QoE evaluation of ICN Congestion Control in Adaptive Video Streaming

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***Abstract*—Information-Centric Networking (ICN) is a network architecture that uses name-based addressing for content and is expected to provide efficient video delivery. In video distribution, traffic control mechanisms operate independently at different layers: Adaptive Bitrate (ABR) algorithms at the application layer and Transport Layer Congestion Control (TCC) at the transport layer. In ICN-based video distribution, there are concerns that the competition between TCC and ABR may lead to a decrease in Quality of Experience (QoE) and Quality of Service (QoS). This paper evaluates the impact of the presence or absence of TCC on QoE to understand the interaction between TCC and ABR on ICN. From the simulation results, it was found that by using TCC, ABR algorithms could select higher bitrates, reduce bitrate fluctuations, and improve QoE. Furthermore, TCC suppresses congestion, enabling stable communication and allowing ABR to select bitrates close to the goodput. However, it was also found that when TCC is performed, fairness in the network is reduced because the communication bandwidth cannot be fully utilized when avoiding congestion. From these findings, we have shown that in adaptive video streaming over ICN, TCC is essential for improving QoE by enabling ABR to select higher bitrates, but appropriate TCC design is necessary to maintain network fairness.**

***Index Terms*—ICN, Adaptive Video Streaming, QoE**

I. Introduction

In recent years, video traffic has come to constitute the largest share of global telecommunications traffic, accounting for 39% of fixed and 31% of mobile internet traffic [1]. Information-Centric Networking (ICN) is a network architecture that utilizes name-based addressing for content retrieval [2]. In ICN, a client transmits an INTEREST packet specifying a name-based address, and a node possessing the corresponding content replies with a DATA packet. Unlike existing TCP/IP networks, ICN routers can inspect content information and directly reply with DATA packets from their cache. By leveraging these capabilities to suppress redundant content requests, ICN is expected to enable efficient video delivery and, video streaming over ICN has been actively researched [3].

In video streaming, traffic control mechanisms operate independently at the application and transport layers. At the application layer, adaptive video streaming is employed to prevent Quality of Experience (QoE) degradation caused by playback interruptions. Adaptive video streaming, such as Dynamic Adaptive Streaming over HTTP (DASH) [4], avoids playback stalls by adjusting the bitrate of video segments using an Adaptive Bitrate (ABR) algorithm. Meanwhile, at the transport layer, Transport Layer Congestion Control (TCC) operates to prevent Quality of Service (QoS) degradation caused by congestion collapse. TCC prevents congestion by adjusting the packet transmission rate via congestion control algorithms. In the context of ICN, congestion control is achieved by regulating the transmission rate of INTEREST packets. Theoretically, if TCC improves communication quality in the transport layer and the ABR algorithm selects an optimal bitrate in the application layer, the resulting QoE should be maximized.

However, video streaming over ICN presents a challenge arising from the independent operation of TCC and ABR algorithms. For instance, when the packet transmission rate is limited during congestion control phase of TCC, and the ABR algorithm may select low bitrate. Consequently, the ABR algorithm may fail to select higher bitrates, leading to degraded QoE. Furthermore, the available bandwidth left unused by the restricted client may be aggressively consumed by other clients, resulting in a loss of network fairness and degraded QoS. Thus, in video streaming, the TCC and ABR algorithms operate independently. Therefore, it is crucial to understand the interplay between congestion control and ABR algorithms and to clarify the division of responsibility for QoE and QoS between them.

In fact, conflicts between congestion control and ABR algorithms have been observed in TCP/IP networks [5], and this phenomenon is likely to occur in ICN as well. Since the behavior of ICN differs fundamentally from that of traditional TCP/IP, existing findings cannot be directly applied. Consequently, there is a need to discuss new methods for improving QoE and QoS through the interoperability of TCC and ABR algorithms within ICN. In this paper, to clarify whether congestion control is feasible solely using ABR algorithms in adaptive video streaming over ICN, we analyze the interaction between congestion control and ABR algorithms and evaluate the viability of this approach.

II. Issues of Adaptive Video distribution over ICN

Adaptive Video Streaming over ICN Adaptive video streaming is a technique designed to prevent playback stalls and enhance Quality of Experience (QoE) by dynamically adjusting the video bitrate according to network congestion. Fig 1 illustrates the overview of adaptive video streaming over ICN. Video provider servers encode video content into short segments, typically several seconds in length, at multiple bitrates. The server lists the bitrate and playback timing of these segments in a Media Presentation Description (MPD) file, which is distributed alongside the video data. Before playback begins, the client retrieves the MPD file and utilizes an Adaptive Bitrate (ABR) algorithm to select the optimal bitrate for each segment based on current network congestion levels. The ABR algorithm enables high-quality playback by selecting high-bitrate segments when the network is uncongested and ensures continuous playback by switching to low-bitrate segments to reduce data size during congestion.

To retrieve a video segment in ICN, the client transmits an INTEREST packet containing specific information such as the content name, bitrate, and segment number (e.g., `prefix/video/seg1/2Mbps`). Upon receiving the INTEREST packet, the server replies by encapsulating the corresponding video segment in a DATA packet. When an ICN router receives an INTEREST packet, it performs routing based on the name address; if the requested content is cached on the path, the router directly replies with the DATA packet from its cache.

As described above, adaptive video streaming over ICN involves both Transport Layer Congestion Control (TCC) and ABR algorithms. Understanding the interaction between these two mechanisms is crucial for improving QoE. However, due to unique characteristics of ICN, such as in-network caching and pull-based communication, research findings from traditional TCP/IP networks cannot be directly applied to this architecture.

A lack of understanding regarding the interoperability between ABR algorithms and TCC can lead to conflicts, potentially degrading both QoE and Quality of Service (QoS). For instance, if TCC restricts the packet transmission rate, the ABR algorithm may fail to select a higher bitrate even when capacity is available. Conversely, if the ABR algorithm aggressively selects a high bitrate, it may trigger an excessive response from the TCC, increasing the likelihood of packet loss. Furthermore, in scenarios where certain clients monopolize network bandwidth, TCC mechanisms may incorrectly diagnose the network state as congested for other users. This prevents other clients from fully utilizing the available bandwidth, thereby deteriorating fairness in QoE.

Such issues have been confirmed in TCP/IP networks [5], and similar problems are likely to manifest in ICN.

To address these issues, this paper evaluates the interaction between ABR algorithms and TCC in adaptive video streaming over ICN from the perspectives of QoE and QoS, using simulations of representative algorithms. The following section outlines the algorithms discussed in this paper.

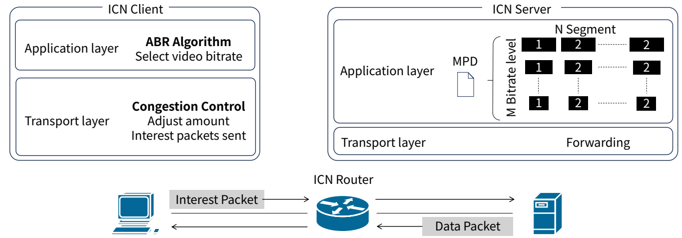


Fig. 1: ABR over ICN

A. Typical ABR Algorithms

This paper uses BOLA [6], PANDA [7], and MPC [8] as representative ABR algorithms. The overview of each algorithm is shown below.

- BOLA

BOLA is an ABR algorithm that selects a bitrate based on the state of the video buffer. It selects a higher bitrate when the buffer is sufficient and a lower bitrate when the buffer is low. relatively moderated.

- PANDA

PANDA is an ABR algorithm that selects a bitrate based on network throughput. It measures the throughput when downloading video segments and selects a higher bitrate if it is high, and a lower bitrate if it is low.

- MPC

MPC (Model Predictive Control) is an ABR algorithm that selects the bitrate based on both the video buffer and network throughput. It is a hybrid algorithm that considers both video buffer and network throughput.

B. Typical Transport Layer Congestion Control

This paper evaluates representative congestion control algorithms, Constant Bit Rate (CBR) and Interest Control Protocol (ICP). The overview of each algorithm is shown below.

- Constant Bit Rate (CBR)

CBR (Constant Bit Rate) is a congestion control algorithm that transmits data at a constant bit rate. CBR transmits data at a fixed rate regardless of network conditions. It is a transmission method without congestion control, as it does not adjust the rate even if congestion occurs.

- Interest Control Protocol (ICP)

ICP (Interest Control Protocol) is a congestion control algorithm that adjusts the sending rate of Interest packets. ICP dynamically adjusts the sending rate of Interest packets according to the network state. The sending rate is controlled by a window size. The window size follows an AIMD (Additive Increase and Multiplicative Decrease) mechanism. That is, the window size decreases when packet loss occurs and increases when packets are successfully received.

III. Performance Evaluation for Combination of ABR and TCC

Representative ABR algorithms and TCC were implemented in an ICN video streaming simulator on NS-3 [16]. The evaluation employed the Rocketfuel topology "1755.r0.cch," consisting of five servers, 172 routers, and 105 clients [12]. This topology is generated using the Flexible Network Simulation Script (FNSS), which provides realistic settings for queue sizes, link bandwidths, and propagation delays [13]. Links are assigned one of three bandwidths: 10 Mbps, 100 Mbps, or 1 Gbps.

Routers perform name-based routing and implement a 150 MB LCE-LRU cache. Clients use a video player with a 30-second buffer, starting playback once segments are buffered.

The simulation handles 100 videos for Video-on-Demand (VoD) streaming, each approximately 600 seconds long. Every video is divided into roughly 600 one-second segments and encoded at 20 bitrate levels ranging from 45 Kbps to 4.7 Mbps. Each VoD server stores 100 videos (approximately 370 GB). VoD clients select videos according to a Zipf distribution and stream them using either PANDA, BOLA, or MPC for more than five hours. The interval between consecutive playback sessions follows an exponential distribution with a mean of 600 seconds.

A. QoE Calculation

To evaluate the Quality of Experience (QoE), we employ the QoE-lin model [10]. This model calculated for each session consisting of N segments (N=596 in this paper) and, considers the video bitrate as a positive metric, while treating stall duration and bitrate fluctuation as negative metrics. QoE-lin is expressed by Eq. 1.

$$QoE_{lin} = \text{BITRATES} - \text{FLUCTUATIONS} - \text{STALLINGS} \tag{1}$$

The details of each term are as follows:

- BITRATES The first term, BITRATES, represents the sum of the bitrates for all viewed video segments. Let R_n denote the bitrate of the n-th segment; this term is calculated as $\sum_{n=1}^{N} R_n$. A higher cumulative bitrate corresponds to an increase in QoE.

- FLUCTUATIONS The second term, FLUCTUATIONS, accounts for the variation in bitrate between consecutive segments. It is defined as $\lambda \sum_{n=1}^{N-1} |R_{n+1} - R_n|$, representing the cumulative bitrate switching amplitude. Significant fluctuations between segments increase this value, thereby reducing the overall QoE. Here, λ is a non-negative weight factor.

- STALLINGS The third term, STALLINGS, represents the re-buffering duration (playback stalls). It is expressed as $\mu \sum_{n=1}^{N} b_n$, where b_n denotes the stall duration incurred while playing the n-th segment. This term sums the total stall time across the entire viewing session; longer stall durations result in a lower QoE. μ represents the non-negative weight for this penalty.

For the weighting factors, we adopt the values suggested in [10], specifically setting $\lambda = 1$ and $\mu = 4.3$.

To measure the fairness of QoE among clients, we use the fairness index F as defined in the Definition of QoE Fairness in Shared Systems [14]. This index is given by Eq. 2 and calculates the fairness of QoE rather than QoS.

$$F = 1 - \frac{2\sigma}{H - L} \tag{2}$$

where σ is the standard deviation of the QoE values, H is the maximum QoE value, and L is the minimum QoE value. The fairness index ranges from 0 to 1; a value closer to 1 indicates higher fairness, while a value closer to 0 indicates lower fairness.

The difference between the bit rate and Goodput is given by the absolute value of the difference between the Bit rate and Goodput, as shown in Eq. 3.

$$\mathit{Diff}_{BG} = |\text{BITRATE} - \text{GOODPUT}| \tag{3}$$

Here, BITRATE refers to the bitrate of the selected video segment, and GOODPUT represents the measured goodput during the download of that segment.

B. QoS calculation

Network fairness is measured using Jain's Fairness Index [11], which is a scale between 0 and 1, with values closer to 1 indicating high fairness and 0 indicating low fairness.

C. Simulation Results and Analysis of QoE Metrics

From the results presented in Table I, it can be observed that scenarios using ICP achieve higher average QoE compared to those using CBR. However, the QoE fairness in ICP-based scenarios is lower than in CBR-based scenarios. These results indicate that while employing TCC improves the overall QoE, it may also lead to a reduction in QoE fairness.

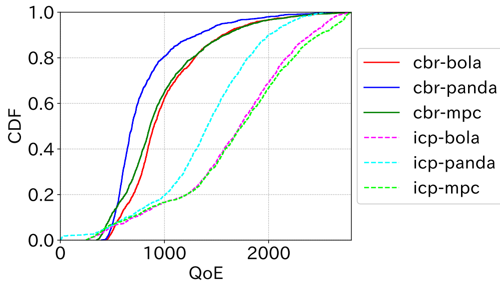
To provide a deeper analysis of QoE, Table II summarizes the average bitrate, average bitrate fluctuation, and average stall duration for each scenario based on the QoE-LIN metrics. Additionally, Fig. 2 presents the Cumulative Distribution Functions (CDFs), Fig. 2(a) for QoE-lin of a session, Fig. 2(b) for BITRATES of a session, Fig. 2(c) for bitrate of a segment, R_n in BITRATES, Fig. 2(d) for bitrate fluctuation between segment n and segment n+1, $|R_{n+1} - R_n|$ in FLUCTUATIONS, and Fig. 2(e) for Stalling time in a segment playback, respectively.

TABLE I: Average QoE and QoE Fairness

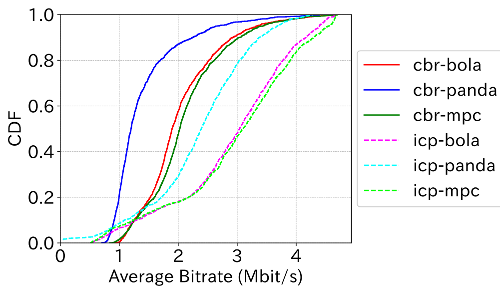
Scenario	Average QoE-lin	QoE Fairness
CBR-BOLA	1008.07	0.653
CBR-PANDA	811.85	0.672
CBR-MPC	965.71	0.640
ICP-BOLA	1655.97	0.527
ICP-PANDA	1380.65	0.600
ICP-MPC	1683.69	0.502

TABLE II: QoE metrics

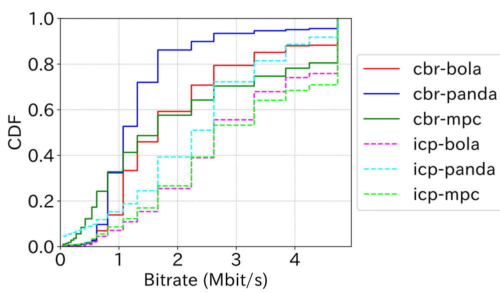
Scenario	Avg Bitrate (Mbps)	Avg Bitrate Fluctuation (Mbps)	Avg Stalling Time (s)
CBR-BOLA	2.04	0.33	0.00157
CBR-PANDA	1.41	0.03	0.00070
CBR-MPC	2.12	0.48	0.00052
ICP-BOLA	2.91	0.12	0.00003
ICP-PANDA	2.34	0.01	0.00001
ICP-MPC	2.97	0.10	0.00658



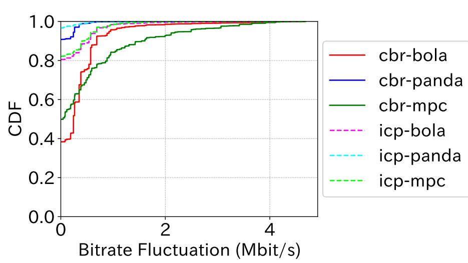
(a) QoE-lin of a session



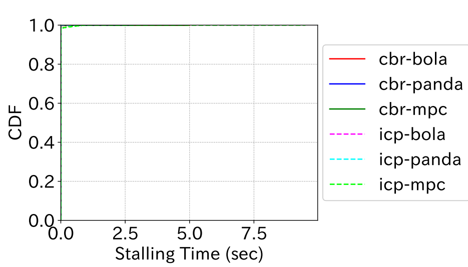
(b) BITRATES of a session



(c) Bitrate of a segment



(d) Bitrate fluctuation of adjacent segments



(e) Stalling time in a segment playback

Fig. 2: CDF of QoE metrics

From the CDF of QoE in Fig. 2(a), it is evident that scenarios with ICP generally achieve higher QoE compared to those without ICP. However, we also observe sessions with low QoE values (e.g., between 0 and 500) even when ICP is employed. This suggests that ICP may excessively restrict packet transmission rates in certain sessions, preventing sufficient communication.

This observation is supported by the bitrate analysis. The CDF of the average selected bitrate per session in Fig. 2(b) indicates that while ICP scenarios frequently select higher bitrates, there remains a subset of sessions selecting low bitrates in the range of 0 to 1 Mbps. Similarly, Fig. 2(c) confirms that scenarios with ICP generally select higher bitrates. However, in the specific case of PANDA, the use of ICP results in a notable increase in the selection of lower bitrates. This is likely due to the interaction between control mechanisms: since PANDA employs an Additive Increase Multiplicative Decrease (AIMD) strategy, its combination with the AIMD mechanism of the ICP may lead to an excessive reduction in packet transmission rates, forcing certain sessions to settle for lower bitrates.

Regarding stability, the CDF of bitrate fluctuation in Fig. 2(d) shows that scenarios with ICP exhibit smaller fluctuations compared to those without ICP. This implies that ICP stabilizes the network throughput, thereby enabling the ABR algorithm to select bitrates more consistently. Furthermore, Fig. 2(e) indicates that stall durations are negligible across all scenarios, demonstrating that the ABR algorithms effectively suppress playback interruptions regardless of the ICP configuration.

In summary, ICP in video streaming generally enables ABR algorithms to select higher bitrates with reduced fluctuation. However, the excessive restriction of packet transmission rates by TCC can negatively impact specific sessions, potentially degrading the fairness of QoE.

D. Simulation Results and Analysis of the Impact of ICP

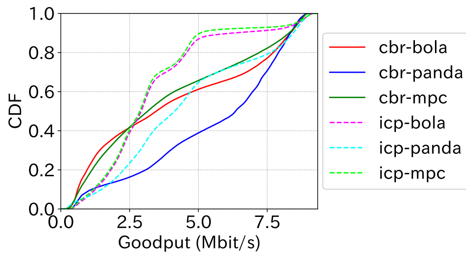
To further investigate the impact of ICP on adaptive video streaming over ICN, we analyzed network performance metrics. Table III summarizes the total packet drop count, average Goodput, Goodput fairness, average Goodput fluctuation, and the average discrepancy between Goodput and bitrate for each scenario. Additionally, Fig. 3 illustrates the Cumulative Distribution Functions (CDFs) for Fig. 3(a) Goodput, Fig. 3(b) Goodput fluctuation, and Fig. 3(c) the difference between Goodput and bitrate. In this study, Goodput is defined as the total volume of DATA packets received by the client divided by the session duration.

Regarding packet drops, Table 3 reveals that scenarios using ICP exhibit significantly fewer drops compared to those using CBR. The high frequency of packet drops observed in the absence of ICP implies that ABR algorithms alone are insufficient for congestion avoidance, leading to network congestion. Conversely, the implementation of ICP effectively suppresses congestion.

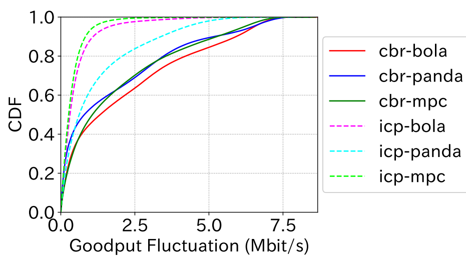
In terms of Goodput fluctuations, Table III and Fig. 3(a) indicate that ICP scenarios yield lower values than CBR

TABLE III: QoS metrics to analyze the impact of TCC

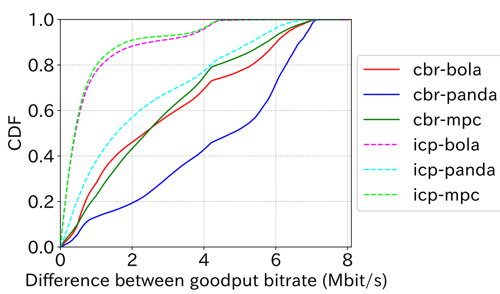
Scenario	Total Drop (GB)	Average Goodput (Mbps)	Goodput Fairness	Avg Goodput Fluctuation (Mbps)	Goodput-Bitrate Diff Avg (Mbps)
CBR-BOLA	26.992	4.10	0.652	2.15	2.81
CBR-PANDA	5.462	5.51	0.822	1.79	4.23
CBR-MPC	38.081	3.90	0.661	1.88	2.72
ICP-BOLA	0.041	3.36	0.728	0.50	0.84
ICP-PANDA	0.104	4.52	0.763	1.17	2.22
ICP-MPC	0.026	3.23	0.732	0.38	0.77



(a) Goodput CDF



(b) Goodput Fluctuation CDF



(c) Difference between Goodput and Bitrate CDF, $Diff_{BG}$

Fig. 3: QoS metrics to analyze the impact of ICP

scenarios. This reduction is attributed to the ICP mechanism, which proactively restricts the packet transmission rate to maintain network stability. In contrast, while CBR scenarios achieve higher Goodput by aggressively consuming available bandwidth, this behavior results in severe congestion.

Goodput fairness, Table III demonstrates that, with the exception of PANDA, ICP scenarios achieve higher fairness indices than CBR scenarios. This suggests that the stability provided by ICP enhances fairness among clients. Specifically, the Goodput CDF in Fig. 3(a) shows that most sessions in ICP scenarios cluster within the 2 to 4 Mbps range, whereas CBR scenarios exhibit a wide variance. Similarly, Goodput fluctuation is lower in ICP scenarios, as shown in Table III. The CDF in Fig. 3(b) confirms that the majority of ICP sessions experience fluctuations in the range of 0 to 2 Mbps, while CBR sessions are subject to significantly higher instability.

As noted in the previous section, the reduced fairness in the PANDA scenario under ICP is likely caused by the compounding effect of the AIMD control logic present in both the ABR algorithm and the ICP. This interaction excessively restricts the packet transmission rate, preventing certain sessions from achieving sufficient throughput.

Alignment of Bitrate and Goodput finally, the discrepancy between Goodput and the selected bitrate is smaller in ICP scenarios compared to CBR, as shown in Table 3. The CDF in Fig.3(c) corroborates this, indicating that a larger proportion of sessions in ICP scenarios maintains a small difference between Goodput and bitrate. This implies that the selected bitrate is well-aligned with the actual network throughput. The superior alignment in ICP scenarios is attributed to the congestion suppression provided by ICP; by ensuring stable communication, ICP allows the ABR algorithm to make more consistent and accurate bitrate selections.

IV. Conclusion

In this paper, we analyzed the interaction between congestion control and ABR algorithms to evaluate whether congestion control in adaptive video streaming over ICN is feasible solely using ABR algorithms. The simulation results demonstrated that employing congestion control yields significantly higher Quality of Experience (QoE), indicating that relying exclusively on ABR algorithms is insufficient for effective congestion avoidance.

Our analysis revealed the mechanism behind these results. In the absence of ICP, while aggressive bandwidth consumption may temporarily increase Goodput, it inevitably leads to network congestion and significant Goodput fluctuation. This instability causes the ABR algorithm to oscillate, resulting in high bitrate variability and degraded QoE. In contrast, the deployment of ICP suppresses congestion and stabilizes communication, thereby enabling the ABR algorithm to consistently select optimal bitrates and enhance overall QoE.

However, it was also observed that ICP can degrade QoE fairness. This is attributed to the excessive restriction of packet transmission rates, which prevents certain sessions from utilizing communication bandwidth efficiently. As a result, sessions that continuously select lower bitrates have increased, leading to a degradation in QoE fairness. Based on these findings, we conclude that ICP is essential for enabling ABR algorithms to select high bitrates and improve QoE in ICN-based adaptive video streaming, however, the QoE fairness issue remains due to TCC's congestion avoidance mechanism.

In future work, we will focus on designing a router-assisted congestion control algorithm that operates cooperatively with ABR algorithms to maintain fairness while maximizing QoE [18].

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