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Near-Optimal Resource Allocation in Cooperative Cellular Networks using Genetic Algorithms

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Abstract. This paper shows how a genetic algorithm can be used as a method of obtaining the near-optimal solution of the resource block scheduling problem in a cooperative cellular network. An exhaustive search is initially implemented to guarantee that the optimal result, in terms of maximizing the bandwidth efficiency of the overall network, is found, and then the genetic algorithm with the properly selected termination conditions is used in the same network. The simulation results show that the genetic algorithm can approximately achieve the optimum bandwidth efficiency whilst requiring only 24% of the computation effort of the exhaustive search in the investigated network.

Keywords: multi-cell· exhaustive search· genetic algorithm· frequency reuse· cooperative transmission

1 Introduction

The optimal solution of resource scheduling is considered difficult to obtain given that it is a nonconvex problem [1,2,3,4]. Previous research work has investigated near-optimal algorithms for scheduling channels or subcarriers under the conditions of fairness and power control [5,6,7,8]. The general optimal solution without those conditions for scheduling resource blocks in a multi-cell network is not well-studied. The exhaustive search technique is commonly used for getting the optimal solution [5], [9]. However, it requires high computational effort to obtain the optimal results as it needs to search all the possible combinations or cases [1], [16]. The genetic algorithm is also a search method for solving nonconvex problems, and it is widely used in the fields such as cloud design, computing, sub-carrier allocation and even project management [11,12,13,14,15,16]. But it is rarely used in resource block scheduling to get as much bandwidth efficiency as possible for a downlink transmission in a multi-cell scenario. Ref. [15] proposed a genetic algorithm for resource block scheduling in the uplink transmission in a single cell model. The search of the genetic algorithm in [15] was stopped by the maximal number of iterations, so the resultant solution gives worse results than the optimum. This contribution investigates the use of genetic algorithm as a solution for getting the optimal bandwidth efficiency by scheduling resource blocks in a cooperative cellular network with the possibility of flexible cooperation. The termination conditions used in the genetic algorithm are properly selected in order to get the optimal solution. The exhaustive search is used to get the optimal results in a 3-cell network layout, and the results from the genetic algorithm applied to the same network and the same user locations are compared with the optimal results. In addition, the computation effort of getting the optimal results by these two methods is compared.

This paper is organized as follows: section 2 and 3 display the system model and the problem statement; section 4 introduces how to get the optimal solution by the exhaustive search; section 5 explains the implementation of the genetic algorithm; section 6 compares and discusses the simulation results and section 7 presents the conclusion.

2 System Model

2.1 Network Layout

The system investigated is a downlink transmission in a hexagonal cellular network. There are in total M resource blocks to be scheduled to at most a total of U users in an N-cell layout. One Base Station (BS) is located in the center of each cell. A Resource Block (RB) is assumed to be the smallest resource unit to be scheduled and it can only be used once by each BS. The power of each RB is assumed to be the same. Frequency reuse is flexible which means that one RB can be used by more than one BS to schedule to the same user (cooperative transmission) or be used by different base stations to schedule to different users (frequency reuse).

The settings used in the simulation are for a typical LTE urban macro environment which are listed in Table 1 [10].

Table 1. Parameter Settings

Parameter	Value
Network layout	Hexagonal 3 cells
Cell radius	500m
Antenna	Omnidirectional
Carrier frequency	2GHz
Bandwidth	10MHz
Bandwidth per RB	180KHz
Number of available RBs	50
Distance-dependent path loss	$128.1+37.6*\log_{10}(d)$ with d in km
Thermal noise power spectral density	-174dBm/Hz
Maximum BS transmit power	40 watts
Mobile station noise figure	9dB
Minimum distance between user and BS	35 m

3 Problem Statement

This paper investigates the optimal solution of getting the total bandwidth efficiency by scheduling M resource blocks to at most U users in a layout of N cells. The SINR expression for the u^{th} user in the m^{th} RB with flexible frequency reuse is

$$S'_{u,m} = \frac{\sum_{n \in \Omega_n} P_{u,n}}{N_s + \sum_{n' \in \Omega_{n'}} P_{u,n'}}, \ \Omega_n, \Omega_{n'} \subseteq [1, N] \tag{1}$$

where $P_{u,n}=P_m/P_{Lu,n}$ (P_m is the transmit power in the m^{th} RB; $P_{Lu,n}$ is the path loss from the u^{th} user to the n^{th} BS) represents the received power of the u^{th} user from the n^{th} BS. Ω_n is the set of base stations that use the m^{th} RB to transmit signals to the u^{th} user (cooperative transmission occurs if there are more than one BS in this set) while $\Omega_{n'}$ stands for the set of the base stations that also use the m^{th} RB but to transmit to the other users in the network. The base stations in Ω_n and $\Omega_{n'}$ are from 1 to N, and no elements may overlap between Ω_n and $\Omega_{n'}$. N_s is the noise power. (1) shows the SINR expression for the case that the m^{th} RB is scheduled for the transmission between the base stations in the set of Ω_n to the u^{th} user, whilst the m^{th} RB is also used by the base stations in the set of $\Omega_{n'}$ but to transmit to the other users in the network as the interference to the u^{th} user.

The capacity of the u^{th} user in the m^{th} resource block is

$$C_{u,m} = B_m \log_2(1 + S'_{u,m}), \tag{2}$$

where B_m is the bandwidth of the m^{th} RB (180KHz in LTE). Thus, the total bandwidth efficiency of the N-cell layout with U users in total and M resource blocks in total ($M \leq 50$) is

$$\rho_{total} = \frac{1}{B_{total}} \sum_{u=1}^{U} \sum_{m=1}^{M} C_{u,m}, \tag{3}$$

where B_{total} is the total bandwidth used in the scheduling problem ($B_{total} \leq 10$MHz). The objective formula of this resource block scheduling problem (which to obtain the maximum total bandwidth efficiency for the network) is

$$\arg\max_{u,m,n} \frac{1}{B_{total}} \sum_{u=1}^{U} \sum_{m=1}^{M} B_m \log_2\left(1 + \frac{\sum_{n \in \Omega_n} P_{u,n}}{N_s + \sum_{n' \in \Omega_{n'}} P_{u,n'}}\right), \ \Omega_n, \Omega_{n'} \subseteq [1, N]. \tag{4}$$

4 Optimal Solution

The exhaustive search is a common method of finding the optimal results [5], [16]. The basic idea of this algorithm is to try all the possible values within the whole variable fields and to generate all the possible objective results. Then, the value of the variable giving the best objective result is considered as the optimum. Therefore, the exhaustive search can guarantee the optimal results while it carries a large computational cost.

4.1 Implementation

As shown in (4), there are three variables for this resource block scheduling problem: which user (u), which resource block (m) and which base station (n). Based on the explanation of the investigated network in section 2.1, each RB can only be used once by each BS and the frequency reuse is flexible, so each RB can be used at most N times. Thus, there are NM resource block positions available for scheduling to at most U users, which can be represented as a 1 x NM scheduling vector to show the RB allocation case. Each element of the 1 x NM vector can be allocated to either none or one user in the network. Therefore, the number of the total possible combinations is $(U+1)^{NM}$.

4.2 Simulation Results and Analysis

The simulation results are for a 3-cell layout with one user per cell and three resource blocks in total. Even in this small network, the number of the total possible combinations is 4^9. For a more realistic problem with larger numbers of BSs, users and RBs, the exhaustive search becomes computationally unfeasible.

Inspection of the simulation results of the exhaustive search for this 3-cell network layout reveals that there are three types of RB allocation cases for the investigated network that may be optimal: full cooperation transmission, 2/3 reuse non-cooperative transmission and reuse 1 non-cooperative transmission. Full cooperation transmission means that all the resource blocks from all the base stations are scheduled to the same user (all the elements of the scheduling vector are scheduled to the same user), and this case occurs when the scheduled user has comparably good channel conditions to all the base stations while the other users have bad channel conditions to all the base stations; 2/3 reuse non-cooperative transmission means that all the resource blocks are used by 2/3 of the base stations (2/3 of the elements of the scheduling vector are scheduled), and this case occurs when the user in the base station not transmitting have a bad channel condition to its own base station but can cause considerable interference to the other users if resource blocks are scheduled to this user; reuse 1 non-cooperative transmission means that all the resource blocks from each base station are scheduled to its own user, and this case occurs when the users have good channel conditions to their own base stations while they have bad channel conditions to the other base stations in the layout.

5 Genetic Algorithm

Although the exhaustive search is able to give the optimal results, it requires a large amount of computation especially when the investigated network contains many users and many resource blocks. The Genetic Algorithm (GA) is also a search method which treats the variable as a chromosome [11], [15]. The chromosome (variable) will get genetic changes, e.g., crossover and mutation, and be measured by a fitness function until it meets the termination conditions which are normally used to control the precision of the outcomes.

5.1 Implementation

The process of the genetic algorithm is that a generation of individuals (chromosomes) get measured by a fitness function and the result from the fitness function is judged by the Termination Conditions (TC): if current result can satisfy the termination conditions, the solution is the current chromosome; if current result can not satisfy the termination conditions, the current generation of individuals will be genetically changed and the next generation of individuals will be generated and be measured by the fitness function and checked again. This process repeats until the result can meet the termination conditions. The details of the genetic algorithm can be found in [11,12,13]. There are four key parameters used in the genetic algorithm:

- Po: population size, more individuals used in a generation causes more computation but gives better results in the genetic algorithm.
- Re: replacement rate, the bad individuals will be replaced by the newly generated individuals.
- Co: crossover rate, one point crossover is used in this paper.
- Mu: mutation rate, a gene of an individual to be mutated is randomly selected, and the value of the selected gene will be changed.

This paper investigates the resource block scheduling in a cellular network to get as much total bandwidth efficiency as possible, and the optimal results have been obtained by the exhaustive search. Thus, the genetic algorithm is implemented in the same deployment as that used in the exhaustive search. The chromosome (variable) is the 1 x NM scheduling vector, of which each element is filled with none or one of the users whose locations are the same as those used by the exhaustive search. The fitness function is the total bandwidth efficiency calculated by (3). The selection of termination conditions for the genetic algorithm will be explained in section 5.2 and section 5.3.

5.2 Validation of the Genetic Algorithm

The first step is to check whether the genetic algorithm can be used to optimize total bandwidth efficiency by scheduling resource blocks.

The termination condition for validating the genetic algorithm should be based on the optimal results from the exhaustive search. Thus, the termination condition is selected to be the difference between the optimal results and the results from the genetic algorithm. The fitness function gives the results from the genetic algorithm, and then the difference from the optimal results can be computed. This difference will be compared with the constraint set in the termination condition to determine whether the optimal resource block allocation has been found by the genetic algorithm or more generations of individuals are needed.

The detailed simulation results are displayed and discussed in section 6.1. The conclusion can be drawn that the genetic algorithm is able to solve the scheduling problem to get optimal bandwidth efficiency.

5.3 Validation of the New Termination Conditions

The results for validating the genetic algorithm are based on the termination condition that requires the optimal results from the exhaustive search. Hence, new termination conditions without knowing the optimal results should be produced for the genetic algorithm to be applied to any network.

The termination condition in section 5.2 sets a constraint on the bandwidth efficiency difference to control the precision of the results from the genetic algorithm, so the new termination condition for any network also uses a constraint on the bandwidth efficiency difference between the current result and the maximal value of the previous results. Therefore, the search stops when the bandwidth efficiency difference between the current result and the maximal previous result is within a small value. Moreover, the minimum generation number for each search is also included in the new termination conditions. This avoids a situation that the search stops at a local optimum.

6 Simulation Results

In this section, the simulation results and the computation for validating the genetic algorithm will be displayed in section 6.1. The simulation results and the computation for validating new termination conditions will be discussed in section 6.2. Three aspects will be compared between the exhaustive search and the genetic algorithm: total bandwidth efficiency, selected resource block allocation case and computation. Total bandwidth efficiency will be shown as “Total bandwidth efficiency ratio” which is the ratio of the total bandwidth efficiency from the GA divided by the total bandwidth efficiency from the exhaustive search. Selected resource block allocation case will be displays as “Correct RB allocation” which is the percentage of the same RB allocation cases selected by the GA as those selected by the exhaustive search. Computation means the number of resource block scheduling combinations searched by the two algorithms. Computation of the GA relates to the population size and the generation number. “Averaged generation number” means the generation number in average in the simulation, and the computation of the GA can be calculated approximately by “Averaged generation number” times the population size [16].

All the simulation results are obtained for a 3-cell layout with one user per cell and three resource blocks in total. 1000 random independent user drops (1 user in each cell per drop) are generated as the user location samples.

6.1 Simulation Results of Validating the Genetic Algorithm

Table 2 displays the parameters of the genetic algorithm in this simulation. These parameters have been selected following extensive experimentation to identify their impact upon the GA performance. The termination condition used in this simulation is that the bandwidth efficiency difference between the optimal result and the GA result is less than 10^{-1} bps/Hz.

Fig.1 shows the CDF curves of the total bandwidth efficiency from three different algorithms: reuse 1 non-cooperation (users get all the resource blocks from their own BSs), the optimum (results from the exhaustive search) and the GA. From Fig.1, both the GA and the optimum always outperform the reuse 1 non-cooperation, and the GA curve is almost the same as that of the optimum. Thus, the results from the GA are very close to those optimal results from the exhaustive search.

Table 3 gives the details of the comparison between the exhaustive search and the GA. Although the GA correctly selects 81.8% resource block allocation cases, the total bandwidth efficiency ratio is 99.98%. This implies that in the cases where the

Table 2. Parameters 1

Parameter	Value
Po	100
Co	0.4
Mu	0.01
Re	0.5

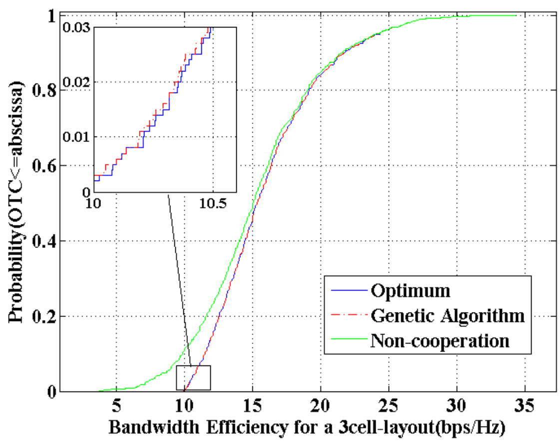

Fig. 1. Comparison of the CDF curves for validating GA

GA makes a non-optimal selection, the selection is nevertheless very close to the optimal one in terms of the bandwidth efficiency obtained. The purpose of using the GA is to achieve a total bandwidth efficiency as close as possible to the optimum, so this result shows that the genetic algorithm is validated for finding the optimal solution of the resource block scheduling problem. Moreover, the computation used in the GA is 2150 (Averaged generation number times the value of Po) while the computation used in the exhaustive search is 4^9 (all the possible combinations for the investigated network), so the GA only uses 0.82% of the computation required by the exhaustive search. Therefore, the GA can significantly reduce the computation compared with the exhaustive search even in this very small size problem.

Table 3. Simulation Results for Validating GA

Parameter	Value
Averaged generation number	21.4960
Correct RB allocation	81.80%
Total bandwidth efficiency ratio	99.98%

Fig.2 shows the distribution of the generation number in the simulation. From Fig.2, the curve tends to be flat after the generation number is 50, and 95.5% of the user drops can get results of the resource block allocation from the genetic algorithm by using no more than 50 generations. Thus, 50 is set as the minimum generation number in the new termination conditions for any network so that the search of the genetic algorithm after 50 generations is based on a near-optimal result for most of the users in a network without knowing the optimum. Fig.2 however also shows that there are a small percentage of cases (around 4.5%) which have to use a larger number of generations to obtain a near optimum solution. This indicates that constraining the maximum generation number can constrain the computational requirement but at the

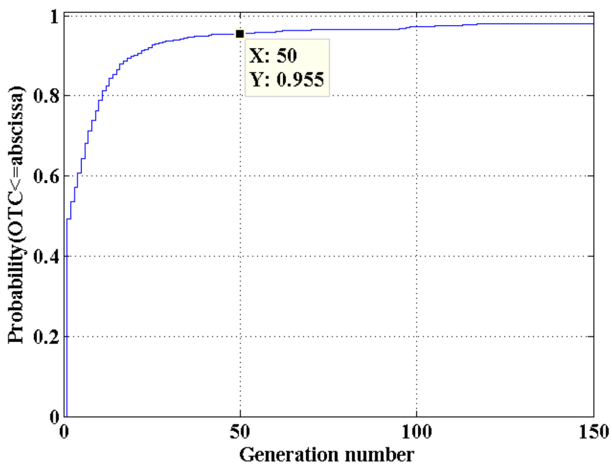

Fig. 2. The CDF distribution of the generation number

cost of optimality. Thus, the balance of the optimality and computation achieved by the genetic algorithm is a subject for further investigation, which is out of this paper but might be done in the future.

6.2 Simulation Results to Validate the Termination Conditions When the Optimum Results are Unknown

Whilst it is useful to show that the GA can achieve near-optimum performance by comparing with the exhaustive search, this is only possible for a small size problem, due to the excessive computation of the exhaustive search in larger problems. For larger problems, it is thus necessary to identify suitable termination conditions for the GA which do not rely on knowledge of the optimum.

Table 4 shows the parameters of the genetic algorithm used in this simulation. These have been modified based upon experimental observation to accommodate the change of termination conditions. The termination conditions for this simulation are that the bandwidth efficiency difference between the current result and the maximal previous result is less than 10^{-6} bps/Hz and each search must use no less than 50 generations.

Table 4. Parameters 2

Parameter	Value
Po	1200
Co	0.6
Mu	0.01
Re	0.4

Fig.3 displays the three CDF curves of the total bandwidth efficiency from reuse 1 non-cooperation, the optimum and the GA. In Fig.3, the curves of the optimum and the GA are almost identical which indicates that the results from the GA are still very close to those from the exhaustive search even when the termination conditions do not rely on knowledge of the optimum. Moreover, the curves of both the optimum and the GA are always superior to that of the reuse 1 non-cooperation.

From Table 5, 98.2% of the RB allocations made by the GA are optimal and the total bandwidth efficiency ratio is approximately 100%. This shows that even those 1.8% non-optimal RB allocation cases selected by the GA can give excellent bandwidth efficiency results. Moreover, the averaged generation number is 51.872, which is very close to the minimum generation number of 50, and the number of the individuals used for each generation is 1200 (population size), so the computation of the GA is around 62247. The exhaustive search needs to calculate all possible RB allocation combinations which is 4^9. Thus, the genetic algorithm requires only 23.75% computation of that of the exhaustive search and still can get approximately 100% optimal total bandwidth efficiency. Therefore, the modified termination conditions for any network in the GA are validated. Additionally, comparing with the results in section 6.1, it can be seen that the termination condition and the population size can have a

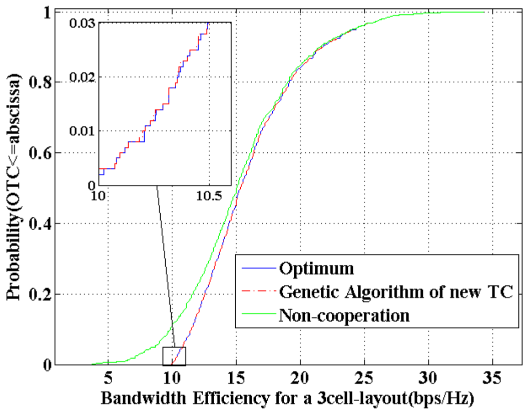

Fig. 3. Comparison of the CDF curves for validating the new TC

Table 5. Simulation Results of the New TC

Parameter	Value
Averaged generation number	51.8720
Correct RB allocation	98.20%
Total bandwidth efficiency ratio	100.00%

considerable influence on the results and the computation required: when larger population size is used or a minimal generation number is set in the termination condition, the results from the genetic algorithm are better while the computation required by the genetic algorithm is increased.

7 Conclusion

This paper has shown that the genetic algorithm can be used for finding a near-optimal resource block allocation solution for maximizing total bandwidth efficiency in a cooperative 3-cell network. The exhaustive search has been applied to a 3-cell network layout for the simulation to guarantee the optimal solution in the investigated network and a scheduling vector was used for representing the resource block allocation cases. Then, the genetic algorithm has been implemented in the same network layout and the same user locations to get results for the comparison with those from the exhaustive search. Firstly, the genetic algorithm has been validated by the termination condition relating to the optimal results from the exhaustive search. As a result, the termination condition has been modified and verified so that the genetic algorithm can be implemented in any network due to that the modified termination conditions no longer being based on the results from the exhaustive search. From the simulation results obtained, the genetic algorithm is capable of achieving a near-optimal resource block solution for maximizing total bandwidth efficiency. Moreover, the genetic algorithm can significantly reduce the computation required by the exhaustive search in the investigated network. Additionally, the population size and the termination condition can impact the results from the genetic algorithm and the computation that the genetic algorithm needs. Work to evaluate the performance of the genetic algorithm in a larger size network (with many users and many resource blocks) and to find solutions with lower complexity is now underway.

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