A Genetic Algorithm Based Approach for Resource Allocation in LTE Uplink

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***Abstract*—LTE has become the *de facto* technology for the 4G networks. It offers unprecedented data transmission and low latency for several types of applications and services. In this paper, we investigate the resource allocation in the LTE uplink, which is widely known as a complex optimization problem. To solve this issue, we present a new scheduling algorithm based on Genetic Algorithms (GA). The proposed algorithm is evaluated using NS-3 in scenarios of video transmission with focus on video chat. The performance of the GA based algorithm is compared with the most relevant algorithms present in the literature. Simulation results show the superiority of the GA based approach to offer better video quality in the scenarios of evaluation.**

I. Introduction

In the past years, we have been witnessing a tremendous growth of mobile network subscribers. This fact has demanded a continuous evolution of the current mobile networks, in order to attend the always crescent expectations of these users. In this context, the Long-Term Evolution (LTE) has emerged as one of the most promising solutions for these new challenges. To provide a good user experience, the LTE network should allocate its resources in an efficient way. However, the plurality of applications and different QoS requirements bring to light complex challenges to resource allocation design.

Downlink and uplink have a radio link with a time variant nature, due to the fast fading phenomenon. In this sense, channel-aware solutions are usually adopted in LTE resource allocation, since they are able to exploit channel quality variations by assigning higher priority to users experiencing better channel conditions. However, the channel quality can not be the only factor in the resource scheduling process. The scheduling algorithm has also to consider the QoS requirements. Thus, a powerful and effective scheduling algorithm should be channel-aware/QoS-aware.

The LTE uplink channel is based on Single Carrier Frequency Division Multiple Access (SC-FDMA). In this scheme, the scheduler has limited degrees of freedom: it has to allocate contiguous Resource Blocks (RBs) to each user without the possibility of choice among the best ones available [1]. The incorporation of the RB contiguity constraint into uplink scheduling algorithms was proven to be NP-hard [2], i.e., it is impractical to perform an exhaustive search.

The aim of this paper is to investigate the resource allocation in LTE networks regarding the uplink direction. We propose a new scheduling algorithm based on Genetic Algorithms (GA). GA is one of the most known tools designed to deal with complex optimization problems. GA is capable of delivering near optimal performance with comparatively low complexity. The proposed algorithm was developed considering the RB contiguity constraint and presents new strategies of initialization, crossover and mutation operations. The performance of the algorithm is evaluated in a simulation environment with scenarios of video chat transmission. We selected the most relevant scheduling algorithms found in the literature and compared their performance with the proposed algorithm to verify the relevance of our findings.

The rest of the paper is organized as follows. Section II introduces the related works that present solutions for the LTE uplink resource allocation. In Section III, we formulate the problem to be solved in this paper. Section IV describes the details of the proposed algorithm. Section V shows the results of the performance evaluation. Finally, concluding remarks are offered in Section VI.

II. Related Work

Resource allocation in the LTE network has been a field of intense research. Despite the fact that the uplink channel has received less attention than the downlink, one can find interesting papers dealing with the uplink scheduling challenges. Among them, we can highlight the two most popular uplink scheduling algorithms: Recursive Maximum Expansion (RME) [3] and Riding Peaks [2]. In these works, the algorithms were evaluated with only one type of traffic source and they do not have any kind of mechanisms to assure QoS requirements.

From these two algorithms, we can find a set of works that compare the performance of these two algorithms [4] [5], or try to improve these solutions and add QoS capabilities, as in [6] and [7].

GA has been used in scheduling algorithms mainly for the downlink. For the uplink, Sun *et al.* [8] proposed a GA based solution to mitigate Co-Channel Interference (CCI) using Successive Interference Cancelation (SIC). This work is more related to Coordinated Multipoint (CoMP) transmission and multi user scheduling. It does not consider the NP-hard issue of the localization constraint for RB assignment.

To the best of our knowledge, there are not any studies about the use of GA as the heuristic of an LTE uplink scheduling algorithm, considering the RB contiguity constraint. In this sense, the novelty in this paper consists of investigating the resource allocation in the LTE uplink using GA as the strategy of resource allocation.

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III. Problem Formulation

We consider a single LTE base station (eNB), which has an uplink bandwidth divided into M RBs. We also consider that there are N active users (UEs) attached to the eNB. Thus, the eNB can allocate M RBs to a set of N users. At each Transmission Time Interval (TTI), multiple RBs (respecting the contiguity constraint) can be assigned to a single user. However, each RB can be assigned to at most one user.

We define the variable $x_n^m(t)$ to indicate whether or not RB m is assigned to user n at TTI t. As said before, the LTE air interface has a time variant nature. Thus, we can define the variable $r_n^m(t)$ as the instantaneous achievable rate of user n for RB m at instant t. This achievable rate is calculated based on the quality of the channel. Thus, if $x_n^m(t) = 1$, user n can transmit at $r_n^m(t)$ bytes/s on RB m at instant t. We also define $R_n(t)$ as the long-term service rate for user n at time t. In this sense, the well-known Proportional Fairness (PF) metric can be defined as:

$$\lambda_n^m(t) = \frac{r_n^m(t)}{R_n(t)}. \tag{1}$$

In this paper, we are interested in video chat transmission. Such chats occur in real time and are extremely sensitive to the end-to-end delay [9]. In this context, to get a better video transmission quality, we must decrease the end-to-end delay as maximum as possible.

In video transmission, the video sequence is divided into a set of frames, which, in turn, are also divided into a set of packets. When a particular UE has a new packet to transmit, it notifies the eNB using a Buffer Status Report (BSR) message. Then, as soon as the eNB receives the notification of data in the UE's buffer, it records this instant and the size of the packet that just arrived in the buffer. Thus, the eNB creates a map with information of each UE buffer status and the Head of Line (HoL) of these queues. From this information, we can derive our metric, given by:

$$\gamma_n^m(t) = \alpha_n(t)\lambda_n^m(t). \tag{2}$$

where $\alpha_n(t)$ is the buffer HoL of user n. The greater the value of $\alpha_n(t)$, the greater the metric of user n, since it has more urgency in transmitting those bytes. The PF metric is used to provide fairness in the allocation. In this sense, our goal is to maximize the metric $\gamma_n^m(t)$, which means that the users with the largest HoL will be prioritized, trying to mitigate the increasing of the HoL and then decreasing the overall end-to-end delay.

IV. Genetic Algorithm Based Approach

Genetic Algorithms were invented by John Holland in the 1970s. Over the years, GA became one of the most famous metaheuristics in problem solving. GA is a population based metaheuristic inspired by biological processes and natural evolution. It is guided by the survival of the fittest principle. In GA, we create a population of individuals. Each of them represents a solution for the particular problem. This is one of the main strength of GA. At each step, GA can deal with a set of solutions rather than with a single one. This approach allows a better exploration of the search space.

The individuals of the population are submitted to a set of genetic operations: representation, initialization, evaluation, selection, recombination and termination. Then, a new population is derived from the older one. The principle of survival of the fittest ensures the evolution of the solutions as the algorithm progresses. Figure 1 shows how GA works.

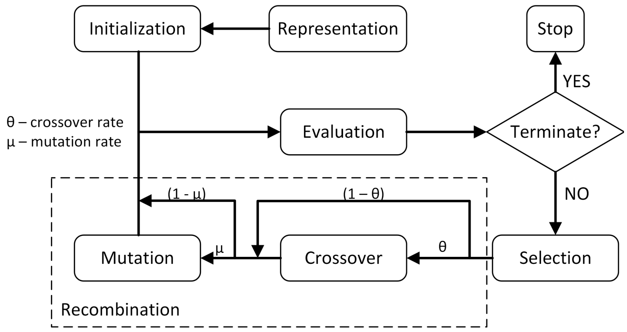

Fig. 1. GA flowchart: how it works.

A. Representation and Initialization

In order to use Genetic Algorithms to find a solution for the resource allocation problem, the first step is to code the solutions into sequences of genes, also known as a chromosome. In LTE resource allocation, we have N users and M resource blocks (RB). The simplest way to code the resource allocation map is considering each resource block as a gene. Each gene can take the value of a particular user, indicating that the RB has been granted to that particular user. Figure 2 illustrates a chromosome example, considering 6 RBs and 5 users.

Fig. 2. GA chromosome coding a feasible scheduling solution.

After establishing the representation, the second step is the initialization of the first population. Differently from the common downlink approaches, which assign a random user to each RB, in the uplink, we have to initiate the chromosome considering the contiguity constraint. Otherwise, we could create a set of infeasible solutions, which requires an extra computational time to correct them.

B. Evaluation

In the evaluation phase, each chromosome is evaluated according to a fitness function. In this paper, the fitness function is given by equation 3:

$$fitness = \sum_n \sum_m x_n^m(t)\gamma_n^m(t) \tag{3}$$

where the variables were defined in Section III.

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C. Selection

In this step, we select the individuals that will produce the offspring, i.e., the individuals of the next generation. The selection should consider the potential of the individual to create good offspring. In this paper, we apply the well known *Tournament* method to select the individuals that will be submitted to recombination. The size of the tournament is set to 2. At the end of each generation, we use the *elitism* technique and select the best individual of the generation to pass to the next generation. This ensures the survival of characteristics of the best solutions during the process.

D. Crossover

The crossover is part of the recombination phase. Crossover mimics the mechanism of reproduction in real world. Two different parents are chosen from the group formed in the selection phase. From these parents, two offspring are derived by recombining parts of the parents chromosome. Due to the peculiarities of resource allocation in LTE uplink, it is not possible to use classical strategies of crossover, which use switching point. These strategies would generate a huge number of infeasible solutions. To solve this problem, we developed a crossover strategy that recombines the parents chromosome, while considering the contiguity constraint. Figure 3 shows an example of this crossover operation.

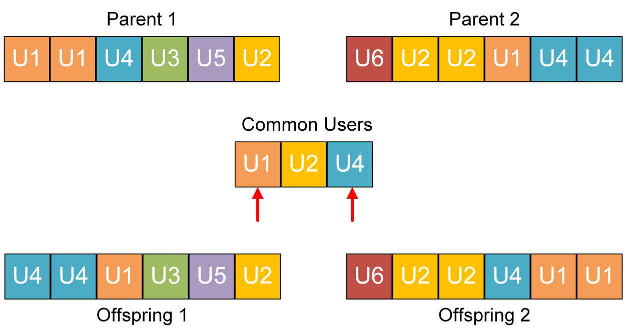

Fig. 3. Crossover operation.

From the chosen parents, we identify which users are present in both chromosomes. In the example of Figure 3, we have users U1, U2 and U4. From this group, we randomly select two users. In the example, we selected U1 and U4. In the next step, there is a permutation: the RBs granted to user U1 are now granted to user U4 and vice versa. The two new chromosomes are the offspring for the next generation.

E. Mutation

The mutation operation is another part of the recombination phase. This operation performs small changes in the chromosome, diversifies the population and prevents the solutions of being trapped in a local optimum. As mentioned for crossover operation, we developed a mutation strategy that respects the contiguity constraint. Figure 4 shows an example of the mutation operation.

Consider the chromosome illustrated in Figure 4. The first step is the identification of the *boundaries* between the RBs granted to different users. In the example, we can identify three

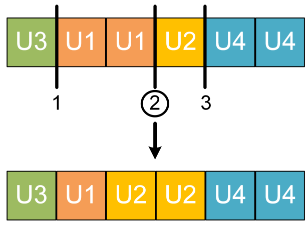

Fig. 4. Mutation operation.

boundaries. In the next step, we randomly choose one of these boundaries. In the example, boundary number 2 was chosen. In the third step, we ”flip a coin” to select one of the users that form boundary number 2. The winner takes the RB of the other user. In Figure 4, user U2 won the challenge and took the RB that was formerly granted to user U1.

F. Termination

As shown in Figure 1, we have to set a termination criterion to end the algorithm. A common end criterion is to define a number of generations (iterations) to terminate the algorithm.

V. Performance Evaluation

A. Simulation Setup

In order to evaluate the performance of the proposed algorithm, we used a simulation environment. Simulations were performed in the Network Simulator 3 (NS-3) [10] version ns-3.19. NS-3 provides an interesting environment to carry out LTE simulations, since the developers already implemented a considerable part of the features of LTE Release 8. In this sense, we implemented and integrated the GA based algorithm into the NS-3 structure. We also implemented the Riding Peaks (RP) and the Recursive Maximum Expansion (RME) algorithms. These algorithms were implemented as proposed by their authors and both are based on the PF metric. The Round Robin (RR) algorithm is already part of the NS-3 official release.

We used a typical outdoor scenario to evaluate the algorithm. We considered a single cell scenario, thus, inter cell interference was not considered in the simulations. On the other hand, we considered the interference among the UEs. Then, we attached a set of UEs into the macro cell. These UEs were randomly deployed into a square area around the eNB. The size of the square area was chosen according to the values of SINR given by the air interface models. The evaluation scenario considered an air interface that behaves according to the COST 231 path loss model and presents a fading loss model for a pedestrian walking at 3 km/h. If we had defined a bigger size of square area, some user could not be in the range of the base station, because of the losses caused by the COST 231 model. The users could move inside the square area according to the Steady State Random Waypoint mobility model. All these models are already implemented in NS-3.

The eNB was connected via the PDN Gateway (PGW) to the Internet. For each UE, a separate remote peer was placed in the Internet and connected to the gateway of the

LTE network (the PGW) via a separate point to point link with over provisioned bandwidth.

Table I summarizes the values of the parameters used in the simulations. For our simulations, we chose the well-known video sequence *akiyo*. This video sequence presents a news reporter talking and it was chosen, since it has similar characteristics with video chat, i.e., a low motion video sequence. We also encoded this video sequence using parameters values close to the ones used in real video chat transmission.

The *akiyo* video sequence presents duration of 12 seconds. Before transmitting the video sequence, we wait for the stabilization of the system, i.e., we wait for all UEs to be attached to the eNB and connected to its remote peer. In this sense, we set the simulation time to 13 seconds.

We used the Evalvid framework [11] to get the files that describe the sending of the video. These files were used as input to the Evalvid module of NS-3. We also used Evalvid to reconstruct the video sequence after the receiving on the destination. GA parameters were chosen in an empirical manner. Further details about the simulation parameters can be found in the NS-3 documentation [10].

TABLE I. SIMULATION PARAMETERS.

eNB antenna model	Isotropic antenna model
eNB TX Power	40 dBm
UE TX Power	30 dBm
Bandwidth	25 RBs (5MHz)
AMC scheme	PiroEW2010
Pathloss model	COST 231
Fading loss model	Pedestrian EPA model 3 km/h
User mobility model	Steady state random waypoint Min speed: 0.8 m/s Max speed: 0.83 m/s Rectangle: 200m x 200m
Position Allocator	Rectangle (200m x 200m)
Simulation time	13 seconds
Video sequence	akiyo (300 frames)
Video resolution	QCIF (176 x 144)
Video info	Bit rate: 180 kbps Frame rate: 25 fps Group of Pictures: 30 MTU: 1460 Bytes Encoder: ffmpeg
GA population size	50
GA tournament size	2
GA elitism size	1
GA crossover rate	0.95
GA mutation rate	0.1
GA generations	20

B. Results

Figure 5 shows the aggregated cell throughput. As expected, the greater the number of users, the greater the sum of the throughput of the UEs. One can see that the four schedulers perform almost equally for up to 40 users in the cell. This occurs because the eNB has sufficient resources to attend the users. However, when we increase the number of users to 60, the resources start to be scarce and the proposed algorithm presents a slightly greater throughput when compared to its competitors.

Although it is important, the throughput information is not enough to indicate the actual quality of the video. In this sense, Figure 6 presents the average delay found in the evaluation. One can note that the GA based algorithm presents smaller values of delay when the network begins to become congested.

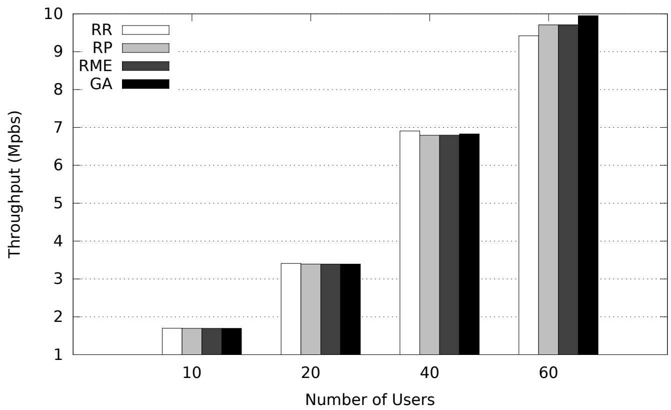

Fig. 5. Aggregated cell throughput.

The superiority of the GA algorithm is more evident when we analyze the Cumulative Distribution Function (CDF) of the end-to-end delay, depicted in Figure 7. It is possible to see that using GA algorithm, almost 90% of the 60 users presented delay up to 250 ms. For RP and RME algorithms this value decrease to 40%, while RR algorithm stays at 7%.

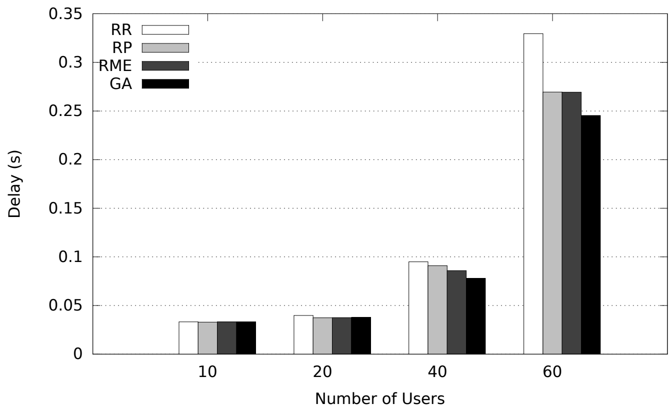

Fig. 6. Average end-to-end delay.

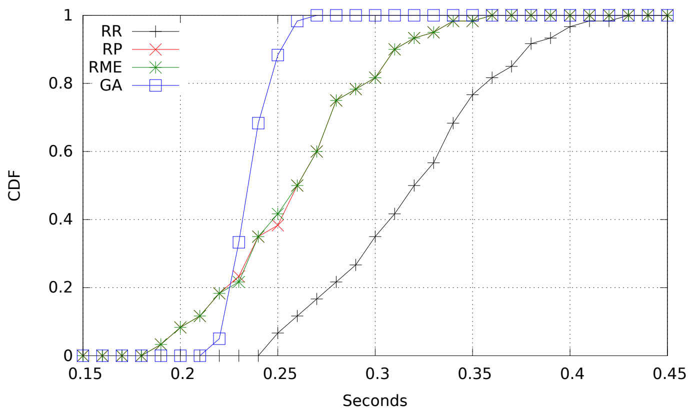

Fig. 7. CDF of the end-to-end delay considering 60 users in the cell.

Another important factor to evaluate video transmission quality is the packet loss ratio. Figure 8 shows the superiority of the GA algorithm in this issue, when compared with the other scheduling algorithms. There are no significative losses until 60 users in cell. Considering 60 users, GA presented the smallest loss rate.

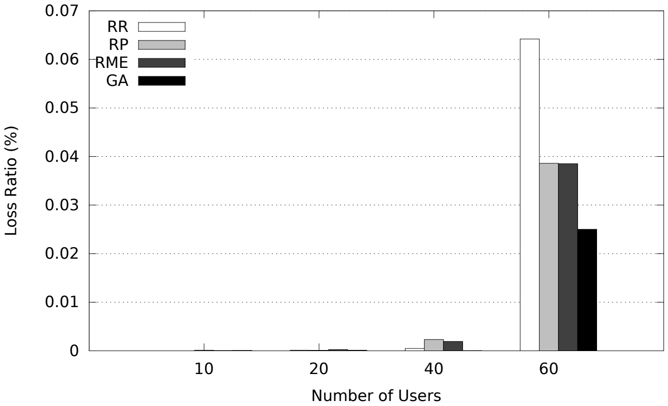

Fig. 8. Average packet loss ratio.

One of the most used objective metrics in evaluation of video transmission quality is the Peak Signal-to-Noise Ratio (PSNR). Figure 9 shows the average PSNR values presented by each scheduling algorithm. One can note that the proposed algorithm also performed better than the other methods.

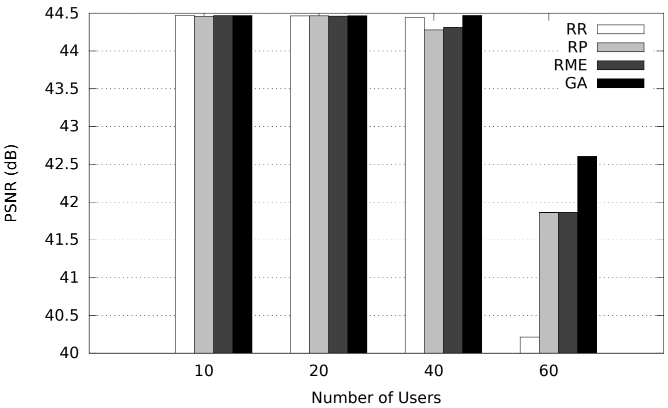

Fig. 9. Average PSNR comparison.

It is worth to say that despite the fact that GA algorithm presents the smallest values of end-to-end delay and packet loss ratio, when we consider the network congested (60 users), the proposed algorithm is not capable of delivering the packets within the QoS requirements limits for this kind of application. In LTE networks, video call should present delay below 150 ms and loss probability of 10^{-3}. This indicates that there is space for improvements in the proposed algorithm.

VI. Conclusions

In this paper, we investigated the resource allocation in LTE uplink. In this sense, we proposed a new algorithm based on Genetic Algorithms. We also defined a metric based on the HoL of the packets in the buffer of the users. We considered a scenario with video chat transmission and evaluated the proposed algorithm using NS-3 and compared its performance against the most known uplink scheduling methods.

From results, we believe that Genetic Algorithms can be an important tool in LTE uplink resource allocation. In our evaluation, the proposed algorithm presented a superior performance in all variables.

However, as future works, we highlight the necessity of a deeper study in the definition of GA parameters such as the size of the population, crossover and mutation rates, etc. Another factor to be studied is the complexity of the GA based algorithm. The optimization of GA parameters may reduce the complexity of the algorithm. It is also important to evaluate the algorithm with a fitness function that considers the QoS requirements for this kind of application in scenarios of mixed traffic.

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