Energy Efficient Resource Allocation in OFDMA Networks Using Ant-Colony Optimization

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***Abstract*—A novel technique for jointly allocating sub-carriers, modulation and coding scheme (MCS) and transmit power in an orthogonal frequency division multiple access (OFDMA) cellular network using ant-colony optimization technique is proposed. Different combinations of user indices, MCS indices and subcarrier indices form the nodes in the graph. Each possible assignment of the above resources is a path in the graph. Resource allocation is carried out by mimicking the behavior of ants, that the ants are likely to choose the path identified as a shortest path, which is indicated by a relatively higher density of pheromone left on the path compared to other possible paths. Likewise, the combination of resource allocation that satisfies the requested data rate with least energy consumption is preferentially allocated and therefore attains a high 'pheromone' level. As such, the aforesaid allocation is preferentially selected by an evolved nodeB (eNB). Also, the simulation results show 6 and 1.4 times increase in throughput, 15% increase in satisfied users and 17% decrease in transmit power when the proposed approach is compared against full chunk reuse system with link adaptation, chosen as a benchmark.**

I. Introduction

Wireless networks of the fourth generation and beyond are expected to cater for higher number of subscribers than those expected in previous generation of wireless networks. Moreover, each user could potentially request different services simultaneously from the network, with different quality-of-service requirements. Unfortunately, the bandwidth is a limited resource and the available bandwidth cannot be increased easily. Therefore, it is a challenging problem to deliver services from a wireless network with a viable value of service to the cost ratio. To this end, energy consumption in wireless networks is one of the key performance indicator that needs to be lowered as far as possible. To reduce energy consumption and enhance the reuse of licensed spectrum, hierarchial cellular architecture consisting of macro-cells, pico-cells and femtocells are standardised within the third generation partnership project (3GPP) standards. In such heterogeneous cellular architecture, the intelligence for managing the network cannot be expected from a centralised coordinator but must be attained from the nodes that cooperate amongst themselves and operate in a self-organising manner.

Interference in cellular network is a major issue that needs to be intelligently addressed in such self-organising networks. Although the time varying and frequency selective nature of the wireless channel necessitates advanced receiver structure and signal processing algorithms, this can be harnessed to combat interference by scheduling different users in an intelligent manner. To this end, different techniques have been proposed on how to exploit the frequency selective channel using orthogonal frequency division multiplexing (OFDM) technique, which converts the wideband frequency selective channel into narrowband sub-carriers which can be seen as frequency-flat channels.

The water-filling algorithm [1] and its variants are widely used for resource allocation in OFDMA systems. The water-filling algorithm using evolutionary algorithm (EA) for multi-user OFDM systems is discussed in [2]. Genetic algorithm (GA) are also one of the EA methods extensively used as given in [2] and [3] where optimization of resource allocation is carried out using genetic search algorithm. The genetic algorithm works in an iterative process by updating a pool of hypotheses, called a population. Unfortunately, the convergence with genetic algorithms are rather slow and this can raise stability concerns in wireless networks where the propagation medium is time variant. To address this, ant colony optimization (ACO) have been first proposed in [4] is an EA which can be used for the optimization problems. Convergence with ACO is achieved much quicker compared to GA, but requires a larger memory space for the computations. Nevertheless, the resource allocation it is carried out at the eNB side and it deemed cost-effective to accomodate the memory requirement at this end.

In the past, the ACO technique has been widely used for optimisation of resource allocation in a single-cell scenario [5], which does not take into account the co-channel interference (CCI) typically present in contemporary cellular networks. This has been addressed in [6], where the CCI arising in multi-cellular scenario has been addressed with inter-cell and intra-cell sub-carrier allocation. The resource allocation process has been divided into inter-cell and intra-cell resource allocation. The inter-cell process includes use of ACO whereas intra-cell process includes allocating sub-carriers to the best users.

In this paper, we investigate the effect of ACO in a seven-cell OFDMA system with two user per cell in order to have the computational complexity to a managable level. To study the applicability of ACO, we implement this algorithm with and without interference scenario. Resource allocation in the cells using ACO is performed over all the cells in the system and considering the interference from the neighboring cells, ACO is again implemented in the central cell to meet the users' requirement. Thus, we not only see the effect of interference due to ACO based allocation but as well investigate the robustness of ACO in mitigating interference compared to full chunk reuse approach. Equal fairness is considered among users in this paperl despite their location which in case of [6] is ignored during intra-cell allocation. To avoid the computation complexity with 3D table defined in [5], we define a two dimensional search table. Also, the simulation results show 2 folds increase in throughput, 15% increase in satisfied users and 17% decrease in transmit power compared to the benchmark system at 3bps/Hz.

The remainder of the paper is arranged as follows-Section II discusses the system model, the proposed ant colony optimisation alogorithm and the benchmark system. The results obtained using simulations are presented in Section Section III. Finally, the conclusions are drawn in Section IV.

II. System Model and Algorithm Description

A. System Model

A seven-cell system with one eNB in each cell is shown in Fig. 1, with K users and N sub-carriers per cell is considered with each user's rate constraint R_k with a target bit error rate (BER) of P_e. The eNB assigns a subset of total sub-carriers with different modulation technique (QPSK, 16-QAM and 64-QAM) to each user and defines the power level in each sub-carrier to meet the rate requirement of the users while minimizing total power requirement. For simplicity, the effects of multipath propagation and fading are not considered. Furthermore, it is also considered that no different users should share the same sub-carrier in each cell. At the first stage, the allocation is performed considering all the cells being independent in terms of interference from adjacent cells. After the preallocation is done, interference from all the cells to the center cell is calculated and again ACO is applied to mitigate the effect of interference. Considering the number of bits carried by the n-th sub-carrier assigned to the k-th user defined as $c_{k,n} \in \{2,4,6\}$, we define the total bit rate of the user as [7],

$$r_k = \sum_{n=1}^{N} c_{k,n} \nu_{k,n} \tag{1}$$

$\nu_{k,n}$ is the sub-carrier indicator and equals to 1 when sub-carrier n is assigned to user k else 0. For the given P_e and constellation of c bit/symbol for the QAM signal, the received power required is calculated from [7] as,

$$f_c = \frac{N_o}{3}\left[\mathcal{Q}^{-1}\left(\frac{P_e}{4}\right)\right]^2 (2^c - 1) \tag{2}$$

where N_0 is the noise variance and $\mathcal{Q}(x)$ is the Q-function defined as,

$$\mathcal{Q}(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{u^2}{2}\right) du \tag{3}$$

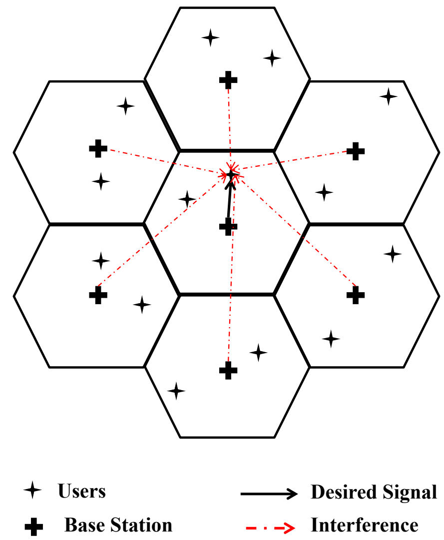

Fig. 1. Cell architecture considered for the study

Now, the power required at the eNB for the k-th user on n-th chunk is given by,

$$P_{k,n} = f\left(c_{k,n}\right) g_{k,n} \tag{4}$$

where, $g_{k,n}$ is the path loss from eNB to the k-th user and is given as [8],

$$g_{k,n} = (44.9 - 6.55\log_{10}(h_{BS}))\log_{10}\left(\frac{d}{1000}\right) + 45.5 +$$
$$(35.46 - 1.1h_{MS})\log_{10}(f_c) - 13.82\log_{10}(h_{BS})\,h_{MS} + C \tag{5}$$

where, h_{BS} is the height of the eNB , d is the distance separation between eNB and UE, h_{MS} is the UE height, f_c is the carrier frequency and C is a constant factor.

The total consumed power of the system will be defined as,

$$P_{\text{total}} = \sum_{n=1}^{N}\sum_{k=1}^{K} f\left(c_{k,n}\right) g_{k,n} \tag{6}$$

The case of minimizing the total power consumption, the problem is formulated as follows:

$$\begin{aligned} \min \quad & \sum_{n=1}^{N}\sum_{k=1}^{K} f\left(c_{k,n}\right) g_{k,n} \qquad (7)\\ \text{subject to:} \quad & r_k \geq R_k \qquad k \in \{1,2,\cdots,K\} \\ & \nu \in \{0,1\} \\ & \sum_{k=1}^{K} \nu_{k,n} \leq 1 \quad \forall n \in \{1,2,\cdots,N\} \end{aligned}$$

B. Modified Ant Colony Optimization Method

ACO is an iterative algorithm inspired by the foraging behavior of ant. The medium of communication among the individuals to help them follow a definite path is called ‘pheromone’. A moving ant lays some pheromone on the path it traverses, thus marking it by a trail of pheromone. An ant moving at random then encounters a previously laid trail and decides to move on the path with high pheromone trials, of course with higher probability and also reinforcing the trail with its own pheromone. The more ants following the same trial makes it more attractive to choose the same path for the other ants. This process is similar to that of a positive feedback loop, where the probability by which an ants selects a particular path increases with the preceding ants choosing the same path. This colony level behavior of ants to find the shortest path between a food source and the nest is used in solving different optimization problems [9].

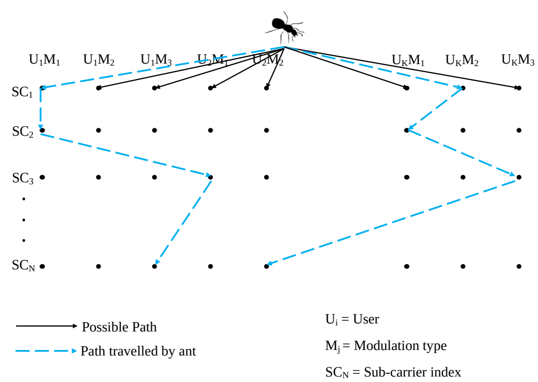

Fig. 2. Process of ACO and path selection

Each sub-carrier cannot be assigned to more than one user and we define the sub-carrier as a ‘vertex’. The combination of user and modulation type are considered ‘edges’. In Fig. 2, the vertex are aligned in the y-axis and edges are aligned in the x-axis making the computation simpler with a 2D search table. Each ant at the starting point has to start its tour by selecting a point and going down the y-axis in Fig. 2. This way the algorithm itself cancels the possibility of allocating one sub-carrier to different users. The tour of an ant which satisfies (8) while minimizing the total power given by (7) is considered as successful while the other not satisfying are considered unsuccessful. The ant tour is completed as soon as (8) is satisfied. The selected vertex and edges are updated in a search matrix (generally termed as tabu list) for the successful ants only. This process is repeated until all the ants in the colony complete their tour (called cycle or iteration), thereafter the trial intensity matrix is updated, based on the tabu list. The trial intensity matrix gives the popularity of the path based on the number of ants traversing through that path with satisfied rate constraint and minimum used power.

For i representing the current sub-carrier allocated with some given modulation level and j representing the other sub-carrier to be allocated, we can define the transition probability as given in (8). This process is repeated for every steps in y-axis in Fig. 2 until (8) is satisfied.

$$p_{ij}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}\left(t\right)\right]^{\alpha}\left[n_{ij}\right]^{\beta}}{\sum\limits_{k\in m_k}\left[\tau_{ik}\left(t\right)\right]^{\alpha}\left[n_{ik}\right]^{\beta}} & \text{for } j \in m_k \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

where m_k is the available sub-carrier to be allocated. We call n_{ij} as the $visibility$ and this quantity is always considered unity throughout the algorithm. Also, α and β are the parameters that control the relative importance of trail versus visibility. α is called the affect of trail intensity whereas β is the affect of visibility. $\tau_{ij}\left(t\right)$ is defined as the trial intensity on the edge (i, j) at the given time t. Each ant at time t chooses next sub-carrier where it will be at time $t{+}1$. The trial intensity update takes place as:

$$\tau_{ij}\left(t+1\right) = \rho.\tau_{ij}\left(t\right) + \Delta\tau_{ij} \tag{9}$$

where, ρ represents the evaporation coefficient of the trail between time t and $t+1$. For s_n number of successful ants,

$$\Delta\tau_{ij} = \sum_{a_n=1}^{s_n}\Delta\tau_{ij}^{a_n} \tag{10}$$

The term $\Delta\tau_{ij}^{a_n}$ represents the pheromone laid on the path from i to j by an ant between time t and $t+1$ and is given as,

$$\Delta\tau_{ij}^{a_n} = \begin{cases} \dfrac{Q}{L_{a_n}} & \text{if } a_n^{th} \text{ ant uses edge } (i, j) \text{ in its tour} \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

where Q is a constant and L_{a_n} is the tour length of a_n^{th} ant corresponding to the total power consumed by that particular ant.

With this process, allocation of sub-carriers with particular modulation level defines the total power required for a particular cell. After the allocation is performed in all the cells, the interference from all the neighboring cells to the central cell is calculated and again the process of ACO is performed in order to investigate the power requirement for the users in order to satisfy their rate constraint.

C. Benchmark System

In order to compare the performance of ACO we use two fixed allocation algorithms, namely: Full Reuse-1 (FR-1) and Full Reuse-2 (FR-2). These two algorithms utilizes all the available resources in the network with the specification given in Table- I. In 3GPP LTE, the transmit power for an eNB is 40 W [10] and the maximum bandwidth available is 20 MHz, assuming no carrier aggregation. When the transmit power is divided equally among the available chunks in the system, the power per resource block is 0.5 W. Hence, we load each chunk with 0.5 W of power and number of required chunk is allocated to users to meet their rate requirements. After interference is considered, FR-1 reallocates the sub-carrier in the same way as done previously and increasing the power in those to meet the requirements. However, in case of FR-2 less interfered sub-carriers are used prior to previous allocation and power is allocated to meet the rate requirement.

TABLE I
SYSTEM PARAMETERS

Parameter	Values
Cellular Layout	Hexagonal grid, 7 cell sites
Inter-site distance	1000m
Pathloss model	COST231 Hata urban
Transmitter height	20m
User height	1.5m
Carrier frequency	2000 MHz
Each chunk bandwidth	200 kHz
Power per chunk	0.5W (26.9 dBm)
Total chunks per cell	6
User distribution	Uniformly distributed in the cell
Number of iterations	1000
Number of ants	100
Number of cycles for ACO	100
α β	1
Evaporation Coefficient (ρ)	0.5

III. RESULTS AND DISCUSSIONS

In this section we present the results of using ACO in a 1-tier OFDMA system. The convergence of ACO is shown in Fir. 3. For the target data rate request of 1.12 bps/Hz in the central cell, we consider $N_o = kTB$, where k is the Boltzman's constant, T is the absolute temperature and B is the noise bandwidth and BER of 10^{-3}. Convergence in fewer number of cycles of ACO is portrayed in the figure.

To verify the robustness of the algorithm described in this paper for power minimization, we compare it with FR-1. Since the resource allocation algorithm of FR-1 and FR-2 are same without interference being considered, we compare ACO with FR-1 only. Fig. 4 illustrates the average power requirement without interference being considered from all neighbor cells for 1000 iterations. A comparison of transmit power required using fixed transmit power of 0.5 W per resource block against dynamic transmit power computation using ACO in an isolated cell is carried out. The power requirement plot for ACO reveals the fact that there is no outage. A user is said to be in outage if the target data rate cannot be satisfied. Later, we discuss the effect of considering equal transmit power in central cell for both the algorithms.

To have fair ground for comparison, we simulate the outage percentage of users due to unsatisfied rate constraints for 1000 number of iterations as shown in Fig. 5 with uniformly distributed user location. The result in Fig. 5 is based on the fact that a total power of 3 W per cell is confined. Also, if we consider the dynamic power allocation for ACO from Fig. 4, we have no user drop case depicted in Fig. 5. Reduction of user outage by 40% in ACO with 3.6 folds increase in power is seen in this case. However, we still see better performance of ACO in case of power confinement compared to FR-1 in terms of outage percentage. The outage percentage seen for ACO algorithm even at lower rate request is due to the fact that ACO tries to meet the rate constraint of atleast one user in case when rate of both cannot be satisfied when fixed power per cell is allocated.

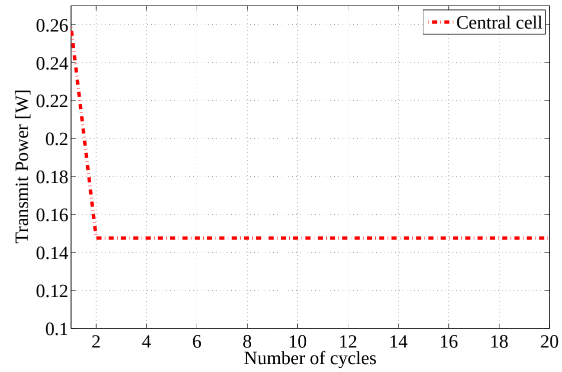

Fig. 3. Convergence of ACO in cells

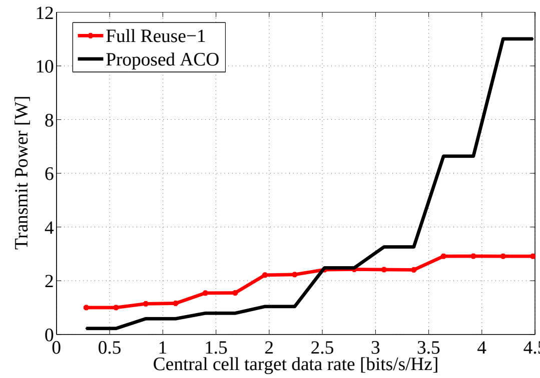

Fig. 4. Power requirement without interference

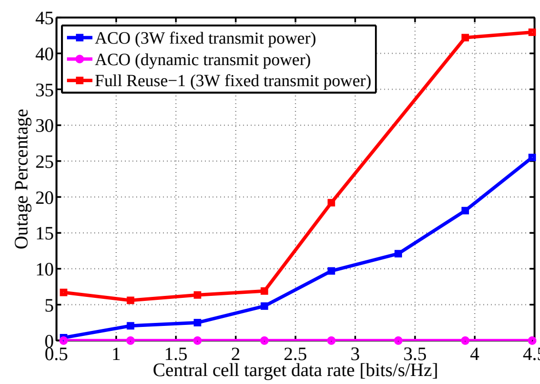

Fig. 5. Outage percentage of user for 1000 iteration

The system throughput compared with target data rate of user is depicted in Fig. 6 for the 10^{th} percentile of simulation for 1000 random UE location. The presented ACO still outperforms the FR-1 algorithm. The linear plot for ACO also reveals the optimum use of the resources in the OFDMA system. Even at offered load less than 3 bps/Hz, where the power requirement does not exceed 3 W, it is seen that the system throughput equals the target data rate for ACO. FR-1 algorithm however having better system throughput in the beginning is due to the fixed power allocation and comparatively low target data rate. As the target data rate increases the system performs significantly better when ACO is applied.

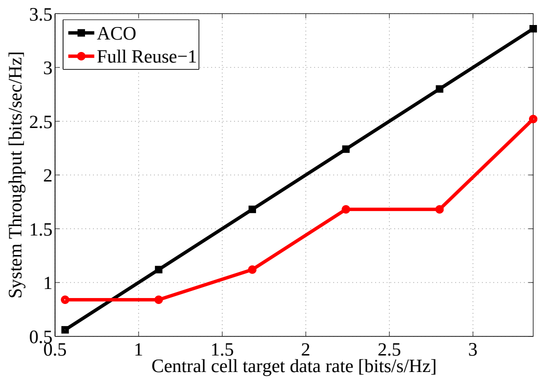

Fig. 6. System throughput compared to target data rate

The stability of ACO algorithm applied needs to be consistent for the real scenario. Fig. 7 depicts the comparison of three algorithms in the central cell when the interference from the neighboring cells are considered. We see ACO outperforms the two given allocation methods significantly. The results are shown until the maximum transmit power of 100 W is reached. Nevertheless, in 3GPP LTE, the maximum transmit power is only 40 W. This means, FR-1 and FR-2 are able to deliver a data rate of 0.28 bps/Hz and 1.2 bps/Hz respectively. By constrast, the ACO technique can deliver a data rate of 1.7 bps/Hz for the same constraint on total transmit power. Fig. 8 depicts the power consumption of a center-cell at the 10^{th} percentile which portrays the power requirement for the cell center users. Comparatively, higher delivered data rate with ACO can be seen here for a given transmit power.

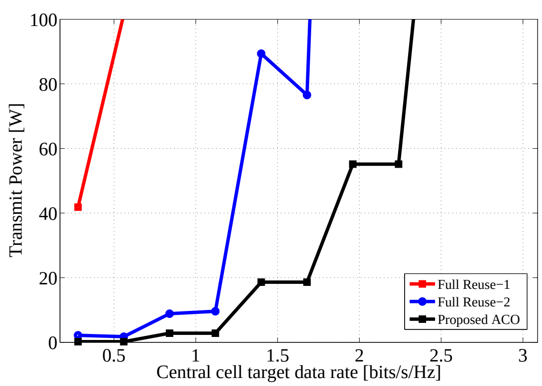

Fig. 7. Power allocation in central cell after interference

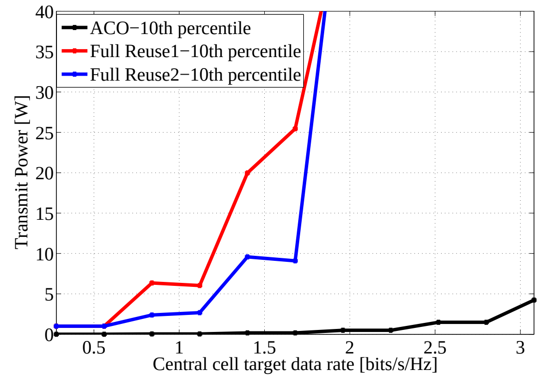

Fig. 8. Power allocation in central cell (10-th percentile) after interference

IV. Conclusions

This paper presents the effectiveness of ACO algorithm for a multi-cell multiuser OFDMA system in terms of delivered data rate, outage probability and required transmit power. Simulation result shows ACO delivering 6 times and 1.4 times more data rate compared to FR-1 and FR-2 at 40 W transmit power when considering CCI. Even with the contraint of fixed transmit power, ACO reduces 15% outage compared to FR-1 without the case of neighboring interference.

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