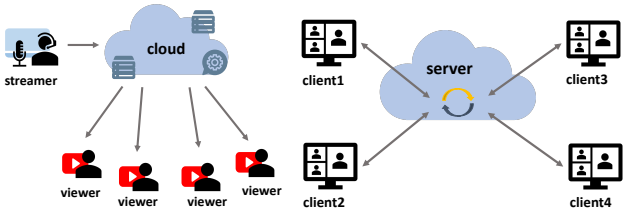
SJA: Server-driven Joint Adaptation of Loss and Bitrate for Multi-Party Realtime Video Streaming

Kai Shen[1,2], Dayou Zhang[1,2], Zi Zhu[2], Lei Zhang[5], Fangxin Wang[2,1,3,4,*], Dan Wang[6]
[1]The Future Network of Intelligence Institute, The Chinese University of Hong Kong, Shenzhen
[2] School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen
[3] Peng Cheng Laboratory
[4] The Guangdong Provincial Key Laboratory of Future Networks of Intelligence
[5] College of Computer Science and Software Engineering, Shenzhen University
[6]Department of Computing, The Hong Kong Polytechnic University
{kaishen, dayouzhang, zizhu}@link.cuhk.edu.cn, leizhang@szu.edu.cn
wangfangxin@cuhk.edu.cn, csdwang@comp.polyu.edu.hk

***Abstract*—The outbreak of COVID-19 has dramatically promoted the explosive proliferation of multi-party realtime video streaming (MRVS) services, represented by Zoom and Microsoft Teams. Different from Video-on-Demand (VoD) or live streaming, MRVS enables all-to-all realtime video communication, bringing significant challenges to service providing. First, unreliable network transmission can cause network loss, resulting in delay increase and visual quality degradation. Second, the transformation from two-party to multi-party communication makes resource scheduling much more difficult. Moreover, optimizing the overall QoE requires a global coordination, which is quite challenging given the various impact factors such as bitrate and loss.**

In this paper, we propose the SJA framework, which is, to our best knowledge, the first server-driven joint loss and bitrate adaptation framework in multi-party realtime video streaming services towards maximized QoE. We comprehensively design an appropriate QoE model for MRVS services to capture the interplay among perceptual quality, variations, bitrate mismatch, loss damage, and streaming delay. We mathematically formulate the QoE maximization problem in MRVS services. A Lyapunov-based relaxation and the SJA algorithm are further designed to address the optimization problem with close-to-optimal performance. Evaluations show that our framework can outperform the SOTA solutions by $18.4\% \sim 46.5\%$.

***Index Terms*—Multi-party realtime video streaming, Adaptive bitrate control, Forward error correction, Quality of Experience**



(a) Live Streaming (b) Video Conferencing

Fig. 1. The representative applications of realtime streaming services.

I. Introduction

The outbreak of COVID-19 has dramatically promoted the explosive proliferation of multi-party realtime video streaming (MRVS) services, which have profoundly affected how people live and communicate. Such applications represented by Zoom and Microsoft Teams are playing an indispensable role in various fields like online education, telemedicine, video conferencing, etc. Different from Video-on-Demand (VoD) services [1] represented by YouTube and crowdsourced live streaming services [2], [3] shown in Fig. 1(a) represented by Twitch, multi-party realtime video streaming or conferencing shown in Fig. 1(b) embraces a new form of communication where each client is able to send its own stream to all other parties and simultaneously receive streams from others in real time. In the near foreseeable future, MRVS will continue to create tremendous revenue. According to the report from Cisco [4], realtime video streaming traffic has tripled within the last five years and reached 17% of Internet video traffic by 2022.

Providing satisfactory quality of experience (QoE) for users is always the key issue in MRVS, while new challenges arise in such a particular service. *The first one lies in the packet loss problem caused by the unreliable transmission in MRVS, which can further lead to delay increase and visual quality degradation if without careful processing.* Unlike TCP-based reliable transmission (e.g., VoD and live streaming), MRVS usually employs light-weight yet unreliable transmission protocols

* Fangxin Wang is the corresponding author.

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based on UDP (or its variants together with some control protocols [5]) to keep fast responses. However, once packet loss occurs, current systems either wait for the re-transmission with higher delay, or directly deliver the incomplete stream to upper applications with potential video quality distortion.

The second challenge arises from the difficulty in coordinating the limited network resources given the transformation from two-party communication to multi-party communication. Traditional VoD or live streaming usually adopts the client-server architecture, where each client only needs to deal with the communication with the other side. MRVS is much more complex, where a central server node serves as the selective forwarding unit (SFU), responsible for receiving streams from different clients, orchestrating streams based on requests, and sending streams as a group to each destination. Previous works on bitrate adaptation [6]–[9] can only handle the two-party communication scenario, while for the multi-party case, there is still a considerable gap in fine-grained resource allocation towards higher user QoE.

The third challenge is how to coordinate the transmission behaviors of different parties so as to maximize the overall QoE of a communication group. Conventional works [10]–[13] mostly start from a client-driven perspective and only make local decisions. Such an independent decision-making strategy can easily cause poor QoE from a global view. However, it is not easy to coordinate the interests of multiple parties, especially when considering a variety of impact factors such as loss, bitrate, and other network conditions.

Pioneer research works have made efforts toward these challenges. Sun et al. [14] developed Deep Reinforcement Learning frameworks to ensure low end-to-end video latency in live streaming services, but lack consideration for packet loss problems. Zhang et al. [15] proposed a joint bitrate and loss adaptation scheme for realtime video streaming, while they only focused on two-party communication. MultiLive [16] addressed the bitrate allocation in a multi-party live streaming scenario, but it only considered reliable transmissions. Therefore, existing works only partially tackle the challenges therein, calling for an integrated solution to address these crucial problems in delay, multi-stream orchestration, and multi-party coordination towards QoE maximization.

In this paper, we propose the SJA framework, a server-driven joint loss and bitrate adaptation framework in multi-party realtime video streaming services towards maximized QoE. In our architecture, senders first generate the initial streaming configurations based on their own policy (e.g., the Adaptive Bitrate (ABR) strategy). The central server then conducts a joint loss and bitrate adaptation decision with global orchestration based on the network conditions and viewer requests. Following the server-side decision, the senders will conduct the globally optimal stream configuration with scalable video coding (SVC), and the server will forward the optimal stream layer to the corresponding receivers. In summary, our contributions are as follows:

- We investigate the problem caused by network loss in realtime video streaming and highlight the importance of joint adaptation of loss and bitrate in MRVS services. We further demonstrate the necessity of a server-driven architecture to optimize overall QoE.
- To our best knowledge, our proposed framework is the first to consider a server-driven joint loss and bitrate adaptation and multi-party stream coordination in MRVS services. We comprehensively design an appropriate QoE model for MRVS services to capture the interplay among perceptual quality, variations, bitrate mismatch, loss damage, and streaming delay.
- We formulate the QoE maximization problem in MRVS services, followed by relaxation and the SJA algorithm.
- We conduct extensive realistic trace-driven evaluations. The results demonstrate that the SJA algorithm can achieve close-to-optimal performance with superior latency and loss alleviation.

TABLE I
SERVICE TYPES OF PIONEER RESEARCH

	realtime	multi-party	loss adaption	global coordination
DRL-Live [14]	✓			
Oppugno [15]	✓		✓	
vSkyConf [17]		✓		✓
AgRank [18]	✓	✓		
MultiLive [16]	✓	✓		✓
SJA	✓	✓	✓	✓

The remainder of the paper is organized as follows. Section II introduces the motivation of our framework. Section III illustrates the framework architecture. Section IV formulates the problem with the QoE model definition. Section V describes the design of the SJA algorithm in detail. We present the simulation results through extensive trace-driven experiments in Section VI. Section VII discusses the related work. Finally, we conclude the paper in Section VIII.

II. MOTIVATION

Researchers have become increasingly interested in multi-party realtime video streaming services given their great market value. Different from VoD or live services, MRVS has several key features: *1) realtime*: an acceptable transmission delay is usually below 150 ms [19], far less than VoD and live services; *2) simultaneous transceiving*: each node can send messages while at the same time receive messages from others, e.g., in a video conference; *3) multi-party*: multiple nodes can have all-to-all communication; *4) unreliable transmission*: existing systems mostly employ UDP-based protocol, which cannot guarantee the reliability in order to satisfy fast response.

The confluence of these features makes the MRVS service provision even more challenging towards maximized user QoE, calling for an integrated framework that jointly considers realtime, multi-party, loss adaptation, and global coordination for transmission optimization. Pioneer works [14]–[18] have

(a) 480p video with 1% loss (b) 480p video with 2% loss

(c) 1080p video with 1% loss (d) 1080p video with 2% loss

Fig. 2. Visual effects when multiple viewers experience different loss rates.

made attempts to address this problem. However, as summarized in Table I, they only consider partial factors and fail to achieve a comprehensive solution. Some other related works try to minimize the global network cost [20], reduce the end-to-end delay [21], or meet the fairness constraints [22], which also only tackle partial problems.

We have closely examined the features of MRVS services and summarized two insights as follows. *Firstly, we argue that extra bandwidth can be leveraged for redundant coding such that loss can be corrected without retransmission.* As shown in Fig. 2, even 1% of bit errors in the transmission can gravely damage viewers' perceptions. Even worse, in multi-party conferencing, if bit errors occur during video uploading, the user experience of its all viewers at different bitrate levels will be degraded. As a result, the impact of network loss problems induced by fast yet unreliable UDP should not be underestimated. Therefore, Forward Error Correction (FEC) mechanisms can be utilized to mask the effect of loss, where the extra bandwidth can be leveraged to facilitate loss recovery.

Secondly, we emphasize that the overall QoE maximization of MRVS can only be achieved through server-driven approaches. Studies towards QoE maximization usually focus on bitrate adaption, where an ABR controller will be responsible for selecting the most appropriate bitrate based on the available network throughput [11], [23], [24], receiver buffer occupancy [25], [26], or utilize reinforcement learning approaches [10]. These client-driven approaches only utilize local state information to request their own most suitable bitrates, while the decisions are usually not globally optimal in such a non-cooperative way. For example, if multiple viewers request the same video with different bitrates from a sender, it will increase the sender encoding time, resulting in higher latency for all receivers and failing to achieve satisfactory overall QoE.

Thus, motivated by non-negligible loss damages and the necessity of server-driven approaches, we take it one step further and explore, for the first time, the effects of server-driven joint loss and bitrate adaptation in MRVS.

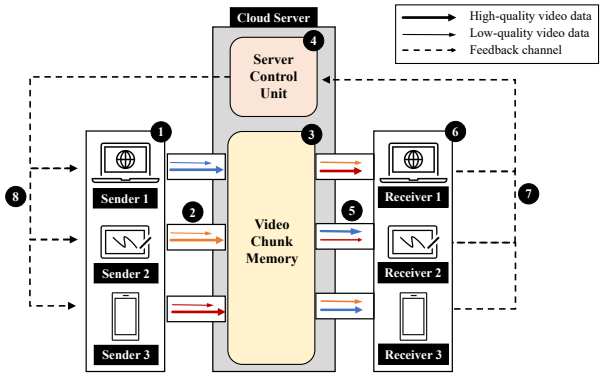


Fig. 3. SJA Framework

III. Framework Overview

The SJA framework for joint bitrate and loss adaptation in MRVS services towards overall QoE maximization. As illustrated in Fig. 3, SJA follows a server-driven architecture responsible for coordinating the streaming configuration of all clients. It mainly consists of four components, i.e., senders, receivers, video chunk memory and server control unit. It is worth noting that different from the logical distinction, a client in MRVS service can serve as both sender and receiver at the same time. The detailed functionalities are as follows:

- **Sender:** A sender is responsible for sending out streams with different bitrates employing scalable video coding [27]. SVC is an extension to the H.264/AVC [28] video codec standard, which can encode a video stream into a base layer and several enhancement layers. Besides, the sender also leverages redundant coding technique (i.e., FEC [29]) in our design, aiming to provide error recovery ability to avoid retransmission.
- **Receiver:** Since the receiver has all the local updated information, such as buffer occupancy and throughput estimation, it first conducts an initial request for bitrate using ABR algorithms, which have been widely explored by pioneer works [1], [12]. In order to support the global coordination, the feedback information such as the receiver's QoE, bitrate decision and network conditions needs to be sent back to the server for further control.
- **Server Control Unit:** The server control unit is the core component in the cloud server responsible for global coordination. It collects the state information from senders and receivers, as well as the receiver feedback information. Through our designed SJA algorithm (§V), it derives the best bitrate and loss adaptation decisions from a global view, and delivers the control signals to the senders for the next chunk streaming.
- **Video Chunk Memory:** Similar to a common selective forwarding unit (SFU) architecture, the video chunk memory at the cloud server will collect streams from multiple senders, conduct stream orchestration, and then

forward corresponding streams with appropriate bitrate to different receivers based on the decision result. Thanks to the SVC format, the video chunk memory is able to conduct light-weight layered streaming without much transcoding overhead.

Our framework operates every time cycle, which is a short time slot. The workflow of a decision cycle is demonstrated in Fig. 3. Every sender (❶) first generates an uplink video stream (❷) with multiple bitrate layers to the video chunk memory (❸) in the cloud server. After receiving the control signals from the server control unit (❹), the downlink streams (❺) with different layered bitrate and different coding redundancy will be forwarded to corresponding receivers (❻).

IV. QoE Model and Problem Formulation

We mathematically model the problem in this section to better understand the challenges under MRVS scenarios. To do so, we introduce our QoE design, which is the ultimate objective, followed by constructing the primary problem formulation and explaining the network constraints.

We assume that there are I senders and J receivers in the multi-party realtime video streaming service, where $\mathbf{I} = \{1, 2, ..., I\}$ represents the set of senders and $\mathbf{J} = \{1, 2, ..., J\}$ represents the set of receivers. Note that I may not equal J. Also, there are $\mathbf{R} = \{R_1, R_2, ..., R_q\}$ types of encoding bitrate levels and $\mathbf{C} = \{C_1, C_2, ..., C_p\}$ types of FEC code rate levels. Additionally, there are K timeslots, where $\mathbf{K} = \{0, 1, 2, ..., K\}$ represents the set of slotted time indexes.

A. QoE Model

Followed by existing works [2], [30], [31], we consider five QoE metrics, i.e., *video rate based perceptual quality*, *perceptual quality variations*, *bitrate mismatch level*, *streaming delay* and *loss penalty*, where we separate the QoE degradation caused by bit errors from the original perceptual quality related to bitrate. Firstly, we can calculate the perceptual quality of sender i's video in receiver j at time slot k as follows:

$$q(r_k^{i,j}) = \log(\frac{r_k^{i,j}}{r_{min}}) \tag{1}$$

where $r_k^{i,j}$ denotes the bitrate level from sender i to receiver j at slotted time k, and r_{min} denotes the minimal bitrate level. Here we adopt the logarithmic function [26] to represent the video quality, where the ratio of real bitrate to minimal bitrate can be utilized to decrease the marginal quality improvement.

Secondly, we take advantage of the perceptual quality variations to penalize changes in video quality to favor smoothness [1]. In more detail, we adopt the absolute value of the difference between current video quality and the video quality of the last moment to represent the variations as follows:

$$\begin{aligned} |q(r_k^{i,j}) - q(r_{k-1}^{i,j})| &= |\log(\frac{r_k^{i,j}}{r_{min}}) - \log(\frac{r_{k-1}^{i,j}}{r_{min}})| \\ &= |\log(\frac{r_k^{i,j}}{r_{k-1}^{i,j}})| \end{aligned} \tag{2}$$

TABLE II
NOTATIONS USED IN THIS PAPER

Variables	Meaning
$r_k^{i,j}$	real bitrate from sender i to receiver j at time k
r_{min}	minimal bitrate level
$\hat{r}_k^{i,j}$	requested bitrate of sender i from receiver j at time k
$d_{i,j}(k)$	streaming delay between sender i and receiver j
c_k^i	FEC code rate of sender i at time k
$\mathbf{r}_k^i$	the set of all bitrates encoded by sender i at time k
$T(\mathbf{r}_k^i)$	encoding time of sender i at time k
$B_i^{up}(k)$	uplink bandwidth of sender i at time k
$B_j^{down}(k)$	downlink bandwidth of receiver j at time k
$p_i(k)$	loss rate between client i and the server at time k
$e_{i,j}(k)$	remaining loss rate from sender i to receiver j at time k
T	duration of each time slot

Thirdly, we argue that the assigned streaming may differ from the requested streaming of the receiver's ABR controller in practice. Thus, the bitrate mismatch penalty demonstrates the dissatisfaction between the receivers' requested bitrate and the transmitted bitrate. We can calculate it as follows:

$$B(r_k^{i,j}, \hat{r}_k^{i,j}) = \log(\frac{\hat{r}_k^{i,j}}{r_{min}}) - \log(\frac{r_k^{i,j}}{r_{min}}) = \log(\frac{\hat{r}_k^{i,j}}{r_k^{i,j}}) \tag{3}$$

The fourth metric denotes streaming delay as follows:

$$d_{i,j}(k) = T(\mathbf{r}_k^i) + \frac{\max_j\{r_k^{i,j}\}}{c_k^i \cdot B_i^{up}(k)} + \frac{\sum_{i=1}^{I} \frac{r_k^{i,j}}{c_k^i}}{B_j^{down}(k)} \tag{4}$$

whose three components are encoding latency, uploading latency, and downloading latency. Since we adopt one server model in this paper, we ignore the transmission time among different servers, the decision-making time, and the feedback transmission time. In the expression, $\mathbf{r}_k^i = \{r_k^{i,j} | r_k^{i,j} \in \mathbf{R}, j \in \mathbf{J}\}$ represents the set of all bitrates that sender i will encode at time k. Note that c_k^i is the FEC code rate, equal to k/n, where an encoder takes a block of k source symbols as inputs and generates a total of n FEC symbols ($n > k$) as output.

Lastly, we consider the QoE degradation caused by bit errors. We denote $e_{i,j}(k) = \max\{p_i(k) + p_j(k) - (1 - c_k^i), 0\}$ to represent the remaining bit error rate after the FEC recovery, and we map the bit errors to the QoE degradation penalty through $L(e_{i,j}(k))$, which will be analyzed in later section.

Therefore, we have considered all five QoE metrics in multi-party realtime video streaming. In conclusion, the QoE for receiver j at slotted time k is defined as:

$$\begin{aligned} QoE_j(k) = \sum_{i=1}^{I} \alpha_j^i \big\{ & \beta_j q(r_k^{i,j}) - \gamma_j |q(r_k^{i,j}) - q(r_{k-1}^{i,j})| \\ & - \delta_j B(r_k^{i,j}, \hat{r}_k^{i,j}) - \epsilon_j d_{i,j}(k) - \zeta_j L(e_{i,j}(k)) \big\} \end{aligned} \tag{5}$$

where α_j^i is the importance factor of receiver j towards the video from sender i, and other Greek letters represent the receiver's personalized viewing demand.

B. Problem Formulation

Integrating the viewers' personalized QoE demands and overall viewing architecture, we have the following optimization objective that aims to maximize the overall QoE driven by the server end under multi-party realtime video streaming:

$$\begin{aligned} \max_{\{r_k^{i,j}, c_k^i\}} \quad & \frac{1}{K}\sum_{k=0}^{K-1}\left[\sum_{j=1}^{J}\eta_j \cdot QoE_j(k)\right] \\ s.t. \quad & \max_j\{\tfrac{r_k^{i,j}}{c_k^i}\} \leq B_i^{up}(k), \forall i \in \mathbf{I} \\ & \sum_{i=1}^{I}\tfrac{r_k^{i,j}}{c_k^i} \leq B_j^{down}(k), \forall j \in \mathbf{J} \\ & \tfrac{1}{K}\sum_{k=0}^{K-1} d_{i,j}(k) \leq \lambda T, \forall i \in \mathbf{I}, \forall j \in \mathbf{J} \\ & r_k^{i,j} \in \mathbf{R}, c_k^i \in \mathbf{C} \end{aligned} \tag{6}$$

where T is the duration of each time slot, and η_j represents the importance of receiver j in the meeting room. Our action space consists of the actual bitrate of each sender-receiver pair and the FEC code rate of every sender. The first constraint is the upload bandwidth constraint for each sender, and the second is the download bandwidth constraint for every receiver. The third constraint is the time-average expected delay requirement, which ensures the low latency of the service. The last one guarantees the available bitrate and FEC code rates, which belongs to pre-setted combinations and are non-negative.

V. SJA Algorithm for Joint Adaptation

In this section, we firstly prove the NP-hardness in Section V-A, followed by insights of designing SJA algorithm. We then introduce several relaxations in Section V-B, converting the original problem to a one-step joint adaptation problem. This conversion turns the long-term dependent problem into a problem that can be solved separately at each period and allows us to resolve the joint adaptation challenge without any knowledge of future predictions. Lastly, we propose SJA algorithm in Section V-C, which takes the coupling constraint and running speed into full consideration with superiority.

A. NP-hardness and Designing Insights

***Theorem** 1:* The server-driven joint loss and bitrate adaptation problem towards maximized overall QoE is NP-hard.

Proof: As the original problem is complex, we consider its simplified case. We first assume that each sender has sufficient encoding ability, i.e., every sender can encode its video fast enough at all bitrate levels. Next, remove the upload capacity constraints so the server can forward the video from any sender at any bitrate level. In this way, we transfer the original problem to a simplified version, that is, assigning senders' video with optimal bitrate (i.e., items) to each receiver (i.e., knapsack) so that the overall QoE (i.e., the total value of the items in all knapsacks) is maximized while the total used bandwidth of each receiver (i.e., the sum of weight for each knapsack) does not exceed the downlink bandwidth capacity (i.e., B_j^{down}). Thus, we can reduce the multiple knapsack (MKP) problem, a known NP-hard problem, to our simplified problem. As our simplified problem is a special case of the original problem, the joint adaptation problem is NP-hard. ■

Although we can solve the NP-hard problem with a time-average objective over a finite horizon by Dynamic Programming (DP) [32] approaches, it is still difficult to achieve an efficient and effective solution using traditional DP-based methods for two main reasons. First, the original problem is much more complex with more constraints. The large state space under a DP formulation consists not only of the timeslot index k and network conditions but also of predicted encoding delay $T(\mathbf{r}_k^i)$, bringing significant challenges to achieving fast or even realtime decisions. Second, the original problem formulation aims to tackle the time-average joint adaptation problem, which needs predictions of future dynamics. In order to overcome the above challenges related to traditional DP-based approaches, we should take an alternative approach.

B. Problem Relaxation

Considering the original time-average joint adaptation problem formulation, we start by putting forward three relaxations. Instead of considering a limited time, we first explore the joint adaption problem in the limiting regime when the video meeting becomes long, i.e., $K \to \infty$. Thus, the objective and the third constraint can be expressed as follows respectively:

$$\max_{\{r_k^{i,j}, c_k^i\}} \quad \lim_{K\to\infty}\frac{1}{K}\sum_{k=0}^{K-1}\left[\sum_{j=1}^{J}\eta_j \cdot QoE_j(k)\right] \tag{7}$$

$$\lim_{K\to\infty}\frac{1}{K}\sum_{k=0}^{K-1} d_{i,j}(k) \leq \lambda T, \forall i \in \mathbf{I}, \forall j \in \mathbf{J} \tag{8}$$

Next, we simplify the upload bandwidth constraint by eliminating its maximum operation:

$$\frac{r_k^{i,j}}{c_k^i} \leq B_i^{up}(k), \forall i \in \mathbf{I}, \forall j \in \mathbf{J} \tag{9}$$

We do the third relaxation by constructing rate stable virtual queues $Q_{i,j}(k)$ for each pair of sender and receiver as follows:

$$Q_{i,j}(k+1) = \max\{Q_{i,j}(k) + d_{i,j}(k) - \lambda T, 0\} \tag{10}$$

Lemma 1: If the virtual queue $Q_{i,j}(k)$ is rate stable, i.e., $\lim_{K\to\infty}\frac{Q_{i,j}(K)}{K} \leq 0$, then we have $\lim_{K\to\infty}\frac{1}{K}\sum_{k=0}^{K-1} d_{i,j}(k) \leq \lambda T$.

Proof: According to (10), we can get:

$$\begin{aligned} & Q_{i,j}(k+1) - Q_{i,j}(k) \\ = \ & \max\{d_{i,j}(k) - \lambda T, -Q_{i,j}(k)\} \\ \geq \ & d_{i,j}(k) - \lambda T \end{aligned} \tag{11}$$

By taking the average from time index 0 to time index $K-1$ on both sides of (11) and letting K goes to infinite, we have

$$\lim_{K\to\infty}\frac{Q_{i,j}(K)}{K} \geq \lim_{K\to\infty}\frac{1}{K}\sum_{k=0}^{K-1} d_{i,j}(k) - \lambda T \tag{12}$$

Thus, if the virtual queue $Q_{i,j}(K)$ is rate stable, we have

$$\lim_{K\to\infty}\frac{1}{K}\sum_{k=0}^{K-1} d_{i,j}(k) \leq \lambda T \tag{13}$$

This completes the proof. ■

By introducing the rate stable virtual queue $Q_{i,j}(k)$, the constraint (8) can be rewritten as:

$$\lim_{K\to\infty}\frac{Q_{i,j}(K)}{K}\leq 0, \forall i\in\mathbf{I}, \forall j\in\mathbf{J} \tag{14}$$

Taking advantage of the above relaxations and motivated by Lyapunov Optimization [33]–[35], we can further transfer the time-average problem to a one-step optimization problem so that the joint adaptation challenge can be resolved separately at each time slot. Before calculating the Lyapunov penalty, we first introduce a concatenated vector of the virtual queues as:

$$\Theta_j(k)\triangleq[Q_{1,j}(k), Q_{2,j}(k), ..., Q_{I,j}(k)] \tag{15}$$

Thus, the corresponding Lyapunov penalty function for every receiver can be calculated as:

$$P(\Theta_j(k))\triangleq\frac{1}{2}\sum_{i=1}^{I}Q_{i,j}(k)^2 \tag{16}$$

With (16), the Lyapunov penalty drift $\Delta(\Theta_j(k))$ is:

$$\Delta(\Theta_j(k))=E\{P(\Theta_j(k+1))-P(\Theta_j(k))|\Theta_j(k)\} \tag{17}$$

Enforcing the virtual queue constraints is equivalent to minimizing the drift penalty. Thus, we can turn the original maximization problem into a minimization problem so that maximizing the overall QoE with virtual queue constraint is equivalent to minimizing the following drift-plus-penalty term:

$$\sum_{j=1}^{J}\Big[\Delta(\Theta_j(k))+V_j(-\eta_j QoE_j(k))\Big] \tag{18}$$

where V_j is a non-negative weight to allow a trade-off between the virtual queue constraint and the objective of overall QoE maximization.

Therefore, original problem formulation (6) can be transformed to the one-step problem as follows:

$$\begin{aligned}\min_{\{r_k^{i,j},c_k^i\}}\quad & \sum_{j=1}^{J}\Big[\Delta(\Theta_j(k))-V_j(\eta_j QoE_j(k))\Big]\\ s.t.\quad & \tfrac{r_k^{i,j}}{c_k^i}\leq B_i^{up}(k), \forall i\in\mathbf{I}, \forall j\in\mathbf{J}\\ & \textstyle\sum_{i=1}^{I}\tfrac{r_k^{i,j}}{c_k^i}\leq B_j^{down}(k), \forall j\in\mathbf{J}\\ & r_k^{i,j}\in\mathbf{R}, c_k^i\in\mathbf{C}\end{aligned} \tag{19}$$

Furthermore, we can simplify the formulation of (19) by finding the upper bound of the penalty drift in (17).

$$\begin{aligned}&P(\Theta_j(k+1))-P(\Theta_j(k+1))\\ =&\frac{1}{2}\sum_{i=1}^{I}\Big[Q_{i,j}(k+1)^2-Q_{i,j}(k)^2\Big]\\ \leq&\frac{1}{2}\sum_{i=1}^{I}\Big[d_{i,j}(k)-\lambda T\Big]^2+\sum_{i=1}^{I}Q_{i,j}(k)\Big[d_{i,j}(k)-\lambda T\Big]\end{aligned} \tag{20}$$

Substituting (20) to (17), we can get:

$$\Delta(\Theta_j(k))\leq C_j+\sum_{i=1}^{I}Q_{i,j}(k)\Big[d_{i,j}(k)-\lambda T\Big] \tag{21}$$

where C_j is constant that always satisfies the below condition:

$$C_j\geq\frac{1}{2}\sum_{i=1}^{I}E\Big[(d_{i,j}(k)-\lambda T)^2|\Theta_j(k)\Big] \tag{22}$$

Thus, after the further Lyapunov optimization and the upper bound substituting, the original time-average problem is now simplified to the following one-step joint adaptation problem:

$$\begin{aligned}\min_{\{r_k^{i,j},c_k^i\}}\quad & \sum_{j=1}^{J}\Big\{\sum_{i=1}^{I}Q_{i,j}(k)\Big[d_{i,j}(k)-\lambda T\Big]-V_j(\eta_j QoE_j(k))\Big\}\\ s.t.\quad & \tfrac{r_k^{i,j}}{c_k^i}\leq B_i^{up}(k), \forall i\in\mathbf{I}, \forall j\in\mathbf{J}\\ & \textstyle\sum_{i=1}^{I}\tfrac{r_k^{i,j}}{c_k^i}\leq B_j^{down}(k), \forall j\in\mathbf{J}\\ & r_k^{i,j}\in\mathbf{R}, c_k^i\in\mathbf{C}\end{aligned} \tag{23}$$

C. SJA Algorithm for Joint Adaptation

The one-step problem in Section V-B still need to make decisions on the two separated action space, and it still need to deal with the coupling objective. To tackle these difficulties, we propose our SJA algorithm based on primal decomposition, which can obtain the near-optimal solution quickly on the server. We first rephrase the formula in (23) as follows:

$$\begin{cases}f_0(\mathbf{r}_j,\mathbf{c},k)=\sum_{i=1}^{I}Q_{i,j}(k)\Big[d_{i,j}(k)-\lambda T\Big]-V_j(\eta_j QoE_j(k))\\ f_1(\mathbf{r}_j,\mathbf{c},k)=\frac{r_k^{i,j}}{c_k^i}-B_i^{up}(k)\\ f_2(\mathbf{r}_j,\mathbf{c},k)=\sum_{i=1}^{I}\frac{r_k^{i,j}}{c_k^i}-B_j^{down}(k)\end{cases} \tag{24}$$

where $\mathbf{r}_j=[r_k^{1,j}, r_k^{2,j}, ..., r_k^{I,j}]^T$ and $\mathbf{c}=[c_k^1, c_k^2, ..., c_k^I]^T$.

Thus, (23) can be represented in the following format:

$$\begin{aligned}&\min_{\{\mathbf{r}_j\},\mathbf{c}_k}\sum_{j=1}^{J}f_0(\mathbf{r}_j,\mathbf{c},k),\\ s.t.\quad & f_n(\mathbf{r}_j,\mathbf{c},k)\leq 0, n=1,2\\ & r_k^{i,j}\in\mathbf{R}, c_k^i\in\mathbf{C}\end{aligned} \tag{25}$$

To cope with the coupling problem, as both bitrate and FEC code rate determine the delay metric, we transfer the original problem into one master problem and several subproblems based on the primal decomposition. We introduce a master agent to account for the information update and action aggregations as shown in (25). We then introduce J slave agents to be responsible for subproblem optimization within each

Algorithm 1 SJA Algorithm for joint loss and bitrate adaption

Input:
Total times: K; Clients: $\mathbf{I}, \mathbf{J}$;
Bandwidth capacity: $B_i^{up}(k)$,$\forall i \in \mathbf{I}$; $B_j^{down}(k)$, $\forall j \in \mathbf{J}$;
Bitrate requests: $\hat{r}_k^{i,j}$, $\forall i \in \mathbf{I}, \forall j \in \mathbf{J}$;
Channel's loss rate: $p_i(k)$, $\forall i \in \mathbf{I}, \mathbf{J}$;
Threshold: ζ; Maximum iterations: n;
Output:
Optimal bitrate and FEC code rate: $r_k^{i,j}, c_k^i$;
Initialize $Q_{i,j}(k)$, $i = 1, 2, ...I$, $j = 1, 2, ..., J$;
for $k = 1$ to K **do**
  Initialize $iteration = 0$, $\triangle = \infty$;
  while $iteration < n$ and $\triangle > \zeta$ **do**
    for all $i, \in \mathbf{I}, j \in \mathbf{J}$ **do**
      $r_k^{i,j} = \underset{\mathbf{r}}{inf}\{f_0 | f_n \leq 0, n = 1, 2\}$;
      Update $\mathbf{r}_j$ to the master agent;
    end for
    for all $i \in \mathbf{I}, j \in \mathbf{J}$ **do**
      $r_k^{i,j} = \arg\min_{r \in \mathbf{R}} |f_0^j(r_k^{i,j}) - f_0^j(r)|$;
      $c_k^i = \arg\min_{c \in \mathbf{C}} \sum_{j=1}^{J} f_0^j(c)$;
    end for
    $\triangle = \sum_{j=1}^{J} f_0^j(k) - f_0^j(k-1)$;
    $iteration++$;
  end while
  Output joint adaption solutions $\mathbf{r}$ and $\mathbf{c}$ for time slot k;
end for

iteration, and every slave agent simulates a receiver to solve the following subproblem with only linear constraints:

$$\mathbf{r}_j^* = \underset{\mathbf{r}}{inf}\{f_0 | f_n \leq 0, n = 1, 2\} \tag{26}$$

We now design the algorithm for joint loss and bitrate adaptation as shown in Algorithm 1, which can be implemented on the server with slave agents running in parallel. The required inputs of state information at each time slot include network conditions such as bandwidth capacity and channels' loss rates, as well as receivers' bitrate requests. Also, the parameters consist of maximum iteration between master agent and slave agents at each time slot and the incremental extent of the objective, which are responsible for the stop criteria.

In each iteration, every slave agent will first perform the subproblem optimization step in (26) on behalf of the corresponding receiver. As only one variable exists in the subproblem, every slave agent will roll a one-step optimization. They first adopt the fixed FEC code rate from the server agent to obtain the optimal bitrate choices for every receiver. It is worth noting that the encoding type constraints are omitted by every slave agent so that the original subproblem can be relaxed and transformed into a linear constraint problem, thus reducing the complexity of the solution. After that, every slave agent will update their optimal solutions to the master agent responsible for aggregations. Without bitrate clustering, It will assign the best encoding bitrate type according to the optimal bitrate solutions from slave agents through minimum objective sacrifice. Similarly, we can generate an optimal FEC code rate for each sender by minimizing the overall penalty drift.

The iteration will stop until it reaches the maximum iteration setting or the extent of the overall performance improvement is insignificant. Opposite to DP-based approaches, we emphasize that SJA algorithm has the superiority in processing time with time complexity of $O(nIJ)$ since it significantly increases the scalability by translating the original problem to a master problem and several one-variable subproblems with linear constraints. Thus, the optimal decisions to encode on senders and to stream forwarding on the server can be effectively and efficiently executed to achieve the optimized overall QoE.

VI. Performance Evaluation

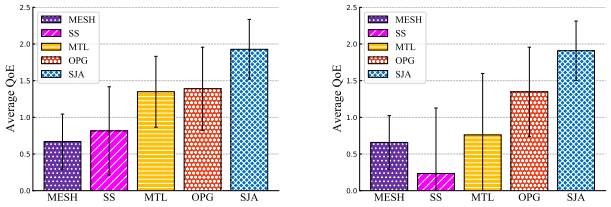
In this section, we compare the SJA framework with state-of-the-art MRVS approaches and evaluate their performance with extensive trace-driven experiments.

A. Methodology

Network Traces: To evaluate SJA and other state-of-the-art solutions under realistic network conditions, we create a corpus of network traces for more than 50 hours by combining two public datasets: (1) the FCC dataset [36] containing over 1 million throughput traces, each of which logs the average throughput over 2100 seconds. (2) the HSDPA dataset [37] on mobile throughput covers multiple usage scenarios such as buses, trains, and cities. To avoid trivial bitrate and FEC code rate selection, the synthesized corpus only considers the original traces with average throughput between 0.3 Mbps and 5 Mbps. Moreover, we collect the loss rate in two lossy network channels with an average of 1% and 2% loss rates.
Baselines: We consider the following methods as the baselines for comparison with SJA in MRVS scenarios:

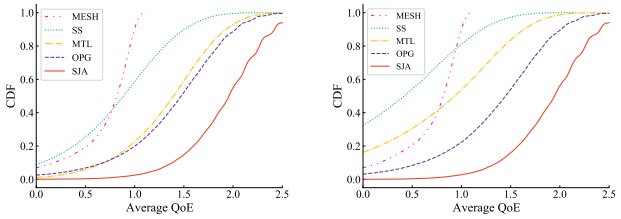
- *MTL:* An adaptive bitrate control algorithm of *MultiLive* for the multi-party realtime scenarios. It is a server-driven approach and comprehensively considers the uplink bandwidth and downlink bandwidth of all clients.
- *OPG:* An integrated *Oppugno* framework that achieves joint loss and bitrate adaption towards maximized QoE in realtime streaming services, which employs deep reinforcement learning algorithms on the receiver side.
- *SS:* Adopts *SVC* for sender-side video encoding and *SFU* architecture to select and forward streams with scalability.
- *MESH:* A simple version of *MTL* where *SVC* and *SFU* architectures are not applied.

Parameter Setting: Given the bandwidth traces, we set the available video bitrate as: $\{0.3, 0.5, 1.0, 2.0, 3.0, 5.0\}$ Mbps. We also set the available FEC code rates to range from 0.9 to 1.0. For the QoE weight setting, we choose $\{1, 1, 1, 2.5, 0.1\}$ and $\{1, 1, 1, 1.5, 0.25\}$ for perceptual quality, fluctuation, bitrate mismatch, loss damage, and streaming delay, respectively. Note that the loss damage weight 0.25 directly maps to the degradation of raw video quality after loss recovery, which is a non-negligible item. In that case, the two QoE preferences are delay-sensitive and loss-sensitive types. Besides, we set all



(a) The overall QoE over synthesized dataset with 1% loss (b) The overall QoE over synthesized dataset with 2% loss

Fig. 4. The overall QoE over synthesized dataset with real-world data



(a) CDF of QoE with 1% loss (b) CDF of QoE with 2% loss

Fig. 5. CDF of QoE metrics with real-world data

V_j as 1 to allow the balance between the time-average delay requirement and the objective of overall QoE maximization. Lastly, we set the maximum iteration in the SJA algorithm as 2 to ensure the fast response of the server-side orchestration.

Experiment Setup: To illustrate how effective our server-driven approach can achieve when facing multiple clients with different viewing preferences, we consider two cases with 5 clients. In the first case, every client in the meeting will request two videos from other clients simultaneously. More specifically, one video is in loss-sensitive type, and the other is in delay-sensitive type. Therefore, the client has different viewing preferences for different videos on its own screen. The detailed results are demonstrated in Section VI-B. In the second case, every client in the meeting will request four other videos; That is, every client can communicate with anyone in the video conferencing service. Moreover, we set three clients in the conference as delay-sensitive users, meaning these three clients will adopt delay-sensitive QoE models wherever the video is from. The remaining two clients in the meeting are loss-sensitive users, and they will adopt loss-sensitive QoE models. The experiment results are revealed in Section VI-C.

B. Performance with Real-world Data

In this section, we compare the performance of the SJA framework with other baselines. Based on our generated corpus, we evaluate the performance with two series of experiments with various loss conditions of 1% and 2% on average. Note that there are 5 clients and each viewer request two videos with loss-sensitive and delay-sensitive QoE preferences. The overall QoE achieved by SJA and other baselines are illustrated in Fig. 4, and the detailed CDF plots in Fig. 5. There are three key observations as follows.

Firstly, SJA is able to outperform all other baselines with higher average QoE, with 33.7% higher QoE than *MultiLive* in low loss rate conditions and 39.2% higher QoE than *Oppugno* in high loss rate conditions. This result confirms the effectiveness of SJA by integrating the loss and bitrate adaptation for overall QoE maximization. An interesting observation is that both *SS* and *MESH* are inefficient in dealing with the multi-party joint adaptation problem, achieving worse performance than other three frameworks as they lack server-driven bitrate orchestration and adaptive loss control mechanisms.

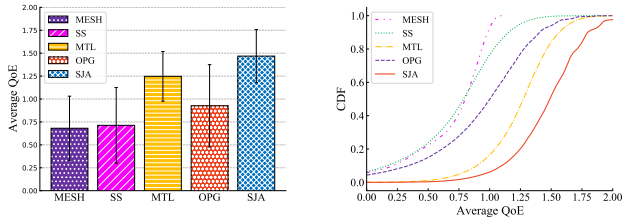
Secondly, SJA can achieve more stable and concentrated QoE scores than all other baselines. The CDF curves in the Fig. 5(a) and Fig. 5(b) show a smaller QoE variance of SJA than *MultiLive* and *Oppugno*. Moreover, the QoE scores of *Oppugno* are mainly concentrated within the range of 1.0 to 2.0, while *MultiLive* is even lower when the loss rate is relatively high. Instead, the QoE scores of SJA are mainly concentrated within the range of 1.5 to 2.5 in different loss conditions, reflecting that SJA can well mitigate the loss impact and can better handle the global streams orchestration with various loss and network throughputs, including the poor network condition with a large loss. The remaining two frameworks achieve quite concentrated but poor QoE performance, which infers that they fail to provide satisfactory QoE in multi-party realtime video streaming services.

The third observation is that the loss adaption is essential in multi-party realtime video streaming services. As shown in Fig. 4(a) and Fig. 4(b), there is a noticeable QoE drop for *MultiLive* as the loss rate increased, which indicates that *MultiLive* is quite sensitive to packet loss problems and insufficient to handle the large loss conditions even with server-side bitrate orchestration. Thus, this observation again confirms the superiority of our joint adaptation in MRVS services.

C. Performance of Generalization

In the experiments above, SJA performs well on the real-world data, while the realistic environment could be more complex with more viewing demands. To evaluate SJA's ability to generalize to more demanding conditions, we conduct two more experiments with various loss rates and more video requests. To be more specific, we evaluate the SJA framework and other baselines on the condition that every participant in the meeting room will request all four videos from other participants. Moreover, among the five participants, three serve as delay-sensitive users to attach great importance to streaming delay, while the other two participants are loss-sensitive and adopt loss-sensitive QoE models. We demonstrate the overall QoE achieved by SJA compared with other baseline methods and the detailed CDF plots in Fig. 6. After the generalization experiments, we have another two critical observations.

Firstly, the SJA framework performs better than all other baseline methods with higher average overall QoE scores and more concentrated QoE distributions in the more generalized multi-party realtime video streaming scenarios. As shown in Fig. 6(a) and Fig. 6(c), the average overall QoE of the SJA framework is at least 18.4% higher than other baseline methods in low loss rate conditions, and is at least 46.5%



(a) The overall QoE with 1% loss (b) CDF of QoE with 1% loss

(c) The overall QoE with 2% loss (d) CDF of QoE with 2% loss

Fig. 6. QoE performance of a more generalized case. There are 5 clients in the conferencing, each client request all 4 videos from others

higher than others in high loss rate conditions. Moreover, the QoE scores of SJA are mainly concentrated within the range of 1.25 to 1.75, reflecting that SJA can better mitigate the loss impact and solve the more challenging bandwidth allocation problem as the number of videos increases.

The second observation reveals the superiority of the server-driven joint adaptation design as the loss rate and the viewers' requested video number increase. Compared with the experiments in Section VI-B, the average overall QoE of all frameworks has been reduced. This result indicates that under the limited upload and download bandwidth, the video quality of users will decrease with the increase of requested video numbers. However, server-driven approaches have better resistance to video quality degradation as the requested video number rises. Opposite to Fig. 4(a), Fig. 6(a) shows that the decline of QoE of SJA and *MultiLive* are less than *Oppugno*, which obviously demonstrated the benefits of adopting server-driven strategies. Furthermore, in the high loss rate group shown in Fig. 6(c), the *MultiLive* solution with server-driven bitrate orchestration achieves similar QoE to the *Oppugno* solution with joint loss and bitrate adaption, while the server-driven SJA framework with joint loss and bitrate adaptation still performs the best. Thus, we can justify the importance of both the idea of server-driven and joint adaptation.

VII. Related Work

Previous ABR algorithm mainly studies how to dynamically adjust the bitrate to utilize the bandwidth of the current network and improve the QoE. According to the decision basis, existing ABR algorithms are mainly divided into four categories: *1) rate-based ABR:* rate-based approaches mainly focus on predicting future throughput and adjusting the bitrate based on predicted results. For example, Sun et al. [38] leveraged a data-driven approach to construct a Hidden-Markov-Model-based midstream predictor to model the stateful evolution of throughput. *2) buffer-based ABR:* buffer-based approaches adjust the bitrate by considering the buffer occupancy of clients. For example, Spiteri et al. [26] formulated bitrate adaptation as a utility-maximization problem and devised an online control algorithm called BOLA that uses Lyapunov optimization to minimize rebuffering and maximize video quality. *3) hybrid ABR:* hybrid methods usually consider multiple factors when deciding the future bitrate. For example, Yin et al. [30] propose a model predictive control algorithm that can optimally combine throughput and buffer occupancy information to outperform traditional approaches. *4) reinforcement-learning-based ABR:* rl-based methods utilize learning algorithms to achieve bitrate adaption. Mao et al. [1] pioneering trained a neural network model named Pensieve that selects bitrates for future video chunks based on observations collected by client video players. However, these studies on reliable TCP transmission do not consider the packet loss problem, which can cause picture distortion and seriously affect the user QoE.

Some previous studies have put forward efforts on multi-party realtime video streaming services. Hajiesmaili et al. [18] cast a joint problem of user-to-agent assignment and transcoding-agent selection, and devised an adaptive parallel algorithm to simultaneously minimize the cost of the service provider and the conferencing delay. Hu et al. [21] considered the multi-server architecture and formulated server selection as a geometric problem to propose fast heuristics with theoretical worst-case guarantees. Wu et al. [17] presented a cloud-assisted mobile video conferencing system to improve the quality and scale of multi-party mobile video conferencing, where the decentralized algorithm can decide the best paths of streams and the most suitable surrogates for video transcoding along the paths to utilize the limited bandwidth fully. Moreover, Wang et al. [16] considered global optimization that takes into consideration of different QoE factors, and designed an adaptive bitrate control algorithm for the multi-party scenario by modeling the many-to-many ABR selection problem as a non-linear programming problem. These MRVS solutions mainly focus on the optimization problem with cost-efficiency, service scalability, and low latency. However, they lack the consideration of the overall orchestration with handling the potential loss problems, which may lead to severe damage to perceptual video quality [39].

VIII. Conclusion

In this paper, we propose SJA, a server-driven joint loss and bitrate adaptation framework in multi-party realtime video streaming services towards maximized overall QoE. We first explored the importance of loss recovery and server orchestration in MRVS, and abstracted its service model to better tackle the challenges of selecting the best bitrate, FEC code rate, and streaming forwarding choices. Afterwards, we investigated the QoE model and mathematically formulated the problem, followed by proposing the SJA algorithm with close-to-optimal performance. Over a broad set of network conditions and QoE metrics, the SJA framework outperformed existing advanced solutions by $18.4\% \sim 46.5\%$.

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