A QUALITY-OF-EXPERIENCE DRIVEN BIDDING GAME FOR UPLINK VIDEO TRANSMISSION IN NEXT GENERATION MOBILE NETWORKS

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ABSTRACT

Centralized approaches to solve resource allocation problems for wireless real-time multimedia communications have been intensively studied but require the availability of meta information about the multimedia content and channel information of all users. In this paper, we propose a Quality of Experience (QoE) driven bidding game for de-centralized uplink resource allocation among multiple mobile video producers. Different from previous works, the price per resource unit is defined on a Mean Opinion Score (MOS) scale and users bid for the resources that maximize their own utility function. Simulations in an LTE environment show the benefits of our distributed approach in terms of convergence time and QoE performance, compared to a centralized greedy scheme and a state-of-the-art game-theoretic approach.

Index Terms— Quality of Experience, LTE, game theory, resource allocation.

1. INTRODUCTION

With the recent proliferation of high-quality video recording capabilities of mobile phones, a vast increase in uplink video traffic over mobile networks is expected. Although the capacities of next generation mobile networks (e.g., 3GPP Long Term Evolution (LTE)) are increasing as well, mobile operators face the problem of allocating limited resources to multiple users. The objective of a mobile operator is to maximize the user satisfaction or QoE at minimum cost. Centralized optimization requires information about the video characteristics and the channel state of each user. In situations with rapidly changing utility functions, for instance when uploading videos with high temporal or spatial activity, the amount of control information required to perform the centralized optimization in real-time becomes critical.

The real-time constraints for multimedia applications and the convergence time of any bidding process have prevented the practical application of de-centralized approaches for multi-user multimedia resource allocation [1]. Game theory, nevertheless, has attracted significant attention in the literature for solving resource allocation problems among multiple selfish competing users. Its application to congestion control [2] or to distributed schemes for routing and resource allocation in multi-hop wireless networks [3] have been thoroughly studied. Specifically, for multimedia communications, a few articles have also considered the framework of game theory to address different problems of resource allocation. The maximization of the sum of users' expected video quality is considered in [4] using a pricing-based resource allocation mechanism which, however, doesn't guarantee convergence. Maximizing the system utility has also been analyzed for a cooperative environment within the framework of bargaining in [5], but this solution cannot be applied in the case of individual selfish users who are competing for some expensive resources. In [6], the authors make use of Ausubel's ascending-bid auction [7] to fairly allocate rate among different users. To cope with the greediness of the users, a price which is linearly proportional to the rate is considered for each user. The proposed scheme in [6] has two main limitations. First, the resulting allocation does not result in the maximization of the sum of utilities of all users, which indicates a loss in performance. Second, it doesn't provide a convergence bound for the proposed auction, especially when the number of users in the system increases.

In this paper, we consider the problem of uplink resource allocation for real-time multimedia communications over next generation mobile networks. Different from previous works, we propose a QoE-driven bidding game where the resource price is defined as a function of the user satisfaction. Each user tries to maximize his own utility function and pays in proportion of his perceived quality. This makes our approach fundamentally different from other schemes where payment is determined by the user data rate [8]. We show that when users are charged based on their allocated data rates, more demanding users in terms of their application requirements will be punished. This leads to performance which is usually not optimal with respect to user perceived quality for multimedia applications. We additionally address the convergence and optimality issues which have mainly hindered the research in designing distributed resource allocation schemes for real-time multimedia communications. We show that there exists, using game-theoretic methods, a distributed scheme that guarantees convergence and that provides a near-optimal performance compared to a centralized solution which is aware of the user utilities.

The rest of the paper is organized as follows. In the next section we describe our application scenario. We then formulate our optimization problem and describe our de-centralized QoE-driven resource allocation auction in Section 3. Section 4 compares our approach to state-of-the-art centralized and game-theoretic approaches and Section 5 concludes the paper.

2. QOE-DRIVEN RESOURCE ALLOCATION

2.1. Application scenario

We consider multiple mobile users which are competing for resources to upstream their video content to a base station (Figure 1). In a centralized QoE-based optimization approach, the base station

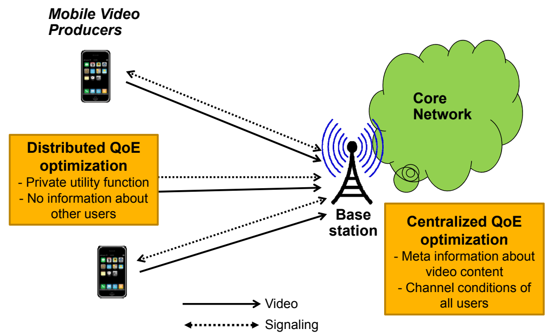

Fig. 1: Schematic depiction of centralized and distributed QoE-based optimization.

is aware of the video characteristics and of the channel conditions of the different users and can optimally allocate the resources among the video producers. In an uplink scenario, where multiple users upstream their video, each user, however, only knows its own utility function and the base station is unaware of the users' utilities. A distributed QoE-based optimization can be used to allocate the resources among the mobile users.

2.2. LTE model

In this paper, we make use of the LTE uplink model originally proposed in [9]. The allocation problem is to assign the resources (physical resource blocks (PRBs)) to the different video producers. We consider a long-term radio link layer model with optimization periods in the order of seconds. We do not take into account small-scale channel effects but rather consider a long-term channel quality indicator (CQI) for each mobile user that follows the typical CQI distribution in an urban macrocell [10]. Hence, the PRBs are considered as indistinguishable items and our objective is to determine the amount of resources (i.e., number of PRBs) assigned to each user in each optimization cycle. This allows us to integrate our QoE-based optimization on top of the state-of-the-art schedulers for LTE uplink. Also, we assume that each user equipment (UE) knows its own channel conditions. We use the link layer model from the 3GPP LTE recommendations [11] to determine the achievable throughput per PRB for a given Signal-to-Noise ratio.

2.3. Application model

We express the user satisfaction or QoE for real-time video streaming on a Mean Opinion Score (MOS) scale [12]. The utility function for video streaming is a function of the application data rate R [13], $U = MOS(R)$. We assume a simple linear mapping between the MOS and the peak signal-to-noise ratio (PSNR) [14]. Please note that more complex mappings could be used. MOS can take on any value between 1.0 (25 dB) and 4.5 (40 dB), which represent the worst and best QoE, respectively.

The UEs' valuation (MOS value) of a given PRB will change depending on two factors: 1) Each user exhibits a different MOS-Rate characteristic depending on its video content. 2) The available data rate depends on the channel conditions. For each additional PRB that a UE gets, the additional improvement in quality decreases. In a multi-user scenario where each user is upstreaming a different video, the transmission rates of the different users can be determined such that the overall QoE is maximized.

3. GAME-THEORETIC AND QOE-DRIVEN RESOURCE ALLOCATION

3.1. Optimization problem

We consider a setting where there are n PRBs available for the use of m UEs. Each user i has a valuation (utility) $v_i(x_i)$ when it gets allocated x_i PRBs, which represents its perceived quality or QoE. The goal is to find an allocation $\underline{x} = [x_1, x_2, \dots, x_m]$ which maximizes the sum of valuations over all the users, or in other terms, which maximizes the overall QoE. We can write this optimization problem as follows:

$$\begin{aligned} \underset{\underline{x}}{\text{argmax}} \quad & \sum_{i=1}^{m} v_i(x_i) \\ \text{subject to} \quad & \sum_{i=1}^{m} x_i \leq n \end{aligned} \tag{1}$$

The optimal solution for (1) can be determined if the valuations of all users are available to a central controller. In the de-centralized resource allocation scheme, the valuation functions are considered as private information. We additionally denote by $p_i(x_i)$ the total price the UE i has to pay for x_i PRBs. The price per PRB is set by the seller (e.g., base station) and represents a target level of user satisfaction for that resource. We define the payoff function for user i as $v_i(x_i) - p_i(x_i)$. Each user has the objective to maximize this function. In other words, each UE will bid for the PRB that provides him an utility increase which is larger than the advertised price. Each UE's local optimization problem can be thus written as:

$$\max_{x_i} \quad v_i(x_i) - p_i(x_i) \tag{2}$$

3.2. Auction

In order to specify the auction, we define the *marginal price* q as the price of one PRB. First, the seller sets a high starting marginal price q^0, a marginal price step size Δq and initializes the iteration index t to 0. The initial allocation is $\underline{x} = [0, 0, \dots, 0]$. The auction is described in Algorithm 1.

In each iteration, the seller broadcasts the current marginal price q^t to all participating UEs. The seller then collects the bids $\underline{b}_t = [b_{1,t}, \dots, b_{m,t}]$ from all the UEs who want to buy PRBs at the current marginal price, where $b_{i,t}$ is the number of PRBs that UE i wants to buy in iteration t. The UEs will decide to buy one or more PRBs if this results in the maximization of their payoff function (2). Therefore, in every iteration, each UE i will calculate its *marginal value* $w_i(x_i) = v_i(x_i + 1) - v_i(x_i)$, which is the additional improvement in MOS it gets with one additional PRB. In the truthful bidding case, a UE will bid as soon as its marginal value exceeds the marginal price, i.e., when $w_i(x_i) \geq q^t$. A user can bid for several PRBs if these PRBs all give him a marginal value which exceeds the marginal price. We denote the set of UEs which want at least one PRB in iteration t as K_t. If there are enough PRBs left, then each UE $k \in K_t$ gets allocated the number of PRBs it wants. If there are not enough PRBs left (i.e., in the last iteration), then the remaining PRBs are allocated in a round robin way. This means that the first

Algorithm 1 Proposed auction

Initialize $n' = n$;
loop
  Broadcast current marginal price q^t;
  Collect bids $\underline{b}_t = [b_{1,t}, \ldots, b_{m,t}]$ from UEs K_t;
  if $n' - \sum_i b_i \geq 0$ **then**
    for $k \in K_t$ **do**
      $x_k = x_k + b_{k,t}; \quad n' = n' - b_{k,t};$
    end for
  else
    Allocate remaining PRBs in a round robin way;
  end if
  if $n' = 0$ **or** $q^t = 0$ **then**
    break;
  end if
  $q^{t+1} = q^t - \Delta q; \quad t = t + 1;$
end loop
Calculate price $p_i(x_i)$ for each user;
Output allocation $\underline{x}$;

user to be served is chosen randomly in K_t, and then the remaining PRBs are allocated iteratively among the users from the set K_t who still want a PRB, until there are no more PRBs to be allocated.

At the end of each iteration, the seller checks if all PRBs have been sold or if the marginal price has reached 0, in which case the auction is terminated. If not, the marginal price is decreased by the step size Δq and the clock index t is incremented. Please note that at a marginal price of 0, all remaining PRBs are sold to the UEs who have not reached their maximum valuation yet, because all UEs will bid for the number of PRBs they need to get their maximum valuation. The auction is guaranteed to converge as the marginal price is decreasing and is bounded by 0. The worst case number of iterations is thus $\lfloor q^0/\Delta q \rfloor + 1$.

Finally the seller evaluates the total price $p_i(x_i)$ each UE i has to pay with the auction history as follows:

$$p_i(x_i) = \sum_t b_{i,t} \cdot q^t \tag{3}$$

3.3. User pricing

Traditionally, users are charged in proportion of their data rates [8]. Let λ_i denote the charge per unit rate for user i and $r_i(x_i)$ its achievable data rate from x_i PRBs, then the user payment is equal to $\lambda_i \cdot r_i(x_i)$.

In contrast, in our work payment is determined on the MOS scale. In other words, users are not directly charged for their allocated PRBs but based on their degree of satisfaction resulting from these resources. The user payment function in (3) represents the sum of prices of the individual PRBs a user bought during the game. The seller defines a charge per PRB q^t which represents the target quality improvement at iteration t. A user will bid for a resource block if his gain in utility is larger than the current target improvement.

In fact, a mobile operator can benefit from this game by charging (in terms of currency) based on the user perceived quality rather than based on the user data rate. Let φ_i denote the price per MOS for user i which is set apriori by the operator and is known to the user. User i will be charged for the outcome of one optimization round an amount equal to $\varphi_i \cdot \sum_t b_{i,t} \cdot q^t$.

4. SIMULATION RESULTS

To evaluate our de-centralized resource allocation scheme, we compare our proposed descending auction with two other algorithms for multimedia resource allocation: a centralized greedy algorithm [15] which finds an allocation close to the optimum by searching on the boundary of the utility space and an ascending auction proposed in [6], where each user has the objective to maximize its video quality and at the same time minimize the rate it needs to stream the video, as the pricing of the game is based on the data rate. The performance evaluation criteria is based both on the number of iterations they need to converge and on the MOS performance they can achieve.

Multiple mobile users compete for resources in a simulated LTE environment. We use a pool of 25 different videos encoded in QCIF format with 30 frames/sec using the H.264/AVC video codec. Each user is streaming a different QCIF video chosen randomly from the pool of videos. The available resources consist of 25 PRBs which is equivalent to 5 Mhz bandwidth in LTE. The simulation results are averaged over 100 runs with varying channel conditions. The auction parameters $\Delta q = 0.1$ and $q^0 = 0.5$ are heuristically chosen in order to balance the convergence time and QoE performance, which are competing metrics. Analysis of these parameters is left for future work.

Figure 2 shows the mean number of iterations the three different algorithms need to converge while varying the number of users. We observe that the number of iterations for our proposed auction is bounded by $\lfloor q^0/\Delta q \rfloor + 1 = 6$. Additionally, the mean number of iterations for the proposed auction decreases as the number of users grows. In Chen et al.'s [6] ascending auction, the mean number of iterations diverges when the number of users increases, due to the ascending price property of their auction. Compared to the two other schemes, our proposed auction provides a reduction in the number of iterations particularly for a large number of users in the cell.

Figure 3 shows the mean MOS as a function of the number of users for the three algorithms. The performance of the proposed descending auction is very close to that of the centralized greedy algorithm, which represents the maximum achievable MOS in real time. The maximum gap between the two curves is equal to 0.026 in absolute MOS value which represents a decrease of 0.7% compared to the centralized greedy algorithm. Chen et al.'s ascending auction doesn't maximize the sum of valuations but considers the rate allocated to each user as the price. As a result, it shows a considerable gap in MOS performance compared to the centralized solution.

4.1. Individual performance

We study the individual MOS performance of each user for the three schemes. We consider 10 users, each upstreaming a different video for a system bandwidth of 5 MHz (25 PRBs). Figure 4 shows the average utility of each user over 100 simulation runs. Our proposed auction provides an individual MOS performance close to the centralized greedy algorithm. The centralized algorithm will provide the *Bus* and *Football* test sequences, which are more demanding sequences, with more resources. The proposed auction, however, treats the different sequences equally that fall in the same Δq range. This results in a small drop in MOS performance for these two users,

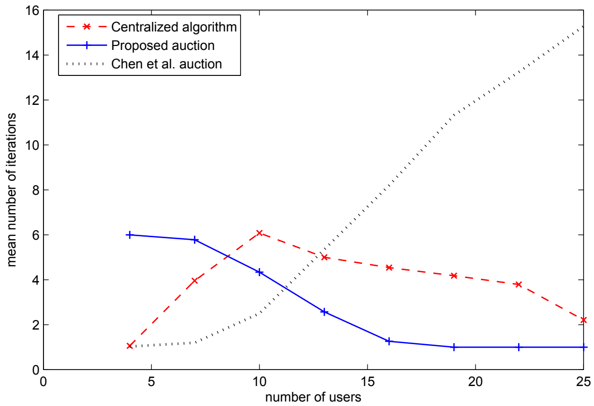

Fig. 2: Number of iterations for $n = 25$ PRBs

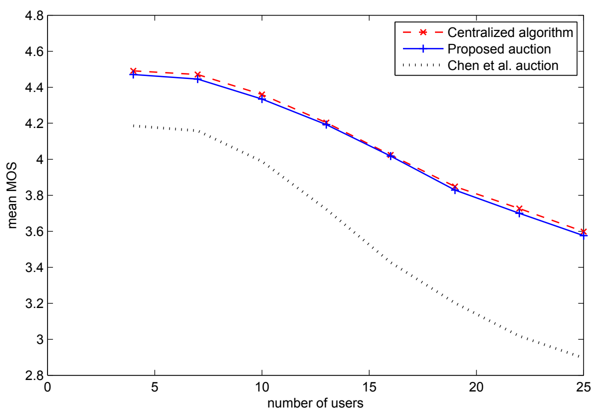

Fig. 3: MOS performance for $n = 25$ PRBs

compensated by a slightly higher MOS performance for other users. Meanwhile, the auction model from Chen et al. [6] shows a substantial drop in MOS for the two demanding *Bus* and *Football* test sequences. As the rate is considered as the price a user has to pay, more demanding users suffer most in perceived video quality.

5. CONCLUSION

In this paper, we address the problem of de-centralized resource allocation for real-time uplink video transmission over next generation mobile networks. Different from the centralized resource allocation problem, the utility function of each user is not available to a centralized controller. We propose a QoE-driven and game-theoretic approach that reaches a level of satisfaction close to the optimal one achieved by a centralized scheme. Different from previous works, the pricing reflects the user perceived video quality rather than the application data rate. Also, different from state-of-the-art work in game-theory, the fast convergence properties of our approach indicate its applicability for real-time multimedia communications. Simulation results show both a substantial reduction in convergence time and a sustainable perceived quality when compared to a centralized scheme.

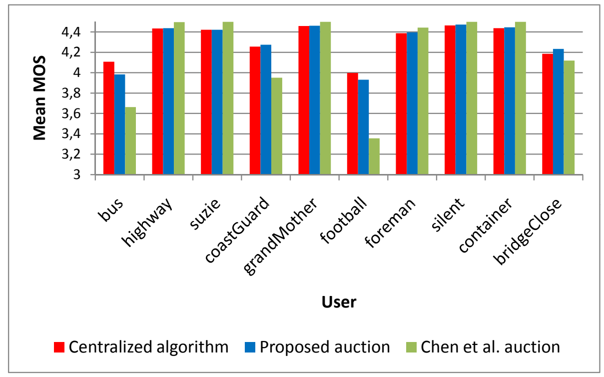

Fig. 4: Individual performance comparison for $n = 25$ PRBs

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