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Joint Physical – MAC Layer Resource Allocation Approach for Heterogeneous Traffics in OFDM

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ABSTRACT

In this paper a novel cross layer resource allocation for downlink transmission with heterogeneous traffic in wireless networks is developed. The problem of efficient resource allocation for multiuser orthogonal frequency division multiplexing over Rayleigh fading channels is addressed. Subcarrier and power allocation are carried out sequentially to reduce the complexity. Assuming that the base station has all the channel information, an optimization problem for an adaptive sub-channel and power allocation scheme that maximizes weighted sum capacities of many traffic queues at the physical (PHY) layer while satisfying the required data rate of each user and the power constraint on each link is considered. The weights are determined using information from the medium access control (MAC) layer. Genetic algorithm, Particle Swarm Optimization and Ant Colony Optimization techniques are used to do subcarrier allocation. Simulation results show that the Hybrid PSO and ACO performance is better than GA in terms of system capacity, throughput and convergence.

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INTRODUCTION

In recent years, data and multimedia services become important in wireless communications. As a result, bandwidth requirement and increasing users become delicate problems. Therefore, it is necessary to improve capacity and spectral efficiency. This is achieved by combining the properties of physical and MAC layer. In communication system, OFDM proves to be a robust technique to mitigate the ISI experienced on frequency selective wideband wireless channels. OFDM divides a broadband channel into N narrow subcarriers of equal width such that the channel frequency response on a particular subcarrier is approximately flat. Appending a guard band or cyclic prefix (CP) to the transmitted symbols converts the linear convolution of the symbols with the channel into a circular one, provided the length of the CP is greater than or equal to the channel length (delay spread). Thus, each subcarrier can be modeled as a gain (time invariant or variant) with additive white Gaussian noise (AWGN).

OFDM is suggested as an approach to be used in multiuser systems, particularly the downlink section of a cellular system. The users of such a system must share resources such as transmit power and subcarriers. In order to increase system performance, it is shown that these resources should be allocated adaptively to users based on their channel information.

One of the major tasks for such a system would be to allocate sub-carriers and transmission power to the different users. There are two approaches to allocate these resources: fixed and adaptive. Fixed allocation approach uses time division multiple access (TDMA) or frequency division multiple access (FDMA) to allocate predetermined time slots or subcarriers to users. Fixed allocation approach is not an optimal approach to share the resources since it does not account for the current wireless channel state between the transmitter and user.

The adaptive resource allocation approach can be formulated in two different optimization techniques. The first one is known as margin adaptive (Cheong Yui Wong *et al*., 1999) minimizes the total transmit power while maintaining a fixed bit rate for each user. The second is called as rate adaptive (Jiho Jang, Kwang Bok Lee, 2003; Wonjong Rhee, John M. Cioffi, 2000) maximizes the summed bit rate for all users (also known as system capacity) while keeping the transmission power constant. Rate adaptive approach is used, since power is restricted and limited quantity in actual systems. In (Zukang Shen *et al*., 2005) maximizes the system rate while maintaining the same data rate for all users all the time. Such a technique may not be helpful for a system which requires different data rates for users depending on their service level agreement (SLA) with their system.

In (Qingwen Liu *et al*., 2006) a cross-layer scheduling scheme for the medium access control (MAC) layer was proposed, which assigns priorities of connections according to the channel quality, QoS satisfaction and service priority across layers. The users are assigned with weight according to their QOS requirement. According to the weight, the users are provided with good number of sub-channels. Optimization is used to achieve the maximum sum capacity. Sequential linear approximation algorithm (SLAA) is used by (Guocong Song, 2005) to do the subcarrier allocation. It considers local optima rather than global optima. For multiuser OFDM system (Yongxue Wang, Fangjiong Chen, Gang Wei, 2005) the subcarrier

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and bit allocation are carried out by employing genetic algorithm. An adaptive resource allocation based on GA is proposed in (Liu Xinping, Liu Ying , 2009) where mutation and crossover adaptively changed on the population diversity instead of using fixed values.

In (Kalpana Goyal *et al*., 2012) a fair resource allocation for cross layer OFDM system was proposed. The method maximizes the weighted sum capacity and also considers the fairness among users. Due to this addition of fairness, it leads to global complexity when compared with (Nan Zhou, Xu Zhu, Yi Huang, Hai Lin, 2010). If physical layer and MAC layerare optimized together it is possible to achieve worthy QOS for the system. In (Zhihua Tang *et al*., 2007) (ESGA) elitist selections genetic algorithm is suggested instead of genetic algorithm. Using ESGA the cross over and mutation probabilities are varied based on population and maximizes the average throughput. Integration of 3 layers namely PHY, MAC and application layers are involved in (Zhihua Tang., 2008).A considerable modification from (Zhihua Tang *et al*., 2007) is proposed here. Instead of ESGA, a low complexity (ESAGA) elitist selection adaptive genetic algorithm is proposed based on varying the probabilities of mutation and cross over based on population diversity. In (Jia Tang, Xi Zhang, 2008) cross layer model based dynamic resource allocation for downlink mobile wireless networks to satisfy QoS requirement of users. The heterogeneous traffic users are dynamically assigned with time slots and power levels. In (Nan Zhou *et al*., 2009), cross layer resource allocation is only with respect to SLAA and Genetic algorithm. We propose the usage of optimization algorithms such as PSO, hybrid PSO and Hybrid PSO/ACO in the cross layer resource allocation. By using the algorithms the overall system capacity gets increased.

Problem Formulation:

In the base station, all channel information is sent to the subcarrier and power allocation algorithm through feedback channels from all mobile users. The resource allocation scheme is forwarded to the OFDM transmitter. The transmitter then selects different numbers of bits from different users to form an OFDM symbol. A multiuser OFDM system for the downlink transmission is considered. The resource allocation scheme is updated as fast as the channel information is collected. Perfect instantaneous channel state information (CSI) is assumed to be available at the base station. It is also assumed that the sub-channel and bit allocation information are sent to each user by a separate channel. The subcarrier and power allocation is handled by (PHY) physical layer and scheduling by MAC layer.

Focus is given to resource allocation in wireless OFDM networks based on joint physical and medium access control layer optimization. A total of K users in the system sharing N sub-channel with total transmit power constraint P_{total}. The objective is to optimize the sub-channel and power allocation in order to achieve the maximum weighted capacity under the total power constraint. In the downlink OFDM system for K users with heterogeneous traffic three cases were considered. They are voice over IP traffic queue (VOIP), variable bit rate traffic queue (VBR) and best effort (BE) traffic queue. The corresponding weight calculation is given by the equation (6-8)

The impulse response of the channel is represented by $H_{channel}$. The H channel gain value is randomly chosen for each user to particular sub-channel. Here the QoS information obtained from the MAC layer is given to the physical layer. The optimization is done in the physical layer. The channel to noise ratio is calculated by using,

$$\gamma_{i,n} = \frac{|h_{i,n}|^2 N}{N_0 B} \tag{1}$$

Let B is the bandwidth, $P_{i,n}$ represents the power allocated to user k on subcarrier i, $h_{i,n}$ is the corresponding channel gain and *No* is the power spectral density of additive white Gaussian noise (AWGN). Assuming perfect channel estimation, the instantaneous data rate of queue i on subcarrier is expressed as

$$R_{i,n} = \frac{B}{N} \log_2(1 + p_{i,n}\gamma_{i,n}) \tag{2}$$

For each user, the total instantaneous data rate to queue i is given by,

$$R_i = \sum_{n \in \Omega i} R_{i,n} \tag{3}$$

Maximum weighted capacity can be calculated using,

$$J = \sum_{i=1}^{3k} W_i R_i \tag{4}$$

J represents the weighted sum capacity and the weight for queue i contain QoS information is determined by scheduling algorithm at MAC layer.

The power allocated to each user for a particular sub-channel is given by,

$$P_{i,n} = \left[\frac{W_i}{\sum_{m=1}^{K} \left(W_m |\Omega_m| \right)} \left(P_T + \sum_{m=1}^{K} \sum_{q \in \Omega_m} \frac{1}{\gamma_{m,q}} \right) - \frac{1}{\gamma_{i,n}} \right] \quad (5)$$

The weights for the maximum weighted capacity for the cross layer allocation are obtained from scheduling operation at MAC layer. Let S_i as the average waiting time and λ_i as the average data arrival rate for user i, respectively. The weights based on the corresponding required QoS for VoIP, Variable bit rate (VBR), and Best effort (BE) traffics are calculated. For voice over IP (VoIP), end-to-end delay is usually required less than 100 ms.
The weight W_i can be calculated using,

$$W_i^{VoIP} = \begin{cases} \dfrac{S_i}{\lambda_i} & S_i \le 25ms \\ \dfrac{S_i^{1.5} - 25^{1.5} + 25}{\lambda_i} & S_i > 25ms \end{cases} \quad (6)$$

Choose delay time as 25ms, comes from one-fourth of 100ms. Good quality transmission of VBR traffic needs end-to-end delay between 150-400ms. The weight for VBR video traffic is expressed as

$$W_i^{VBR} = \begin{cases} \dfrac{S_i^{0.6}}{\lambda_i} & S_i \le 100ms \\ \dfrac{S_i - 100 + 100^{0.6}}{\lambda_i} & S_i > 100ms \end{cases} \quad (7)$$

The waiting time is 100ms, one-fourth of 400ms.
The weight W_i for BE traffic is given by,

$$W_i^{BE} = \begin{cases} \dfrac{S_i^{0.5}}{\lambda_i} & S_i \le 100ms \\ \dfrac{100^{0.5}}{\lambda_i} & S_i > 100ms \end{cases} \quad (8)$$

MATERIALS AND METHODS

Optimization based on SLAA:

In this paper, SLAA (Sequential Linear Approximation Algorithm) is used to achieve local optimization. The other name for SLAA is called Frank-Wolfe method. The non-linear optimization problem can be approached by a series of linear optimization problems by means of the sequential–linear–approximation algorithm.

1. Initially, power to the user for a particular subcarrier is equally divided by using the formulae,

$$P_{i,n}^{0} = P_T \,/\, N \quad (9)$$

Power given to queue i on subcarrier n is equal to total power divided by number of subcarriers. For the subcarrier allocation, the channel to noise ratio (CNR) is calculated by equation 1. After calculating CNR, the channel that has maximum CNR is allocated to the first user. Then the second maximum value is allocated to second user. Likewise third, fourth value and so on is allocated to the next users. Each user is assigned with a subcarrier which has maximum channel to noise power ratio.

2. According to equation 2, data rate is calculated and given to each channel. Data rate for each user is calculated by the sum of the channel to user and data rate for channel given by equation 3. Remaining subcarriers are iteratively assigned to each user according to its J value.

3. Power allocated to each user for a particular sub channel $P_{i,n}$ is calculated using 5. Power is calculated for each channel.

4. The data rate for the user at the particular subcarrier and the total data rate for the user is updated using equation 2 and 3.

5. Repeat steps 2, 3, and 4 until $\sum_{i=1}^{k} W_i(R_{i+1} - R_i) < \varepsilon$ condition is satisfied. The satisfying condition is

$$\varepsilon = 0.01 \sum_{i=1}^{k} W_i R_i^{\,i}$$

Power is allocated according to the subcarrier allocation. The power to the user is proportional to the weight of the corresponding user. Using SLAA algorithm, number of carriers allocated will be equal.

Optimization based on GA:

GA is inspired by the mechanism of natural selection, a biological process in which stronger individuals are likely be the winners in a competing environment. GA prevents local optimization in the search space. It can jump to various locations on the search space. Genetic algorithms are acknowledged as good solvers for tough problems. Let an OFDM system have K (k = 1, 2…K) users and N (n = 1, 2 . ., N) subcarriers. The system assigns a subset of N subcarriers to a user and determines the number of bits/symbol per each assigned subcarrier on downlink transmission.

In GA based cross layer resource allocation the population size is N_{pop}= 30, consisting of N_{elite} = 10 ,N_{cross} = 14 cross over children and N_{mu} = 6 mutation children, the mutation probability is P_{mu} = 0.01 and the maximum generation is N_{gen}= 100 is taken for simulation.
The steps involved in the operation of GA are given below.

1. **Initialization**: Initial population is created from a random selection of solutions which are analogous to chromosomes. Chromosomes are a string of N element where each element represents user index to which the corresponding subcarrier is allocated. Generate a population N_{pop} of chromosomes, where each bit of all the chromosomes is randomly picked from 1, 2, K (number of users).
2. **Fitness evaluation:** Update power allocation for each chromosome by using the subcarrier allocation presented by the chromosome and utilizing the corresponding power and subcarrier allocation of each chromosome, obtain the fitness value of each chromosome, which is the value of $J = \sum_{i=1}^{3k} W_i R_i$.
3. **Elitism:** The suitable members of each generation are guaranteed to be selected. Find N_{elite} chromosomes with the highest fitness values. Copy them into the next generation directly.
4. **Crossover:** Pick two chromosome parents from the current generation to create chromosome children for the next generation. Randomly obtain a crossover point for the parents. Using those parents, single point crossover is done. Similarly, generate N_{cross} crossover children chromosomes for the next generation.
5. **Mutation:** This operator forms a new chromosome by making alterations to the value of genes in a copy of a single parent chromosome. Randomly pick a chromosome from the current generation; each bit of it can be changed with a chance of P_{mu} Generate $N_{mu\ mutation}$ children chromosomes for the next generation.
6. Repeat Steps 2, 3, 4 and 5 until reaching the maximum generation limit N_{gen}.
7. Unlike SLAA, the number of subcarriers to the users varies according to the weight of the user.

Optimization based on PSO:

An alternative solution to the complex non-linear optimization problem by emulating the collective behavior of bird flocks, particles, the bird's method of Craig Reynolds and socio-cognition and called their brainchild the particle swarm optimization (PSO). It is one of the population based search technique. PSO has good convergence rate when compared to other algorithms.

Population contains particles. They are initialized randomly in the search space. Each particles update velocity and position based on its own finest occurrence and the whole population.
The general procedures involved in PSO are as follows.
1. Initialize the population - locations and velocities
2. Evaluate the fitness of the individual particle (pBest)
3. Keep track of the individual's highest fitness (gBest)
4. Modify velocities based on pBest and gBest position
5. Update the particles position
6. Terminate if the condition is met else
7. Go to the second step

Initialize
a. Set constants K_{max}, c_1, c_2.
b. Randomly initialize particle position.
c. Randomly initialize particle velocities.
d. Set K=1

Optimize
a. Evaluate function value current swarm.
b. If current swarm <pbest then pbest = current swarm.
c. If gbest<pbest then gbest = pbest.
d. Update all particle velocities using (11).
e. Update all particle positions using (12).
f. Increment K

Stop.

$$V_i^{k+1} = WV_i^k + C_1 rand_1 (Pbest_i - S_i^k) + C_2 rand_2 (Gbest - S_i^k) \tag{10}$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{11}$$

Steps:

1. Initialization: Generate a population N_{swarm} of swarms, where each particle of all the swarm is randomly picked from 1, 2…K. Randomly generates velocities for each particle of the swarm.

2. Fitness Evaluation: From the subcarrier allocation, data rate and power is calculated using equations 2, 3 & 5. The equation 4 forms the fitness function. For each swarm Pbest is updated with the best of the current iteration swarms.
3. Gbest (global best) is updated with the best of Pbest.
4. Swarm Updating: Each particle's velocity is updated using equation 10.
5. Particle updating: Each particle in the swarm is updated using equation 11.
6. Repeat until number of iterations reached.

Choose the best swarm from the Gbest. From the subcarrier allocation, data rate and power is calculated.

The advantage of PSO is faster convergence and requires very few parameters to be adjusted and the disadvantage is the dependence of velocity values. In PSO, all the particles converging quickly towards best solution. This property is reflected in the simulation output. It is observed that the convergence rate of PSO is faster when compared with GA from figure 2.

Optimization based on Hybrid PSO:

PSO and GA are population based heuristic search technique which can be used to solve the optimization problems modeled on the concept of Evolutionary Approach. In standard PSO, the non-oscillatory route can quickly cause a particle to stagnate and also it may prematurely converge on suboptimal solutions that are not even guaranteed to be local optimum. Here the modification strategies are proposed in PSO using GA.

The GA-PSO and PSO-GA hybrids offer a combination of the two algorithms with the hope of utilizing the qualities and uniqueness of the two algorithms. This is done by taking the population of one of the algorithms, when the improvement began to level off, and using it as the starting population of the other algorithm. For GA-PSO hybrid, the GA population was used to start the PSO after some fitness evaluations. For the PSO-GA hybrid the population from the PSO was used to start the GA after some fitness evaluations.

Hybrid PSO type I (GA-PSO):

Need for Hybrid PSO:

In standard PSO, the non-oscillatory route can quickly cause a particle to stagnate and also it may prematurely converge on suboptimal solutions that are not even guaranteed to be local optimum. Stochastic approaches have problem dependent performance. This dependency usually results from the parameter settings in each algorithm. The different parameter settings for a stochastic search algorithm result in high performance variances.

In this model the initial population of PSO is assigned by solution of GA. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by GA and the solutions are given as initial population of PSO. Remaining iterations are run by PSO. In this GA operation is performed for 50 iterations and then PSO iteration is done for 50 times. Here C1=2, C2=2, N_{par}=30 and N_{pop}=30 and N_{gen} =100. The use of hybrid increased the final fitness value for PSO and GA respectively. This asserts the value of hybrid PSO as an effective way to optimize difficult engineering problems.

Hybrid PSO type II (PSO-GA):

In this model the initial population of GA is assigned by solution of PSO. The total numbers of iterations are equally shared by GA and PSO. First half of the iterations are run by PSO and the solutions are given as initial population of GA. Remaining iterations are run by GA. In this PSO operation is performed for 50 iterations and then GA iteration is done for 50 times. Here N_{par}=30, N_{pop}=30 and N_{gen}= 100.

Optimization Based on Hybrid PSO/ACO (HACO):

Ant colony optimization (ACO) is a class of optimization algorithms modeled on the actions of an ant colony. ACO methods are useful in problems that need to find paths to goals. Ants find the way from nest to food source. Shortest path is revealed via pheromone trails. Each ant moves at random and pheromone is deposited on path. Ants detect lead ant's path, inclined to follow. More pheromone on path increases probability of path being followed. Real ants lay down pheromones directing each other to resources while exploring their environment. Ant Colony Optimization provides a combinatorial optimized solution.

In this model, the ant's pheromones are tracked using PSO equation. The N_{ant} number of ants is followed by the other ants depending on the pheromone intensity. Here N_{ant} represents different subcarrier allocation. The pheromone intensity represents the weighted capacity of the corresponding subcarrier and power allocation. The optimized value is the ant arrived with best weighted capacity after N_{it} iterations.

RESULTS AND DISCUSSION

Simulation parameters considered for the cross layer design is shown in Table.1. The channel has six independent Rayleigh fading paths with an exponential delay profile and a root-mean square (RMS) delay spread of 0.5 ms and the total transmit power is 1W. The maximum delay tolerances for VoIP, VBR video and BE traffic are 100 ms, 400 ms and 1000 ms, respectively. The VoIP traffic queue and BE traffic queue have a constant data rate of 64 Kbps and 500 Kbps, respectively. The data rate of the VBR video traffic follows a truncated exponential distribution with a minimum of 120 Kbps, a maximum of 420 Kbps, and a mean of 239 Kbps. The duration for each data rate of the VBR video traffic follows an exponential distribution with a mean of 160 ms. Table 2 shows the parameters considered for GA and Table 3 shows simulation parameters for PSO. Table 4 shows the simulation parameters for Hybrid PSO Parameters and Table 5 shows parameters for Hybrid ACO Parameters. From figure 2, it is implicit that the convergence rate of PSO is faster than GA and the performance of ACO comes in between GA and PSO.

Table 1: General Simulation Parameters.

Parameters	Values
Number of subcarriers	512
Number of users	4-64
T_{slot}	4 ms
N	512
BER	1e-3
Total power	1 W
Bandwidth	5MHz
Noise density	1e-8

Table 2: GA Parameters.

Parameters	Values
N_{pop}	30
N_{elite}	10
N_{cross}	14
N_{mu}	6
P_{mu}	0.01
N_{gen}	100

Table 3: PSO Parameters.

Parameters	Values
N_{par}	30
C_1	2
C_2	2
N_{gen}	100

Table 4: Hybrid PSO Parameters.

Parameters	Values
N_{par}	30
N_{pop}	30
N_{gen}	100

Table 5: Hybrid ACO Parameters.

Parameters	Values
N_{pop}	30
N_{ant}	5
N_{gen}	100

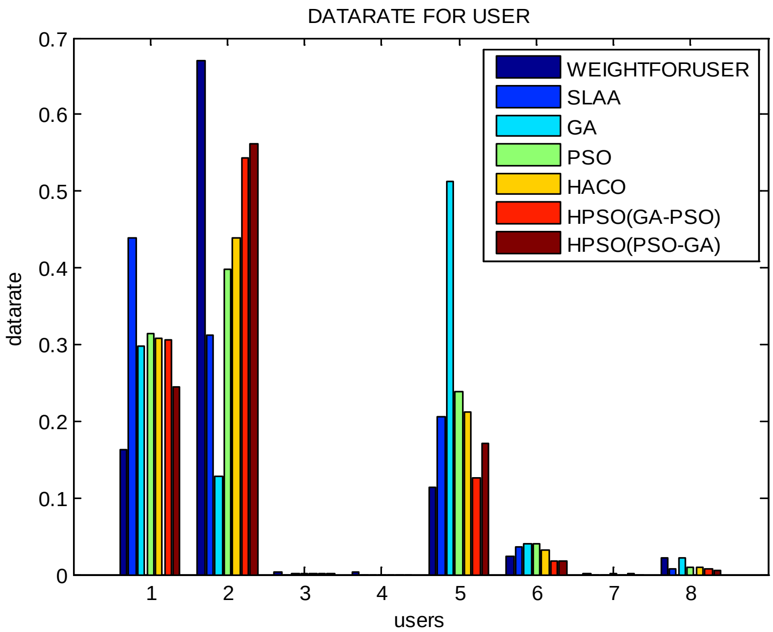

Fig. 1: Data rate vs. user index.

Figure 1 shows the comparison of SLAA, GA, PSO, Hybrid PSO and HACO in terms of data rate with respect to the user index. From the graph, it can be noted that HPSO and HACO gives better performance when compared to SLAA and GA. Its performance can be increased by using Hybrid PSO. Thus by using GA and PSO, we can get both advantage characteristics in a single optimization. PSO has the advantage of good convergence compared to GA.

Figure 2 shows the relation between number of iterations and the fitness function. HACO convergence comes in between PSO and GA. Hybrid PSO-GA combination offers good convergence compared to the other methods.

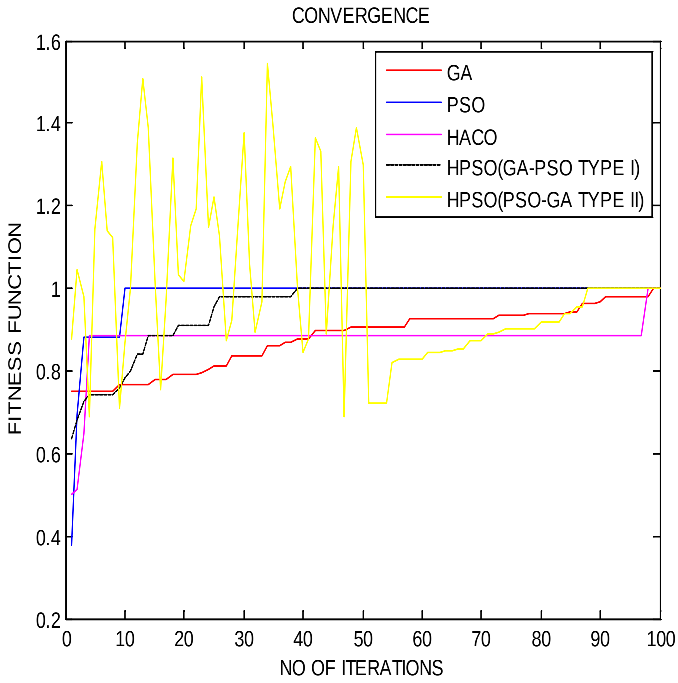

Fig. 2: Iterations vs. Fitness.

Table 6: Iterations vs. Fitness Values.

Itera tions	GA	PSO	HACO	HPSO1 (GA-PSO)	HPSO2 (PSO-GA)
1	0.7520	0.3795	0.4993	0.6367	0.8782
11	0.7652	1.0000	0.8856	0.7999	0.9994
21	0.7904	1.0000	0.8856	0.9105	1.1511
31	0.8359	1.0000	0.8856	0.9788	1.0568
41	0.8755	1.0000	0.8856	0.9999	0.8784
51	0.9075	1.0000	0.8856	1.0000	0.7237
61	0.9259	1.0000	0.8856	1.0000	0.8433
71	0.9270	1.0000	0.8856	1.0000	0.8885
81	0.9405	1.0000	0.8856	1.0000	0.9176
91	0.9780	1.0000	0.8856	1.0000	1.0000

Table 6 shows the fitness values obtained for different iterations. The fitness values of HPSO greater than the PSO and HACO.

Figure 3 depicts the capacity improvement of Hybrid PSO and GA with respect to the other algorithms. Higher capacity is achieved using hybrid PSO followed by HACO and PSO. SLAA and GA provide capacity less than the other methods.

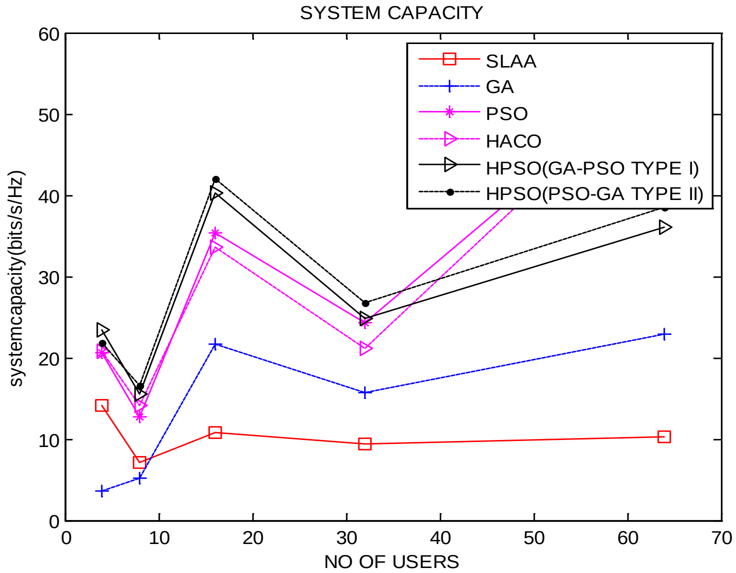

Fig. 3: System capacity vs. no. of users.

Table 7: System Capacity vs. Users.

No of Users	System Capacity					
	SLAA	GA	PSO	HACO	HPSO (GA-PSO)	HPSO (PSO-GA)
4	14.1901	3.5607	20.7009	20.7570	23.3419	21.8326
8	7.0949	5.2479	12.7198	14.0872	15.5603	16.6422
16	10.7793	21.6856	35.3932	33.6304	40.1768	41.9385
32	9.4496	15.6826	24.3691	21.2188	24.8159	26.7823
64	10.2233	22.8706	55.3297	55.7436	36.1221	38.4842

Table 7 shows the system capacity for users varied from 4-64. HPSO1 achieved better capacity than other methods.

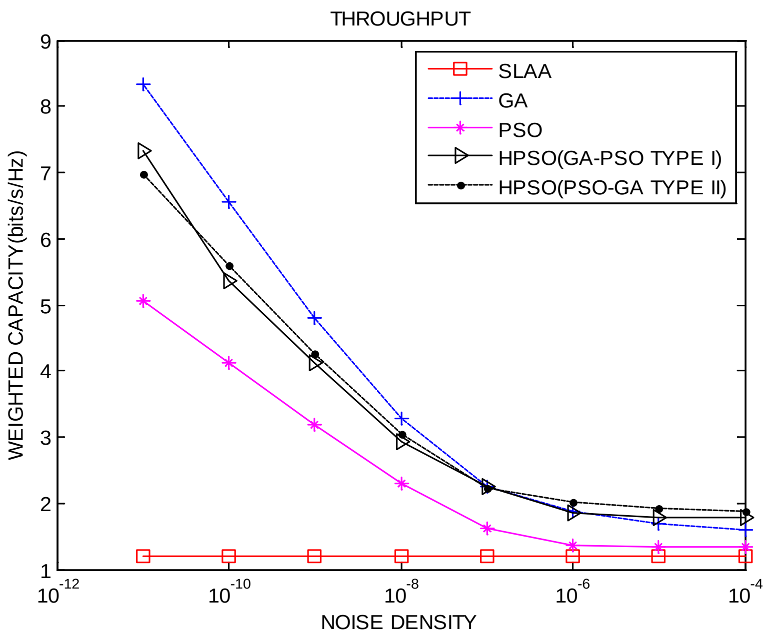

Fig. 4: Throughput vs. Noise density.

From figure 4 it is implicit that GA performs well at less noise atmosphere. But at noisier environment, the performance is not well good when compared with other algorithms. But the hybrid PSO performance is moderate at all type of environment.

Conclusion:

This paper has proposed HPSO (combination of Particle swarm and Genetic Algorithm) for cross layer resource allocation for the downlink multiuser OFDM system with heterogeneous traffic. The convergence rate of PSO is faster than GA and the performance of ACO is better when compared to GA. Simulation results reveal that the hybrid PSO-GA combination affords substantial performance benefits over the SLAA and GA based cross layer resource allocation in terms of the system capacity, throughput and convergence rate with a wide range of the number of users.

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