Profit Optimization for Multiuser Video Transmission over Mobile Networks

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Abstract—With the increasing demand for high quality mobile video, how to receive higher quality video through mobile network with lower payment is a becoming an emerging problem. Existing approaches for Dynamic Adaptive Streaming over HTTP (DASH) face tremendous challenges when applying to video streaming in devices with different resolutions. In this paper, we propose a comprehensive profit optimization model with consideration of the cost of Content Provider, traffic payment, QoE factors and the relationship between device resolution and video quality. For ensuring the optimal profit of Content Provider and End Users at same time, we formulate both of their profit as a hybrid-objective optimization model. By solving the model, the optimum bitrates and the resulting profit can be obtained through our proposed algorithm. The simulation results demonstrate that the proposed method increases the average profit of End Users in 10%-15% compared with existing approaches.

1. INTRODUCTION

Video streaming traffic is becoming the domination of current and future Internet traffic. Cisco predicts that global IP video traffic will be 82 percent of all consumer Internet traffic by 2021, up from 73 percent in 2016\cite{1}. Ensuring the Quality of Experience (QoE) of End User (EU) is becoming challenging due to the diversity of factors which affect QoE. These key factors include playback bitrate, variability of bitrate delivered, rebuffering time and traffic payment\cite{9}. In particular, the traffic payment is currently becoming an emphasis on QoE optimization\cite{2}.

Recently, there are many research works focus on enhancing quality of video delivery and the QoE of EUs from various aspects. Among them, some research efforts focus on analyzing HTTP Adaptive Bitrate (ABR) Streaming logic in different network conditions. For instance, the study in \cite{3} proposed an optimal bitrate selection by solely considering buffer occupancy. The work in \cite{15} used neural network to generate next bitrate selection policy. The study in \cite{4} proposed a Model Predictive Control (MPC) model to make bitrate decision considering both bitrate and buffer state. However, these proposed methods do not take traffic price into consideration. That is, when network condition is well, the selected bitrate will be so high that EU’s traffic exhausts too quickly.

From the quality of video delivery aspect, some research efforts focus on the bandwidth allocation for user. In \cite{5} and \cite{6}, the authors presented a game-theoretic approach to allocate bandwidth for
ensuring the QoE of EUs. Although the cost of Content Provider (CP) is considered, the fluctuation of video quality and rebuffering time have not been considered yet.

Jointly considering QoE, the payment of EU and the cost of CP to provide better video streaming service is becoming more and more attractive. Sponsoring data has been proved effective in reducing the traffic payment of users[12]. The study in [13] took advantage of advertisement insertion to increase profit for CPs by EU’s tolerance of advertisement into consideration. The study in [7] proposed an allocation policy to optimize the balance between the QoE of EUs and the profit CP. The work in [8] took traffic price rate into consideration to prevent EUs from receiving too much load of traffic. However, most of the related works seldom considered the factors of QoE, such as device resolution relationship, fluctuation of video quality and rebuffering time. In this paper, we emphasize on not only the cost of CP and the payment of EUs, but also the more comprehensive consideration of the factors influenced QoE. The contributions of this paper are listed as follows:

- 1) we explore the relationship between QoE and video resolution and propose a device-related QoE model. Furthermore we define a joint profit model by taking video quality fluctuation and rebuffering time into consideration.
- 2) we propose an adaptive bitrate algorithm called Optimal Joint Profit Solution (OJPS) based on the profit models of CP and EUs.
- 3) we evaluate our adaptive bitrate scheme in three perspectives: average profit of EUs, traffic payment with different resolution and the performance of OJPS.

The rest of this paper is organized as follows. In Section II, we give the system model and problem formulation. Then the optimal bitrate and lost reduction algorithm are presented in Section III. In Section IV, we present and discuss the performance evaluation results. Finally, this study is concluded in Section V.

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Figure 1. General DASH Streaming Model.

2. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we consider a wireless video streaming network where CP transmits videos to EUs through cellular network. The following description firstly analyzes the characteristics of DASH (Dynamic Adaptive Streaming over HTTP) and the QoE (Quality of Experience) model based on device resolution. Then, we introduce the network pricing model and proposed the joint profit model among CP and EUs.

2.1. DASH Streaming Model

Consider a DASH network system shown in Fig. 1, where video $V$ is delivered to $N$ EUs. $V$ is encoded to $K$ chunks. Let $R$ be the set of the available bitrates provided by CP, where $R = \{\omega_1, \omega_2, ..., \omega_Z\}$, the policy of the EU $s$ for bitrate selection can be represented by a vector $r_s = \{r_{s,1}, r_{s,2}, ..., r_{s,K}\}$, where $r_{s,k} \in R$. When an EU starts to watch video, the EU $s$ will download a chunk with bitrate $r_{s,k} \in R$ at time $t_k$. 

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where the chunk has a duration of $L$. Suppose that the EU $s$ requests a new chunk from CP until current chunk has completely downloaded, let $B_{s,k}$ be the buffer size of EU $s$ after the chunk with bitrate $r_k$ has entirely transited, the buffer size $B_{s,k+1}$ at time $t_{k+1}$ can be calculated by

$$B_{s,k+1} = \max(0, B_{s,k} - d(r_{s,k})C_{s,k} + L)$$  \hfill (1)

$$B_{s,1} = L$$  \hfill (2)

where the $d(r_{s,k}) = Lr_{s,k}$ represents the size of chunk $k$ EU $s$ requests, $C_{s,k}$ is the throughput for downloading chunk $k$. For a stably video playing, ensuring the buffer positive is necessary. When $B_{s,k} \leq 0$, the rebuffering event will happen thereby the QoE is influenced[10].

2.2. QoE Model with Device Resolution

In mobile video network systems, EUs watch videos on mobile devices such as cellphone and laptop. The resolutions of these devices are diverse. Considering that an EU uses a device with resolution $\mathit{h}$ to request video chunks, the bitrate of the chunk $r_k$ can influence the clarity of video display.

![Figure 2. The relationship between MOS and bitrate under different resolution.](image)

According to [14], we observe the positive correlation between bitrate and EU’s Mean Opinion Score (MOS). As shown in Fig. 2, with different resolution from QCIF to VGA, more bitrates are required for obtaining the same MOS. In order to fit this trend, we use the log function to define EU’s QoE as follows:

$$q(r_{s,k}) = \alpha \ln(1 + \beta r_{s,k})$$ \hfill (3)

where $\alpha_s$ and $\beta_s$ are parameters varying with user’s device resolution. The a vertical shift of 1 is to ensure that the QoE $q(r_{s,k})$ is positive.

Since the upper bound of MOS is 5, the QoE $q(r_{s,k})$ should be less than 5. Hence, (3) can be rewritten as:

$$q(r_{s,k}) = \begin{cases} 
\alpha_s \ln(1 + \beta r_{s,k}), & r_{s,k} \leq \frac{1-\exp(\frac{5}{\beta_s})}{\beta_s} \\
5, & r_{s,k} > \frac{1-\exp(\frac{5}{\beta_s})}{\beta_s}
\end{cases}$$ \hfill (4)

Given the QoE $q(r_{s,k})$, the relationship between $h$ and $r_{s,k}$ can be represented as follows:
where the $k_{q_{s,k}}$ and $b_{q_{s,k}}$ are induced from [14]. Given the device resolution $h$, by changing $q_{s,k}$, so we can obtain the bitrate $r_{s,k}$ to reach the corresponding $q_{s,k}$. Let $D = \{(r_{s,k}^1, q_{s,k}^1), (r_{s,k}^2, q_{s,k}^2), \ldots, (r_{s,k}^n, q_{s,k}^n)\}$, where $(r_{s,k}^n, q_{s,k}^n)$ are calculated by (5). By making Non-linear least squares for (3) in $D$, the the parameters $\alpha$ and $\beta$ are determined.

2.3. Network Profit Model

![Diagram of Network Profit Model](image)

**Figure 3.** Basic price relation among CP, ISPs and EUs.

This subsection introduces the profit model for video streaming system over mobile networks. The basic profit relationships among CP, ISP and EUs are shown in Fig. 3. The EUs request video contents from CP through the ISP. The EUs buy traffic from ISP to receive video contents. The CP provide video streaming service to EUs to get revenue from EUs. Meanwhile, the CP must pay to ISP for data transmission service.

1) **Profit Model for CP:** In a DASH system, EUs request the video chunks from CP (e.g., the EU $s$ request chunk $k$ with the bitrate $r_{s,k}$). Derived from[12], let $a_s$ to be the average revenue per unit data for providing video to EU $s$, the utility of CP to EU $s$ is defined as

$$U_s^{CP}(r_{s,k}) = a_s r_{s,k}$$

(6)

To provide video streaming service, the CP needs to pay to the ISP for the data transmission services. The CP gets paid from EUs meanwhile pays for the services of ISP. Let $w$ be the price for transmitting per unit data to EU $s$, the payment $v(r_{s,k})$ of CP is defined as follows:

$$v(r_{s,k}) = wr_{s,k}$$

(7)

We introduce the same method proposed in [12, 13] to generate the total profit model of CP as

$$P^{CP} = \sum_{k=1}^{K} \sum_{s=1}^{N} (a_s r_{s,k} - wr_{s,k})$$

(8)

The profit of CP must be positive for ensuring that CP can get revenue by providing video, so (8) implicates $a_s > w$. In practice, the data transmission capacity of CP is always limited. That is, CP could set an upper bound for the sum of the bitrates of EUs where $\sum_{s=1}^{N} r_{s,k} \leq \bar{R}$. So the objective of CP is to maximize the profit model (8) as follows within this upper bound:

$$\max \sum_{k=1}^{K} \sum_{s=1}^{N} (a_s r_{s,k} - wr_{s,k})$$

(9)

s. t. $r_{s,k} \in \bar{R}$

(10)

$$\sum_{s=1}^{N} r_{s,k} \leq \bar{R}$$

(11)
where $\bar{R}$ is the upper bound for the sum of the bitrates of EUs.

2) Profit Model for EUs: Similar to the profit model of CP, the profit models for EUs are also defined based on utility and payment. The utility of EU indicates EU’s QoE for watching video, the EU’s payment is that EU buys traffic from ISP.

Derived from [15], we define the user’s utility as three parts:

- QoE for each chunk with bitrate $r_{s,k}$, as (4) shows.
- QoE fluctuation during playing:
  $$\sum_{k=1}^{K} \left| q(r_{s,k}) - q(r_{s,k-1}) \right|,$$
  where the $q(r_{s,0}) = 0$.
- Total rebuffering time:
  $$\sum_{k=1}^{K} \left( \frac{d(r_{s,k})}{C_{s,k}} - B_{s,k} \right)^+,$$
  where $C_{s,k}$ is the throughput for EU $s$ to download the $k$th chunk.

As the EU’s utility is positively affected by QoE and negatively affected by QoE fluctuation and rebuffering time, we define the EU’s utility as

$$U_{EU}^s = \sum_{k=1}^{K} \left[ \alpha_s \ln \left( 1 + \beta_s r_{s,k} \right) - \lambda_s \left| \alpha_s \ln \left( \frac{1+\beta_s r_{s,k}}{1+\beta_s r_{s,k-1}} \right) \right| \right] - \mu_s \left( \frac{d(r_{s,k})}{C_{s,k}} - B_{s,k} \right)^+,$$

where the parameters $\lambda_s$ and $\mu_s$ respectively represent EU’s tolerance of the QoE fluctuation and rebuffering time, $(\cdot)^+ = \max(0,\cdot)$.

In mobile DASH system, the EUs will consider the traffic price before making bitrate policy. Similar with the payment of CP, we can obtain the EU’s payment function as follows:

$$\varphi_s(r_{s,k}) = p_s r_{s,k},$$

(13)

where $p_s$ is the price for per bit traffic.

The profit of EU can be similarly defined as follows[12]:

$$P_{EU}^s \sum_{k=1}^{K} \left( \alpha_s \ln \left( 1 + \beta_s r_{s,k} \right) - \lambda_s \left| \alpha_s \ln \left( \frac{1+\beta_s r_{s,k}}{1+\beta_s r_{s,k-1}} \right) \right| \right] - \mu_s \left( \frac{d(r_{s,k})}{C_{s,k}} - B_{s,k} \right)^+ - p_s r_{s,k},$$

(14)

The objective of EU $s$ is to find a bitrate policy vector $r_s$ and maximize its profit as follows:

$$\max P_{EU}^s,$$

(15)

s. t. $r_{s,k} \in \bar{R}$

(16)

$$\sum_{k=1}^{K} C_{s,k} \leq \bar{C},$$

(17)

where $C_{s,k}$ is the throughput when EU $s$ download the $k$th chunk. $\bar{C}$ is the max bandwidth constraint of CP.

2.4. Problem Formulation for Joint Profit Optimization

In previous subsections, we have studied the characteristics of DASH and the profit models CP and EUs. The profit models of CP and EUs implicate a contradiction. If the total bitrate is less than the upper bound of CP, CP also prefer high bitrate. However, for EUs, higher bitrate means higher traffic payment, they may be reluctant with high bitrate.

To address this problem, we need to consider a joint profit model. The joint profit model is written as follows:

$$\max (P_{CP}, P_{EUs}),$$

(18)
where \( X \) is the policy space of EUs, \( X = (r_1^T, r_2^T, ..., r_N^T) \). The \( X \) is a \( K \times N \) matrix that the rows represent different EUs, the columns represent the all bitrate policy of video \( V \) by one EU. The \( 1 \) and \( g \) are vectors with \( N \) rows of 1 and \( \overline{R} \) respectively.

Our goal is to find a optimal policy matrix \( X^* \) to maximize (18). There are some difficulties for solving this joint optimization problem. Due to the discrete bitrate set and the multiple objectives, (18) is a nonlinear-integer and multiple objectives optimization problem, which is known to be difficult in general[17].

3. OPTIMAL BITRATE AND MAXIMAL JOINT PROFIT SOLUTION

In this section, we focus on the solution of the joint profit model as (18). Our idea is that we can firstly transform the multiple objectives optimization problem to single objective optimization problem by scalarization. Then, we transform the nonlinear-integer programming problem to nonlinear programming problem. Finally, we analyze the effect of CP bandwidth constraint on optimal bitrate solution.

3.1. Scalarization for Joint Profit Model

Scalarization is a frequently used method to deal with multiple objectives optimization problem. The idea is that choosing a weight vector \( v = (v_{CP}, v_{EUS})^T \) to transform the objective functions \( F(x) \) to \( v^T F(x) \). The value of each \( v_i \) in \( v^T \) can represent the importance of entity \( i \) in the mobile streaming system.

To find an ideal \( v \), many factors need to be considered such as the preference of EUs and the number of EUs in an ISP. In this paper, we do not focus on explore the optimal \( v \), instead, we equate CP and EUs. That is,

\[
\forall i, j > 0, v_i = v_j
\]

(22)

For the streaming system in this paper, there are one CP and \( N \) EUs. According to (22), (18) can be written as follows:

\[
\max v^T (P_{CP} \circ P_{EUS})
\]

(23)

where \( v \) is a vector fullfilled with \( \frac{1}{N+1} \).

After scalarization, the original multiple objectives optimization problem (18) is transformed to the single objective optimization problem. Now we can further explore the characteristics of the single objective optimization problem (23).

3.2. Optimal Bitrates Policy

In the previous subsection, we have transformed the multiple objectives optimization problem to single objective optimization problem by scalarization. We now explore the way to get optimal bitrates policy. Note that in this subsection we do not consider the CP bandwidth constraint (21). We will discuss it in next subsection.

In the proposed mobile streaming model in this paper, EUs do not download next chunk until the current chunk have completely downloaded. Thus, we can calculate the bitrate policy at each time \( k \) respectively. Let \( r_{s,k}^* \) be the \( k \)th row of \( X^* \), our objective is to:

\[
\text{s.t. } r_{s,k}^* \in R
\]

(19)

\[
X1 \leq g
\]

(20)

\[
\sum_{s=1}^{N} c_{s,k} \leq \overline{C}
\]

(21)

The operator \( \circ \) places two vectors end to end, e.g., \( x = (a, b)^T, y = (b, c)^T, x \circ y = (a, b, b, c)^T \)
\[
\text{max} \frac{1}{N+1} \left(A^{CP} + \sum_{s=1}^{N} A^{EU}_s\right) \tag{24}
\]
\[
s. t. r_{s,k} \in R \tag{25}
\]
\[
\sum_{s=1}^{N} r_{s,k} \leq \bar{R} \tag{26}
\]
where,
\[
A^{EU}_s = \sum_{s=1}^{N} \left( a_s r_{s,k} - w r_{s,k} \right) \tag{27}
\]
\[
A^{EU}_s = \alpha_s \ln \left( 1 + \beta_s r_{s,k} \right) - \lambda_s \left| \frac{1 + \beta_s r_{s,k}}{1 + \beta_s r_{s,k-1}} \right| - \mu_s \left( \frac{d(r_{s,k})}{C_s} - B_s \right)_+ - p_s r_{s,k} \tag{28}
\]

To achieve the optimal solution of model described by (24) to (28), we first need the following theorem.

**Theorem 1.** (24) is quasi-concave, such that for any \( r_k \in R^N \), there is one \( r^*_k = \arg \max \frac{1}{N+1} \left(A^{CP} + \sum_{s=1}^{N} A^{EU}_s\right) \).

**proof.** For simplicity, we omit the subscript \( k \). We first consider the relaxed situation that \( r_k \) is continuous. As the joint profit function (24) is continuous but not differentiable, we discuss the quasi-concavity from the definition of quasi-concave function.

As for \( A^{EU}_s \), there exists that \( a_s - w > 0 \). Obviously, \( A^{EU}_s \) is concave.

Let \( A^{EU}_s = E^{Q}_s + E^{D}_s + E^{B}_s \), where
\[
E^{Q}_s = \alpha_s \ln \left( 1 + \beta_s r_{s} \right) - p_s r_{s} \,
\]
\[
E^{D}_s = -\lambda_s \left| \frac{1 + \beta_s r_{s}}{1 + \beta_s r_{s,k-1}} \right| \,
\]
\[
E^{B}_s = -\mu_s \left( \frac{d(r_{s})}{C_s} - B_s \right)_+ \,
\]
\( \alpha_s > 0 \) and \( \beta_s > 0 \), so \( \frac{d^2 E^{Q}_s}{dr^2} = -\frac{\alpha_s \beta_s^2}{\left(1 + \beta_s r_{s}\right)^2} < 0 \), induces that \( E^{Q}_s \) is concave.

As \( E^{D}_s \) is not differentiable, we can not analyze the its concavity through second order differential.

Let \( U(r) = \ln \left( \frac{1 + \beta_s r_{s}}{1 + \beta_s r_{s,k-1}} \right) \), without loss of generality, we assume \( r_1 \leq r_2 \), thus, we can obtain that \( U(r_1) \leq U(r_2) \). Let \( \theta_1, \theta_2 > 0 \) and \( \theta_1 + \theta_2 = 1 \), we have
\[
E^{D}_s(\theta_1 r_1 + \theta_2 r_2) = -\lambda_s \alpha_s \left| \theta_1 U(r_1) + \theta_2 U(r_2) \right| \,
\]
\[
\geq -\lambda_s \alpha_s \left| \theta_1 U(r_1) - \lambda_s \alpha_s \left| \theta_2 U(r_2) \right| \right| \,
\]
\[
= \theta_1 E^{D}_s (r_1) + \theta_2 E^{D}_s (r_2) \,
\]
This is consistent with the definition of concave function, so \( E^{D}_s \) is quasi-concave.

For \( E^{B}_s \), we can rewrite it as:
\[
E^{B}_s = -\frac{\mu_s}{2} \left( \frac{L_{r_s}}{C_s} - B_s \right) + \frac{L_{r_s}}{C_s} - B_s \,
\]

Similar with \( E^{Q}_s, E^{B}_s \) is quasi-concave.

Because addition is a kind of operation that reserves concavity, \( A^{EU}_s \) is concave. Going one step further, we can obtain that (24) is concave optimization problem, which has an optimal solution.

This completes the proof.

Theorem 1 reveals that (24) is a concave optimization problem which has a optimal solution, and we can solve this concave optimization problem by general concave optimization algorithms. Due to the limited space, we omit the detailed process here.
3.3. Analysis of the Effect of CP Bandwidth Constraint on Optimal Solution

The bandwidth constraint of CP shows that the bandwidth of CP is limited. When the number of EUs increases, the bandwidth allocated to each EU will decrease and may cause rebuffering events. Although the optimal bitrate solution is obtained in the previous subsection, the total system profit is also affected by the bandwidth allocated to each EU. Our goal is to find a policy to allocate available bandwidth to EUs and obtain the maximal system profit when available bandwidth of CP is limited.

Given the optimal bitrate policy for $k$th chunk $r_k^*$, the optimal bandwidth allocation policy can be obtained by solving the model as follow:

$$\max \sum_{s=1}^{N} e_{s,k} - \mu_s \left( \frac{d(r_{s,k}^*)}{c_{s,k}} - B_{s,k} \right)_+$$  \hspace{1cm} (29)

subject to

$$\sum_{s=1}^{N} e_{s,k} = C_k$$  \hspace{1cm} (30)

By solving the model (29)-(30), the optimal bandwidth allocation policy $C_{s,k}^*$ can be obtained. Once we obtain the optimal bandwidth allocation policy, we have the final Optimal Joint Profit Solution (OJPS) algorithm. The OJPS algorithm shows as follow:

**Algorithm 1 Optimal Joint Profit Solution Algorithm**

Input: available bitrate set $R$, throughput prediction $C_k$

Output: optimal bitrate policy $r_k^*$, optimal bandwidth allocation policy $C_k$

1: solving model (24)-(26) to obtain $r_k^*$
2: if $\sum_{k=1}^{N} \hat{C}_{s,k} > \hat{C}$ then
3: solving model (29)-(30) to obtain $C_k^*$
4: return $r_k^*$, $C_k^*$
5: else
6: $C_k^* = \hat{C}_k$
7: return $r_k^*$, $C_k^*$
8: end if=0

The OJPS algorithm run on CP and the complexity of OJPS algorithm is $O(N)$. When EUs request for playing video, CP will run OJPS algorithm for every chunk, meanwhile notify EUs to select the optimal bitrate and allocate appropriate bandwidth to EUs to ensure their QoE.

**Figure 4.** Average Profit of EUs Comparison Between Baselines and Proposed Method.

4. Simulation Results and Discussions

In this section, we use computer simulations to evaluate the performance of the proposed Optimal Joint Profit Solution (OJPS). In our simulation, each bitrate is chosen from \{300, 750, 1000, 1250, 1500, 1850, 2850, 4300\}. For different device resolution, we induce the value of $\alpha$ and $\beta$ from [14], as shown in TABLE 1. For simulating real network, we refer to the network throughput introduced in [19]. To
predict throughput for obtaining optimal bitrate policy, we use Autoregressive Moving Average Model (ARMA)[18]. The coefficient of AR and MA are 1 and 2 respectively.

Our simulations consist of three evaluations: 1) The comparison of profit of EUs among Xie et al.[8], MPC[4] and offline optimal. 2) The comparison of traffic payment during video play. 3) Analysis of the performance of OJPS with CP bandwidth constraint.

Table 1: Value of $\alpha$ and $\beta$ for Different Device Resolution

| Resolution   | $\alpha$   | $\beta$   |
|--------------|------------|-----------|
| 720*480      | 1.134      | 0.01453   |
| 1280*720     | 1.065      | 0.009437  |
| 1920*1080    | 1.147      | 0.004581  |

4.1. Profit Evaluation of EUs

In this evaluation, we assume that EUs use cellphone with 1920*1080 resolution to watch video. The parameters $\lambda$ and $\mu$ are set to 1 and 0.1 respectively, which indicates that the EUs can tolerate the bitrate jump to 300kbps from 4300kbps and 10 seconds rebuffering time at most. The payment coefficients $p_x$ of EUs are all set to 0.00002 per kb. This is consistent with the traffic price of Mobile Network Operators in China.

As shown in Fig. 4, our method achieves 80% of the offline optimal profit in average profit of EUs, while the MPC proposed in [4] can achieve 75% and the method in [8] can achieve 65%. An important reason is that we take traffic payment and relatively comprehensive network conditions into consideration. Under these conditions, EUs will not make an aggressive bitrate decision despite the network conditions become better in short term.

4.2. Traffic Payment with Different Resolution

The purpose of this simulation is to examine the effect of our device related model. In this simulation, all parameters and network conditions are set as subsection A, except for the device resolutions. The device resolutions are set to 1920*1080 and 720*480.

As shown in Fig. 5, without considering the network conditions, the method proposed by Xie et al always select the optimal bitrate with a specific traffic price. However this optimal bitrate will not be optimal in real network conditions. With the resolution of 1920*1080, the traffic payment of MPC and the method proposed in this paper are fairly close. When the device resolution is set to 720*480, the traffic payment of our method is obviously decreased. The results indicate that, by taking the device resolution into consideration, our method can reduce traffic payment of EU meanwhile ensure the QoE of EUs.
4.3. Performance of OJPS with CP Bandwidth Constraint

This simulation evaluates the average profit of EUs under the bandwidth constraint of CP. We assume that the EUs use devices with random resolutions shown in TABLE 1, the number of EUs is set to 100. As the maximal throughput in our series is less than 7Mbps, we set the bandwidth of CP to 256Mbps and 128Mbps.

The results are shown in Fig. 6. When the bandwidth of CP decreases, the average profit of EUs is affected. By utilizing the proposed OJPS algorithm, the profit of EUs only decreases by 20% under the half bandwidth constraint.

5. Conclusion and Future Work

In this paper, we propose the OJPS algorithm to optimize the profit of CP and EUs. By considering the device resolution and traffic payment, the proposed algorithm decreased traffic payment by selecting the appropriate bitrate. The simulation results show that our method outperforms the existing MPC method and the work of Xie et al by 10% and 15% respectively. In the future, we plan to conduct further research on the pricing schemes in video streaming and better profit models.

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