particle
  - Calculate particle velocity according equation (3.4)
  - Update particle position for both the power vector and channel matrix according to equation (3.5)
  - Check power vector to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.
  - Randomly select a single channel for each SU, if there is assignment of more than one channel to a SU.
  End
  While maximum iterations has not been reached.
- 1.4 g_{best} set as the final solution of PSO.

Step 2

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

Step 3

- 3.1 Calculate the fitness value of each firefly using equation (4.1) and rank the fireflies according to their fitness values.
- 3.2 Find the current best solution.
- 3.3 Apply crossover mechanism separately for both the channel matrix and power vector on the top two best solutions.
- 3.4 Select the best offspring out of the four offsprings created through crossover and use it as the current best solution of FA if its fitness is better than that of the current best.

Step 4

- 4.1 For every firefly, move it to the better solution according to equation (4.1).
- 4.2 Check firefly x_i to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.

Step 5

- 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.

6. Performance Evaluation

Simulation was done using Matlab R2016a. Matlab is chosen because it is rich in in-built functions. Fig. 2 shows the network diagram generated in Matlab. 1000 SUs are distributed over an area of 1 km^2. Initially SUs are distributed randomly across 10 channels. Initial channel and power assignment is also done randomly. The free space path loss model was used to model path loss:

$$PL(d) = 20\log(d) + 20\log(f) - 147.55, \qquad (6.1)$$

where d is the distance in meters and f is the frequency of operation. The proposed resource allocation algorithm is then used to assign power and spectrum to SUs. Simulation parameters used are outlined in Table 6.1. Parameters used for FA are as follows: $\beta_o = 1, \alpha = 30, \gamma = 10$, number of fireflies $NP = 50$. Parameters used for PSO are as follows: number of particles = 50, inertia weights: $w_{max} = 4\ and\ w_{min} = 2$, social parameter $c_1 = 2$ and cognitive parameter $c_2 = 2$. Parameters used for GA are as follows: number of chromosomes=50, mutation rate = 0.8 and selection rate = 0.5. For FA, GA and PSO, the number of iterations used is 50. For FAGAPSO, the number of iterations for FA (half that used by pure FA) is set to 25 while that of PSO is set to 25 (half that used by pure PSO).

Table 6.1: Simulation Parameters

Parameter	Value	Description/Comment
B	6 MHz	Bandwidth of TV channel
f_a	650 MHz	Centre frequency of DTV signal
P_{DTV}	-70.6 dBm	Power of DTV signal at victim TV receiver
δ_n^2	-102 dBm	Noise power
ω_o	23 dB	TV receiver SINR threshold
ρ_o	7 dB	SU SINR threshold
P^{BS}	36 dBm (4W)	Transmit power of base station
p_{max}	30 dBm	Maximum SU transmit power
$\mu(x_i, a)$	0, -28 dB	Adjacent channel interference co-efficient
G_{SU}	10 dB	SU antenna gain
G_{PU}	10 dB	PU antenna gain
G_{BS}	10 dB	Access point antenna gain

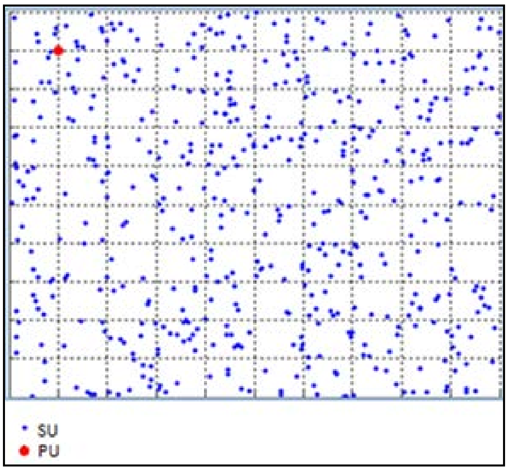

Figure 2: Network diagram

7. Simulation Results

In this section, simulation results for joint optimization of power and spectrum allocation using FAGAPSO are presented. FAPSOGA is compared with FA, PSO, GA, heuristic algorithm (HA) [17], spatial adaptive play (SAP) [18]. Simulation results are generated for 10 simulation runs and an average is done. The performance of the algorithm is compared using the following metrics: running time of algorithm, objective function value, sum throughput, PU SINR and SU SINR. Two P_{max} values are considered: 20dBm (for mobile WSDs) and 36dBm (for fixed devices).

7.1. Objective Function Value

Tables 7.1 and 7.2 show comparison of FAGAPSO with the rest of the algorithms in terms of achieved objective function value for N=1000 and N=500, respectively. The results show that the FAGAPSO achieves the best (highest) objective function value represented by equation (4.1) for both N=500 and N=1000 and for both cases of P_{max} values except for SAP.

Table 7.1: Comparison of Objective Function Values for N=1000

	$\mathrm{P_{max}}$ = 20dBm		$\mathrm{P_{min}}$ = 36dBm	
Algorithm	Objective Function Value	Percentage Improvement	Objective Function Value	Percentage Improvement
FAGAPSO	7.9517×10^9		2.0741×10^9	
FA	4.1682×10^9	91%	0.25438×10^9	715%
PSO	4.1682×10^9	91%	0.26538×10^9	682%
GA	4.1682×10^9	91%	0.25248×10^9	721%
HA	0.01×10^9	79417%	0.0677×10^9	2964%
SAP	13.3939×10^9	134%	9.38809×10^9	-78%

Table 7.2: Comparison of Objective Function Values for N=500

	P_{max} = 20dBm		P_{min} = 36dBm	
Algorithm	Objective Function Value	Percentage Improvement	Objective Function Value	Percentage Improvement
FAGAPSO	5.6434×10^9		1.07988×10^9	
FA	3.2313×10^9	75%	0.29342×10^9	268%
PSO	3.2313×10^9	75%	0.31063×10^9	247%
GA	3.2313×10^9	75%	0.28891×10^9	273%
HA	0.015×10^9	37523%	0.097×10^9	1013%
SAP	10.1199×10^9	-44%	6.12207×10^9	-82%

7.2. Sum Throughput

Tables 7.3 and 7.4 show comparison FAGAPSO with the rest of the algorithms in terms of sum throughput in the network for N=1000 and N=500, respectively.

The results show that the proposed algorithm achieves the highest sum throughput for both N=500 and N=1000 except for SAP.

This is because of the improved power and spectrum allocation that minimizes interference in the network. According to Shannon channel capacity theorem, reduction in interference improves throughput.

Table 7.3: Comparison of Sum Throughput for N=1000

	P_{max} = 20dBm		P_{min} = 36dBm	
Algorithm	Sum Throughput (Gb/s)	Percentage Improvement	Sum Throughput (Gb/s)	Percentage Improvement
FAGAPSO	16.1147		5.274	
FA	11.5609	39%	1.8067	192%
PSO	11.2829	43%	1.3463	292%
GA	11.305	43%	2.0025	163%
HA	0.227	6999%	1.165	353%
SAP	33.702	-50%	18.1058	-71%

Table 7.4: Comparison of Sum Throughput for N=500

	P_{max} = 20dBm		P_{min} = 36dBm	
Algorithm	Sum Throughput (Gb/s)	Percentage Improvement	Sum Throughput (Gb/s)	Percentage Improvement
FAGAPSO	10.1145		2.8583	
FA	7.3583	37%	1.5157	88%
PSO	7.2025	40%	1.344	112%
GA	7.1945	41%	1.6011	78%
HA	0.199	4983%	1.031	177%
SAP	20.0027	-49%	10.6692	-73%

7.3. Percentage of SUs less than SU SINR Threshold

Tables 7.5 and 7.6 show comparison of FAGAPSO with the rest of the algorithms in terms of percentage of SUs with SU SINR less than required threshold of 7dB in the network for N=1000 and N=500, respectively.

The results show that the FAGAPSO achieves the lowest percentage of SUs with SU SINR below threshold for N=500 and N=1000 except for SAP.

This is because of the improved power and spectrum allocation that minimizes interference in the network.

Table 7.5: Comparison of Percentage of SUs less than SU SINR Threshold for N =1000

	P_{max} = 20dBm		P_{min} = 36dBm	
Algorithm	% of SUs Less Than SU SINR Threshold	Percentage Improvement	% of SUs Less Than SU SINR Threshold	Percentage Improvement
FAGAPSO	8		43	
FA	28	20%	95	52%
PSO	29	21%	97	54%
GA	29	21%	95	52%
HA	29	21%	95	52%
SAP	2	-6%	11	-32%

Table 7.6: Comparison of Percentage of SUs less than SU SINR Threshold for N = 500

	P_{max}= 20dBm		P_{min} = 36dBm	
Algorithm	% of SUs Less Than SU SINR Threshold	Percentage Improvement	% of SUs Less Than SU SINR Threshold	Percentage Improvement
FAGAPSO	2		42	
FA	10	8%	90	48%
PSO	11	9%	93	51%
GA	12	10%	89	47%
HA	12	10%	89	47%
SAP	0	-2%	15	-27%

7.4. Average SU SINR

Tables 7.7 and 7.8 shows comparison of FAGAPSO with the rest of the algorithms in terms of average SU SINR in the network for N=1000 and N=500, respectively. The results show that the proposed algorithm achieves the highest SU SINR for both N=500 and N=1000 except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network.

Table 7.7: Comparison of Average SU SINR for N=1000

	P_{max} = 20dBm	P_{min} = 36dBm
Algorithm	Average SU SINR (dB)	Average SU SINR (dB)
FAGAPSO	15.6967	-0.02424
FA	10.86369	-6.43356
PSO	10.54429	-8.39994
GA	10.58621	-5.23181
HA	-16.7004	-7.1581
SAP	30.61641	17.92071

Table 7.8: Comparison of Average SU SINR for N=500

	P_{max} = 20dBm	P_{min}= 36dBm
Algorithm	Average SU SINR (dB)	Average SU SINR (dB)
FAGAPSO	20.11969	1.12824
FA	14.38521	-3.64051
PSO	14.04466	-3.6699
GA	14.01739	-1.93461
HA	-13.0819	-13.0819
SAP	40.97158	21.27982

7.5. PU SINR

Tables 7.9 and 7.10 show comparison of FAGAPSO with the rest of the algorithms in terms of PU SINR in the network for N=1000 and N=500, respectively. The results show that the FAGAPSO achieves the highest PU SINR for both N=500 and N=1000 except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network.

Table 7.9: Comparison of PU SINR for N=1000

	P_{max} = 20dBm	P_{min} = 36dBm
Algorithm	PU SINR (dB)	PU SINR (dB)
FAGAPSO	92.50881	74.25305
FA	83.64993	64.77535
PSO	81.96864	61.27855
GA	82.81724	66.69795
HA	51.0569	60.1476
SAP	120.36414	88.88775

Table 7.10: Comparison of PU SINR for N=500

Algorithm	P_{max} = 20dBm PU SINR (dB)	P_{min}= 36dBm PU SINR (dB)
FAGAPSO	92.72474	75.59842
FA	83.01269	63.65845
PSO	83.81617	67.03158
GA	83.07426	67.43987
HA	51.5723	51.5723
SAP	110.66509	90.7

7.6. Running time

Table 7.11 shows comparison running time FAGAPSO with other algorithms. The run time in the table is for 1000 SUs in a network. The results show that SAP has the highest running time and FA has the lowest running time. The running time for FAGAPSO is higher than that of FA, PSO and HA but lower than that of GA and SAP. It can also be seen that the running time of almost the same as that of PSO. This can be attributed to the number of iterations used for FAGAPSO being half that used by both FA and PSO as well as the additional features of PSO and GA that have been incorporated into pure FA.

Table 7.11: Comparison of Algorithm Running Time for N=1000

Algorithm	Running Time (Seconds)	Percentage Difference
FAGAPSO	274	
FA	185	+32%
PSO	270	-1%
GA	548	-100%
HA	236	+16%
SAP	1539	+460%

8. Conclusion

Results also show that FAGAPSO performs better in terms of SU SINR, PU SINR and throughput compared to the three other evolutionary algorithms (FA, PSO and GA). In terms of running time, the algorithm has almost the same running time as PSO but it is faster than GA and slightly slower than that of FA. The slight degradation of FA running time can be tolerated for improved resource allocation in a TVWS network. Although SAP has the best resource allocation as measured by SU SINR, PU SINR and throughput, it has the worst running time. Performance of the proposed algorithm shows that that the solution quality of FA can be improved by using the final solution of PSO as initial solution of FA as well as incorporating crossover feature of GA and PSO concepts of P_{best} and g_{best}. The results also show that both FA and PSO can be modified to solve a continuous-binary problem where there decision variables consist of both binary and continuous values.

9. Recommendations

The performance of FA can be improved through the use of initial solution from PSO as well as incorporating GA's feature of crossover and PSO's concepts of P_{best} and g_{best}. Since results have shown that FAGAPSO performs better than existing algorithms, FAGAPSO should be applied for resource allocation in a TVWS network.

10. Limitations and Future Work

In the study conducted, simulation was used. Simulation may not give a true reflection of a real world scenario. In future, we intend to test the algorithm in a real world TVWS network in order to validate its performance.

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