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A Genetic Algorithm Approach for Multiuser Scheduling on the LTE Downlink

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***Abstract*—The problem of multi-user radio resource scheduling on the downlink of a Long Term Evolution (LTE) cellular communication system is addressed in this paper. The optimization model used imposed that the radio resources for multiple users are jointly allocated at the air-interface. The study shows that optimal and near optimal solutions to such a problem may provide reasonable gain over a simply greedy approach using global and local/heuristic approaches. On one hand, the complexity of the global optimal approach appears prohibitively high, on the other hand, the heuristic approach, namely Genetic Algorithm (GA), provides much better near-optimal results with significant reduction in complexity.**

***Index Terms*—Multiuser scheduling, LTE scheduling, Genetic Algorithms, Mathematical programming, Heuristic optimisation.**

I. Introduction

One of the recent shift in radio access technologies is in the use of Code Division Multiple Access (CDMA) to Orthogonal Frequency Division Multiple Access (OFDMA), which causes very important differences in radio resource management. As the result of this significant shift, standards like Worldwide Interoperability for Microwave Access (WiMAX) [1] and Long Term Evolution (LTE) [2] have been developed to handle these new changes. The aim not only simplifies the design of channel equalizers at the air interface [1], [2], but also provides an additional degree of freedom in exploiting frequency diversity during multiuser resource allocations.

CDMA-based standards such as the High Speed Downlink Packet Access (HSDPA) only involves the time domain while OFDMA-based standards such as LTE requires to allocate resources for users in both the time domain (TD) and the frequency domain (FD). This additional flexibility has been shown to provide throughput and coverage gains of around 40% [3]. In order to take into account the scheduling requirement in both TD and FD, various schemes have been proposed [4], [5], [3], [6]. Assume that we have packets for N_{users} users waiting in the queue and that resources can only be allocated at the beginning of a pre-defined time period known as the Transmission Time Interval (TTI) or scheduling period. In TD scheduling, U users from the total of N_{users} users are selected based on some priority metric. Let $\{P_u,\ u = 1, 2, \ldots, N_{users}\}$ be the set of priority metrics associated with the users. These metrics are then ranked in a descending order. Subsequently, the U users associated with the largest metrics would be selected. After the U users have been selected, appropriate subcarrier frequencies and Modulation and Coding Schemes (MCSs) are then assigned by the FD scheduler. Note that the metrics used for TD and FD scheduling can be different in order to provide a greater degree of design flexibility. Typically, the metrics can take the form of a proportional fair (PF) or maximum C/I metrics. More details and proposals regarding the TD/FD scheduling metrics can be found in [7], [4]. In this paper, the focus will be on the frequency domain scheduling.

In the downlink, the selection of frequency resources and MCSs is done at the base station, which is called eNB for short in the LTE terminology, based on Channel Quality Indicator (CQI) obtained from users over the uplink. A good channel quality can support a higher order MCS, and thereby providing a higher bit-rate, while the reverse if true with a bad channel quality. As specified in [8], frequency-selective CQIs from the users must be available for FD scheduling.

While a smallest unit of frequency resource is a sub-carrier, the smallest unit of channel quality is usually represented for a group of sub-carriers due to limited feedback signalling resources. If a single CQI value is used to convey the channel quality over a large number of sub-carriers, the scheduler may not be able to distinguish the quality variations within the reported range of sub-carriers. This is a severe problem for highly frequency-selective channels. On the other hand, if a CQI value is used to represent each sub-carrier, many CQI values may need to be reported back, resulting in a high signalling overhead.

According to [8], [2], it has been decided that sub-carriers in LTE are grouped into resource blocks (RBs) of 12 adjacent sub-carriers with an inter sub-carrier spacing of 15 kHz. Each RB has a time slot duration of 0.5 ms, which corresponds to 6 or 7 OFDM symbols. The smallest resource unit that a scheduler can assign to a user is a Scheduling Block (SB), which consists of two consecutive RBs, spanning a sub-frame time duration of 1 ms [8], [2].

Note that one important constraint in LTE downlink scheduling is that all SBs belonging to a single user can be assigned to only one Modulation and Coding Scheme (MCS) in each Transmission Time Interval (TTI) or scheduling period in the non multiple-input-multiple-output (MIMO) configuration. [2, page 326]. In [9], an optimization model for multi-user frequency-selective scheduling in the context of LTE has been presented. The computational complexity of the problem, to the best knowledge of the authors, is believed to be NP-hard as discussed, therefore, is time-consuming to obtain an exact optimal solution. In order to reduce the time-complexity whilst producing near-optimal solutions, a genetic algorithm as a population-based heuristic optimisation algorithm, is implemented and tested to achieve

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a reasonable gain over a simple greedy algorithm at the expense of a higher complexity.

The rest of this paper is organized as follows: Section II presents the system model for the original problem, and is followed by Section IV, which introduces the genetic algorithm implementation for the mathematical programming model. Subsequently, relative performances among different schemes are compared in Section V, which is followed by the conclusion in Section VI.

II. System Model

The radio resources of an OFDMA system such as LTE are selected from the time-frequency grid. In the time domain, each SB consists of N_{sb} OFDM symbols. Let L be the total number of sub-carriers and $L_d(\nu) \leq L$ be the number of data-carrying sub-carriers for symbol ν, where $\nu = 1, 2, \ldots, N_{sb}$. Also, let $R_j^{(c)}$ be the code rate associated with the MCS $j \in \{1, 2, \ldots, J\}$, M_j be the constellation size of the MCS j and T_s be the OFDM symbol duration. Then, the basic bit rate, r_j, associated with a single SB is given by

$$r_j = \frac{R_j^{(c)} \log_2(M_j)}{T_s N_{sb}} \sum_{\nu=1}^{N_{sb}} L_d(\nu). \qquad (1)$$

As mentioned earlier, we assume U users are to be scheduled simultaneously, which have already been pre-selected from N_{users} users during the TD scheduling phase. Also, let N_{tot} be the total number of SBs that are available during each TTI, $\mathcal{N}_i$ be a subset of the N_{tot} SBs whose Channel Quality Indicator (CQI) values are to be reported by user i. The size of $\mathcal{N}_i$ is denoted by N_i. It is assumed that only the N_i highest SB CQI values are fed back. Such a limited feedback scheme requires a smaller bandwidth albeit at the cost of a degraded system performance. We also assume that the total available power is shared equally among the users. As suggested in [10], [11], the system throughput degradation resulting from such an assumption is small when adaptive modulation and coding (AMC) is used, as is the case in LTE.

Let $\theta_{i,n}, n = 1, 2, \ldots, N_i$ be a real scalar or vector reported (via a feedback channel) by user i to indicate the collective channel qualities of all the sub-carriers within the n-th reported SB. Furthermore, let $q_{i,max}(\theta_{i,n}) \in \{1, 2, \ldots, J\}$ be the index of the highest-rate MCS that can be supported by user i for the n-th SB at CQI value $\theta_{i,n}$, i.e. $q_{i,max}(\theta_{i,n}) = \arg\max_j \left(R_j^{(c)} \log_2(M_j) | \theta_{i,n}\right)$.

Due to frequency selectivity, the qualities of the sub-carriers within a SB may differ. However, the indicator $\theta_{i,n}$ should provide a good collective representation of the qualities for all the sub-carriers within the n-th SB [12], [13], [14], [15]. For convenience, we assume that the MCS rate $R_j^{(c)} \log_2(M_j)$ increases monotonically with j and that the rate of MCS 1 is zero. SBs whose CQI values are not reported back are assigned to MCS 1.

III. Optimal Scheduler

A. Joint Optimization Model

Let $R_{i,n}(\theta_{i,n})$ be the bit rate of SB n selected for user i given the channel quality $\theta_{i,n}$, and is given by

$$R_{i,n}(\theta_{i,n}) = \sum_{j=1}^{q_{i,max}(\theta_{i,n})} y_{i,j} r_j, \qquad (2)$$

where $y_{i,j} \in \{0, 1\}$ is a binary decision variable. Also, let $Q_{max}(i) = \max_{n \in \mathcal{N}_i}\{q_{i,max}(\theta_{i,n})\}$. In order to ensure that the MCS for user i can only take on a single value between 1 and $Q_{max}(i)$, the following constraint is introduced, i.e.

$$\sum_{j=1}^{Q_{max}(i)} y_{i,j} = 1. \qquad (3)$$

Note that the above formulation allows the selected bit rate for SB n to be less than what $\theta_{i,n}$ can potentially support, as may be the case if user i is assigned more than one SB during a TTI. From (2) and (3), it can be seen that SB n might be selected for user i only if the MCS j^* chosen for user i satisfies $j^* \leq q_{i,max}(\theta_{i,n})$.

Finally, the problem of jointly maximizing the sum of the bit rates for all users can be expressed as

$$Z_1 : \quad \max_{\mathbf{X}, \{\mathbf{y}_i\}} \sum_{i=1}^{U} \sum_{n \in \mathcal{N}_i} x_{i,n} \sum_{j=1}^{q_{i,max}(\theta_{i,n})} y_{i,j} r_j \qquad (4)$$

subject to (3) and

$$\sum_{i=1}^{U} x_{i,n} = 1, \; n \in \mathcal{N}_i \qquad (5)$$

$$x_{i,n}, y_{i,j} \in \{0, 1\}, \; \forall\, i, j, n. \qquad (6)$$

In problem $(P1)$, $\mathbf{X} = \{x_{i,n}, i = 1, \ldots, U, n \in \mathcal{N}_i\}$, $\mathbf{y}_i = [y_{i,1}, y_{i,2}, \ldots, y_{i,Q_{max}(i)}]$ is an MCS selection vector for user i, and $x_{i,n}$ is a binary decision variable, with value 1 if SB n is assigned to user i and 0 otherwise. The objective in (4) is to select optimal values for $\mathbf{X}$ and the set $\{\mathbf{y}_i\}$ to maximize the aggregate bit rate

$$R_{tot} = \sum_{i=1}^{U} R_i, \qquad (7)$$

where

$$R_i = \sum_{n \in \mathcal{N}_i} x_{i,n} R_{i,n}(\theta_{i,n}), \; n \in \mathcal{N}_i. \qquad (8)$$

It is important to point out that (8) corresponds to the assigned bit rate for user i that the system can provide. It does not correspond to the actual throughput T_i, which is given by

$$T_i = R_i \left(1 - \epsilon_i(\theta_{i,n})\right), \; n \in \mathcal{N}_i, \qquad (9)$$

where $\epsilon_i(\theta_{i,n})$ is the block error rate (BLER) associated with user i. However, as it is a requirement that the CQI feedbacks $q_{i,max}(\theta_{i,n})$ selected by user i should fulfill $\epsilon_i(\theta_{i,n}) \leq 0.1$ [16], the user throughput is tightly bounded by the assigned user bit rate R_i, i.e. $0.9 \times R_i \leq T_i \leq R_i$. Thus, the optimization of the aggregate assigned bit rate R_{tot} serves as a good approximation to the optimization of the actual system throughput. Due to the high nonlinearity between

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$\epsilon_i(\theta_{i,n})$ and $\theta_{i,n}$, the incremental benefit in optimizing the actual throughput does not necessarily justify the added complexity. This slight simplification allows us to formulate the problem without resorting to further approximate the actual non-linear relationship between T_i and $\theta_{i,n}$.

While solutions can be obtained using standard optimization techniques, global optimality is not guaranteed. In [9], it has been shown that additional auxiliary decision variables can be included in order to linearise the problem, and thereby avoiding local optimality. However, these additional auxiliary variable effectively increases the solution space of the problem, and thereby imposing an additional cost in solving the original problem.

B. A Sub-Optimal Scheduler

The complexity of joint optimal scheduling model, which requires the MCSs, SBs, and users to be jointly assigned, remains very high. As it is also very non-linear, one way to solve the problem without loss of integrity is linearisation, which can avoid local optimal solutions, but, it does introduce an additional cost via the introduction of the auxiliary variable. One way to reduce complexity is to perform the optimization in separate stages as described in [9]. This approach imposes a two-stage method, where each SB is assigned to the user who can support the highest bit rate in the first stage. In the second stage, the best MCS for each user is searched and determined. The idea behind the sub-optimal scheduler is to assign a disjoint subset of SBs to each user,thereby reducing a joint multiuser optimization problem into U parallel single-user optimization problems. The complexity reduction is further discussed in both [9] and [17].

IV. Genetic Algorithms

Heuristic optimisation is the sub-field of problem solving using human expertise in the form of heuristic algorithms. Genetic algorithms (GA) is perhaps one of the most famous meta-heuristic in problem solving, which was invented by John Holland three decades ago inspired of natural selection and recombination of surviving alive creatures. The main idea is to recombine fresh solutions from couples of existing solutions and to promote the more useful solutions produced for next generations with respect to some certain performance measures. A population of solutions is adopted and kept evolving throughout so as to achieve a virtually alive environment [18].

This approach facilitates search (problem solving) across a problem space via genetic operator called recombination and selection operators in which the problem states are altered. Mainly, crossover and mutation operators are used to recombine child (new) solutions, and selection and replacement rules are utilised to evolve a population generation-by-generation. Although there are various genetic algorithms implemented, we preferred to introduce a standard generational genetic algorithm, which is the most common GA used in the literature. The idea is described in the following.

Let $\mathcal{S}_p \subseteq \mathcal{S}$ be a set of solutions adopted as a population, where $\mathcal{S}_p = \{s_i : i = 0, ..., \mid \mathcal{S}_p \mid\}$, and $\mathcal{S}$ is the whole set of search space. In each generation, a new set of solutions, $\mathcal{S}_c \subseteq \mathcal{S}$, where $\mathcal{S}_c = \{s_i : i = 1, ..., \mid \mathcal{S}_c \mid\}$, is produced with which crossover, $C(s_i, s_j)$, and mutation, $M(s_i)$, functions operate on randomly chosen coupled parent solutions. $C(s_i, s_j)$ recombines a set of children solutions from at least two parent solutions, while $M(s_i)$ works with a single individual changing a minor information. Both operators are utilised subject to certain probabilities. Once a predefined number of children solutions were born, a selection operator promotes a population for the next generation among all existing individuals. The new population for the $(k+1)^{th}$ generation is formed by combining the population of parent solutions and the population of new born children according to $\mathcal{S}_p(k+1) = \mathcal{S}_p(k) \bigotimes \mathcal{S}_c(k)$, where k is the generation index and $\bigotimes$ is the relation identified for replacing the old population with a new set from the mixture of newly born individuals and their parents. The policy to be adopted for such a relation identifies the type of GA, where it can be an elitist policy with generational replacement as undertaken in this study or something else. This evolving process repeats until a predefined number of generations is met.

There are various crossover, mutation and selection operators introduced with records of success within the literature. Due to the sensitivity of this problem, non-standard crossover and mutation operators are preferred to use. Specifically, the standard operators may reproduce infeasible solutions, which require further computation time to repair with particular algorithms. The crossover operator works with two parent-solutions selected by a binary tournament selection operator for reproduction in a similar way that fusion-based crossover operators [19] work. A child solution is built copying successive user's information from different parents in such a way that user j's decision information, $\mathbf{x_j}$ and $\mathbf{y_j}$, is copied from one parent, and then user $j+1$'s corresponding information is copied from the other parent. Note that each solution in GA is represented with a chromosome, which is a particular encoding scheme. Suppose $s_i = \{\mathbf{X}^i, \mathbf{y}^i\}$ and $s_j = \{\mathbf{X}^j, \mathbf{y}^j\}$ are two chromosomes representing the i^{th} and j^{th} parent-solutions selected with binary tournament selection operator. The crossover operator creates the chromosome of a new child solution from scratch copying the complete information of one users, e.g. user 1, from one of the selected parent randomly, say i^{th} parent and the information of the next user, e.g. user 2, from j^{th} parent, the other parent. Thus, the chromosome of the new solution, $\acute{x}_i$, will be built as follows:

$$\acute{x}^i_n = \begin{cases} x^i_n & r \geq 0.5 \\ x^j_n & \text{otherwise} \end{cases} \tag{10}$$

$$\acute{y}^i_n = \begin{cases} y^i_n & r \geq 0.5 \\ y^j_n & \text{otherwise} \end{cases} \tag{11}$$

where n is the user index, $r \in [0,1]$ is uniform random number and $\mathbf{X}_n$ and $\mathbf{y}_n$, are the decision variables make up a solution/chromosom as identified in Section III with (3)-(6).

On the other hand, the mutation operator uses the following logic to make a slight change in the randomly selected The states of the problem are represented with $\mathbf{X}$ and $\mathbf{y}$, where the former is used to choose SB indexes for each user and the latter is to choose the MCS index. New solutions are generated by applying $f(\mathbf{X}, \mathbf{y})$ in which either $\mathbf{x_i}$ or $\mathbf{y_i}$ is uniformly randomly selected to be operated once. If $\mathbf{x_i}$ is selected, then a particular column of $\mathbf{X}$, say j, is randomly chosen to assign the j^{th} SB to one randomly selected user, say i. Therefore, if j^{th} column $\mathbf{x_j} = (x_{0,j}, ..., x_{i,j}, ..., x_{k,j}, ..., x_{N,j})^T$ is $(0, ..., 0, ..., 1, ..., 0)^T$ then the resulted new solution $\mathbf{x'_j} = (x_{0,j}, ..., x'_{i,j}, ..., x'_{k,j}, ..., x_{N,j})^T$ will be $(0, ..., 1, ..., 0, ..., 0)^T$. This operation must not violate (5).

On the other hand, if the selected decision variable is $\mathbf{b}$, then $\mathbf{y_i} = (y_{i,0}, ..., y_{i,j}, ..., y_{i,k}, \ ..., y_{i,Q_{max}(i)})$ with a possible value of $(0, ..., 0, ..., 1, ..., 0)$ will be randomly chosen to be operated for producing the next state subject to (3). Then the resulted state will be $\mathbf{y_i}' = (y_{i,0}, ..., y'_{i,j}, ..., y'_{i,k}, ..., y_{i,Q_{max}(i)})$ with a possible value of $(0, ..., 1, ..., 0, ..., 0)$.

Typically, in order to obtain good results, the mutation rate is configured as higher than crossover rate. Otherwise, higher crossover rate results in more frequent switching between neighbourhoods, and less time would be available for mutation to fine-tune the result within a particular neighbourhood.

V. Experimental Results

Simulations to illustrate the performance of the proposed heuristic algorithm in comparison to the global optimisation approach have been done. Linear integer programming (LIP), sub-optimal-model-based greedy algorithm (Sub-Opt), and genetic algorithm (GA) are the problem solving approaches examined through this study. LIP is a global optimization method which guarantees the optimum solution even for NP-Hard and NP-Complete problems. This is done based on the linearisation formulation as proposed in [9], and corresponding solutions are obtained by the LINGO optimisation package [20]. On the other hand, the Sub-Opt. solves the problem very quickly with a lower solution quality. Furthermore, the genetic algorithm (GA) is producing very near optimum solutions with much lower, polynomial, complexity. GA is a population based approach, which usually provides good quality of solutions. The level of parameters used for configuring GA is presented in Table I.

Genetic Algorithm

Parameter	Level
Population Size	50
Number of Generations	200
Crossover rate	0.05
Mutation rate	0.75

TABLE I
THE LEVELS OF PARAMETERS USED TO CONFIGURE GA

The assumptions made in these simulations are as follows: $N_{tot} = 12$ SBs per TTI, $L = 12$ sub-carriers per SB, $N_1 = N_2 = \ldots = N_U = N$ and that the normal cyclic prefix configuration is used [2]. For each sub-carrier and user, the fading amplitude follows the Rayleigh distribution [21]. The SINRs for all sub-carriers of each user are assumed to be correlated, but identically distributed (c.i.d.), and that the resource blocks follow the localized configuration [8]. The correlation coefficient between a pair of sub-carriers is given by $\rho^{|i-j|}$, where i and j are the sub-carrier indices. The SINR of each sub-carrier is assumed to be independent at the beginning of each scheduling period, and constant throughout the entire period. It is also assumed, for simplicity, that the set of MCSs consists of QPSK 1/2 and 3/4, 16-QAM 1/2 and 3/4, as well as 64-QAM 3/4 [1], and the L1/L2 control channels are mapped to the first OFDM symbol within each sub-frame. For illustration purposes, the parameters associated with the MCS thresholds were obtained from [1]. Furthermore, each sub-frame consists of 8 reference symbols [2]. The feedback method is based on the Exponential Effective SINR Mapping (EESM) [13], in which the effective SINR per SB is given by $\gamma_{i,n} = -\beta \ln \frac{1}{K} \sum_{k=1}^{K} e^{-\frac{\gamma_{n,k}^{(i)}}{\beta}}, = \theta_{i,n}$, where $\gamma_{n,k}^{(i)}$ corresponds to the SINR for user i at the k-th sub-carrier of SB n, the channel quality, $\theta_{i,n}$, is defined to be the effective SINR, $\gamma_{i,n}$, over the K sub-carriers within the SB n for user i under EESM. The quantity β is a positive real parameter which is associated with EESM obtained from [22]. Note that EESM maps a set of sub-carrier SINRs, $\{\gamma_{n,k}^{(i)}\}_{k=1}^{K}$, to a single effective SINR, $\gamma_{i,n}$, in such a way that the block error probability (BLEP) due to $\{\gamma_{n,k}^{(i)}\}$ can be well approximated by that at $\gamma_{i,n}$ in additive white Gaussian noise (AWGN) [1], [13]. The main idea is to reduce uplink signalling feedback overhead.

In order to study the effect of three important aspects of packet scheduling for LTE, three sets of experiments were included in this paper, where each set consists of different values of a specific variable to be studied (while fixing the rest of the parameter values according to the above assumptions). Each given value is calculated on 2500 channel realizations generated according to the assumptions described earlier. In the first set of experiments, the number of SBs, N, is varied from 2 to 12 so that each CQI feedback can support in order to study the sensitivity of the performance due to the amount of feedback information available to the schedulers. This test is important as more information may improve the accuracy of the channel feedback, but at the expense of a higher signalling overhead. In the second set of experiments, the effect of correlations between sub-carriers is studied. In this scenario, the correlation is varied from 0.1 (less frequency-selective) to 0.9 (more frequency-selective). For the first two set of experiments, a maximum of $U = 3$ simultaneously scheduled users are assumed, and their average signal-to-interference plus noise ratios (SINRs) are 10 dB, 11 dB, and 12 dB respectively. Note that each user is assumed to be fading independently, while the SINRs for each user are correlated among sub-carriers according to the model described earlier. In the third set of experiments, the number of users, U, that can be scheduled simultaneously at each TTI is varied from 1 to 8. The aim of this test is to examine the extent to which the schedulers can benefit from the user diversity. To maintain a fair comparison, the average SINRs for all users are now assumed to be 10 dB.

Let R_{tot}^* be the total bit rate defined in (4), and $E[R_{tot}^*]$ be the value of R_{tot}^* averaged over 2500 channel realizations.

Figs. 1 and 2 show the performances of all four algorithms with respect to the average total bit rate, $E[R_{tot}^*]$, as a function of ρ and N respectively. Fig. 1 shows that the performance improves with increasing correlation among sub-carriers for all algorithms. At a lower correlation, the variation among $\gamma_{n,k}^{(i)}$ tends to be higher. Thus, while there are more sub-carriers may take on higher values of SINR, more sub-carriers may also take on lower values. Due to

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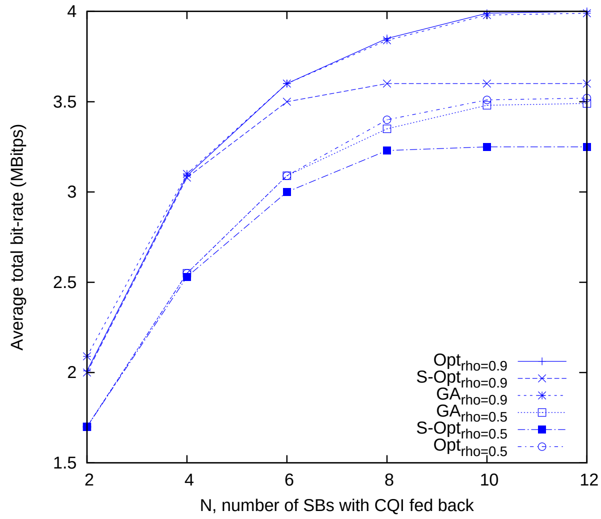

Fig. 1. Average total bit rate as a function of N, with $U = 3$. $\rho = 0.5$ and 0.9.

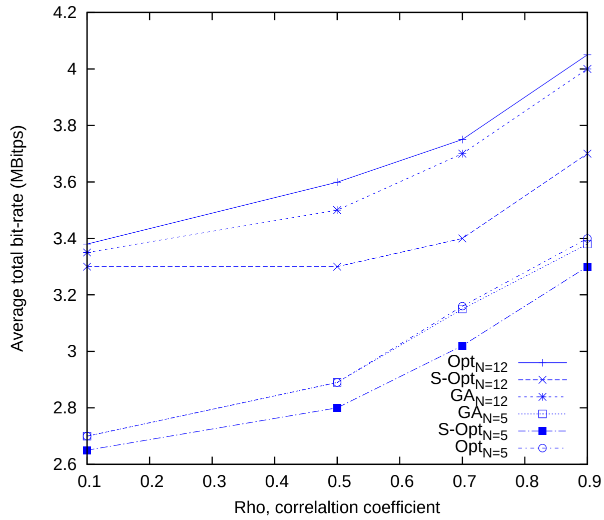

Fig. 2. Average total bit rate as a function of ρ, with $U = 3$. $N = 5$ and 12 with $U = 3$.

the nature of EESM as described in (V), a higher SINR tends to be de-emphasized compared to a lower SINR. Thus, for the case of lower correlation, the effective SINR $\gamma_{i,n}$ tends to be skewed towards SINRs of the weaker sub-carriers. Such a conservative approach is characteristic of EESM in order to maintain an acceptable BLEP. Therefore, at a low value of ρ, sub-carriers with large SINRs are not effectively utilized, leading to a relatively poor performance. In Fig. 2, it can be seen that the performance improves with N, but the rate of improvement decreases. There is little performance improvement as N increases beyond 8 in our example. This observation suggests that a full CQI feedback is not necessary, and the feedback signalling overhead can potentially be reduced without significant degradation to the system. The explanation is as follows. Recall that the quantity N refers to the SBs associated with the N highest channel quality for each user. As the schedulers make use the CQI feedback for SB assignments, it is the SBs associated with better channel qualities that are more important for each user during the assignment process. Thus, as N reaches up to

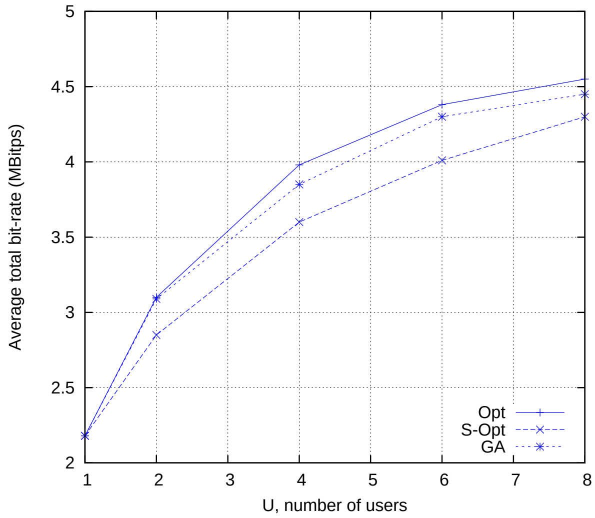

Fig. 3. Average total bit rate as a function of the number of users, U, with $\rho = 0.9$ and $N = 12$.

a certain level, further increase in N would only include additional SBs that are of lower channel qualities and lower chances of being scheduled, and are less likely to contribute to the actually process of scheduling.

It can be seen from Figs. 1 and 2 that the performance of GA tends to be closer to the global optimum than the others. This is especially true with a higher value of N. Also, GA clearly outperform Sub-Opt., especially in the region of higher N and ρ. Fig. 3 shows $E[R^*_{tot}]$ as a function of the number, U, of users for $\rho = 0.9$ and $N = 12$. In this study, the average SINRs for all users are set to 10 dB. As U increases, $E[R^*_{tot}]$ increases due to the more pronounced benefits from multiuser diversity. The performance of GA remains a little bit below, but quite above the sub-optimal. This is because GA changes neighbourhood to conduct search within more frequently.

The complexity of GA for this problem is linear as explained in the following. A typical GA implementation goes through a number of generations, $\mathcal{G}$, where a number of reproduction cycles, usually equals to the size of population, $|\mathcal{S}_p|$, is iterated in each generation. The complexity associated with these two loops is $\mathcal{O}(\mathcal{G} \times |\mathcal{S}_p|)$, which reduces to $\mathcal{O}(1 \times 1)$ since both $\mathcal{G}$ and $|\mathcal{S}_p|$ are fixed values. The last remaining complexity issue with GA is created by genetic operators applied per reproduction cycle through which selection, crossover and mutation operators are applied usually based on domain-specific procedures. In this implementation, a binary tournament selection operator is used with constant settings, which results in a complexity of $\mathcal{O}(1)$, while the crossover and mutation operators described above operate subject to certain probabilities, where the mutation rate dominates the crossover resulting in a complexity of $\mathcal{O}(U + U)$ in the worst case. Therefore, the overall complexity becomes $\mathcal{O}(U)$.

As indicated in Fig. 4, the complexity for GA is polynomial and linear in terms of the number of users, and is shown to be visibly lower than that of the global optimum method. The overall results indicate that the proposed GA scheduler is an attractive alternative to the global optimal scheduler, as it provides significant reduction in complexity with near

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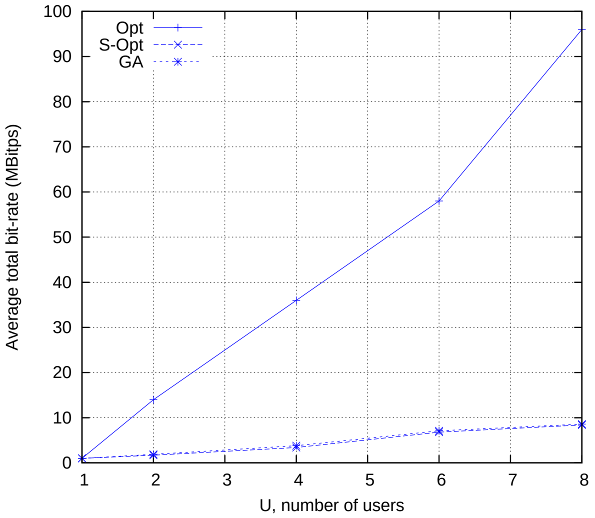

Fig. 4. Normalized CPU time as a function of the number of users, U, with $\rho = 0.9$ and $N = 12$.

optimum performance.

VI. Conclusion

The downlink multiuser scheduling problem for LTE systems is addressed in this paper. The problem is particularly tackled with GA in solving the optimization model originally proposed in [9]. The numerical results show that the genetic algorithm approach proposed in this paper significantly reduce computational complexity relative to the exact approach using linear integer programming, while providing near-optimal performance.

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