Fast converging auction-based resource allocation for QoE-driven wireless video streaming

Damien Schroeder
Chair of Media Technology
TU München, Germany
email: damien.schroeder@tum.de

Ali El Essaili
Ericsson GmbH, Germany
email: ali.el.essaili@ericsson.com

Eckehard Steinbach
Chair of Media Technology
TU München, Germany
email: eckehard.steinbach@tum.de

***Abstract*—Quality-of-Experience (QoE)-driven centralized resource allocation approaches for video streaming have been studied intensively but require the availability of utility information about the video content and channel conditions of all users at the central optimization entity to perform an optimal allocation. On the other hand, the practical application of game-theory-based decentralized resource allocation approaches for potentially selfish users has been limited so far. This is mainly because the varying network conditions and the delay constraints for wireless multimedia communications require low-complexity methods with fast convergence. We propose an auction-based radio resource allocation method which is shown to converge within a bounded number of iterations. The achieved allocation maximizes the average QoE over all users, while the users are maximizing their own payoff. The users pay a price for the requested resources which is defined on the utility scale. The proposed game-theory framework is compatible with cross-layer optimization approaches, as the resources are abstracted to provide an interface between the application and the lower layers. We implement the proposed resource allocation scheme in a simulated LTE uplink environment with multiple video streaming users. Experimental results confirm the derived properties and additionally show that, unlike state-of-the-art decentralized resource allocation schemes, our proposed auction is scalable, as the number of iterations to converge decreases with an increasing number of participating users.**

I. Introduction

Video represents most of the internet traffic nowadays, and is expected to further grow in the next years, especially in mobile networks [1]. In order to keep up with the increasing traffic, resource allocation among multiple users is an important part of network management and has been extensively studied [2-4][7-14], especially for multimedia communications, which exhibit specific particularities (e.g., delay constraints, content-dependent utility functions, etc.).

Early resource allocation work considered throughput and various Quality-of-Service (QoS) metrics as the utility metric, e.g., [2]. Later approaches have then started considering user satisfaction or Quality-of-Experience (QoE) as the utility [3]. Similarly, users have been traditionally charged in proportion to their data rates [4], but a paradigm shift can be observed, as more and more users are now paying for a service [5].

QoE-based resource allocation typically relies on cross-layer optimization mechanisms, where information is exchanged between application and lower layers [6]. The utility information as well as the network information generally need to be centrally available at the resource allocation entity in order to solve an optimization problem [7]. Gathering this information in real time, however, can be challenging [8], e.g., in the uplink of a wireless network, where only the users know their utility function. Therefore, decentralized resource allocation schemes based on game theory have been developed (e.g., [9], [10], [11]), which are able to cope with independent, potentially selfish users, who are interested in maximizing their own utility.

In the case of wireless networks, the changing channel conditions require the resource allocation to be performed periodically. Thus, the practical usefulness of game theory based methods has been limited so far due to their convergence time [12] and due to real-time constraints for multimedia applications. The convergence of the resource allocation method is additionally challenged when the number of users in the system is growing [13].

In this paper, we tackle the problem of convergence time for decentralized resource allocation. We propose an auction-based resource allocation and derive an upper bound on the number of iterations needed for convergence. We further show that the auction scales to a large number of users as the number of iterations decreases when the number of users in the system increases. Furthermore, we make the auction compatible with cross-layer optimization approaches, by defining the price per resource in proportion to the utility a user achieves with that resource and by abstracting the radio resources to items, which makes the method independent of the underlying wireless technology. In addition, the proposed resource allocation maximizes the overall QoE and is shown to be cheat-proof.

This paper builds on our preliminary work in [14] where we presented a descending auction for resource allocation. The main added contributions are as follows. Conceptually, we abstract the resource units as items to make the resource allocation method independent of the underlying wireless technology and make the method compatible with cross-layer optimization approaches. We introduce a new payment rule in the auction based on the *Vickrey-Clarke-Groves* (VCG) mechanism. Analytically, we show that the proposed resource allocation method maximizes the QoE. In the simulations, we show the influence of the auction parameters and we compare our proposed method with state-of-the-art methods.

The rest of the paper is organized as follows: Related work is discussed in Section II. The system model is presented in Section III and the auction-based resource allocation is proposed in Section IV. Experimental results are presented in Section V. Section VI concludes the paper.

II. RELATED WORK

Game theory has been widely used to solve engineering problems with decentralized entities. In the field of resource allocation for multimedia communications, decentralized resource allocation for selfish multimedia users has been studied. [9] proposes a cheat-proof ascending-bid auction where a price per bitrate-unit is increased in each iteration of the auction until an equilibrium where the users' demand matches the available resources is reached. When the number of users increases, the equilibrium price increases as well, because each user has to reduce his/her demand. This leads to an increase in the number of iterations. The proposed ascending-bid auction achieves a proportional fair allocation. The solution relies on a specific utility model that enables to find a closed-form solution to the bidding problem, but no general solution is proposed. Authors in [10] reuse a similar framework with a specific utility-distortion model which leads to a special closed-form solution. A transfer payment between the users is introduced as in [8], so that users can buy or sell bitrate from each other. With an iterative process where 4 messages per user have to be exchanged with the central entity each iteration, the proposed resource allocation scheme achieves maximization of the sum of users' utilities. The monetary transfers between users, however, are not feasible in a practical scenario. Authors in [11] study the impact of an α-fairness criterion on the resource allocation performance and derive a utility loss bound depending on α, compared to a maximization of the sum of utilities. A non-cheat-proof bidding game which can implement the α-fairness is proposed.

A common limitation to the three bidding based schemes [9], [10], [11] is that, for a fixed set of parameters, the number of iterations needed to converge increases with the number of users who are participating. Another limitation of these schemes is that the price during the bidding is defined in proportion to the bitrate. First, this is not transparent to the users, as they are not directly aware of the underlying bitrate of their video. The price should be related to the user satisfaction, which a user experiences him/herself, in order to be acceptable to a user. Second, a price defined in proportion to the bitrate binds the bitrate to the actual auction-based resource allocation mechanism. This means that the bitrate is bound to be the resource which is allocated among the users. However, while the utility of a multimedia application directly depends on the application bitrate, in wireless communications, the actual bitrate achieved with a portion of the radio resources depends on the current channel conditions of a specific user. Thus, the auction resources for wireless communications should not be defined as bitrate, but as a portion of the radio resources. With a price defined in proportion to the utility, the auction is independent of the bitrate. In contrast to these papers, our proposed approach:

- has a bounded number of iterations and has a decreasing number of iterations when the number of users grows,
- defines the price for the resources on the utility scale and abstracts the resources to items (portions of the radio resources), both of which are necessary conditions for making the auction-based resource allocation compatible with cross-layer optimization approaches.

III. SYSTEM MODEL

In this section, we first present the game-theory framework with abstracted resources and then introduce the underlying application and radio model. Eventually, we review the definition of a VCG mechanism.

A. Game-theory framework

We consider a system where the resources are divided into a set $\mathcal{N}$ of n identical items. The items are sold to a set $\mathcal{B}$ of m users. A user i achieves a perceived video quality or QoE $v_i(x_i)$ when it gets allocated x_i items. In the scope of the game-theory framework, we denote a user's QoE as the *utility* as a more general term.

We assume that the users have concave utility functions, i.e.:

$$v_i(j+1)-v_i(j) \leq v_i(j)-v_i(j-1) \text{ for all } j \in \{1,\dots,n-1\} \tag{1}$$

Rate-distortion theory proves that the rate-distortion function of a lossy compressed signal is convex [15]. In general, a utility function can be expressed as an inverse function of the distortion and is thus concave.

Each user has to pay a price p_i for the items it gets allocated, which is defined on the same scale as the utility. Therefore, the payoff U_i of each user is the difference of its utility and the price that has to be paid.

$$U_i = v_i - p_i \tag{2}$$

An assumption of game theory is that each user tries to maximize its payoff.

B. Application model

We consider a single LTE cell where the radio resources have to be shared among multiple uplink video streaming users. The uplink scenario is chosen as an illustration of a case where the base station, responsible for the resource allocation, is not aware of the users' utilities. Both the QoE functions of each user at the application layer and the channel conditions of each user at the physical layer are taken into account in the decentralized cross-layer optimization in order to maximize the overall QoE.

The QoE functions used in this work represent the users' perceived video quality. A QoE function can be expressed (as in [16]) as a function of the application bitrate R:

$$v = f(R), \quad f: \mathcal{R} \rightarrow \mathcal{U} \tag{3}$$

where $\mathcal{R}$ is the set of possible bitrates and $\mathcal{U} = [0, 100]$, with 0 representing the worst video quality and 100 the best video quality. We evaluate the perceived video quality with a state-of-the-art objective quality metric which takes into account the video content [17]. We use a sequence-level parametric model [18] to interpolate the quality-bitrate curves. Fig. 1 shows an example of perceived video quality curves as a

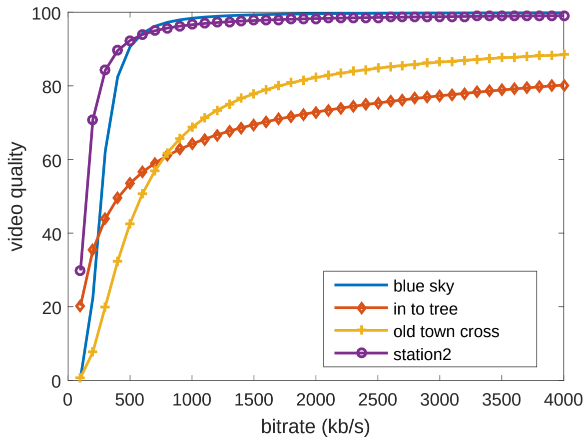


Fig. 1: Example of four video quality curves as a function of the bitrate.

function of the bitrate for four different videos encoded with the HEVC codec [19] at full HD resolution (1920×1080 pixels).

C. Radio model

We consider a long-term radio layer model with resource allocation periods of one second [16], [20]. That is, we do not take into account short-term channel variations but rather consider an average channel quality for each user over the resource allocation period. We are allocating portions α_i of the resources, with $\sum_{i \in \mathcal{B}} \alpha_i \leq 1$, which is a level above the scheduling. This allows us to integrate our resource allocation on top of state-of-the-art schedulers without the need to modify the existing scheduling mechanisms. The current data rate R_i for user i is calculated depending on its resource share α_i and its maximum achievable data rate $R_{\max,i}$ for this resource allocation period if all resources would be allocated to user i.

$$R_i = \alpha_i R_{\max,i} \quad 0 \leq \alpha_i \leq 1 \quad \forall i \in \mathcal{B} \tag{4}$$

The resource share is a portion of the total available resources over the resource allocation period. In the case of LTE, this corresponds to a portion of the total available resource blocks over the resource allocation period.

The granularity of the resource allocation depends on the number of items n in the game-theory framework. One item corresponds to a resource share $\alpha_{\text{item}} = \frac{1}{n}$ and is the smallest resource unit that can be allocated in our scheme. As each user knows its current channel conditions, it can determine its QoE or utility for x_i allocated items as:

$$v_i(R_i) = v_i(x_i \cdot \alpha_{\text{item}} \cdot R_{\max,i}) \tag{5}$$

with x_i being the only variable during one allocation period where α_{item} and $R_{\max,i}$ are fixed.

Every resource allocation period, each user determines its current $R_{\max,i} = T_i \cdot BW_{\text{cell}}$ based on its average channel quality over the last period. BW_{cell} is the cell bandwidth and the spectral throughput T for a given Signal-to-Noise Ratio (SNR) γ is approximated using the LTE link level performance model [21]:

$$T = \begin{cases} 0 & \text{for } \gamma < \gamma_{\min} \\ \beta \log_2 (1 + \gamma) & \text{for } \gamma_{\min} \leq \gamma < \gamma_{\max} \\ T_{\max} & \text{for } \gamma \geq \gamma_{\max} \end{cases} \tag{6}$$

The model from [21] approximates the spectral throughput in the uplink after link adaptation and hybrid automatic repeat request, by an implementation loss $\beta = 0.4$ compared to the Shannon capacity. Further parameters are the minimum SNR $\gamma_{\min} = -10\,\text{dB}$, the maximum SNR $\gamma_{\max} = 15\,\text{dB}$ and the maximum spectral throughput $T_{\max} = 2\,\text{bit/s/Hz}$.

D. Vickrey-Clarke-Groves mechanism

The resource allocation problem can be solved using mechanism design. We follow the definitions and notations in [22]. A selling mechanism consists of a set of messages, or “bids”, an allocation rule and a payment rule. The *revelation principle* states that to any mechanism with an equilibrium, there exists a payoff equivalent *direct mechanism*, where the bids consist of the utilities of the users. Thus, if our mechanism has an equilibrium, we can conceptually restrict our attention for analysis to an equivalent direct mechanism, which can be formally represented with a pair of functions $(\boldsymbol{Q}, \boldsymbol{M})$, with an allocation rule $\boldsymbol{Q} : \mathcal{V} \rightarrow \mathcal{X}$ and a payment rule $\boldsymbol{M} : \mathcal{V} \rightarrow \mathbb{R}^m$. $\mathcal{V} = \times_i^m \mathcal{V}_i$ denotes the product of the sets of users' utility functions and $\mathcal{X} \subset \mathbb{N}^m$ is the set of all possible allocations over the set of users $\mathcal{B}$. The set $\mathcal{X}$ constrains the allocation problem as at most n items can be allocated:

$$\sum_{i \in \mathcal{B}} x_i \leq n \tag{7}$$

An *efficient mechanism* maximizes the social welfare, that is, the sum of utilities over all users. Formally, an allocation rule $\boldsymbol{Q}^* : \mathcal{V} \rightarrow \mathcal{X}$ is said to be *efficient* when for all $\boldsymbol{v} \in \mathcal{V}$:

$$\boldsymbol{Q}^*(\boldsymbol{v}) = \underset{\boldsymbol{Q}(\boldsymbol{v}) \in \mathcal{X}}{\arg\max} \sum_{i \in \mathcal{B}} v_i \left(Q_i(\boldsymbol{v})\right) \tag{8}$$

User i gets allocated $x_i = Q_i^*(\boldsymbol{v})$ items. Practically, efficiency is a desirable property of a resource allocation scheme, as a network operator can maximize the sum of QoE over all users, which is equivalent to maximizing the average QoE.

Given an efficient allocation rule $\boldsymbol{Q}^*$, the maximized value of social welfare is defined by:

$$W(\boldsymbol{v}) = \sum_{i \in \mathcal{B}} v_i \left(Q_i^*(\boldsymbol{v})\right) \tag{9}$$

Similarly, the welfare of all users except user i is:

$$W_{-i}(\boldsymbol{v}) = \sum_{j \neq i} v_j \left(Q_j^*(\boldsymbol{v})\right) \tag{10}$$

The VCG-mechanism $(\boldsymbol{Q}^*, \boldsymbol{M}^V)$ is an efficient mechanism with the payment rule $\boldsymbol{M}^V : \mathcal{V} \rightarrow \mathbb{R}^m$ given by:

$$M_i^V(\boldsymbol{v}) = W(\boldsymbol{v}_{-i}) - W_{-i}(\boldsymbol{v}) \tag{11}$$

$$D_i(q^t) = \begin{cases} 0 & \text{if } v_i(1) - v_i(0) < q^t \\ \max_{j \in \{0,1,\dots,n\}} j \quad \text{s.t.} \quad v_i(j) - v_i(j-1) \geq q^t & \text{otherwise} \end{cases} \tag{12}$$

That is, the VCG payment $p_i = M_i^V(\boldsymbol{v})$ for user i is equal to the difference of the welfare that would be achieved if user i was not participating and the achieved welfare of all other users when user i is participating.

IV. Auction-based resource allocation

There are different ways to implement a VCG mechanism. As we are interested in a rapidly converging resource allocation scheme, we consider a descending price auction, also called Dutch auction, which is used to sell goods rapidly. We propose a descending auction based on our previous work [14], with additional VCG payments, similar to the Vickrey-Dutch (VD) auctions introduced by Mishra and Parkes in [23]. Conceptually, the proposed VD auction consists of two parts. First, an efficient allocation is determined and then the VCG payments are calculated.

A. Definitions

Additionally to the total price p_i that a user has to pay, introduced in Eq. (2), the *marginal price* q is defined as the price for a single item. In a multi-item descending auction, the marginal price is decreased in each iteration. In iteration t, the marginal price is q^t. The items are *homogeneous*, that is, they are not distinguishable for the users, as each item corresponds to an equal share of the total radio resources.

The *maximal demand* is the number of items that a user wants to buy at a given marginal price. The user wants to buy an item if the utility it gets with this item is greater or equal to the current marginal price. The maximal demand $D_i(q^t)$ of a user i at a marginal price q^t is thus defined as in Eq. (12). The maximal demand is used in the first iterations of the auction in order to iteratively determine the allocation of the items to the different users until all items are allocated in the *final allocation* in iteration t_{final}.

In the following iterations, the maximal demands are used to determine the *residual demand* of each user in order to determine the VCG payments. The residual demand $r_{-i}(q^t)$ without user i is the sum of differences of the maximal demand and the allocated items over all users except user i and is bounded by the allocation to user i. It can be written as:

$$r_{-i}(q^t) = \begin{cases} 0 & \text{if } t < t_{\text{final}} \\ \min\left(x_i^t, \sum_{j \neq i}\left(D_j(q^t) - x_j^t\right)\right) & \text{if } t \geq t_{\text{final}} \end{cases} \tag{13}$$

B. Vickrey-Dutch auction

The proposed VD auction is described in Algorithm 1.

At the beginning of the auction, a high starting marginal price q^0 as well as a small marginal price decrement Δq are set. Additionally, the allocation x_i as well as the payment p_i of each user is set to zero.

Algorithm 1 Vickrey-Dutch auction

```
Set a high starting marginal price q^0
Set a small marginal price decrement Δq
Set t := 0
Set allocation (x_1, ..., x_m) = (0, ..., 0)
Set payment (p_1, ..., p_m) = (0, ..., 0)
loop
    Broadcast current marginal price q^t
    Collect maximal demand D_i(q^t) of each user i
    if Σ_{i∈B} D_i(q^t) < n then
        x_i = D_i(q^t) for all i ∈ B
        q^{t+1} = q^t − Δq
        t = t + 1
        Go to beginning of the loop
    end if
    if Σ_{i∈B} D_i(q^t) = n and Σ_{i∈B} D_i(q^{t−1}) < n then
        x_i = D_i(q^t) for all i ∈ B
        Set t_final := t
    else if Σ_{i∈B} D_i(q^t) > n and Σ_{i∈B} D_i(q^{t−1}) < n then
        n_left = n − Σ_{i∈B} D_i(q^{t−1})
        while n_left > 0 do
            B' = {i ∈ B | D_i(q^t) > x_i}
            x_k = x_k + 1 with k chosen randomly from B'
            n_left = n_left − 1
        end while
        Set t_final := t
    end if
    p_i := p_i + q^t(r_{−i}(q^t) − r_{−i}(q^{t−1})) for all i ∈ B
    if r_{−i} = x_i for all i ∈ B or q^t = 0 then
        Break loop
    else
        q^{t+1} = q^t − Δq
        t = t + 1
        Go to beginning of the loop
    end if
end loop
Final allocation is (x_1, ..., x_m)
Final payment is (p_1, ..., p_m)
```

In each iteration, the seller announces the current marginal price q^t. The users respond with their maximal demand $D_i(q^t)$ at that price. If the sum of all maximal demands is less than the number of available items to sell, then each user gets allocated its maximal demand. The marginal price is then decreased by the amount of the decrement and a new iteration round is started.

If the sum of all maximal demands is greater than or equal to the total number of items n for the first time, the current iteration number is saved as t_{final}. The remaining items are allocated to the users which have maximal demand greater than their current allocation ($D_i(q^{t_{\text{final}}}) > x_i$). If the sum of all maximal demands is equal to the total available number of items, then the final allocation is unique. On the contrary, if the sum of all maximal demands is greater than the total available number of items, then not all users can be served at their maximal demand. The remaining items n_{left} are allocated randomly to the users $\mathcal{B}'$ who haven't reached their maximal demand yet, until no item is left unallocated.

In the following iterations ($t > t_{\text{final}}$), the residual demand indicates at what marginal price the items allocated to user i would be allocated if user i was not participating. With that information, the VCG payments p_i are determined for each user based on the current marginal price and the current residual demand.

The auction terminates when the allocation of each user equals the residual demand of the other users or when the marginal price q^t reaches 0, because the maximal demand of each user at a marginal price of 0 is n and thus all items are allocated and the residual demand equals the allocation of each user.

C. VCG mechanism

We provide a comprehensive proof that the proposed VD auction implements a VCG mechanism. For this, we have to show that the achieved allocation is efficient (Eq. (8)) and that the payment of each user is a VCG payment (Eq. (11)).

We assume that the users are bidding truthfully, that is, they are reporting their maximal demand as defined in Eq. (12). If the auction is a VCG mechanism, users maximize their payoff by bidding truthfully [22]. This leads to an ex-post equilibrium of the auction.

1) Efficient allocation: Due to the descending marginal price and the concave utility functions of the users (Eq. (1)), each item is allocated to the user which obtains the highest increase in utility for it. Indeed, the first item is allocated when a user's demand is one, that is, when the utility for this item is greater than or equal to the current marginal price $v_i(1) - v_i(0) \geq q^t$. This utility is the highest as the utility of other users who haven't bet is less than the marginal price $v_{-i}(1) - v_{-i}(0) < q^t$ and because due to the concavity of the utility curves, the utility for further items will be smaller. The second item is then allocated to the user with highest utility for this second item, and so on.

In the iteration t_{final}, a tie between different users occurs if the sum of maximal demands is strictly greater than the total number of items $\sum_{i \in B} D_i(q^t) > n$. This tie is resolved by allocating the last remaining items randomly to users who still have their maximal demand higher than their current allocation. This is the only possible factor of inefficiency in the proposed VD auction.

A tie can be avoided if the marginal price decrement is chosen small enough. Indeed, if the marginal price decrement is chosen smaller than the smallest difference between utilities of two users for an item, the marginal price q^t will decrease such that no tie occurs in iteration t_{final} as the sum of maximal demands equals the total number of items $\sum_{i \in B} D_i(q^t) = n$. As a conclusion, the proposed VD auction is efficient if the marginal price decrement is chosen small enough.

2) VCG payment: At iteration t_{final} where the final allocation is determined, the welfare $W_{-i}(\boldsymbol{v})$ without user i consists of the sum of utilities for the $n - x_i$ items that haven't been allocated to user i. Similarly, the welfare $W(\boldsymbol{v}_{-i})$ if user i wouldn't participate consists of the same sum of utilities for the $n - x_i$ items plus the sum of utilities $W_{x_i}(\boldsymbol{v}_{-i})$ for the x_i items which are now allocated to the other users. That is, the VCG payment (Eq. (11)), which is the difference of the two discussed welfares, is the sum of utilities $W_{x_i}(\boldsymbol{v}_{-i})$ of the x_i items allocated to users except user i.

The residual demand (Eq. (13)) enables us to determine the allocation of the x_i items to other users if they wouldn't have been allocated to user i. When an item is virtually allocated to another user, it is priced to user i with the current marginal price q^t. Indeed, q^t is an approximation of the utility achieved by a user for an item, because a user bids for an item if its utility is greater or equal to the current marginal price. That is, $q^{t-1} > v_i(j) - v_i(j-1) \geq q^t$ for the user's j^{th} item. If the marginal price decrement tends to zero, the approximation error of the item utility with the current marginal price goes to zero as well. As a conclusion, the proposed VD auction determines VCG payments for each user if the marginal price decrement is small enough.

D. Properties

1) Cheat-proof: As it implements a VCG mechanism, the proposed VD auction is cheat-proof [22], that is, users maximize their payoff by bidding truthfully.

2) Bounded number of iterations: The maximal number of iterations for the proposed VD auction to converge is given by:

$$\left\lceil \frac{q^0}{\Delta q} \right\rceil + 1 \tag{14}$$

The marginal price starts at q^0 in the first iteration and is decreased by Δq in each iteration. The proposed VD auction finishes when the residual demand r_{-i} equals the allocation x_i or latest when the marginal price reaches 0, which provides an upper bound on the number of iterations.

V. Experimental Results

A. Settings

To simulate the varying channel conditions in an LTE cell, we generate SNR traces with an OPNET simulator. The parameters are summarized in Table I. Users are moving in the cell with different mobility patterns and each user is streaming

TABLE I: OPNET LTE parameters

Base frequency	1920 MHz
Bandwidth	5 MHz
eNodeB antenna gain	15 dBi
UE antenna gain	0 dBi
Cell model	Urban macrocell
Shadowing standard deviation	8 dB
Correlation distance of shadowing	50 m

TABLE II: Simulation parameters

VD auction parameters	
Number of items	50
Starting marginal price q^0	20
Marginal price decrement Δq	0.2
Simulation parameters	
Number of users	8
Simulation runs	150

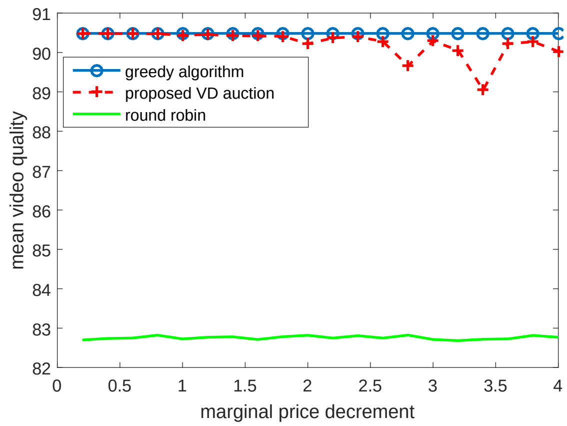


Fig. 2: Mean perceived video quality over all users for three resource allocation schemes as a function of the proposed VD auction marginal price decrement Δq.

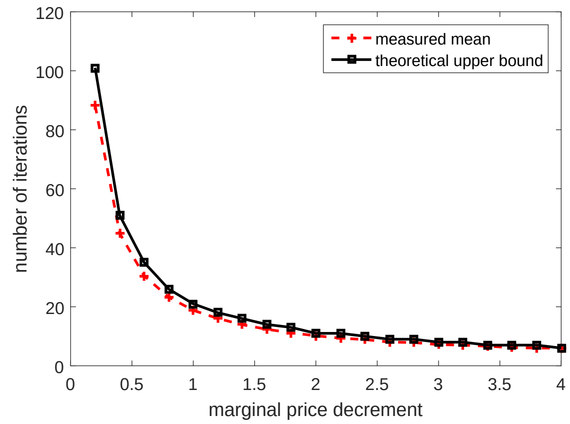


Fig. 3: Theoretical upper bound and measured number of iterations for the proposed VD auction as a function of the marginal price decrement Δq.

a different video from a pool of 18 different full HD videos from [24].

The auction parameters are summarized in Table II. During the following simulations, we vary the marginal price decrement in Section V-C and the number of users in Section V-D in order to assess the influence of these parameters on the proposed VD auction.

B. Centralized resource allocation schemes for comparison

We first compare our proposed VD auction based resource allocation with two centralized resource allocation techniques. The *greedy algorithm* proposed in [16] requires the knowledge of the utility functions of all users as well as their channel condition information. The resources are allocated such that the average QoE is maximized in the case of concave utility functions. We use this algorithm as the reference for the optimal resource allocation, in the sense that the average QoE is maximized. The *round robin* resource allocation is used as a reference for a utility unaware allocation scheme. The items are allocated one user after another starting with a random user.

C. Influence of the auction parameters

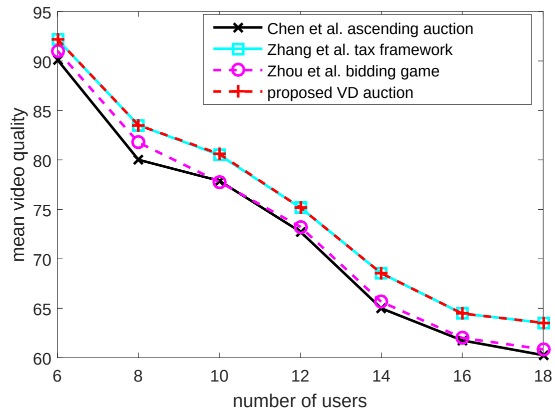
Fig. 2 shows the achieved mean perceived video quality over all users and all simulation runs for three different resource allocation schemes as a function of the marginal price decrement Δq. The greedy algorithm does not depend on Δq and thus the perceived video quality is constant over the displayed interval. The round robin scheme is slightly varying because the number of items is not divisible by the number of users, thus the random allocation allocates a slightly varying number of items to the users in each simulation round. The proposed VD auction achieves the optimal solution (same as the greedy algorithm) when the marginal price decrement is small. When the marginal price decrement increases, the performance of the proposed VD auction decreases. Having a small marginal price decrement makes the proposed VD auction go through the marginal prices with a fine granularity and thus reduces the probability of having a tie between multiple users in the iteration where the final allocation is achieved, a tie having to be solved randomly and thus potentially leading to suboptimality.

Fig. 3 shows the theoretical upper bound on the number of iterations as given by Eq. (14) and the mean number of iterations over 150 simulations as a function of the marginal price decrement. The mean number of iterations is always less than or equal to the theoretical upper bound, as expected. Our data also shows that the theoretical upper bound is never exceeded in a single simulation. The number of iterations decreases with an increasing marginal price decrement.

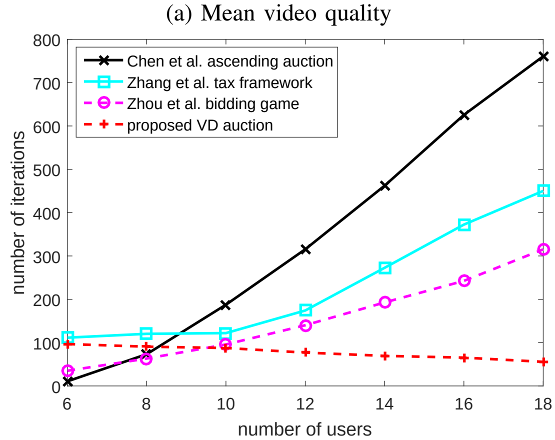
One way to determine Δq in a practical scenario is to define a maximum tolerable number of iterations. Then Δq should be chosen as small as possible within the limits of Eq. (14) in order to have the best possible video quality.

D. Influence of the number of users

We assess the influence of the number of users sharing the constant available resources for our proposed VD auction and three state-of-the-art resource allocation schemes based on game-theory. Fig. 4a shows the average video quality over 150 simulations. Both the proposed VD auction and the tax framework from Zhang et al. [10] achieve average QoE maximization. The average QoE performance of the ascending auction by Chen et al. [9] and the bidding game by Zhou et al. [11] is lower due to the fairness criterion imposed on the resource allocation scheme The mean video quality decreases with an increasing number of users as the resources are kept



(a) Mean video quality



(b) Mean number of iterations

Fig. 4: Mean video quality and number of iterations as a function of the number of users.

constant and thus with more users, every user will get less resources on average, which leads to a lower achievable video quality.

Fig. 4b shows the convergence behavior in terms of mean number of iterations to converge. The number of iterations increases with increasing number of users for all three game theory based resource allocation schemes whereas the proposed VD auction is the only method which shows decreasing number of iterations with increasing number of users, from 100 iterations for 6 users to 60 iterations for 18 users. As the number of items is kept constant, when more users participate in the proposed VD auction, the overall demand will be higher and thus it is more likely that the auction terminates at a high marginal price, before the marginal price reaches 0.

VI. Conclusion

In this paper, we address the problem of decentralized resource allocation for video streaming, where the utility information of the users is not available at a central controller. We propose a cheat-proof auction-based resource allocation scheme which maximizes the average QoE over all users. Unlike state-of-the-art decentralized resource allocation approaches, our proposed auction only needs a bounded number of iterations to converge and the number of iterations decreases with an increasing number of users. Furthermore, the proposed resource allocation method is compatible with cross-layer optimization schemes, due to the auction price defined on the utility scale and to the abstraction of the wireless resources to items. This makes the proposed auction widely applicable.

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