Downlink Resource Allocation in OFDMA using HPSOGA AND HGAPSO

[1]Sumathi K, [2]Abirami M

[1,2] Department of Electronics and Communication Engineering, Dr. Mahalingam College of Engineering and Technology, Pollachi-642003, Tamil Nadu, India.

[1]sumathimin@gmail.com, [2]abirami.m@drmcet.ac.in

Abstract: *Resource allocation is very essential at the base station (BS) to have a fair allocation of resources among the users. Orthogonal Frequency Division Multiple Access (OFDMA) allows many users to transmit simultaneously on different subchannels per Orthogonal Frequency Division Multiplexing (OFDM) symbol. The system capacity of downlink OFDMA system can be maximized by adaptively assigning subchannels to the user with the best possible gain using hybrid particle swarm optimization and genetic algorithm (HPSOGA). PSO and GA are combined in a sequential manner resulting in two different techniques namely HPSOGA and HGAPSO. The idea behind the hybrid algorithm is to use PSO to generate initial population of GA and vice-versa. Simulation results show that HPSOGA and HGAPSO provide capacity improvement over PSO. Among the two hybrid models, compared to the PSO method HGAPSO provides improvement in fairness with respect the users.*

Key Words: *Orthogonal frequency division multiple access, resource allocation, particle swarm optimization, genetic algorithm.*

I. INTRODUCTION

High data rate is essential for 4G and future wireless communication systems to satisfy the diversified demands of users. The limited resources namely frequency and power have to be effectively allocated to the users. Resource allocation plays an important role in wireless communication systems. Different algorithms have been proposed for allocating the resources in the downlink OFDMA system. Several optimization techniques are used for efficient resource allocation in wireless communication systems. Orthogonal Genetic Algorithm (OGA) is considered in [1] for adaptive resource allocation to maximize the minimum user capacity in multiple input multiple output - orthogonal frequency division multiplexing (MIMO-OFDM) system. The use of GA and PSO separately for dynamic subchannel and bit allocations to reduce the transmit power in multiuser OFDM system is proposed in [2]. GA is recommended in [3] to allocate resources adaptively in multiuser OFDM. The effective optimal power allocation algorithm is based on GA with proportional constraints to ensure that all the users are allocated with necessary data rate. To solve the subchannel allocation problem in wireless OFDMA, Ant Colony Algorithm (ACO) is suggested in [4] to achieve an optimal solution within short period of time to improve the system capacity. GA based cross layer resource allocation for the downlink OFDM system with heterogeneous traffic is discussed in [5] to maximize the weighted sum capacity. A novel GA for resource allocation in OFDMA with proportional rate constraint is proposed in [6]. The proposed algorithm combines the characteristic of both deterministic and GA to maximize the throughput and maintaining the proportionality among the users in OFDMA. Two suboptimal algorithms are proposed in [7] for OFDMA system with fixed or variable rate constraints. In [8] the author recommended the use of ACO for subchannel and bit allocation in single cell OFDMA system. The overall transmit power at the base station is minimized by the proposed algorithm. The proposed method is able to converge faster at the cost of memory.

Two optimization methods such as differential evolution (DE) and PSO for dynamic subchannel and bit allocation to minimize the transmit power in [9] for multiuser OFDM system. In [10], the combination of PSO and GA to improve the performance of multiuser OFDM system is proposed. It combines PSO and GA for the subchannel and power allocation for three different scenarios with different objectives. Two adaptive resource allocation schemes for OFDM using GA and fuzzy rule based system (FRBS) have been proposed in [11]. Customized particle swarm optimization technique in [12] for subchannel allocation in downlink OFDMA system was applied to OFDMA considering the proportional rate constraints among users. This paper mainly concentrates on subchannel allocation using the hybrid combination of PSO and GA. In [13] three different hybrid approaches based on PSO and GA for global maximization to overcome the premature convergence of the particles that are unable provide guaranteed solutions for an optimization problem is suggested. Type 3 (PSO-GA) is adopted in this work. The proposed methods able to achieve high convergence rate with conventional methods.

The paper is organized as follows: Section 2 introduces the downlink OFDMA system model. Need for hybrid optimization technique is described in Section 3 and the proposed HPSOGA and HGAPSO optimization techniques for resource allocation in downlink OFDMA systems are illustrated in Section 4. Simulation parameters, results and discussions are presented in Section 5. Conclusions are provided in Section 6.

II. DOWNLINK OFDMA SYSTEM MODEL

The system model of an OFDMA downlink system is shown in Figure 1. The system consists of ‘K’ users sharing ‘N’ subchannels with the total power constraint of $P_{tot.}$

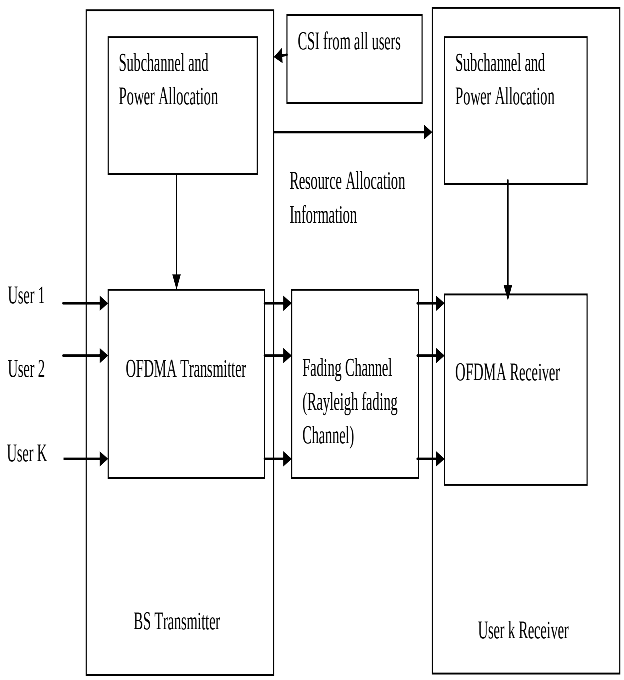

Figure 1. Orthogonal frequency division multiple access downlink system model

The following assumptions are made during the analysis:

1. It is assumed that perfect Channel State Information (CSI) is known at the Base Station.
2. Single cell having a centralized BS supporting multiple users are considered.
3. Channel conditions are estimated at the receiving end and the resulting Channel State Information (CSI) is fed back to BS.
4. Based on the CSI provided by the user, the number of subchannels and power required for the subchannels are computed by BS. It is conveyed to the receiver through a separate channel.
5. Prediction of the channel conditions is done by the users prior to the start of every OFDM symbol transmission.

Capacity of user 'k' is given by

$$R_k = \sum_{n=1}^{N} \frac{1}{N} c_{k,n} \log_2 \left(1+\gamma_{k,n}\right) \quad (1)$$

The Signal to Noise Ratio (SNR) of k[th] user, on n[th] subchannel $\gamma_{k,n}$ is given by,

$$\gamma_{k,n} = p_{k,n} H_{k,n} = \frac{p_{k,n} h_{k,n}^2}{N_o \frac{B}{N}} \quad (2)$$

where 'B' is the system bandwidth, 'N' is the number of subchannels, 'K' is the number of users in the system, $p_{k,n}$ is the power allocated to user 'k' in subchannel 'n'; $c_{k,n}$ is the subchannel allocation indicator; $H_{k,n}$ is the channel to noise ratio of user 'k' on subchannel 'n' and N_o is the one sided power spectral density of Additive White Gaussian Noise (AWGN).

The Equation (1) may be rewritten as,

$$R_k = \sum_{n=1}^{N} \frac{c_{k,n}}{N} \log_2 \left(1 + \frac{p_{k,n} h_{k,n}^2}{N_o \frac{B}{N}} \right) \quad (3)$$

The resource allocation problem considered for optimization is given by Equation (4) with constraints mentioned from Equation (5) - Equation (9).

As defined in [14], the optimization problem is defined as,

$$R_k = \max_{c_{k,n},\, p_{k,n}} \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{c_{k,n}}{N} \log_2\left(1 + \frac{p_{k,n} h_{k,n}^2}{N_o \frac{B}{N}}\right) \qquad (4)$$

Subject to the constraints,

$$\sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le P_{tot} \qquad (5)$$

$$p_{k,n} \ge 0 \quad \forall \quad k,n \qquad (6)$$

$$c_{k,n} = \{0,1\} \quad for\, all \;\; k,n \qquad (7)$$

$$\sum_{k=1}^{k} c_{k,n} = 1 \quad for\, all \;\; n \qquad (8)$$

$$R_1 : R_2 : \ldots\ldots : R_k = \alpha_1 : \alpha_2 : \ldots\ldots : \alpha_k \qquad (9)$$

where α_k , is the proportional rate constraint. The optimization problem stated in Equation (4) is a mixed binary integer problem since it involves both binary variable $c_{k,n}$ and continuous variable $p_{n,k}$. The following constraints are considered for the allocation of subchannels and power:

1. Subchannel allocation is based on the constraints mentioned in Equation (7) and Equation (8).
2. $c_{k,n}$ can take either the binary value '1' or '0' to indicate the allocation of subchannels to the users. If it is '1', the subchannel is assigned to the users and if the indicator is '0', subchannel is not allocated.
3. The subchannel is allocated to only one user and it cannot be shared by more than one user at a time is indicated in Equation (8).
4. The constraint for power allocation depends on Equation (5) and Equation (6).
5. The last constraint in Equation (9) deals with the proportionality among users. Proportionality constraints denoted by $[\alpha_1 : \alpha_2 : \ldots\ldots\ldots\ldots : \alpha_k]$ are used to ensure proportional rate fairness among users, when the users are not allocated with the minimum requirement. Proportional data rates can be varied to satisfy the demands of different users having different QoS requirements.

As considered in [7], Fairness Index is defined as,

$$FI = \frac{\left(\sum_{k=1}^{K} \frac{R_k}{C_k}\right)^2}{K\left(\sum_{k=1}^{K} \frac{R_k}{C_k}\right)^2} \qquad (10)$$

R_k is the achieved rate by the kth user and α_k is the proportional rate for the kth user. Fairness Index (*FI*) is used to evaluate the performance of optimization algorithms. Fairness Index can have values in the range from 0 to 1. The maximum value of fairness index is 1. If all the users are assigned with the equal resources, it is considered as the fairest case. Fairness may be realized in the form of same data rate or same power or equal number of subchannels to the users. As the number of users increases, it is difficult to maintain fair allocation among the users. A tradeoff has to be maintained between fairness and the throughput.

III. PSO AND NEED FOR HYBRID APPROACH

PSO operation depends on two specific values such as P_{best} and g_{best}, where P_{best} is the personal best position of a particle and g_{best} is the global best position among all the particles across iterations. If current fitness value is greater than P_{best}, update P_{best} value with the current position. If P_{best} is better than g_{best}, then update g_{best} as P_{best}. For each particle the velocity and position are updated. The steps are,

Initialize the population - locations and velocities

1. Evaluate the fitness of the individual particle (P_{best})
2. Keep track of the individual with the highest fitness (g_{best})
3. Modify velocity and position of the particles using Equation (11) and Equation (12).
4. Update the particles position with the obtained velocity
5. Terminate if the condition is met.
6. Else go to the second step

$$V_p^{k+1} = wV_p^k + C_1\, rand_1\,(P_{best} - C_p^k) + C_2\, rand_2\,(g_{best} - C_p^k) \tag{11}$$

$$C_p^{k+1} = C_p^k + V_p^{k+1} \tag{12}$$

where C_1 and C_2 are cognitive and social learning factors and w is the inertia weight, $rand_1$ and $rand_2$ are independent random numbers in the range 0 and 1. Current velocity and position are used to compute the particle's new velocity. V_p is the velocity of particle and C_p is the position of a particle. Position and velocity values are updated using Equation (11) and Equation (12) based on the values P_{best} and g_{best}. Premature convergence problem is addressed by combining the best features of PSO with GA. The downlink resource allocation problem in multiuser OFDM is handled by the hybrid combination of PSO and GA. The hybrid mechanism of PSO and GA improves the searching ability by improving the diversity. As suggested in [13], the initial population of GA is obtained using PSO. The best particles obtained from PSO are taken as input to GA algorithm and vice versa. The total iterations are equally shared by PSO and GA. The hybrid approach provides a better solution and looks for global optimal point instead of local optimum point. The algorithm steps of HPSOGA are given below.

1. Get the total number of iterations.
2. Divide the iterations equally among PSO and GA.
3. Run first half of the iterations by PSO.
4. Assign the particles position from PSO as the input to GA as initial population.

The above four steps are with respect to HPSOGA. HGAPSO differs in third and fourth step.

IV. PROPOSED HPSOGA AND HGAPSO OPTIMIZATION ALGORITHMS

Figure 2 and Figure 3 shows the flowchart with the sequence of operations in HPSOGA and HGAPSO.

HPSOGA Scheme

1. Initialize the algorithm with number of generations (N_{gen}), populations (N_{pop}), channel state matrix (H), bandwidth (B), number of channels (N), number of users (K), total available power p_{tot} and PSO parameters $C_1 = C_2 = 2$ and $\omega = 0.2$.
2. Evaluate fitness for all the particles using Equation (4) and Compare P_{best} with g_{best} values. If $P_{best} > g_{best}$, then set $P_{best} = g_{best}$.
3. Update the particles velocity and position based on Equation (11) and Equation (12) and repeat the above steps for the specified iterations till it becomes zero and select the best particles, otherwise go to Step 2.
4. Feed the best particles obtained from PSO as the input to GA.
5. Calculate fitness for each chromosome in the population based on the Equation (4).
6. Choose N_{elite} chromosomes from the entire population based on their fitness values.
7. Choose N_{cross} chromosomes and perform single point crossover.
8. Perform mutation over the new generation with mutation probability of 0.01.
9. Convince all the users by allocating at least one channel based on the steps given below.

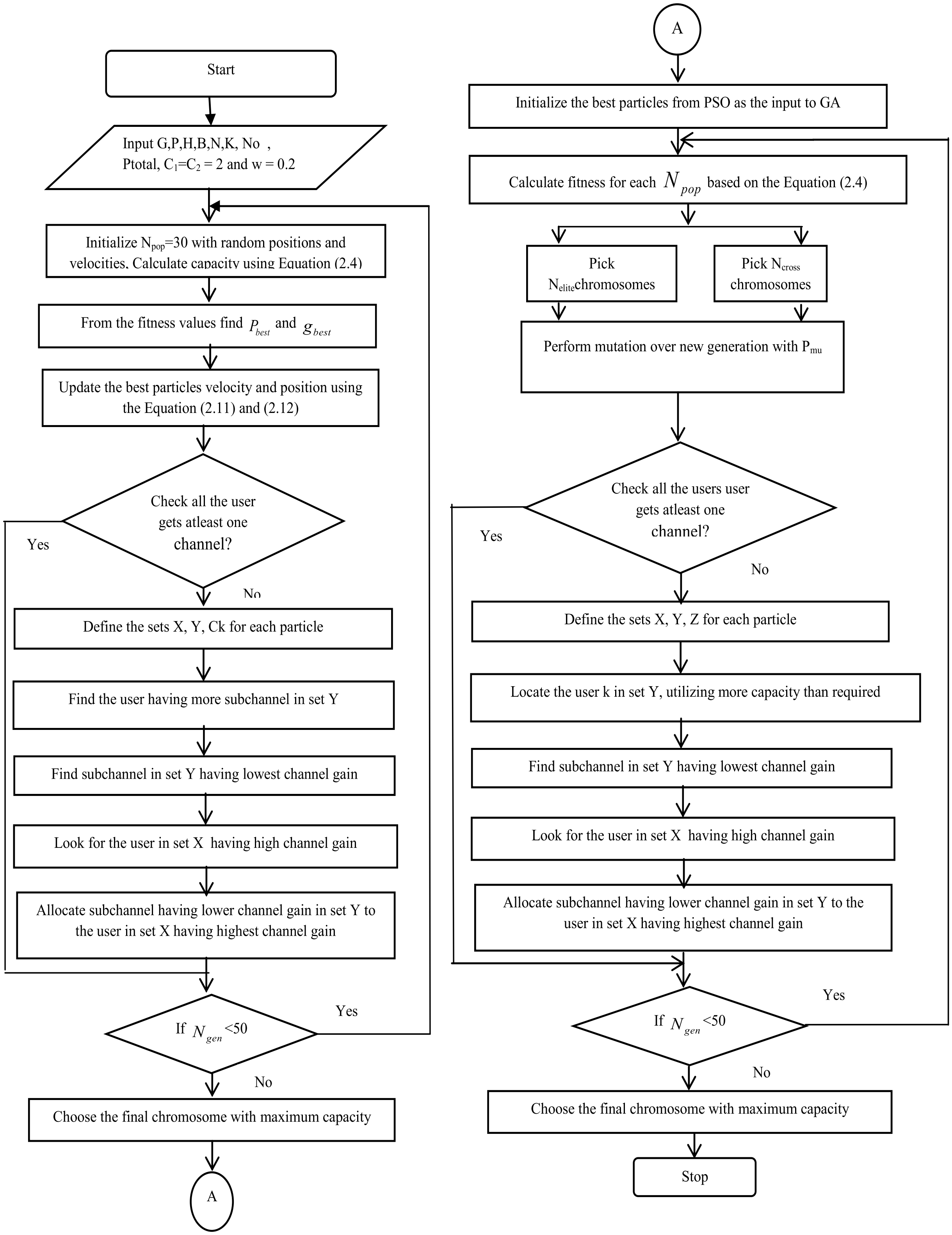

Figure 2. Flow chart of the HPSOGA algorithm

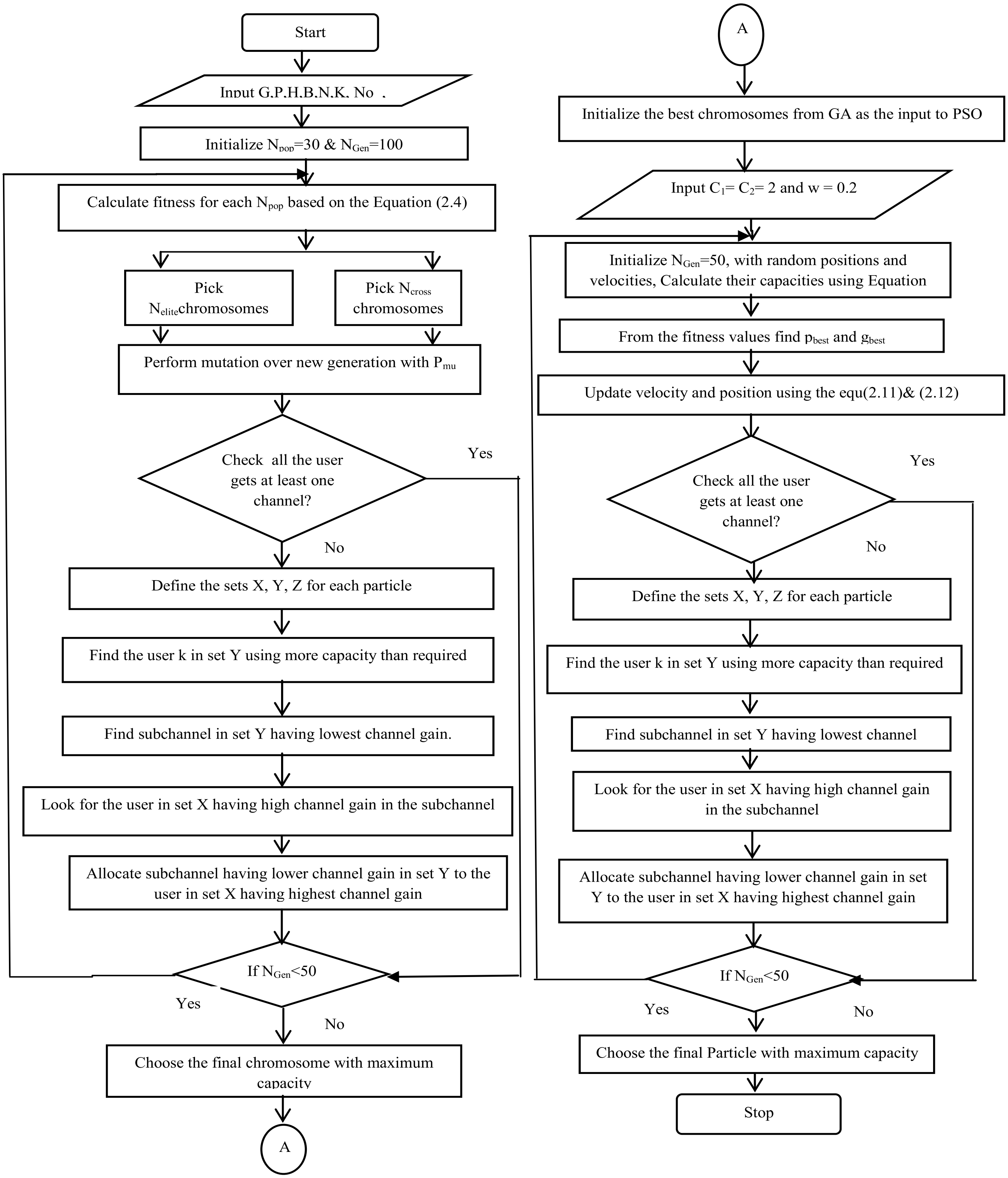

Figure 3 Flow chart of the HGAPSO algorithm

- For each particle X, Y, Z sets are defined, where $X = [X_1, X_2 ...... X_i]$, denotes list of users who are not allocated with at least single subchannel, $Y = [Y_1, Y_2 ...... Y_j]$ denotes list of users who are allocated with subchannels more than one; Z_k is the subchannel allocation detail of user k.
- While $X \neq \Phi$, locate the user k in set Y, having maximum capacity, i.e., find k satisfying $\frac{R_k}{\alpha_k} \geq \frac{R_b}{\alpha_b}$ for all $b \in Y$.
- Find the sub channel in set Y, having the lowest channel gain, and name the subchannel as q that is, $|h_{k,q}| \leq |h_{k,c}| \; for\, all \;\; c \in Z_k$
  - Look for the user in set X, having high channel gain, find for p satisfying $|h_{p,q}| \geq |h_{a,q}| \; for\, all \;\; a \in X$
  - For the found k, p and q, for $Z_k = Z_k - \{q\};\; Z_p = Z_p + \{q\};\; X = X - \{p\};$ Update set Y.

10. After reaching the maximum number of iterations, stop the process, otherwise go to step 5.

V. RESULTS AND DISCUSSION

The proposed HPSOGA and HGAPSO algorithms for capacity improvement in OFDMA system are designed using MATLAB 7.1 on a PC with Core 2 Duo processor operating with a clock 2.53 GHz. Simulations are carried out using the parameters specified in Table 1. The performance of HPSOGA and HGAPSO techniques are compared with PSO method in terms of sum capacity, convergence and fairness. The algorithm used for comparison (PSO) is also designed using MATLAB 7.1 on a PC with Core 2 Duo CPU operating at 2.53 GHz.

Figure 4 shows the comparison of sum capacity using PSO, HGAPSO and HPSOGA optimization methods for K= 16 and N = 64. The capacity increases with respect to the number of users due to multiuser diversity. Experimental evaluation shows that there is significant capacity improvement with the proposed HPSOGA method compared with PSO. The performance comparison of convergence of PSO, HPSOGA and HGAPSO to the number of iterations are graphically shown in Figure 5.

TABLE I SIMULATION PARAMETERS

Parameters	Values
N	64
K	16
N_o	1.1565 x 10^{-8} W / Hz
B	1 MHz
p_{tot}	1 Watt
α_k	1 : 2 : 4
N_{gen}	100
N_{pop}	30
N_{par}	30
P_{mu}	0.01
$C_1 = C_2$	2
ω	0.2

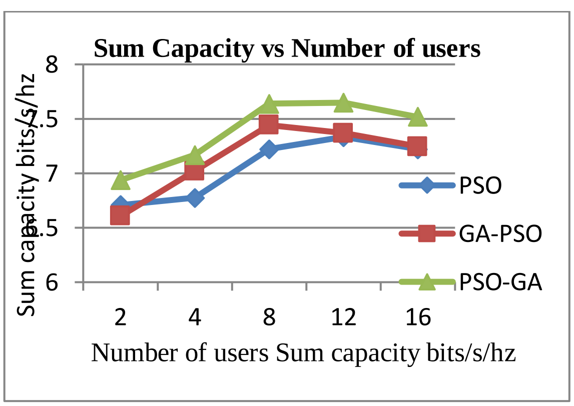

Figure 4. Sum capacity Vs number of users

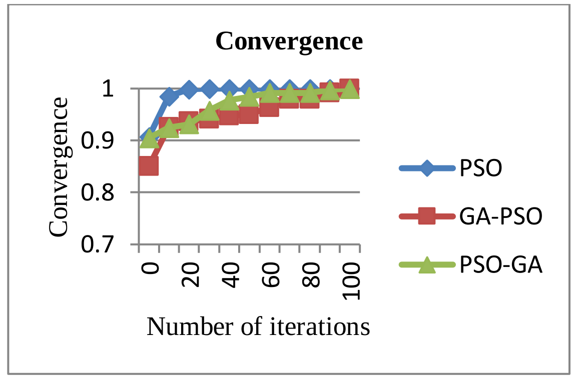

Figure 5. Convergence vs number of iterations

Convergence rate of PSO is faster than PSO-GA. PSO is converged to the maximum point i.e. 1 within 30 iterations. HGAPSO and HPSOGA converged to maximum value only at the end of iterations. However, the faster convergence of PSO is due to stagnation of particles. It leads the particles to converge to local minima and hence unable to achieve better capacity than hybrid schemes. The comparison of sum capacity to the number of particles is graphically represented in Figure 6.

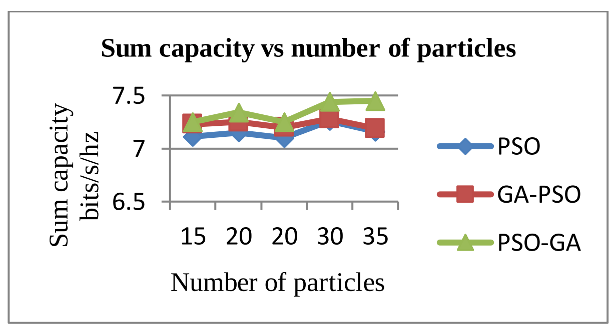

Figure 6. Sum Capacity Vs number of particles

Sum capacity increases with the number of particles. If the number of particles is increased above 30, there is no significant improvement in terms of sum capacity. It increases the computational time. HPSOGA provides better performance in terms of capacity than the other methods. The performance of fairness to the number of users is tabulated in Table 2. HPSOGA and HGAPSO provide better fairness than PSO as the number of users is increased. The required user proportions are fairly allocated by HGAPSO by 15 % compared with PSO and 21 % with PSO-GA. The performance of minimum user capacity and average user capacity are graphically represented in Figure 8 and 9 respectively.

TABLE II FAIRNESS VS NUMBER OF USERS

K	Fairness		
	PSO	HGAPSO	PSO-GA
2	0.99852	0.75976	0.79081
4	0.65478	0.75181	0.75767
8	0.61969	0.82086	0.69483
12	0.55846	0.79482	0.71771
16	0.34667	0.75764	0.70917

Figure 7 shows the comparison of the minimum user capacity for the users varied from 2-16. The minimum user capacities obtained by hybrid schemes are less than PSO. Average user capacity for the users varied from 2-16 is shown in Figure 8. Average user capacity of the proposed algorithms is comparatively good with PSO. There is a reduction in the average user capacity when the number users are increased. Figure 9 shows the normalized proportions for the four users under the proportionality constraints. The normalized proportions for four users are taken. Different algorithms provide different normalized values to the users are indicated by bars. For the proportions 1: 2: 4, Hybrid schemes provides the necessary ratio compared to PSO.

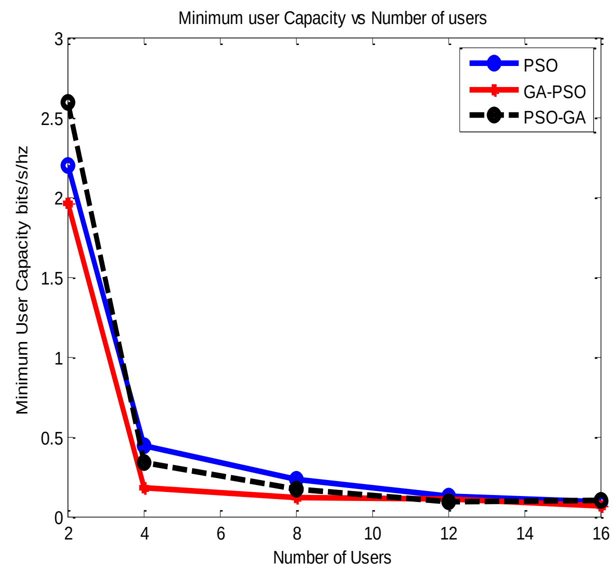

Figure 7. Minimum user capacity vs number of users

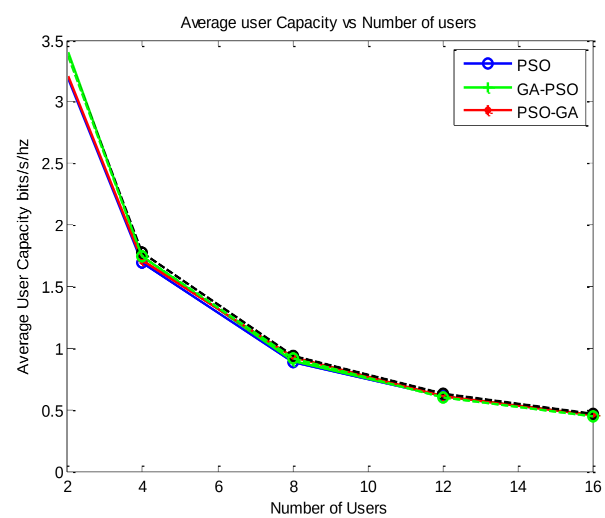

Figure 8. Average user capacity vs number of users

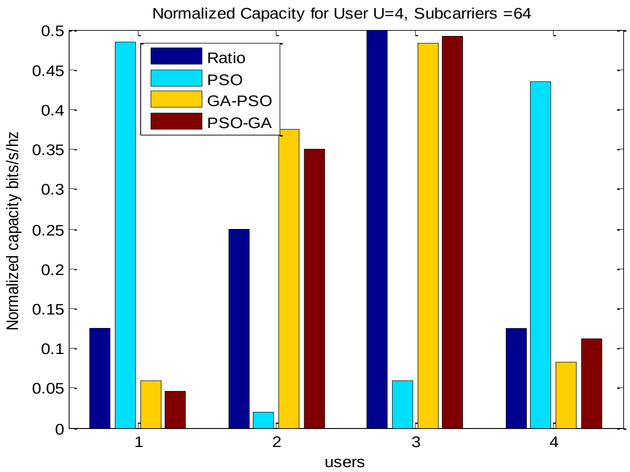

Figure 9. Normalized capacity vs number of users

VI. CONCLUSIONS

Resource allocation plays a significant role in wireless communication systems. To support more number of users, it is necessary to allocate the limited resources efficiently. For downlink scenario, the BS has to perform the effective resource allocation with limited bandwidth to improve the system performance to accommodate more number of users. Resource allocation in downlink OFDMA system based on HPSOGA and HGAPSO is proposed to improve the system capacity and fairness. HPSOGA achieved better capacity improvement over PSO. Compared to the PSO method HGAPSO provides improvement in fairness among the users. Multi objective optimization techniques can be applied with multiple objectives to improve capacity and fairness in wireless communication systems.

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