Adaptive Bitrate Streaming in Multi-user Downlink NOMA Edge Caching Systems with Imperfect SIC

Nhu-Ngoc Dao[a], Duc-Nghia Vu[b], Woongsoo Na[c], Trong-Minh Hoang[d], Dinh-Thuan Do[e], Sungrae Cho[b]

[a] *Department of Computer Science and Engineering, Sejong University, Seoul 05006, South Korea*
[b] *School of Computer Science and Engineering, Chung-Ang University, Seoul 06974, South Korea*
[c] *Department of Computer Science and Engineering, Kongju National University, Cheonan 31080, South Korea*
[d] *Posts and Telecommunications Institute of Technology, Hanoi 100000, Viet Nam*
[e] *Department of Electrical and Computer Engineering, The University of Texas at Austin, Austin, TX 78712, USA*

Abstract

Recently, mobile networks have witnessed an increasing dominance of video traffic streams to simultaneously distribute real-time contents to massive number of user devices. In this context, fifth-generation (5G) technologies and beyond expose their advanced new radio access interfaces to facilitate multi-user associations with successive interference cancellation (SIC)-based non-orthogonal multiple access (NOMA) mechanisms. However, the imperfectness of the SIC in reality may result in significant performance decrease in NOMA owing to inter-channel interference existence. Motivated by this observation, this paper studies adaptive bitrate streaming services given such a challenging transmission environment assumed. In this context, our objectives are to maximize the video bitrate (accordingly the video resolution) of the online streams while retaining the playback smoothness. The problem is transformed into a drift-plus-penalty balancing optimization, which is then resolved by an approximation algorithm. Numerical results highlight the outperformance of the proposed approach compared to existing algorithms in terms of video quality and smoothness in various system scenarios.

Keywords: Adaptive bitrate streaming, edge caching system, imperfect SIC, multi-user downlink NOMA

1. Introduction

Adaptive bitrate streaming (ABS) is an advanced technology that delivers videos to the users with the best-possible experience by dynamically adapting to any changes in network and playback environments [1, 2]. To support this adaptability, a standard network-assisted architecture, namecoded SAND [3], has been introduced to enable video streams are continuously transcoded and/or cached by network elements (referred to as DANE) on the delivery path using dynamic adaptive streaming over HTTP (DASH) protocol. Within the fact that mobile traffic has significantly dominated streaming services recently, an integration of SAND into the fifth-generation (5G) networks has been recommended by the third Generation Partnership Project (3GPP) organization in Technical report TR 26.957 V16.0.0 for Release 16 [4]. In particular, the 5G point of attachment, i.e., the next generation NodeB (gNB), takes responsibilities for DANE functions as a proxy cache in close proximity of ABS users.

Unfortunately, the gNB is considerably constrained by limited computational resources and time-varying wireless channels. While the computational resources drive transcoding and caching capabilities, the wireless channels significantly impact stream delivery to the ABS users. Especially in the 5G networks and beyond, non-orthogonal multiple access (NOMA), as a foundational access technology, simultaneously multiplexes users in the power domain on the same orthogonal subchannels [5, 6]. As an intrinsic component of NOMA, the successive interference cancellation (SIC) technique exploits a sufficient difference of relative channel gains among users to extract received signals efficiently. However, the networks mostly face imperfect SIC condition as the higher-gain components cannot be completely cancelled from the superimposed signals obtained at the receiver in reality [7]. Efficiently optimizing the video quality (via appropriate video bitrate selection) of ABS services in such an imperfect environment is considered a great challenge.

A comprehensive literature review in [8] reveals that most recent studies have resolved several aspects of the ABS services over wireless networks along with an assumption of orthogonal communication whilst some rare studies worked on NOMA, however, with ideally perfect SIC [9, 10, 11, 12]. For instance, Ali *et al.* considered the dynamicity of multihop cognitive radio environment to minimize end-to-end latency of ABS services [13]. Although an optimal radio resource selection has been obtained for service latency minimization, the solution is based on wireless channel observation passively instead of handling sources of channel variations. In [14], Sunny *et al.* proposed the D-VIEWS radio resource scheduler, which balanced

Email addresses: nndao@sejong.ac.kr (Nhu-Ngoc Dao), dnvu@uclab.re.kr (Duc-Nghia Vu), wsna@kongju.ac.kr (Woongsoo Na), hoangtrongminh@ptit.edu.vn (Trong-Minh Hoang), dodinhthuan@utexas.edu (Dinh-Thuan Do), srcho@cau.ac.kr (Sungrae Cho)

between video bitrates and wireless channel conditions to offer service quality fairness among adjacent users. However, the D-VIEWS comes with a consideration of ideally orthogonal communications as in 4G systems. To capture time-varying wireless channel conditions, Guo *et al.* exploited the power of deep reinforcement learning to jointly optimize computation and communication resource allocations for ABS services [15]. This approach can be regarded as a reactive solution against the change of wireless environment predicted through learning activities. On the other hand, Zhang *et al.* worked on optimizing ABS services by jointly considering resource allocation and bitrate adaptation in NOMA systems [12]. This work actively handled resource allocation on NOMA channels, notwithstanding ideally perfect SIC was assumed towards the optimization. To the best of our knowledge, improving quality of ABS services in terms of video resolution and playback smoothness in NOMA systems especially with imperfect SIC remains a challenging issue for cross-domain research communities.

Inspired from the above investigation, this paper jointly controls video bitrate adaptation and transmission power allocation to maximize the video resolution of online ABS streams while maintaining playback smoothness in NOMA edge caching systems with imperfect SIC. The research methodology of this paper is described as follows:

- First, the challenging environment was thoroughly investigated. Particularly, a comprehensive realistic model of ABS services in multi-user downlink NOMA edge caching systems with imperfect SIC is analyzed. Here, various environmental factors are considered such as the number of active users, the imperfectness of SIC, and available communication resources.

- Second, the optimization problem was mathematically formulated. We transformed the playback time budget into a smoothness buffer where incoming video bits are temporarily stored before presented on screen of user devices. The Lyapunov-derived drift-plus-penalty (DPP) policy was integrated into NOMA power allocation model with imperfect SIC to develop a joint optimization of video bitrate adaptation and playback smoothness.

- Third, to resolve the optimization, the logarithmic barrier method was exploited. As a result, a balanced ABS algorithm is proposed to maximize video bitrate of the online streams while managing their buffer tolerance to maintain playback smoothness.

- Fourth, to validate the effectiveness and advantages of the proposed approach intensive simulation was conducted. Numerical results demonstrated that the proposed approach outperforms existing approaches in terms of video quality and playback smoothness.

As a result, the novelties in this paper can be highlighted as follows:

- To the best of our knowledge, our study is the first attempt to maximize QoE by jointly optimizing the video resolution (via optimal video bitrate selection) and playback smoothness of ABS services in a multi-user downlink NOMA edge caching systems with imperfect SIC.

- To address the mentioned problem, two actions are performed. First, the problem is mathematically formulated adopting the Lyapunov-derived DPP policy. Then, a balanced ABS algorithm is developed based on the logarithmic barrier method to resolve the problem.

- Our studies demonstrate that improving QoE of ABS services in nonideal 5G NOMA environment can be significantly achieved by balancing between video bitrate and playback smoothness.

The remainder of this paper is organized as follows. Section 2 reviews state-of-the-art studies related to ABS systems and current NOMA studies with imperfect SIC. Section 3 provides problem statement with detailed analyses of transmission model and bitrate adaptation in multi-user downlink NOMA edge caching systems with imperfect SIC. Section 4 describes our proposed balanced ABS algorithm. Subsequently, Section 5 illustrates simulation setups and numerical result discussions. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. NOMA with Imperfect SIC

Recently, investigating the impacts of imperfect SIC on NOMA wireless environment has been attractive to research communities. For example, Wang *et al.* [16] proposed a low-complexity power allocation and user scheduling scheme to maximize the sum-rate in multi-carrier NOMA networks by managing power order constraints with consideration of SIC errors at user devices. The problem was transformed into a convex optimization, which then was resolved by iterative algorithms. Assuming improper Gaussian signaling adoption at user devices, Mahady *et al.* [17] derived the sum-rate maximization problem in NOMA systems with imperfect SIC subject to minimum quality-of-service requirements, then developed an iterative algorithm to find the suboptimal coefficient factor to this end. In [18], Hota et al. considered the ergodic performance of NOMA systems by optimizing the decoding orders through an approximation method in an imperfect SIC environment. On the other hand, Sena *et al.* [19] investigated a multi-user multi-cluster massive multiple-input-multiple-output (MIMO) NOMA system with imperfect SIC. In this scenario, an iterative power allocation algorithm was proposed for fairness improvement among users per cluster. In addition, beamforming and cluster formation were designed to jointly optimize outage probability and ergodic performance whilst maintaining user fairness in terms of service quality. From another perspective, Khan et al. [20] studied a backscatter-enabled NOMA system. To maximize sum-rate, transmit power of NOMA antennas and reflection coefficient factors of backscatter tags were jointly optimized with a consideration of imperfect SIC, then resolved by the sub-gradient method. In a small-cell NOMA network, Khan et al. [21] investigated the trade-off between system capacity and energy consumption when controling transmit power subject to imperfect SIC. To address this problem, an iterative algorithm was developed based on the sequential quadratic programming method. In summary, NOMA systems with imperfect SIC have been considered a critical problem that deserves to be thoroughly investigated in various application scenarios towards its maturation.

2.2. ABS Systems

Literature review found that existing works in the field of ABS have focused on addressing various technological aspects, which can be taxonomized into two major categories: user experiencing [22, 23, 24, 25, 26, 27, 28, 29] and system performance [30, 31, 32, 33, 34, 35, 36, 37] optimizations.

To improve user experiences, current studies investigated multiple factors of the entire systems, which influence video quality during streaming time such as access bandwidth, wireless interference, in-network computing capacities, link stability, user mobility, user preference, and the capability of user devices. Experimental study in [23] exposed that behaviors and reactions of streaming algorithms significantly impact quality of experience (QoE) on ABS services. For instance, Gao *et al.* exploited video semantic information among users who share the same interests to predict viewing behaviors of current users [24]. In addition, retention rate of a video stream technically depends on codec selection, playback delay, and stalling frequency [25]. The prediction is used to suggest appropriate video bitrate for individual user with a consideration of time-varying access bandwidth. Typically, an increase of video bitrate comes with a cost of bandwidth consumption. To cope with this issue, Kimura *et al.* proposed the BANQUET algorithm, which helps to minimize user traffic while maintaining desired viewing experiences requested by users [22]. The BANQUET algorithm adjusts user bandwidth allocation based on current context in terms of available playback buffer and channel conditions [26]. To jointly handle bitrate maximization and end-to-end latency minimization, Wang *et al.* proposed the MultiLive bitrate control algorithm to specify optimal bitrate for each pair of streamer and player communication [27]. Adopting the MultiLive algorithm, video streams, which are characterized by similar features, are aggregated using scalable coding for transmission. On the other hand, Taraghi *et al.* considered system stability and its effects on stalling frequency and duration during the streaming time in [28]. The findings show that a short stall event of 4 ms does not notably influence user experiences, whereas most of the users prefer high video bitrate along with several long stall events rather than smooth-but-low video bitrate. Recent studies [29] demonstrated that machine learning techniques are a promising approach to handle complex and heterogeneous environmental conditions towards QoE improvements in ABS systems.

Focusing on system performance maximization, existing studies gave their efforts to orchestrate available communication, computation, and storage resources at networking components to support ABS systems for transcoding and temporarily caching video contents on the delivery throughout the networks. For instance, Gao *et al.* exploited the power of network function virtualization to propose a virtual caching scheme, namely vCache [30], which enable video streams buffering their searchable metadata at the cache in advance. Meanwhile, video data are physically stored at the edge servers whenever a request arrived. This mechanism significantly improves resource utilization efficiency in the network. Moreover, Xu *et al.* jointly considered caching and communication resource allocation at multi-access edge computing (MEC)-empowered mobile base stations to assist ABS services with flexible bitrate adaptation [31]. A Stackelberg game model was developed to harmonize cache and wireless resources for every video content based on the content popularity. To improve hit ratio at the cache, Tran *et al.* considered cooperative caching and processing operations at the edge servers to optimize cache placement of multiple video variants for access traffic and service delay reductions [32]. Aiming to provide a flexible transcoding strategy in a MEC-enabled ABS system, Liu *et al.* considered available edge computing capacity, transcoding power requirements, and communication resources to select proper video bitrate versions. As a result, low latency experience and viewing smoothness are achieved for multiple players [33]. On the other hand, Li *et al.* targeted energy efficiency in ABS edge caching servers by jointly analyzing the caching capacity, computing power, and backhaul resources to tradeoff between video bitrate and energy consumption while satisfying user service requirements [34]. In a hybrid mode, network capacities and user preferences are considered by Lebreton *et al.* in [35] to estimate optimal bitrate ladders according to upcoming network conditions and user interests. To protect sensitive user information and data, blockchain-assisted and secure data delivery frameworks are proposed in [36, 37] in ABS caching systems. The proposed frameworks provide trustful service request transactions and the integrity of data transferred.

According to the aforementioned taxonomy, our paper can be classified into the user experiencing category as the paper aims at adapting video bitrate to mobile network condition fluctuations. Different from existing studies in the same category, our our proposed algorithm is particularly incorporated within current advanced access technologies, i.e., NOMA, in 5G and beyond networks. In addition, we developed an adaptive tradeoff function between video bitrate and playback smoothness, which considers current time-varying system state. As a result, video streams are smoothly played at the best-possible resolution supported by the system.

3. Problem Statement

This paper considers a network model of ABS services in multi-user downlink NOMA edge caching systems with imperfect SIC, as illustrated in Fig. 1. In this model, 5G gNB access point equipped with edge caching capabilities assists the ABS services in two folds: (*i*) DANE functionalities, which transcode and cache suitable bitrate versions of video streams acquired from the content server for users temporarily access and (*ii*) wireless fronthaul medium, which delivers appropriate

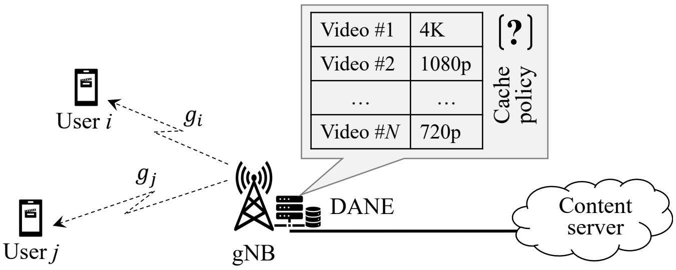

Figure 1: Network model of ABS services in multi-user downlink NOMA edge caching systems with imperfect SIC.

video streams to multiple users on demand [38]. Here, NOMA is utilized as the access technology, however, with imperfect SIC. Without loss of generality, we assume that user clusters are organized in advance.

3.1. Transmission Model

In this network model, the gNB concurrently serves all users in the set $\mathcal{U}$ with its cardinality U. Assume that the downlink channel gain from the gNB to user i is g_i and all users are labeled by their gains in ascending order, i.e.,

$$g_1 \leq \ldots \leq g_i \leq \ldots \leq g_U. \tag{1}$$

Briefly, NOMA superimposes all user signals into a single waveform at the gNB before transmitting (a.k.a. superposition coding), while every users independently decode the received signals by consequently extracting individual signals based on the signal strength in descending order, i.e., first user U last user 1 (a.k.a. SIC). In fact, SIC cannot completely subtract the higher-strength signals to obtain desired signal expected by the user owing to hardware limitation and so on. Therefore, residual interference exists during SIC, referred to as imperfect SIC. Accordingly, inter-user interference I_i of user i is given by

$$I_i = \sum_{j=1}^{i-1} p_j g_i + \beta \sum_{j=i+1}^{U} p_j g_i, \quad 0 \leq p_j \leq p^{\max}, \beta \in [0, 1], \tag{2}$$

where p_j and $p^{\max}$ denote the current and maximum transmit powers of user j while β is the coefficient factor of interference from higher-strength signals, which can be investigated through long-term measurements [39]. Hence, the data rate r_i of user i yields

$$r_i = w \log_2 \left(1 + \frac{p_i g_i}{I_i + n_0 w} \right), \tag{3}$$

where w and n_0 represent the downlink bandwidth and the noise power spectral density, respectively.

To perform SIC properly, the necessary power constraints associated to user i is expressed as follows:

$$p_i g_i - (I_i + n_0 w) \geq \epsilon, \qquad \epsilon > 0, \tag{4}$$

where ϵ is the minimum power difference required to distinguish between the signal expected by user i and the remaining components in the received signals.

3.2. Video Bitrate Adaptation

As illustrated in Fig. 1, the gNB performs DANE functions to assist ABS services in terms of video transcoding and caching capabilities. Here, a maximum playback time budget ($\theta^{\max}$) are predefined by the DANE functions at the gNB to temporarily buffer video streaming data at user devices before playing [40, 41]. The maximum playback time budget specifies the duration a user service can accept to wait for the video data arrived. Obviously, current status $\theta_i(t)$ of user i at timeslot t is updated as follows:

$$\theta_i(t) = \max \left\{ 0, \theta_i(t-1) - \tau \left(1 - \frac{r_i(t)}{v_i(t)} \right) \right\}, \forall t, \tag{5}$$
$$\theta_i(0) = \theta^{\max},$$

where τ is the timeslot duration and $v_i(t)$ is the video bitrate streamed on the downlink to user i during timeslot t. $v_i(t) \in \mathcal{V}$, which is a deterministic set of applicable bitrates. It is observed that $\theta_i \propto \frac{r_i}{v_i}, \forall t$. In layman's terms, if the video bitrate increases and/or the data rate decreases, the playback time of buffered data decreases accordingly, and vice versa. For example, a video stream has initially a maximum playback time budget of 5000 ms. In next 100-ms timeslot, if the data rate is 2-time higher than the selected video bitrate, the user device can play the video stream instantly and smoothly and the current playback time budget is $5000 - 100 * (1 - 2) = 5100$ ms. However, if the data rate is 2-time lower than the selected video bitrate, the user device must to wait during this timeslot to buffer the video data, i.e., the current playback time budget is decreased to be $5000 - 100 * (1 - 0.5) = 4950$ ms. Service quality is considered unsatisfied if the current playback time budget is less than 0 ms. To serve a smooth video playback, θ_i must to maintain as mean rate plus $\theta^{\max}$ stable, i.e.,

$$\lim_{t \to \infty} \frac{\mathbb{E}[\theta_i(t)] - \theta^{\max}}{t} = 0. \tag{6}$$

Based on this observation, we refer θ_i to as a *virtual smoothness buffer* with the upper-bound θ. Here, our objective is to optimally select $v_i(t)$ and control $r_i(t)$ to maximize the time-average bitrate of the video streams while satisfying (6),

$$\max \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[v_i(t)]. \tag{7}$$

By considering status fluctuation of the smoothness buffer as queuing drift and the video bitrate as penalty according a given selection of $v_i(t)$ and $r_i(t)$, the Lyapunov-derived drift-plus-penalty policy [42] can be exploited to develop the optimization, that is,

$$\max_{\{v_i, r_i\}} \alpha \sum_{i=1}^{U} v_i(t) - \sum_{i=1}^{U} \theta_i(t) \left[\tau \left(1 - \frac{r_i(t)}{v_i(t)} \right) \right], \qquad \forall t, \tag{8}$$

where α is a non-negative coefficient factor to prioritize the penalty term against the drift term. Derived from (3), r_i is controlled by p_i as in NOMA systems. Hence, the optimization is transformed into

$$\max_{\{v_i,p_i\}} \sum_{i=1}^{U}\left(\alpha v_i - \theta_i\left(\tau - \frac{w\log_2\left(1+\frac{p_i g_i}{I_i+n_0 w}\right)}{v_i}\right)\right) \quad (9)$$
$$\text{s.t.} \ \ (2),(4),(5).$$

4. Proposed Balanced ABS Algorithm

It is seen that (9) is a mixed-integer programming problem where optimal variables $\{v_i\}$ and $\{p_i\}$ are decided in predefined set $\mathcal{V}$ and range $[0, p^{\max}]$, respectively. Let $F(v, p)$ defines the functions of $\{v_i\}$ and $\{p_i\}$. Consequently, the objective function for problem (9) can be represented as

$$\begin{aligned}\max F(v,p) = \max_{\{v_i,p_i\}} \sum_{i=1}^{U}\Bigg(\alpha v_i - \bigg(\theta_i(t-1) - \tau\Big(1-\frac{r_i(t)}{v_i(t)}\Big)\bigg) \\ \times\Bigg(\tau - \frac{w\log_2\left(1+\frac{p_i g_i}{\sum_{j=1}^{i-1} p_j g_i + \beta\sum_{j=i+1}^{U} p_j g_i i + n_0 w}\right)}{v_i}\Bigg)\Bigg) \quad (10)\end{aligned}$$

$$\text{s.t.} \ \ p_i \geq 0, \quad (11)$$
$$p^{max} - p_i \geq 0, \quad (12)$$
$$p_i g_i - \left(\sum_{j=1}^{i-1} p_j g_i + \beta \sum_{j=i+1}^{U} p_j g_i + n_0 w\right) - \epsilon \geq 0, \quad (13)$$
$$\theta_i(t-1) - \tau\left(1-\frac{r_i(t)}{v_i(t)}\right) \geq 0. \quad (14)$$

Accordingly, the logarithmic barrier function associated with (10) is given by

$$\begin{aligned}B(v,p,\mu) =& F(v,p) - \mu\Bigg(\ln p_i + \ln(p^{max}-p_i) \\ &+ \ln\left(p_i g_i - \left(\sum_{j=1}^{i-1} p_j g_i + \beta\sum_{j=i+1}^{U} p_j g_i + n_0 w\right) - \epsilon\right) \\ &+ \ln\left(\theta_i(t-1) - \tau\left(1-\frac{r_i(t)}{v_i(t)}\right)\right)\Bigg). \end{aligned} \quad (15)$$

We define

$$\begin{aligned} C_1(v,p) =& p_i(p^{max}-p_i), \\ C_2(v,p) =& p_i g_i - \left(\sum_{j=1}^{i-1} p_j g_i + \beta\sum_{j=i+1}^{U} p_j g_i + n_0 w\right) - \epsilon, \\ C_3(v,p) =& \theta_i(t-1) - \tau\left(1-\frac{r_i(t)}{v_i(t)}\right). \end{aligned}$$

Hence, the logarithmic barrier function (15) is represented as

$$B(v,p,\mu) = F(v,p) - \mu\sum_{m-1}^{3} \ln C_m(v,p). \quad (16)$$

Here, μ is a small positive scalar called the "barrier parameter". As μ converges to zero, the maximum of $B(v, p, \mu)$ will converge to a solution objective function (10). The gradient of barrier function (16) is

$$g_b = g - \mu\sum_{m-1}^{3} \frac{\nabla C_m(v,p)}{C_m(v,p)}, \quad (17)$$

where g is the gradient of the original function $F(v, p)$ and $\nabla C_m(v, p)$ is the gradient of $C_m(v, p)$ Let λ is a Lagrange multiplier inspired dual variable

$$C_m\lambda_m = \mu, \qquad m = 1,2,3. \quad (18)$$

Eq. (18) is the complementary slackness in Karush-Khun-Tucker (KKT) conditions [43]. The solution of problem (10) can be obtained by finding $(v_\mu, p_\mu, \lambda_\mu)$ for which the gradient of the barrier function is zero. Applying (18) to (17), we derive an equation for the gradient

$$g - A^T\lambda = 0, \quad (19)$$

where the matrix A is the Jacobian of the constraints $C(v, p)$. Applying Newton's method [44] to (18) and (19), we obtain an equation for (v, p, λ) to update (x_v, x_p, x_λ)

$$\begin{pmatrix} W & -A^T \\ \Lambda A & C \end{pmatrix}\begin{pmatrix} X_{v,p} \\ X_\lambda \end{pmatrix} = \begin{pmatrix} -g + A^T\lambda \\ \mu 1 - C\lambda \end{pmatrix}, \quad (20)$$

where W is the Hessian matrix of $B(v, p, \mu)$, Λ is a diagonal matrix of λ, and C is a diagonal matrix with $C_{mm} = C_m(v, p)$. According to (10) and (18), the condition $\lambda \geq 0$ should be enforced at each step. This can be done by choosing appropriate α.

$$(v,p,\lambda) \rightarrow (v+\alpha X_v, p+\alpha X_p, \lambda+\alpha X_\lambda). \quad (21)$$

The proposed scheme is described in Algorithm 1. In this scheme, we initialize the value of $u^0 = 0$, $v^0 = 0$, and $\lambda^0 = 0$ in the first step. In each step k, we solve the problem (20) with the given u^k, v^k, and λ^k in sequence to derive step size X_v^k, X_p^k, and X_λ^k, respectively. The new value u^{k+1}, v^{k+1}, and λ^{k+1} is updated following the (21) with given appropriate $\alpha = 0.1$. According to the Newton's method, the value of $F(v, p)$ increases after each iteration and converges to the near optimal value. When the magnitude $|F_{k+1} - F_k|$ is less than a very small tolerance ξ, the iteration stops. Subsequently, we obtain the near optimal value $v(t)^* = v^k$, $p^*(t) = p^k$, and $\lambda^*(t) = \lambda^k$ which results in $F(v, p)_{\max}$.

Remarks: Computational Complexity Analysis. As described in Section 4, the problem (9) for finding the optimal video bitrate v and transmit power p is transformed to the equivalent problem (19) by using the barrier method and KKT conditions. The near optimal solution of problem (19) can be achieved by using an Balanced ABS scheduling optimization algorithm based on Newton's method. Because of quadratic convergence to the optimal value of Newton's method, the proposed algorithm can obtain the solution rapidly and effectively. The computational complexity of proposed algorithm is $O(\xi^{-2})$ [45], where ξ is the tolerance used for the stop condition of the iteration. It is observed that problem (10) can also be solved by

Algorithm 1 Balanced Adaptive Bitrate Streaming

Input: $\theta(t-1)$, τ, $r_i(t)$, $n_0 w$
Output: $v_i^*(t)$, $p_i^*(t)$, $\lambda_i^*(t)$

- Initialization
  v^k, p^k, and λ^k are v, p, and λ at k-th step, respectively, $u^0 = 0$, $v^0 = 0$, and $\lambda^0 = 0$
  X_v^k, X_p^k, and X_λ^k is the step size of v^k, p^k, and λ^k at k-th step, respectively
  ξ is the tolerance, $\alpha = 0.1$
  repeat
      Given v^k, p^k, and λ^k, solve the problem (20) derive X_v^{k+1}, X_p^{k+1}, and X_λ^{k+1}
      v^{k+1},p^{k+1}, and λ^{k+1} is respectively derived from (21)
      $v^k = v^k + \alpha X_v^{k+1}$
      $p^k = p^k + \alpha X_p^{k+1}$
      $\lambda^k = \lambda^k + \alpha X_\lambda^{k+1}$
      $k = k + 1$
  until $|F_{k+1} - F_k| \leq \xi$
  $v^* = v^k$, $p^* = p^k$, and $\lambda^* = \lambda^k$

using the ellipsoid method or the cutting plane method [46]. The complexity of these approaches is $O(n^4)$, where n is number of v and p variables. Because n is relatively large, these algorithms have a much higher complexity than the proposed algorithm.

5. Performance Evaluation

5.1. Simulation Setups

To investigate performance of the proposed balanced ABS algorithm, we constructed a NOMA system model with imperfect SIC constituted by a central gNB and multiple user devices in a coverage area of 1000 m × 1000 m. Here, user devices are randomly distributed in the coverage area. In this simulation scenario, environmental conditions are setup with the noise power spectral density of -169 dBm/Hz and varying coefficient factor of interference in range of $[0, 1]$. Regarding communication settings, the maximum transmit power of user device is 40 dBm and the minimum power difference ϵ is 10 dBm [47], while the available access bandwidth is in $[2, 20]$ MHz. In terms of ABS service configurations, video bitrate, without loss of generality, is assumed to be in a predefined set of $\{3400, 2930, 1789, 1144, 374, 283\}$ kbps [41, 48]. In addition, the maximum playback time budget is assigned as 5 s. Detailed simulation parameters are summarized in Table 1.

The simulation has been conducted using MATLAB R2021a framework. We measured system performances during 100 Monte Carlo experiments for each simulation configuration. The proposed balanced ABS algorithm was compared with the following schemes:

- Location-aware ABS [49]: This scheme prioritizes user devices with low channel qualities at the edge of the coverage area to be assigned with appropriate transmit power and video bitrate while satisfying all constraints.

- Lightweight ABS [50]: This scheme adopts the first-come-first-serve policy, where the first applicable solution is selected to assign transmit power and video bitrate to user devices until the system resources are exhausted.

Table 1: Simulation parameters

Parameter	Value
Coverage area	1000 m × 1000 m
Number of clusters	8
Number of users per cluster	[0, 10]
v_i	{3400, 2930, 1789, 1144, 374, 283} kbps [48]
$p^{\max}$	40 dBm
$\theta^{\max}$	5 s
τ	100 ms
β	[0, 1]
α	$[10^{-3}, 10^0]$
ϵ	10 dBm
n_0	-169 dBm/Hz
w	[2, 20] MHz

- Low-delay MultiLive [27]: This scheme prioritizes the playback smoothness of video streams by maximizing playback time budget as desired by user devices with considerations of environment changes.

- Bitrate upper bound: This baseline establishes the maximum video bitrate available for user devices according to the channel environment regardless of the playback time budget.

5.2. Numerical Performance Analyses

Fig. 2 shows proportional relationships between the average video bitrate and available access bandwidth. In a given network condition, the average bitrate of video streams obviously increases as more bandwidths are available to serve user associations. In general, average video bitrate supported by the proposed balanced ABS scheme is 35.06% and 39.92% higher than those of the location-aware and lightweight ABS schemes, respectively. In particular, the proposed balanced ABS algorithm reveals its advantages especially in a system condition with poor communication resources. In case the available access bandwidth is in range of (2, 8) MHz, the proposed balanced ABS scheme significantly increases the average video bitrate up to 58.35% and 75.01% compared to the location-aware and lightweight ABS schemes, respectively. It is observed that average bitrate provided by the balanced ABS scheme stays in the middle between those of bitrate upper bound and low-latency MultiLive schemes. When the available access bandwidth is sufficient to serve all user devices (i.e., $\geq$ 20 MHz), the average video bitrate reaches the highest value of 3400 kbps in all schemes.

Fig. 3 illustrates effects of the coefficient factor of interference on the average video bitrate. Similar to the way that the available access bandwidth impacts the video bitrate, the coefficient factor of interference represents channel quality and then, partially decides data rate of user connections. A high value of the factor exposes high interference resulting in a low data rate, and vice versa. Because of the imperfectness of the SIC in NOMA association, average video bitrate in all schemes decreases as the coefficient factor increases. In this circumstance, the proposed balanced ABS scheme mitigates the impact of interference by controlling the transmit powers to user devices.

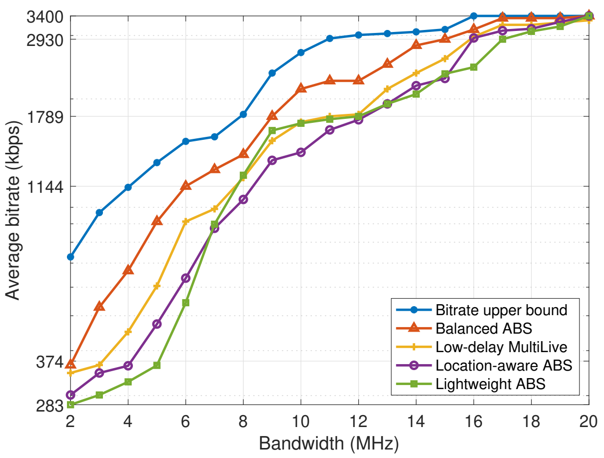

Figure 2: Average video bitrate in different access bandwidth assignment.

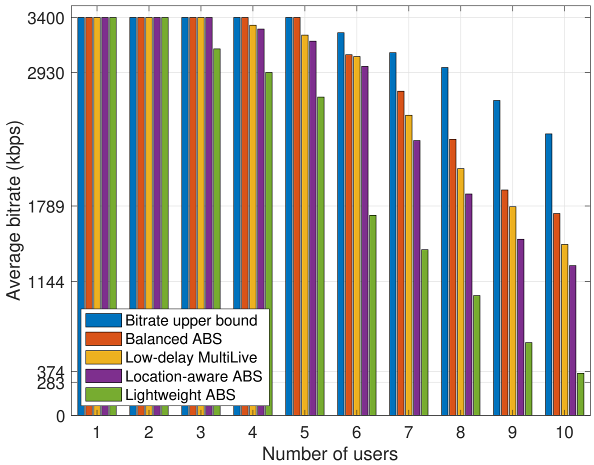

Figure 4: Average video bitrate in case the number of users changes.

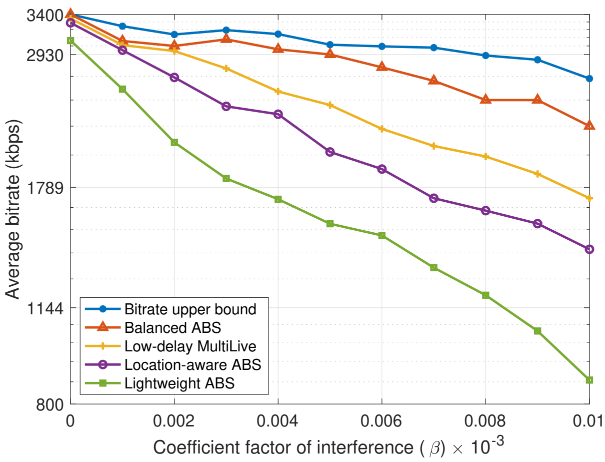

Figure 3: Effects of the coefficient factor of interference on the average video bitrate.

As a result, the proposed balanced ABS scheme efficiently resists against bitrate reductions. In particular, average bitrate reductions in the balanced, location-aware, and lightweight ABS schemes are 33.96%, 56.87%, and 71.65% respectively as the interference factor increases from 0 to 10 ($\times 10^{-3}$). Intuitively, video bitrate supported by the balanced ABS scheme is in between 1789 and 2930 kbps, while video bitrate in the location-aware and lightweight ABS schemes are less than 1789 and 1144 kbps, respectively.

Fig. 4 demonstrates the average video bitrate when the number of concurrent user services changes. In a given system condition with constrained resources, data rates of user connections decrease when the number of concurrent users increases; hence, this results in average video bitrate reductions. The reasons are because of smaller assigned bandwidth for each user device and higher interference among user connections. As the proposed balanced ABS scheme optimally selects appropriate transmit powers for every user to efficiently control the interference, the scheme offers higher average video bitrate in all cases. Particularly, average video bitrate is decreased by 49.28%, 62.37%, and 89.42% in the balanced, location-aware, and lightweight ABS schemes, respectively, when the number of concurrent users increases from 1 to 10. Especially, within the 10-user scenario, the balanced ABS scheme provides the average video bitrate around 1789 kbps, while the location-aware and lightweight ABS schemes offer the average video bitrate around 1144 and 374 kbps, respectively. The results show that the proposed balanced ABS scheme clearly exposes its advantage in poor system conditions. It is worth noting that the balanced ABS scheme generally maintains the average bitrate around the middle between those provided by bitrate upper bound and low-latency MultiLive schemes in all cases.

Regarding the video playback smoothness, Figs. 5, 6, and 7 represent the simulation results with different configurations of access bandwidth, interference factor, and number of concurrent users. As shown in Fig. 5, the average playback time budget increases proportionally to the available access bandwidth. Obviously, a larger amount of assigned bandwidth provides a higher data rate for user connections. Consequently, video bitrate as well as buffered data increase resulting in high playback time budget. Although all algorithms expose the same time budget improvement fashion, the proposed balanced ABS scheme provides better performance compared to the others. In particular, the average playback time budget provided by the balanced ABS scheme is 10.88% and 26.89% higher than those of the location-aware and lightweight ABS schemes, respectively. Derived from Figs. 2 and 5, the average playback time budget increases quickly when the available access bandwidth is sufficient to serve user services with intermediate video quality (i.e., 1144 and 1789 kbps). The increase velocity is slower when high video quality is provided within high available bandwidth (e.g., 20 MHz). This observation is be-

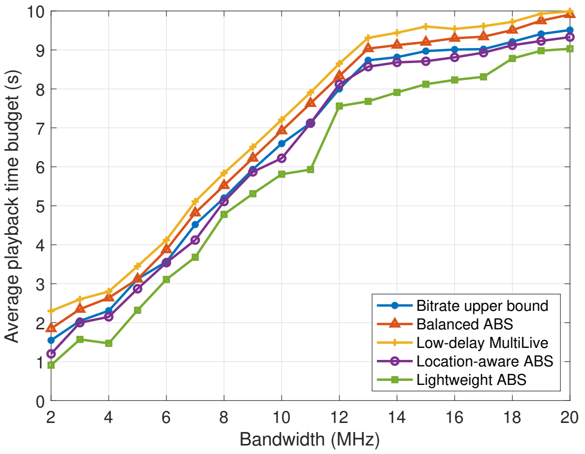

Figure 5: Average playback time budget in different access bandwidth assignment.

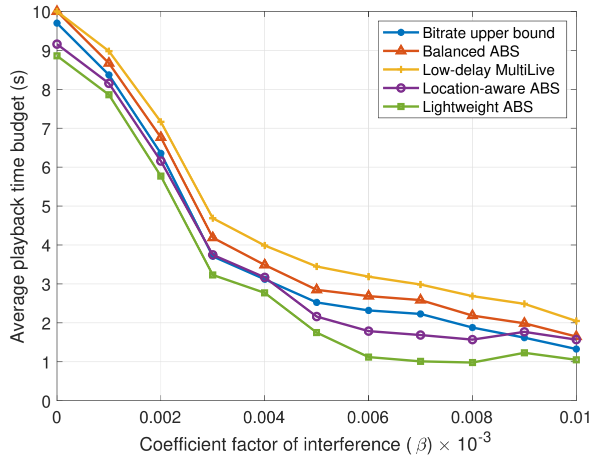

Figure 6: Average playback time budget within various imperfectness values of SIC.

cause jumping to high video bitrate requires significant additional amount of bandwidth to transfer the data and a large amount of data needed to be buffered for time budget improvement.

Fig. 6 demonstrates the relationship between the average playback time budget and the imperfectness of SIC represented by the coefficient factor of interference. Obviously, high values of the interference factor lead to poor channel quality and hence, low data rate. Consequently, the average playback time budget decreases due to smaller amount of video data can be downloaded. Although all the simulated algorithms illustrate the same effect of the imperfectness of SIC, the proposed balanced ABS scheme retains a higher average playback time budget of 0.56 and 1.04 s compared to those provided by the location-aware and lightweight ABS schemes, respectively. To obtain this advantage, the balanced ABS scheme dynamically decides a trade-off between video bitrate and playback time budget to ensure video playback smoothness at the highest video quality. Compared to the bitrate upper bound scheme, the proposed balanced ABS scheme maintains a higher playback time budget for a stable playback smoothness of video streams in dynamic environments.

Fig. 7 shows the relationships between the average playback time budget and the number of concurrent users in the systems. It is easy to capture that a larger number of user devices associated in the network results in a higher interference as well as a reduction in assigned bandwidth for user services. These issues significantly decrease user data rates and therefore, the playback time budgets. In this circumstance, the proposed balanced ABS schemes handle the video quality (represented by the bitrate metrics) to stabilize the playback time budgets in one side. On another side, the proposed scheme optimizes transmit powers for user devices to improve channel qualities. Subsequently, 0.86 and 1.93-second differences of the playback time budget are retained in the balanced ABS schemes compared to those of the location-aware and lightweight ABS schemes, re-

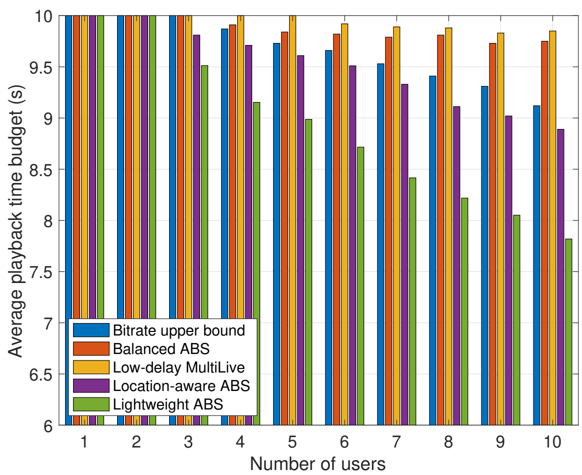

Figure 7: Average playback time budget with different numbers of user devices.

spectively. The results demonstrate that the proposed balanced ABS scheme well adapts to the change in environmental conditions and user requirements, especially in uncertain and poor system conditions. In particular, average playback time budget provided by the balanced ABS scheme maintains an approximate value compared to that of the low-delay MultiLive scheme.

6. Conclusion

As video streaming services increasingly dominate mobile traffic in advanced 5G networks and beyond, this paper developed an optimal solution to efficiently and dynamically balance between video quality and playback smoothness of the ABS services. The proposed balanced ABS scheme jointly optimize video bitrate and playback time budget with considerations of environmental conditions in a multi-user downlink NOMA edge caching system with imperfect SIC. Simulation results demonstrated that the proposed scheme outperforms existing works in terms of video quality and smoothness in various system scenarios with different configurations of SIC imperfectness, available access bandwidth, and the number of concurrent user associations. Particularly, the balanced ABS schemes exposed their flexible adaptations to the change of system configuration to obtain bitrate improvements while remaining stable playback time budget of video streams. In addition to the imperfect SIC, the imperfect channel state information (CSI) has been considered a challenging problem in NOMA environment, which highly affects the performance of NOMA and SIC. Hence, to expand this work, future research will be dedicated to investigating the imperfect CSI issue in such an ABS system.

Acknowledgment

This work was supported under the statement of work number POS-459341/Project 3 of the Research Agreement Number POS-458996 between Qualcomm Technologies, Inc and Posts and Telecommunications Institute of Technology. The work of Nhu-Ngoc Dao was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1G1A1008105).

References

[1] A. Bentaleb, B. Taani, A. C. Begen, C. Timmerer, R. Zimmermann, A survey on bitrate adaptation schemes for streaming media over HTTP, IEEE Communications Surveys & Tutorials 21 (1) (2018) 562–585.

[2] X. Jiang, F. R. Yu, T. Song, V. C. Leung, Resource allocation of video streaming over vehicular networks: A survey, some research issues and challenges, IEEE Transactions on Intelligent Transportation Systems (2022) 1–1To be published.

[3] ISO/IEC 23009-5:2017, Information technology – Dynamic adaptive streaming over HTTP (DASH) – Part 5: Server and network assisted DASH (SAND) (Feb. 2017).

[4] 3GPP TR 26.957 V16.0.0, Study on server and network-assisted dynamic adaptive streaming over HTTP (DASH) (SAND) for 3GPP multimedia services (Release 16) (Jul. 2020).

[5] Y. Liu, S. Zhang, X. Mu, Z. Ding, R. Schober, N. Al-Dhahir, E. Hossain, X. Shen, Evolution of NOMA toward next generation multiple access (NGMA) for 6G, IEEE Journal on Selected Areas in Communications (2022) 1–1To be published.

[6] A. Akbar, S. Jangsher, F. A. Bhatti, NOMA and 5G emerging technologies: A survey on issues and solution techniques, Computer Networks 190 (2021) 107950.

[7] M. Vaezi, R. Schober, Z. Ding, H. V. Poor, Non-orthogonal multiple access: Common myths and critical questions, IEEE Wireless Communications 26 (5) (2019) 174–180.

[8] A. Bentaleb, B. Taani, A. C. Begen, C. Timmerer, R. Zimmermann, A survey on bitrate adaptation schemes for streaming media over HTTP, IEEE Communications Surveys & Tutorials 21 (1) (2019) 562–585.

[9] E. Iradier, J. Montalban, L. Fanari, P. Angueira, L. Zhang, Y. Wu, W. Li, Using NOMA for enabling broadcast/unicast convergence in 5G networks, IEEE Transactions on Broadcasting 66 (2) (2020) 503–514.

[10] S. Rezvani, S. Parsaeefard, N. Mokari, M. R. Javan, H. Yanikomeroglu, Cooperative multi-bitrate video caching and transcoding in multicarrier NOMA-assisted heterogeneous virtualized MEC networks, IEEE Access 7 (2019) 93511–93536.

[11] H. Lu, X. Jiang, C. W. Chen, Distortion-aware cross-layer power allocation for video transmission over multi-user NOMA systems, IEEE Transactions on Wireless Communications 20 (2) (2020) 1076–1092.

[12] J. Zhang, H. Wu, X. Tao, X. Zhang, Adaptive bitrate video streaming in non-orthogonal multiple access networks, IEEE Transactions on Vehicular Technology 69 (4) (2020) 3980–3993.

[13] A. Ali, S. Tariq, M. Iqbal, L. Feng, I. Raza, M. H. Siddiqi, A. K. Bashir, Adaptive bitrate video transmission over cognitive radio networks using cross layer routing approach, IEEE Transactions on Cognitive Communications and Networking 6 (3) (2020) 935–945.

[14] A. Sunny, R. El-Azouzi, A. Arfaoui, E. Altman, S. Poojary, D. Tsilimantos, S. Valentin, Enforcing bitrate-stability for adaptive streaming traffic in cellular networks, IEEE Transactions on Network and Service Management 16 (4) (2019) 1812–1825.

[15] Y. Guo, F. R. Yu, J. An, K. Yang, C. Yu, V. C. Leung, Adaptive bitrate streaming in wireless networks with transcoding at network edge using deep reinforcement learning, IEEE Transactions on Vehicular Technology 69 (4) (2020) 3879–3892.

[16] X. Wang, R. Chen, Y. Xu, Q. Meng, Low-complexity power allocation in NOMA systems with imperfect SIC for maximizing weighted sum-rate, IEEE Access 7 (2019) 94238–94253.

[17] I. A. Mahady, E. Bedeer, S. Ikki, H. Yanikomeroglu, Sum-rate maximization of NOMA systems under imperfect successive interference cancellation, IEEE Communications Letters 23 (3) (2019) 474–477.

[18] P. K. Hota, S. Thapar, D. Mishra, R. Saini, A. Dubey, Ergodic performance of downlink untrusted NOMA system with imperfect SIC, IEEE Communications Letters 26 (1) (2021) 23–26.

[19] A. S. de Sena, F. R. M. Lima, D. B. da Costa, Z. Ding, P. H. Nardelli, U. S. Dias, C. B. Papadias, Massive MIMO-NOMA networks with imperfect SIC: Design and fairness enhancement, IEEE Transactions on Wireless Communications 19 (9) (2020) 6100–6115.

[20] W. U. Khan, X. Li, M. Zeng, O. A. Dobre, Backscatter-enabled NOMA for future 6G systems: A new optimization framework under imperfect SIC, IEEE Communications Letters 25 (5) (2021) 1669–1672.

[21] W. U. Khan, X. Li, A. Ihsan, M. A. Khan, V. G. Menon, M. Ahmed, NOMA-enabled optimization framework for next-generation small-cell IoV networks under imperfect SIC decoding, IEEE Transactions on Intelligent Transportation Systems (2022) 1–1To be published.

[22] T. Kimura, T. Kimura, A. Matsumoto, K. Yamagishi, Balancing quality of experience and traffic volume in adaptive bitrate streaming, IEEE Access 9 (2021) 15530–15547.

[23] A. Mondal, S. Chakraborty, Does QUIC suit well with modern adaptive bitrate streaming techniques?, IEEE Networking Letters 2 (2) (2020) 85–89.

[24] G. Gao, H. Zhang, H. Hu, Y. Wen, J. Cai, C. Luo, W. Zeng, Optimizing quality of experience for adaptive bitrate streaming via viewer interest inference, IEEE Transactions on Multimedia 20 (12) (2018) 3399–3413.

[25] P. Lebreton, K. Yamagishi, Predicting user quitting ratio in adaptive bitrate video streaming, IEEE Transactions on Multimedia 23 (2021) 4526–4540.

[26] T. Kimura, T. Kimura, K. Yamagishi, Context-aware adaptive bitrate streaming system, in: IEEE International Conference on Communications (ICC), 2021, pp. 1–7.

[27] Z. Wang, Y. Cui, X. Hu, X. Wang, W. T. Ooi, Z. Cao, Y. Li, MultiLive: Adaptive bitrate control for low-delay multi-party interactive live streaming, IEEE/ACM Transactions on Networking (2021) 1–1To be published.

[28] B. Taraghi, M. Nguyen, H. Amirpour, C. Timmerer, INTENSE: In-depth studies on stall events and quality switches and their impact on the quality of experience in HTTP adaptive streaming, IEEE Access 9 (2021) 118087–118098.

[29] L. Meng, F. Zhang, L. Bo, H. Lu, J. Qin, J. Han, Fastconv: Fast learning based adaptive bitrate algorithm for video streaming, in: IEEE Global Communications Conference (GLOBECOM), 2019, pp. 1–6.

[30] G. Gao, Y. Wen, J. Cai, vCache: Supporting cost-efficient adaptive bitrate streaming, IEEE MultiMedia 24 (3) (2017) 19–27.

[31] X. Xu, J. Liu, X. Tao, Mobile edge computing enhanced adaptive bitrate video delivery with joint cache and radio resource allocation, IEEE Access 5 (2017) 16406–16415.

[32] T. X. Tran, D. Pompili, Adaptive bitrate video caching and processing in mobile-edge computing networks, IEEE Transactions on Mobile Computing 18 (9) (2018) 1965–1978.

[33] C. Liu, H. Zhang, H. Ji, X. Li, MEC-assisted flexible transcoding strategy for adaptive bitrate video streaming in small cell networks, China Communications 18 (2) (2021) 200–214.

[34] L. Li, D. Shi, R. Hou, R. Chen, B. Lin, M. Pan, Energy-efficient proactive caching for adaptive video streaming via data-driven optimization, IEEE Internet of Things Journal 7 (6) (2020) 5549–5561.
[35] P. Lebreton, K. Yamagishi, Network and content-dependent bitrate ladder estimation for adaptive bitrate video streaming, in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2021, pp. 4205–4209.
[36] K. Akpinar, K. A. Hua, PPNet: Privacy protected CDN-ISP collaboration for QoS-aware multi-CDN adaptive video streaming, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 16 (2) (2020) 1–23.
[37] Y. Li, Z. Wan, Blockchain-enabled intelligent video caching and transcoding in clustered MEC networks, Security and Communication Networks 2021 (2021) 7443260.
[38] N.-N. Dao, A.-T. Tran, N. H. Tu, T. T. Thanh, V. N. Q. Bao, S. Cho, A contemporary survey on live video streaming from a computation-driven perspective, ACM Computing Surveys (2022) 1–1To be published.
[39] X. Chen, Z. Zhang, C. Zhong, R. Jia, D. W. K. Ng, Fully non-orthogonal communication for massive access, IEEE Transactions on Communications 66 (4) (2018) 1717–1731.
[40] N.-N. Dao, D. T. Ngo, N.-T. Dinh, T. V. Phan, N. D. Vo, S. Cho, T. Braun, Hit ratio and content quality tradeoff for adaptive bitrate streaming in edge caching systems, IEEE Systems Journal 15 (4) (2021) 5094–5097.
[41] A.-T. Tran, N.-N. Dao, S. Cho, Bitrate adaptation for video streaming services in edge caching systems, IEEE Access 8 (2020) 135844–135852.
[42] L. Bracciale, P. Loreti, Lyapunov drift-plus-penalty optimization for queues with finite capacity, IEEE Communications Letters 24 (11) (2020) 2555–2558.
[43] Z.-Q. Luo, W. Yu, An introduction to convex optimization for communications and signal processing, IEEE Journal on selected areas in communications 24 (8) (2006) 1426–1438.
[44] C. T. Kelley, Solving nonlinear equations with Newton's method, SIAM, 2003.
[45] C. Cartis, N. I. Gould, P. L. Toint, On the complexity of steepest descent, newton's and regularized newton's methods for nonconvex unconstrained optimization problems, Siam journal on optimization 20 (6) (2010) 2833–2852.
[46] S. Bubeck, Convex optimization: Algorithms and complexity, Foundations and Trends in Machine Learning 8 (2017).
[47] M. S. Ali, H. Tabassum, E. Hossain, Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems, IEEE Access 4 (2016) 6325–6343.
[48] S. Pham, P. Heeren, C. Schmidt, D. Silhavy, S. Arbanowski, Evaluation of shared resource allocation using SAND for ABR streaming, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 16 (2s) (2020) 1–18.
[49] F. Liu, W. Zhang, Y. Wen, QoE-driven mobile streaming: A location-aware approach, in: IEEE International Conference on Multimedia and Expo (ICME), 2019, pp. 1708–1713.
[50] X. Zhao, S. Zhang, W. Dou, Multi-request scheduling and collaborative service processing for DASH-video optimization in cloud-edge network, in: IEEE International Conference on Cloud Computing (CLOUD), 2020, pp. 582–589.

Author Biography

Nhu-Ngoc Dao (Senior Member, IEEE) received the B.S. degree in electronics and telecommunications from the Posts and Telecommunications Institute of Technology, Hanoi, Vietnam, in 2009, and the M.S. and Ph.D. degrees in computer science from the School of Computer Science and Engineering, Chung-Ang University, Seoul, South Korea, in 2016 and 2019, respectively. He is currently an Assistant Professor with the Department of Computer Science and Engineering, Sejong University, Seoul, South Korea. Prior to joining Sejong University, he was a Visiting Researcher with the University of Newcastle, Callaghan, NSW, Australia, in 2019 and a Postdoc Researcher with the Institute of Computer Science, University of Bern, Switzerland, from 2019 to 2020. His research interests include network softwarization, mobile cloudization, intelligent systems, and the Intelligence of Things. He is currently the Editor of the *Scientific Reports*.

Duc-Nghia Vu is a senior engineer at Innowireless Inc., Seongnam, South Korea. He received his B.S. degree in Electronics and telecommunications from Hanoi University of Science and Technology, Viet Nam, in 2015. He also received the M.S. degree in computer science from Chung-Ang University, South Korea, in 2018. He is a PhD candidate in computer science from Chung-Ang University, South Korea from 2021. His research interests include wireless network and fog computing.

Woongsoo Na received the B.S., M.S., and Ph.D. degrees in computer science and engineering from Chung-AngUniversity, Seoul, South Korea, in 2010, 2012, and 2017, respectively. He is currently an Assistant Professor with the Division of Computer Science and Engineering, Kongju National University, Cheonan, South Korea. Prior to joining Kongju National University, he was an Adjunct Professor with the School of Information Technology, Sungshin Womens University, Seoul, South Korea, from 2017 to 2018, and a Senior Researcher with Electronics and Telecommunications Research Institute, Daejeon, South Korea, from 2018 to 2019. His current research interests include mobile edge computing, flying ad hoc networks, wireless mobile networks, and beyond 5G.

Trong-Minh Hoang (Member, IEEE) received the bachelor's degree in physic engineering (1994) and electronic and telecommunication engineering (1999) from Hanoi University of Science and Technology, the master's degree in electronic and telecommunication engineering (2003), and the Ph.D.'s degree in telecommunication engineering (2014) from Posts and Telecommunications Institute of Technology. He is currently a lecturer in the Telecommunication Faculty of Posts and Telecommunications Institute of Technology. He is head of the telecommunication network department. He has been working on the issues surrounding the performance of wireless networks. His research interests include routing, security, and network performance in mobile edge computing, flying ad hoc networks, wireless mobile networks, and beyond 5G. He applies mathematical analysis to model and analyze the behavior of complex systems and uses discrete event simulation tools to provide comprehensive solutions. He is a member of the IEEE and IEEE Circuits and Systems Society.

Dinh-Thuan Do (Senior Member, IEEE) received the B.S., M.Eng., and Ph.D. degrees from Vietnam National University (VNU-HCMC), in 2003, 2007, and 2013, respectively, all in communications engineering. Prior to joining The University of Texas at Austin, UAS, he was an assistant professor at Ton Duc Thang University and a Senior Engineer with VinaPhone Mobile Network. His research interests include signal processing in wireless communications networks, NOMA, fullduplex transmission, and energy harvesting. Dr. Thuan was a recipient of Golden Globe Award from Vietnam Ministry of Science and Technology in 2015 (Top 10 most excellent scientist nationwide). He is currently serving as an Editor of COMPUTER COMMUNICATIONS (Elservier), an Associate Editor of EURASIP JOURNAL ON WIRELESS COMMUNICATIONS AND NETWORKING (Springer), ELECTRONICS, ICT EXPRESS, and KSII TRANSACTIONS ON INTERNET AND INFORMATION SYSTEMS. His publications include over 100 SCIE/SCI-indexed journal articles, over 60 SCOPUS-indexed journal articles and over 50 international conference papers. He is sole author in one textbook, one edited book and six book chapters.

Sungrae Cho is a professor with the school of computer sciences and engineering, Chung-Ang University (CAU), Seoul. Prior to joining CAU, he was an assistant professor with the department of computer sciences, Georgia Southern University, Statesboro, GA, USA, from 2003 to 2006, and a senior member of technical staff with the Samsung Advanced Institute of Technology (SAIT), Kiheung, South Korea, in 2003. From 1994 to 1996, he was a research staff member with electronics and telecommunications research institute (ETRI), Daejeon, South Korea. From 2012 to 2013, he held a visiting professorship with the national institute of standards and technology (NIST), Gaithersburg, MD, USA. He received the B.S. and M.S. degrees in electronics engineering from Korea University, Seoul, South Korea, in 1992 and 1994, respectively, and the Ph.D. degree in electrical and computer engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2002. His current research interests include wireless networking, ubiquitous computing, and ICT convergence. He has been a subject editor of IET Electronics Letter since 2018, and was an area editor of Ad Hoc Networks Journal (Elsevier) from 2012 to 2017. He has served numerous international conferences as an organizing committee chair, such as IEEE SECON, ICOIN, ICTC, ICUFN, TridentCom, and the IEEE MASS, and as a program committee member, such as IEEE ICC, MobiApps, SENSORNETS, and WINSYS.