Adaptive Resource Allocation to Multicast Services in LTE Systems

Giuseppe Araniti, Massimo Condoluci, Leonardo Militano, Antonio Iera

Abstract—This paper addresses the design of an adaptive resource allocation policy for the efficient delivery of multicast services in Long Term Evolution (LTE) systems. The proposed approach overcomes the intrinsic inefficiencies of Conventional Multicast Scheme (CMS) related to the different channel quality experienced by the involved users. The basic idea is to split any multicast group into subgroups and apply subgroup-based adaptive modulation and coding schemes, which enable a more efficient exploitation of multi-user diversity. The distribution of users into subgroups is determined by the solution of an optimization problem, aiming to improve the network throughput while guaranteeing fairness among multicast members.

Index Terms—Multicast communication, Cellular networks, Radio spectrum management.

I. INTRODUCTION

Long Term Evolution (LTE) [1] is the emerging standard for wireless communications which will lead the growth of next-to-come mobile broadband services. Among them, multicast services [2] are expected to be promising enablers of an easy access to the ubiquitous multimedia experience through mobile terminals. However, several open research issues still exist for multicast over Orthogonal Frequency Division Multiple Access (OFDMA), mainly related to different quality and data rate requirements of multicast users of the same Multicast Group (MG) and to possible different channel conditions. Generally speaking, User Equipments (UEs) close to the base station can obtain high data rate, while cell-edge users are forced to reduce the data rate to have an error free data reception. Conventional Multicast Scheme (CMS) [3] adopts a conservative approach, which foresees a system data rate bounded by the user with the worst channel conditions. This approach maximizes the fairness among multicast members (i.e., all destinations are served at the same data rate). At the same time, it introduces severe inefficiencies when some users (even if just a few) experience poor channel conditions: (i) the high potential of OFDMA spectrum management is not fully exploited; (ii) a high spectral efficiency is not guaranteed; (iii) users with good channel conditions suffer from a significant “dissatisfaction”.

The aforesaid issues motivated recent researches on the multicast resource allocation in OFDMA-based systems. Many studies propose solutions, based on efficient sub-carrier and power distribution among MGs, to improve the system throughput [4], [5] and fairness [6] when multiple MGs are simultaneously served by the same base station. In managing multicast groups, most of the studies use conservative approaches like CMS, which suffer of the aforementioned inefficiencies. Authors in [7] adopt an Opportunistic Multicast Scheduling (OMS) approach for resource allocation, which foresees that in any given time slot only the “best” portion of users to serve are chosen. In this way, the multiuser diversity is exploited, which may limit the multicast gain. Approaches proposed in [8], [9], [10], and [11] overcome the limitations of the CMS and OMS policies and maximize the throughput by forming, for each MG, multicast subgroups. Allocating the available resources to each subgroup separately, minimizes the negative effects of users with poor channel conditions and allows serving all multicast destinations in each time slot. Unfortunately, a drawback of these approaches is that an acceptable fairness among multicast members is not guaranteed.

The main objective of the present paper is to address the raised issues in the design of policies for multicast resource allocation in the frequency domain of LTE networks. In analogy to [11], we propose a frequency domain scheduler which foresees to (i) split a given MG into subgroups according to the channel quality experienced by users, and (ii) design a subgroup-based Adaptive Modulation and Coding (AMC) mechanism. Besides, we take forth our research by defining a novel Radio Resource Management (RRM) policy, the so-called Minimum Dissatisfaction Index (MDI), able to guarantee a good trade-off between network throughput and user fairness in creating the multicast subgroups. The novel policy is compared with alternative multicasting solutions from the literature, with a keen attention to resource allocation solutions adopting the subgrouping approach. Finally, a novel solution search algorithm able to reduce the computational burden of the proposed multicast scheme is introduced.

II. SYSTEM MODEL

The reference scenario for this paper is a single-cell multicast system where an LTE base station (eNodeB) serves a single MG. LTE represents indeed one of the most promising
wireless technology able to support the growth of high-quality group-oriented service demand. This is obtained by coupling with the enhanced Multimedia Broadcast Multicast Service (eMBMS) [12], which allows an optimized transmission of multicast and broadcast services.

The LTE air interface uses OFDMA in the downlink direction and the available sub-carriers are grouped into Resource Blocks (RBs). In details, each RB is a sub-channel of 180 kHz formed by 12 consecutive and equally spaced sub-carriers, each one lasting 0.5 ms. The total number $N$ of available RBs depends on the system bandwidth configuration [1] and is managed by the packet scheduler, implemented at the eNodeB in three phases (Fig. 1). During the first phase, the scheduler collects information on the schedulable services according to the buffer states. The second phase involves the time domain and consists in selecting the users to serve and meet their QoS constraints (e.g., latency and drop ratio). Finally, the Frequency Domain Packet Scheduler (FDPS) executes the RRM procedures to meet the rate constraints imposed by the time domain scheduler. Similarly to what proposed, for instance, in [13], the time domain scheduler and the frequency domain scheduler operate in two separate phases. This guarantees the QoS service constraints for the users and optimizes the resource allocation and system performance, respectively. Focus of the present paper is the phase in which the FDPS is involved. It receives in input from the time domain scheduler a set of parameters, such as the set of users to serve and the minimum data rate required. The FDPS allocates the RBs according to the Channel Quality Indicator (CQI) feedback forwarded by the UEs every CQI Feedback Cycle (CFC) [1]. In particular, in single-cell mode, the Physical Uplink Control Channel (PUCCH) is exploited in the uplink direction to allow multicast members to send control messages (e.g., the channel state information) to the eNodeB. The CQI is related to the maximum Modulation and Coding Scheme (MCS) supported by the terminal [1]. In LTE systems, $C = 15$ different CQI levels are foreseen. Let $CQI_c = c$ be the $c$-th CQI value (with $c = 1, 2, \ldots, C$) and let $MCS_c$ be the MCS associated to $CQI_c$ (please refer to Table I). A UE experiencing a CQI value equal to $CQI_c$ can successfully demodulate the received signal only if it is served with an MCS equal to $MCS_j$ with $j \leq c$. The attainable data rate, depending on the number of assigned RBs, varies between $b_{cMIN}^{RB}$ and $b_{cMAX}^{RB}$, corresponding to 1 RB and $N$ RBs respectively assigned for each $CQI_c$ level.1

Let $K$ denote the set of multicast users, with $K = |K|$ users forming the multicast group, and let $CQI^k$ be the CQI feedback transmitted by the $k$-th user to the eNodeB. The proposed subgrouping RRM aims at splitting the users into $S$ multicast subgroups and distributing the available RBs based on the collected CQI values. Let $K_c$ and $K_S = |K_S|$ be the user set and the number of UEs in the $s$-th multicast subgroup (with $s = 1, 2, \ldots, S$), respectively; where $\bigcup_{s=1}^{S} K_s = K$ and $\sum_{s=1}^{S} K_s = K$. Considering that each subgroup is characterized by a different MCS, the number of subgroups $S$ varies from 1 to $C$. We assume that all UEs with the same CQI value are associated to the same subgroup, although not necessarily all UEs in a subgroup reported the same CQI value. In particular, the $s$-th subgroup is served with the MCS such that $MCSS = \min \{CQI^k\}$, with $k \in K_S$, i.e., according to the minimum value of CQI experienced by UEs in the subgroup. The CMS policy can be seen as a particular case of subgroup-based resource allocation with a single group activated ($S = 1$). In the next section, the proposed mechanism to split users into subgroups and to associate to each subgroup the number of RBs that maximizes a given cost function will be described in details.

### III. SUBGROUP-BASED RRM ALGORITHM

The RRM proposed in this paper foresees three phases.

1. **CQI collection**: the eNodeB collects the CQI feedbacks from each UE belonging to the multicast group (i.e., $CQI^k \forall k \in K$). Subsequently, it creates the user CQI distribution vector $U = \{u_1, u_2, \ldots, u_c\}$, where $u_c$ is the number of UEs with a CQI value equal to $CQI_c$; thus $\sum_{c=1}^{C} u_c = K$.

2. **Subgroup creation**: the multicast members are split into $S$ subgroups. Based on the $U$ vector, the proposed RRM algorithm determines the subgroup configuration (i.e., number of subgroups $S$ and RBs associated to each subgroup) that: (i) allows to maximize the system capacity; (ii) guarantees that each served UE can successfully demodulate the received signal; (iii) optimizes a given cost function $P$. Three possible definitions of $P$ are given in the next subsections: Maximum Throughput [11], Proportional Fairness [15] and the novel Minimum Dissatisfaction Index. The configuration of the enabled subgroups is described by the RB distribution vector $R = \{r_1, r_2, \ldots, r_C\}$, where the generic $c$-th element of the vector assumes values $0 \leq r_c \leq N$ and $\sum_{c=1}^{C} r_c = N$. If

![Fig. 1. LTE Packet Scheduler block diagram.](image-url)

<table>
<thead>
<tr>
<th>CQI index</th>
<th>Modulation Scheme</th>
<th>Code rate</th>
<th>Spectral Efficiency [bit/Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>QPSK</td>
<td>0.076</td>
<td>0.1523</td>
</tr>
<tr>
<td>2</td>
<td>QPSK</td>
<td>0.120</td>
<td>0.2344</td>
</tr>
<tr>
<td>3</td>
<td>QPSK</td>
<td>0.190</td>
<td>0.3770</td>
</tr>
<tr>
<td>4</td>
<td>QPSK</td>
<td>0.300</td>
<td>0.6016</td>
</tr>
<tr>
<td>5</td>
<td>QPSK</td>
<td>0.440</td>
<td>0.8770</td>
</tr>
<tr>
<td>6</td>
<td>QPSK</td>
<td>0.590</td>
<td>1.1758</td>
</tr>
<tr>
<td>7</td>
<td>16-QAM</td>
<td>0.370</td>
<td>1.4766</td>
</tr>
<tr>
<td>8</td>
<td>16-QAM</td>
<td>0.480</td>
<td>1.9141</td>
</tr>
<tr>
<td>9</td>
<td>16-QAM</td>
<td>0.600</td>
<td>2.4063</td>
</tr>
<tr>
<td>10</td>
<td>64-QAM</td>
<td>0.450</td>
<td>2.7305</td>
</tr>
<tr>
<td>11</td>
<td>64-QAM</td>
<td>0.550</td>
<td>3.3223</td>
</tr>
<tr>
<td>12</td>
<td>64-QAM</td>
<td>0.650</td>
<td>3.9023</td>
</tr>
<tr>
<td>13</td>
<td>64-QAM</td>
<td>0.750</td>
<td>4.5234</td>
</tr>
<tr>
<td>14</td>
<td>64-QAM</td>
<td>0.850</td>
<td>5.1152</td>
</tr>
<tr>
<td>15</td>
<td>64-QAM</td>
<td>0.930</td>
<td>5.5547</td>
</tr>
</tbody>
</table>

1For more details on the admissible data rate values per MCS level refer to Table 7.1.7.2.1-1 in [14].
where $c \neq 0$ the subgroup associated to the $MCS_c$ is enabled and $r_c$ represents the amount of RBs assigned to the subgroup. The number of enabled subgroups, i.e., $S$, is given by the number of items in $\mathcal{R}$ greater than zero.

3. Resource Allocation: depending on the configuration defined by $\mathcal{R}$, all the UEs reporting a CQI value equal to $CQI_c$ will be served with a data rate

$$d_c^R = \max \{ b_i^{MIN} r_i \}, \quad i = 1, 2, \ldots, c$$

meaning that each UE is associated to the subgroup with the closest supported MCS. Equation (1) also guarantees that $d_c^R \leq B_c^{MAX}$.

A. Maximum Throughput

The performance achieved in terms of throughput by the CMS approach is usually poor. This can be improved by adopting a Maximum Throughput (MT) algorithm [11] based on the maximization of a cost function $P$ defined as the Aggregate Data Rate (ADR), that is the sum of data rate values obtained by all the multicast members. A maximization problem can be designed for the MT approach in the addressed scenario as follows:

$$\Pi^{MT} = \arg \max_{\mathcal{R} \in \mathcal{R}} \left\{ \sum_{c=1}^{C} d_c^R u_c \right\}$$

subject to constraints (3a), (3b), and (3c).

B. Proportional Fairness

In practical systems, both throughput and fairness should be considered in resource allocation procedures. Although the CMS approach guarantees the highest fairness, the Proportional Fairness (PF) scheduling can be a suitable policy because it aims at improving the fairness while increasing the multicast throughput. In [15] it was proven that a proportional fairness resource allocation can be achieved through the maximization of the sum of the logarithm of the data rate. Thus, we define the following optimization problem tailored for the PF scheduling:

$$\Pi^{PF} = \arg \max_{\mathcal{R} \in \mathcal{R}} \left\{ \sum_{c=1}^{C} (\log d_c^R) u_c \right\}$$

subject to constraints (3a), (3b), and (3c).

C. Minimum Dissatisfaction Index

The novel RRM policy proposed in this paper is the so-called Minimum Dissatisfaction Index (MDI). This is based on the optimization of a cost function conceived to guarantee an increased throughput with respect to the PF policy without meaningfully affecting the fairness among the multicast members.

The maximum data rate supported by a UE with a CQI equal to $CQI_c$, i.e., $B_c^{MAX}$, is achieved when the UE is served with an MCS equal to $MCS_c$ and all the $N$ RBs are assigned to the user. The weighted difference between the data rate achieved by the UE and this maximum value, i.e., $(B_c^{MAX} - d_c^R) \alpha_c$, is a reasonable parameter to measure the “dissatisfaction” experienced by the multicast destinations. A weighting factor $\alpha_c$ is introduced to maintain the fairness among multicast users. The same philosophy is followed in [16]; however, a new weighting factor, specifically tailored for the reference problem, is designed in our paper. In particular, the proposed weight is $\alpha_c = 1/B_c^{MAX}$; that is, the weight $\alpha_c$ is inversely proportional to the maximum data rate supported by a UE with a CQI equal to $CQI_c$. In details, we define the User Dissatisfaction Index (UDI), $w_c^R$ for a UE served with the subgroup configuration $\mathcal{R}$ and experiencing a CQI value equal to $CQI_c$, as follows:

$$w_c^R = \frac{B_c^{MAX} - d_c^R}{B_c^{MAX}}$$

The minimum dissatisfaction ($w_c^R = 0$) is achieved when the assigned data rate is equal to the maximum allowable one ($d_c^R = B_c^{MAX}$), while we define a cost function $P$ representing the average UDI over the set of $K$ users, named Group Dissatisfaction Index (GDI) as:

$$GDI^R = \frac{1}{K} \sum_{c=1}^{C} w_c^R u_c$$

The proposed RRM aims at selecting the subgroup configuration $\mathcal{R}$ that minimizes the GDI and meets both fairness and throughput requirements:

$$\Pi^{GDI} = \arg \min_{\mathcal{R} \in \mathcal{R}} \left\{ \frac{1}{K} \sum_{c=1}^{C} w_c^R u_c \right\}$$

subject to constraints (3a), (3b), and (3c).

Remark 1. Since the number of configurations assumed by $\mathcal{R}$ is bounded, the optimization problems in (2), (4), and (7) admit at least one solution.

Remark 2. If problems in (2), (4), and (7) admit more than one solution, then a reasonable choice can be any configuration that maximizes the system throughput.

IV. COMPUTATIONAL BURDEN REDUCTION

The search space definition is a key aspect for the computational cost analysis of the proposed RRM algorithms. In fact, the computational time for optimization problems (2), (4), and (7) is tightly related to the number of possible configurations to be analyzed. According to the Exhaustive Search Scheme (ESS) [11], the number of possible configurations assumed by
when $N$ RBs are split among $C$ subgroups (worst case) is bounded by $N^C$, with a consequent prohibitive computational cost. In this section we propose a solution aiming at reducing the search space (and, consequently, the computational costs), named Optimized Search Scheme (OSS). In particular, the benefits in the multicast delivery given by the sub grouping policy are in terms of an increased data rate for the multicast members. However, given two subgroups characterized by $MCS_i$ and $MCS_j$ (with $j > i$) in a generic configuration $R$, this increase is attainable if and only if the data rate of the subgroup with higher-order MCS, i.e., $d_j$, is higher compared to the rate of the subgroup with lower-order MCS, i.e., $d_i$; otherwise, the multicast sub grouping technique does not introduce any gain.

This condition can be expressed by:

$$d_j > d_i \forall i, j : j > i, j \leq C, i = 1, \ldots, j - 1$$

(8)

The idea proposed for the OSS approach is to include in the search set $R$ all the candidate solutions $R$ that satisfy the conditions (3a) and (8). In this way, the overall number of configurations to evaluate is significantly decreased with respect to the ESS, while avoiding to discard any admissible solutions for problems (2), (4), and (7). This result is highlighted in Fig. 2, which shows the number of configurations generated by the ESS and OSS approaches when the number of RBs varies from 2 to 15. As expected, OSS allows to drastically reduce the configurations to be evaluated in the resource allocation when compared to the ESS. In particular, it can be noticed that this gain increases when the number of RBs becomes large. Moreover, by exploiting the frequency-aggregated granularity [14] introduced in LTE, OSS guarantees a reasonable search space dimension when the number of RBs is higher than 15.

By reducing the cardinality of the $R$ set, OSS guarantees a reduction in terms of convergence time for the subgroup formation. Further reductions of the convergence time can also be achieved by considering that $R$ can be generated based on the knowledge of the maximum number of available RB (i.e., $N$) and CQI levels (i.e., $C$), since it does not depend on the user distribution. Consequently, the $R$ set can be pre-computed off-line, and similarly also $d^R$, $\log d^R$, and $e^R_c \forall R \in R$. Only the subgroup creation will, then, be performed on-line just consisting in a product of matrices and in a minimum (or maximum) value search. The consequent computational time reduction allows to complete the subgroup creation within a CFC.

V. PERFORMANCE EVALUATION

The performance evaluation is based on the guidelines defined in [17]. According to the LTE standard, $N = 15$ RBs are available on a 3 MHz bandwidth. The considered multicast group is composed of $K = 100$ subscribers either uniformly distributed within the cell (Uniform scenario) or distributed in limited areas as in a typical on-campus environment (Sparse scenario) with pedestrian mobility [18]. The channel conditions for each UE are evaluated in terms of the SINR experienced over each subcarrier when path-loss, slow and fast fading affect the signal reception. The effective SINR, estimated according to the Exponential Effective SIR Mapping [19], is mapped onto the CQI level ensuring a Block Error Rate smaller than 10% [20]. The results shown are obtained with a 95% confidence interval. Main simulation parameters are listed in Table II. Unless differently stated, in the conducted simulation campaigns we considered as the minimum data rate for each enabled subgroup $b_c = b_c^{MIN}$.

![Fig. 2. Comparison of ESS and OSS approaches.](image)

The first evaluation is in terms of ADR, see Fig. 3(a). Subgrouping-based policies outperform the results achieved by CMS in both Uniform and Sparse scenarios. Being strongly affected by cell-edge users with poor channel conditions, CMS provides the lowest ADR, i.e., 42 Mbps on average. As expected, MT reaches the highest value, that is 196 Mbps on average. A small reduction in terms of ADR is obtained with MDI, 161 Mbps on average, whereas PF guarantees an average ADR equal to 132 Mbps. Based on the results, it can be stated that MDI allows an ADR gain equal to 21% with respect to PF.

The second evaluation is in terms of user Fairness Index (FI) [16], defined as:

$$FI = \frac{\left(\sum_{c=1}^{15} d_c u_c\right)^2}{K \left(\sum_{c=1}^{15} d^2_c u_c\right)}$$

(9)

where $FI \in [1/K, 1]$; $FI = 1$ is the maximum fairness, achieved when all UEs are served with the same data rate. As expected, the obtained behaviour is somewhat dual to
ADR results. The maximum fairness is reached by CMS; MT has a very low FI value (i.e., 0.48) whereas PF offers an FI equal to 0.81. Particularly interesting results are obtained by MDI, which reaches a FI value close to PF, that is 0.78 on average, with a difference in fairness of about 3% only between the two solutions. Hence, MDI offers an improved ADR compared to PF without meaningfully affecting the user fairness. As a further analysis, we comment on the GDI. As plotted in Fig. 3(c), the MDI solution guarantees the minimum GDI, 0.58 on average, while the GDI values for CMS, MT, and PF are 0.79, 0.67 and 0.63, respectively. Finally, we consider the Transmitted to Received Data Ratio, measured as ratio between the number of bits transmitted over the radio channel (i.e., the channel data rate) and the mean number of bit successfully received by the multicast members (i.e., user throughput). From Fig. 3(d) one can observe that the CMS is the most performing policy in terms of Transmitted to Received Data Ratio, since all the bits transmitted by the base station are received by all the multicast members. On the contrary, the MT is the poorest scheme with a performance equal to 0.47, on average, which means that a high percentage of the transmitted bits is successfully received by only a restricted portion of multicast destinations. Finally, the Transmitted to Received Data Ratio of PF and MDI is equal to 0.75 and 0.77, respectively. This underlines that the improvements obtained by the proposed MDI scheme are achieved without affecting

![Fig. 3. Performance evaluation for addressed scenarios.](image)

![Fig. 4. Network coverage in the Sparse scenario.](image)

The results of a further performance evaluation study are plotted in Fig. 4, where the focus is on the network coverage of the Sparse scenario. For a given data rate \( x \), the coverage is defined as the percentage of UEs served with a data rate equal or lower than \( x \), which can similarly be understood as the probability of a UE to be served with a data rate equal or lower than \( x \). It emerges that the CMS serves all the UEs with the same data rate. By using PF and MDI only the 22% and the 25% of users, respectively, experiences a data rate lower than CMS, whereas for the remaining portion
of UEs it is higher. With the MT approach the mentioned percentage values become 55% and 45%; this demonstrates that MT enhances the system throughput at the expenses of fairness. While the MT slowly approaches to full coverage, the steeper slope of the MDI and PF curves demonstrates that multicast members achieve similar data rates. MDI reaches a better performance in terms of ADR than PF as it allows a higher data rate to multicast members.

The next study case analyzes the situation in which QoS constraints are set in terms of minimum data rate required for the activated subgroups, i.e., \( b_a \), where \( b_a > b_a^{MIN} \). The results plotted in Figure 5, report the ADR, the FI, and the Transmitted to Received Data Ratio for the four resource allocation solutions where a variable \( b_c \) in the range \([10 – 120]\) kbps is considered (x-axis in the plots). As shown, the relation among the solutions is still confirmed. MT introduces the highest ADR (ranging from 206 to 161 Mbps), but lowest FI (0.48 on average) and Transmitted to Received Data Ratio (i.e., 0.46). CMS always guarantees FI and Transmitted to Received Data Ratio equal to 1, but with a very low ADR. Finally, the novel MDI solution has a better ADR w.r.t PF, where the gain varies from 22%, when \( b_c \) is set to 20 kbps, to 4%, when \( b_c \) is 120 kbps, but achieves almost the same FI and Transmitted to Received Data Ratio performance (differences range from 1% to 3% ).

To conclude the performance evaluation, Table III offers a comparison between OMS and subgrouping approaches. In particular, OMS is implemented in association with ADR maximization and GDI minimization policies for the selection of the portion of served UEs in a given time slot. The difference in terms of mean throughput experienced by the multicast users is almost equal to 115 kbps, on average, whereas the differences in terms of FI is less than 4%. The cost for OMS to reach this performance is the reduction in the number of served UEs in a given CFC (61.9% on average). Differently, the subgrouping technique always serves the whole set of multicast destinations, with a consequent better exploitation of the multicast gain. Although OMS and subgrouping could offer similar performance during several CFCs, OMS policies require an additional data coding (e.g., fountain or erasure codes) and a consequent overhead to guarantee a reliable data delivery, which is instead not the case for subgrouping.

**VI. Conclusion**

In this paper we proposed a subgroup-based resource allocation scheme for LTE multicast systems. We analyzed the subgroup creation according to MT and PF approaches and enhanced the performance by defining a new algorithm, the MDI, which optimizes a new parameter, the GDI. The results confirm that MDI introduces a similar degree of fairness among users compared to PF while improving the multicast throughput. A future enhancement may be the study of the proposed policy in multi-carrier systems based on carrier aggregation, such as LTE-Advanced networks.

**References**


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