

An End-to-End Pipeline Perspective on Video Streaming in Best-Effort Networks: A Survey and Tutorial

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Video streaming continues to captivate attention of users and service providers, dominate in Internet traffic, and form a vibrant research field. Taking a pragmatic approach to reviewing recent research in the field, this paper considers the most dominant streaming paradigm, the main aspects of which include transmission of two-dimensional videos over the best-effort Internet, support from content delivery networks, and client-side bitrate adaptation. To make the survey more accessible, we incorporate extensive tutorial materials. In contrast with the siloed approaches of existing surveys, our paper holistically covers the end-to-end streaming pipeline from video capture and upload for server processing to distribution for playback on diverse user devices. Reflecting the practical interests of respective stakeholders, our survey presents a novel perspective on end-to-end streaming and sheds light on the relationships and interactions between its ingestion, processing, and distribution stages. At each stage, we classify streaming designs in regard to their methodology depending on whether intuition, theory, or machine learning serves as a methodological basis for their core contribution. In addition to tasks confined to a single stage, the survey also examines transversal topics such as coding, super resolution, and quality of experience. After surveying more than 200 papers, we synthesize current trends and project future directions in video streaming research.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Networks** → **Application layer protocols**; **In-network processing**; • **Information systems** → **Multimedia streaming**; • **Computing methodologies** → **Machine learning**.

Additional Key Words and Phrases: Video streaming, best-effort network, end-to-end pipeline, ingestion, processing, distribution, methodology, intuition, theory, learning, adaptive bitrate algorithm, coding, content delivery network, quality of experience.

1 INTRODUCTION

Fueled by video streaming for more than a decade, Internet traffic grows dramatically and shows no signs of abating. Estimates of video traffic quadruple from 2017 to 2022, increasing its share in total Internet traffic from 75% to 82%, with a 15-time increase in live streaming traffic [39]. The estimated portion of ultra-high-definition television sets (TVs) among all flat-panel TVs rises from 33% in 2018 to 66% in 2023 [40]. The proliferation of remote work, spurred by the COVID-19 pandemic, also contributes significantly to the importance of video streaming. The comparison of streaming time during the fourth quarters of 2019 and 2020 shows a 44% increase [41], with a 13% growth between the second quarters of 2020 and 2021 [42]. The increase in streaming time remains a stable trend, as evidenced by 90% (in Asia) and 14% (globally) year-over-year increases between the first quarters of 2021 and 2022 [43].

End-to-end video streaming involves different kinds of stakeholders, and this ecosystem becomes more diverse. Netflix, Amazon Prime Video, and other established over-the-top *streaming platforms* face competition from newer services such as Disney+, Apple TV+, HBO Max, and Peacock. To boost the number of subscriptions and hence revenue, the streaming platforms seek to enhance the users' *quality of experience (QoE)*. The platforms obtain videos from *content providers (CPs)*. *Content delivery networks (CDNs)* focus on distributing these videos with low latency from cache servers located near the users, while striving to minimize costs and maintain high cache hit rates for efficient delivery. *Internet service providers (ISPs)* supply network connectivity and characterize it via bandwidth, loss rate, and other network-level *quality of service (QoS)* metrics. Meanwhile, *equipment manufacturers* produce devices necessary for creating, processing,

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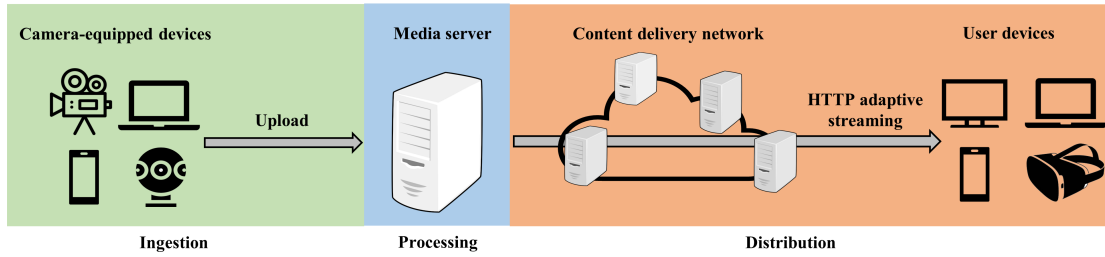


Fig. 1. End-to-end pipeline of video streaming.

storing, delivering, and consuming video content. Involved entities often play multiple roles, and the relationships between the entities keep evolving.

While our paper surveys two-dimensional (2D) streaming over best-effort networks exemplified by the current Internet, there also exist large bodies of research on video streaming in different formats and alternative network architectures. Future Internet architectures, such as named data networking and software-defined networking, constitute disparate environments for video streaming and enable new kinds of solutions [10, 59, 131]. Although 360-degree and immersive forms of streaming are on the rise, their market share is still low. These advanced variants struggle to gain widespread adoption because they require large bandwidth and specialized equipment, e.g., head mounted displays (HMDs).

Figure 1 illustrates the process of 2D streaming where *ingestion*, *processing*, and *distribution* stages comprise an *end-to-end pipeline*. The pipeline begins with video capture by a camera and ends with playback on a remote device. Codecs compress the video as a sequence of frames, with each frame being a 2D pixel matrix, to minimize its size for efficient communication and storage. The ingestion stage encodes raw footage before uploading the video to a media server. At the processing stage, this server executes long-term storage, content analysis, ad insertion, and other tasks. In particular, video segmentation splits the video into *chunks* aka segments, and transcoding converts these chunks into multiple representations. The resultant *encoding ladder* describes the representation levels of the video chunks. At the distribution stage, a CDN delivers the video to user devices for decoding and playback. The reliance on the hypertext transfer protocol (HTTP) makes this stage compatible with browsers and CDN-operated HTTP caches and enables its stateless connections to bypass firewalls and network address translators. An *adaptive bitrate (ABR) algorithm* dynamically selects the representation level for the next chunk retrieved to a user device. To support scalable distribution, the ABR algorithm typically runs in the user device, i.e., on the client side. Whereas there exist alternative proposals where the server, network, cloud, or peer devices provide ABR support, our survey focuses on classical *HTTP adaptive streaming (HAS)* with client-side ABR algorithms.

This survey covers an extensive body of recent work on video streaming from an end-to-end pipeline perspective. Recognizing the topic breadth and intricacy, we make the survey more accessible and self-contained by including substantial tutorial materials, which is especially beneficial for newcomers to the field. Unlike earlier surveys that focus on one stage of the streaming pipeline or just a specific task at a single stage, our survey pursues a holistic approach to provide integrated understanding of the area. Fragmented studies are no longer sufficient because the practice of video streaming exhibits increasingly common settings where a single stakeholder, solution technique, or evaluation metric spans multiple stages of the pipeline. By exposing the interconnected nature of problems in the area, our survey opens opportunities for integrated designs with higher performance. Also, while video streaming is a rapidly evolving field,

our paper improves on previous surveys by providing an up-to-date coverage of recent results. Moreover, our survey distinguishes itself by introducing a new classification scheme centered on the methodology of the reviewed designs.

When surveying research results across the streaming pipeline, we pay the closest attention to a set of key tasks. The uneven coverage is unavoidable because research in more active areas produces more results. The survey thoroughly examines video compression and upload at the ingestion stage, transcoding at the processing stage, ABR algorithms and CDN support at the distribution stage, as well as the transverse topics of super resolution (SR) and QoE that span multiple stages. Also, while the survey classifies the recent results in regard to their underlying methodology, we scrutinize the increasingly prominent role of machine learning (ML) in streaming designs. After reviewing more than 200 papers, we extract major current trends and promising future directions in video streaming research. To sum up, our survey makes the following main contributions:

- We present an extensive review of recent research in video streaming over the best-effort Internet with CDN assistance, HAS protocols, and client-side ABR logic.
- To support holistic understanding of the topic, we discuss the results from an end-to-end pipeline perspective. The survey exposes interdependencies and advancements across the ingestion, processing, and distribution stages of the pipeline.
- The novel classification of research results according to their methodology differentiates between intuition, theory, or ML as a basis for the main design contribution.
- Based on the literature review, we distill prominent current trends and project promising directions in video streaming research.

The rest of the paper has the following structure. Section 2 describes the end-to-end streaming pipeline in more detail. Section 3 elaborates on considered modes of video streaming. Section 4 classifies methodologies that underlie streaming designs. Sections 5, 6, and 7 review recent research on the ingestion, processing, and distribution stages of the pipeline, respectively. Section 8 presents current trends and future directions. Section 9 discusses differences from related surveys. Finally, we conclude the paper with its summary in Section 10.

2 END-TO-END STREAMING PIPELINE

Our survey uses the ingestion, processing, and distribution stages of the end-to-end streaming pipeline as a basis for classification of research literature. The pipeline starts at the *ingestion stage* with capture of a raw video by a camera. While cameras, e.g., built-in laptop and omnidirectional cameras, vary dramatically in their capabilities and purpose, the raw footage typically consumes a lot of space, and a codec in the camera-equipped device applies spatial (intra-frame) and temporal (inter-frame) compression to reduce the video size. Then, the device transfers the encoded video over the Internet to a media server. The real-time messaging protocol (RTMP) is the most dominant protocol for video upload [140]. Deployment of the media server in a cloud becomes increasingly common. Video quality, encoding latency, consumed network bandwidth, and upload latency represent important performance metrics at the ingestion stage. This stage recently attracts a substantial research interest due to new requirements posed by live streaming and video content analysis.

The processing stage, which does not involve any communication, takes care of storing and transforming the ingested video in the media server. The transformation tasks cope with heterogeneity in network connectivity and device capabilities and include video segmentation (i.e., partition into chunks), ad insertion, content analysis, and transcoding. The latter converts video chunks into multiple representations that differ in such parameters as a resolution (number of

pixels in a frame), bitrate, and frame rate (measured in frames per second, or fps). Numerous research efforts target integration of transcoding with tasks at the ingestion and distribution stages of the pipeline.

The distribution stage deals with real-time delivery of the video from the media server to a user device and playback of the video to the user. In addition to ISPs which provide network connectivity, this stage also involves CDNs to disseminate the content from their edge servers with low latency. The complexity increases further due to the diversity of user devices, which include laptops, phones, tablets, and HMDs, and heterogeneity of their network connections. As discussed in Section 1, the distribution stage handles the scalability, heterogeneity, and deployment challenges by relying on HAS. Apple’s HTTP Live Streaming (HLS) represents the prevalent HAS protocol [54, 137]. Besides a decoder which reconstructs the distributed video, the user device incorporates a media player which executes an ABR algorithm. A manifest file provided by the server describes the video representations available to the client, e.g., chunk duration and representation levels. Based on the manifest file and predicted network conditions, the ABR algorithm dynamically selects the representation level for the next chunk downloaded to the media player. While the large number of stakeholders results in diverse problem formulations at the distribution stage, many considered performance metrics reflect the ultimate goal of providing the users with high QoE. Being complex and facing the users directly, the distribution stage keeps attracting significant research efforts.

3 STREAMING MODES

While the end-to-end pipeline described in Section 2 supports different modes of streaming, our survey adheres to its pragmatic overall philosophy in this specific regard as well and focuses on 2D streaming, which heavily prevails in practice. We leave the topics of 360-degree videos, virtual reality (VR), augmented reality (AR), and mixed reality to other surveys. This section elaborates on two key variants of 2D streaming.

Video on demand (VoD) constitutes the most dominant variant of 2D streaming. Originated together with the end-to-end pipeline, this mode aligns its requirements closely with the pipeline structure. In particular, VoD serves a prestored video from an intermediate location, i.e., media server. This decouples ingestion and processing from distribution: while the latter operates in real time, the two former stages accomplish their tasks beforehand under less stringent latency constraints. The dichotomy results in dissimilar communication designs for VoD at the ingestion and distribution stages.

Live streaming refers to an increasingly popular variant that requires real-time operation of the entire pipeline from video capture to playback. This mode commonly composes a session from multiple streams that proceed in different directions, involve many users, and are interdependent, e.g., a device streams out a video of its user and concurrently plays to the user another video streamed from elsewhere. Because real time is a relative notion where acceptable latency depends on the particular application, live streaming encompasses several forms operating on distinct timescales and subjected to different limits on the session size. For instance, videotelephony typically requires subsecond end-to-end latency and constrains sessions to one-to-one or few-to-few communications. On the other hand, live broadcasting distributes a video to millions of users via one-to-many communications and tolerates tens of seconds in end-to-end latency. Figure 2 depicts variants of live streaming along with their latency requirements and suitable protocols, e.g., HLS and RTMP [180]. The real-time end-to-end operation of live streaming justifies integrated designs that cross the boundaries between the traditional pipeline stages.

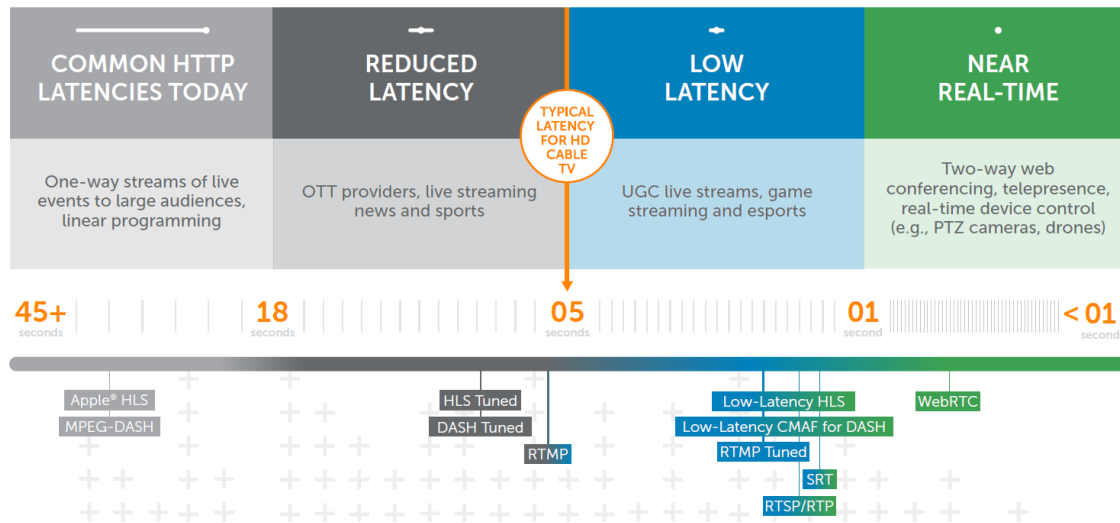


Fig. 2. Live streaming variants, their latency requirements and protocols [180].

4 METHODOLOGY

Video streaming research advances in not only contributed designs but also underlying methodology. This section presents the current methodological landscape by describing three broad classes that rely on intuition, theory, or ML. Our survey of research results exposes changes in popularity among the three method classes over time.

4.1 Intuition-based methods

In an intuition-based method, a human expert leverages domain knowledge to tackle a specific problem at hand. Typically guided by unstructured reasoning and trial-and-error experiments, such a method develops and refines a heuristic solution, which is often simple and easily implementable. Even when the intuition-based method is fully informal, a subsequent rigorous analysis might formally characterize properties of the heuristic and provide a rationale for the intuition. Also, the heuristic might turn out to be insightful and of a more general applicability than only for the targeted problem. The additive-increase multiplicative-decrease (AIMD) algorithm [37] constitutes a notable example: while developed for transmission adjustment in network congestion control, AIMD now enjoys wide adoption in video streaming and other fields.

4.2 Theory-based methods

A theory-based method casts the tackled problem into a general formal theory which abstracts problem specifics. Within the theoretical formulation, the method systematically follows principles of rational logic to derive a solution, typically along with guarantees of its correctness and performance. In comparison to intuition-based methods, the derived algorithm might be less intuitive or even counterintuitive. Whereas theoretically optimal solutions might have prohibitively high complexity, it is common to simplify them to practicable heuristics. Branch and bound [109], dynamic programming [19], and Lyapunov optimization[133] exemplify theory-based methods. Control theory is a particularly fruitful source of solutions for video streaming, with model predictive control (MPC), linear quadratic regulator (LQR),

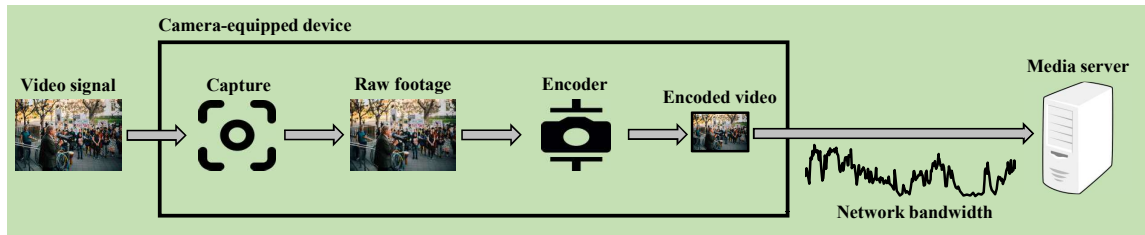


Fig. 3. Ingestion stage for VoD.

and proportional-integral-derivative (PID) controllers [65] underlying a number of highly successful streaming designs, e.g., at the distribution stage.

4.3 ML methods

Instead of following explicit instructions, an ML method trains a model on sample data so that, when presented with different data, the trained model produces an accurate answer. ML places the main emphasis on learning of generalizable statistical properties from the sample data. The objective to minimize the error on unseen samples differentiates ML from theory-based methods that optimize for available data. Domain expertise plays a smaller role in the design of ML techniques and helps a human less in understanding their operation and answers. Concerns about model biases and overfitting dilute trust in ML even further. Nevertheless, superior performance in a variety of applications results in wide adoption of ML methods. As in other fields, decision trees (DTs), random forests (RFs), naive Bayes (NB), and other relatively simple ML methods [9] remain popular in video streaming, especially when explainability and computational constraints are key concerns. With time, deep learning techniques gain larger attention and range from basic multilayer perceptrons (MLPs) to advanced transformer architectures [145]. Similarly, the interest in training methods shifts from supervised learning (SL) and unsupervised learning (UL) to reinforcement learning (RL) and imitation learning (IL) [169].

5 INGESTION STAGE

While the end-to-end streaming pipeline consists of three stages, the next three sections survey research results stage by stage. Each section first presents additional background for the respective stage and then reports on recent results in accordance with the methodology classification in Section 4. We start with the ingestion stage.

5.1 Background

Figure 3 depicts a typical setup of the ingestion stage for VoD where a camera-equipped device converts a video signal into raw footage, leverages an encoder to compress the footage, and transmits the encoded video over a network with fluctuating bandwidth to a media server. In both VoD and live streaming, it becomes common to host the media server in cloud infrastructure [134]. Some variants of 2D streaming rely on edge nodes as intermediaries between the camera-equipped device and media server or do not employ a dedicated media server at all, e.g., where a peer-to-peer (P2P) system carries the video from the camera to the viewing device [117].

5.1.1 Video compression. We first present background on video compression, which is pertinent for not only ingestion but also processing stage of the pipeline.

General principles: One can classify compression in general as lossy or lossless depending on whether the compressed version is decodable to the original form with or without loss of information, respectively. Lossy compression has a potential to significantly reduce the storage and communication requirements while keeping the content quality high. Spatial and temporal methods constitute two major categories of video compression. Spatial compression reduces information redundancy within a frame – e.g., by discarding less significant pixels via a discrete cosine transform (DCT) and quantization – and then decreases the bit count by encoding. On the other hand, temporal compression is computationally more intensive and lowers redundant information across multiple frames through motion estimation and compensation [93]. A codec or separate post-processing step performs filtering to deal with distortions – e.g., ringing, mosquito-noise, and block-boundary artifacts – introduced into the video by lossy compression.

A compressed video comprises frames of different types. I-frames (intra-frames) come from spatial compression only, serve as coding references for other frames, avoid error accumulation, and support search within the video. P-frames (predictive frames) rely on motion compensation in regard to previous frames. The compression behind B-frames (bipredictive frames) uses both preceding and following frames. A group of pictures (GOP) is a separately encoded frame sequence that starts with an I-frame followed by P-frames and B-frames. A single container format file stores the encoded video along with audio, synchronization, subtitle, and metadata information.

Encoding parameters: Latency, throughput, video quality, and other metrics of compression performance pose conflicting optimization objectives. A codec controls trade-offs via a number of knobs, as discussed below. The resolution refers to the frame size in pixels. While requiring more storage and communication resources, a higher resolution supports sharper images, as long as it matches the display resolution in the user device. The frame rate represents the frequency of frames in the video and has to be sufficiently high for a human to perceive the video as a smooth motion rather than a sequence of individual images. With the typical value range between 24 and 60 fps, the frame rate reaches 120 fps in video games [120]. The GOP structure describes GOPs with two parameters N and M . N expresses the GOP size in frames, and M captures the distance between two consecutive anchor frames, which refer to I-frames and P-frames. Larger GOPs with a higher fraction of B-frames support greater reductions in the video size. The bitrate specifies the number of transferred or processed bits per second.

Codecs: We now describe existing codecs and begin with widely adopted ones. H.264 or advanced video coding (AVC) refers to a compression standard based on macroblocks and motion compensation [49]. Its features include an integer DCT, variable block-size segmentation, inter-frame prediction over multiple frames, and in-loop deblocking filtering. H.264 is the most popular codec due to its widespread support by commercial devices [29].

H.265 or high efficiency video coding (HEVC) is an H.264 successor that provides the same video-quality level while improving the compression efficiency by up to 50% and significantly reducing the bitrate. H.265 replaces 16×16 macroblocks with coding tree units (CTUs) that support block structures sized up to 64×64 samples. In addition to an integer DCT, HEVC employs a discrete sine transform (DST). Compared to H.264, the deblocking filtering is simpler and easier to parallelize [166]. Despite the superior performance, H.265 experiences slow adoption due to royalty issues and lack of support by major browsers.

VP9, an open royalty-free compression format, relies on 64×64 superblocks partitioned adaptively into a quadtree (QT) coding structure. The intra-frame prediction benefits from six oblique directions for linear extrapolation of pixels. Compared to H.265, VP9 reduces encoding latency and has lower compression efficiency [69]. Developed by Google and used on its YouTube platform, VP9 enjoys broad browser support.

AOMedia Video 1 (AV1) emerges as an open royalty-free successor of VP9. AV1 diversifies coding options for improved handling of different video inputs. The transformation employs rectangular DCTs and asymmetric DSTs. The

superblocks become as large as 128×128 . The filtering involves in-loop and loop-restoration filters. While AV1 improves on the compression efficiency of H.265 at the cost of larger computational complexity [35], subjective tests of video quality do not reveal significant differences [99].

Scalable video coding (SVC) extends H.264 to support layered encoding of a video into multiple streams such that enhancement layers augment the base layer. The enhancement dimensions include the frame rate, resolution, bitrate, or their combinations [155]. While inferior in compression efficiency, SVC copes better with highly variable bandwidth [57]. Hybrid SVC uses H.264 for the base layer and SVC for the enhancement layers [66].

Versatile video coding (VVC), also known as H.266, is a standard adopted in 2020. Viewed as a successor to H.265, VVC supports lossless and subjectively lossless compression. VVC derives its name from the aspiration to broadly support existing and emerging video applications. VVC adopts layered coding as well as extraction and merging of bitstreams [30]. Compared to H.265, VVC significantly improves the compression efficiency at the cost of higher computational overhead [173]. While VVC is expected to bear royalties, the royalty situation remains unclear.

Essential video coding (EVC) refers to another compression format from 2020. EVC incorporates such innovative techniques as a binary-ternary tree for the coding structure, split unit coding order, and adaptive loop filter [38]. By increasing the computational complexity fivefold vs. H.265, EVC improves the compression efficiency by about 30% [68]. EVC has both royalty-based and royalty-free profiles.

Low complexity enhancement video coding (LCEVC) constitutes a new approach to video enhancement. Given a base layer encoded with a different codec, LCEVC produces an enhancement layer for the video. As indicated in the name, LCEVC seeks to reduce encoding and decoding complexity [123].

All modern codecs employ rate control (RC), an important and yet unstandardized mechanism, to adapt the output bitrate of the encoder to avoid buffer overflow and underflow in the decoder. The algorithm maintains a target bitrate by tuning a low-level encoding parameter, e.g., quantization parameter (QP), DCT coefficient, frame rate, or motion detection threshold [181].

5.1.2 Perceptual compression. Unlike the aforementioned codecs that exploit statistical redundancy, perceptual compression of videos leverages properties of the human visual system to reduce the video size without degrading the perceived quality. The perceptual compression involves detecting spatial, temporal, or spatio-temporal portions of the video that are critical for the video perception. The approach losslessly encodes such areas of high visual saliency, called *regions of interest (ROIs)*, and applies stronger compression to the other parts of the video. The process involves two main phases. ROI detection is the first phase that utilizes techniques ranging from user input to non-visual information [111]. ROI-aware encoding constitutes the second phase occurring either as preprocessing (e.g., blurring of the non-ROI areas) or during the actual encoding (e.g., via the encoder's RC algorithm) [124, 158].

5.1.3 Upload protocols. RTMP and real time streaming protocol (RTSP) are protocols with heavy domination over upload during the early years of video streaming. RTSP controls media streams between end points and relies on other protocols – such as the real-time transport protocol (RTP) – for actual stream delivery. RTSP enables the user to play, record, pause, and terminate the media streams in real time. RTMP and RTSP employ the transmission control protocol (TCP) and user datagram protocol (UDP) as the underlying transport, respectively. Despite the subsequent emergence of HTTP-based streaming, RTMP and RTSP preserve their prominent roles on the ingestion stage. Based on data from 391 global broadcasters in live streaming, sports, radio, gaming, and other industries [170], Figure 4 reports on the usage of streaming protocols by the broadcasters and ranks RTMP second overall, with a share of 33%, due to its dominance as a low-latency upload protocol. Surveillance applications routinely rely on RTSP for video upload from cameras.

Secure reliable transport (SRT) and WebRTC represent recently emerged alternatives to RTMP and RTSP. The UDP-based SRT supports low latency by leveraging an error-correction mechanism. Not a protocol per se, WebRTC comprises a set of technologies enabling real-time P2P communications between web browsers and mobile applications [164]. Due to its ultra-low latency, WebRTC is highly suitable for video conferencing [91].

5.1.4 Super resolution. SR is a computer-vision task that reconstructs a high-resolution (HR) image from its low-resolution (LR) version [97]. SR presents an ill-posed inverse problem because an LR image has multiple HR counterparts. Single-image SR (SISR) and multi-image SR (MISR) consider, respectively, one and many LR images when reconstructing the HR image. Compared to MISR, SISR attracts a larger attention due to its lower computational overhead. Applications of SR to video streaming consume low network bandwidth by communicating LR frames and play a high-quality video back to the user by rendering the reconstructed HR frames. Surpassing the traditional

reliance on spatial-frequency band substitution and geometrical techniques, SR sees wide adoption of deep neural networks (DNNs) such as convolution neural networks (CNNs) and generative adversarial networks (GANs) [178].

Video streaming derives its main benefits from SR through the ability to consume less network bandwidth and increase video quality at the cost of more computation. Applications of ML-based SR methods face challenges due to poor generalization, high dimensionality of the parameter space, and struggle to operate both quickly and accurately. Respective solutions include video-specific SR models, micro-models (i.e., SR models for short video segments), and anytime predictors that progressively refine a fast crude initial prediction [74].

5.2 Recent results

A methodology-based classification of designs faces a complication because a design might make multiple contributions based on different methods. We classify each design according to the main method of its core contribution.

5.2.1 Intuition-based methods. [179] proposes dynamic selection of the upload protocol by a mobile broadcasting application. The application considers latency, join-time, goodput, and overhead metrics, picks one of them, monitors this metric in real time, and periodically assesses whether to switch to another upload protocol. While this method performs as well as the best protocol for each individual metric, the switching between protocols incurs undesirable delay. [118] focuses on tracking the TCP uplink throughput in a radio access network. This monitoring enables a reduction in the number of bitrate levels in the encoding ladder, thus conserving bandwidth. This technique combines real-time and historical throughput data, using the former for ongoing sessions and the latter at the start of sessions or during

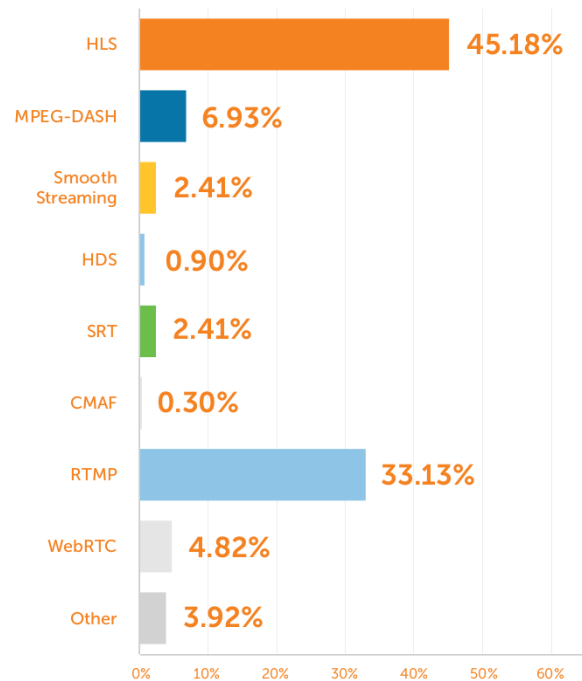


Fig. 4. Protocol usage by 391 broadcasters [170].

handovers. [139] monitors the average inter-arrival time of video frames and dynamically adjusts the encoding rate in a camera-equipped mobile device via the AIMD algorithm. By increasing the average encoding rate and decreasing the packet loss, the algorithm improves real-time up-streaming under changing network conditions. *NeuroScaler* enhances the scalability of SR-based live streaming by lowering both overhead and encoding time of SR [188]. The design includes a novel scheduler and enhancer of the anchor frames used by SR. The anchor scheduler leverages codec-level information to select the anchor frames in real time without any neural inference. The anchor enhancer complements a video codec with a simple image codec and employs the latter for compression of the anchor frames only.

5.2.2 Theory-based methods. In *DNN-driven streaming (DDS)*, a camera adapts the bandwidth usage by its two streams in order to increase the inference accuracy while reducing the bandwidth consumption in analytics-oriented applications [52]. The first stream uploads a low-quality video to the server that detects ROIs for DNN inference. The second stream delivers a high-quality video for the detected ROIs so as to boost the inference accuracy while utilizing the bandwidth prudently. DDS estimates the base bandwidth with a Kalman filter and adjusts the bandwidth usage by tuning the resolution and QP.

Assuming SVC encoding, [160] strives to maximize video quality for live streaming in multiclient scenarios with heterogeneous upload latencies. The design involves a series of algorithms that leverage a low-complexity greedy approach and dynamic programming. Pursuing a similar goal, *Vantage* uploads a live stream and improves QoE for the users who view the stream with different shifts in time by adopting frame retransmissions [151]. When the available bandwidth is abundant, the design complements live streaming with retransmission of earlier frames at a higher bitrate to benefit the time-shifted viewing. *Vantage* formulates the frame scheduling as a mixed-integer program.

A *content harvest network (CHN)* supports both low latency and sustainable bandwidth consumption at the ingestion stage [136]. Edge devices in CHN act as relays redirecting traffic from broadcasters to servers. The selection of an optimal path for each broadcaster involves two strategies operating on different time scales. A centralized server periodically solves a global NP-hard optimization problem by means of a polynomial-time greedy rounding algorithm. [34] selects both upload server and encoding bitrate with a joint objective of maximizing the video rate and minimizing the end-to-end latency. The paper develops algorithms for one-hop-overlay and full-overlay architectures. The one-hop-overlay algorithm is an optimal polynomial-time solution. [34] proves the NP-completeness of the full-overlay problem and designs an efficient heuristic solution based on convex relaxation.

LiveNAS employs SR for high-quality live streaming and significantly outperforms WebRTC in QoE and other metrics [100]. Along with the live video, the camera uploads patches of high-quality frames. The server utilizes the patches for online training of a DNN that performs SR. To split the available upload bandwidth between the video and patches, *LiveNAS* applies gradient ascent to jointly maximize video quality and DNN accuracy while imposing minimal overhead on ingest clients. *LiveSRVC*, an SR-based solution for live-stream ingestion, performs similarly to *LiveNAS* in video quality with reductions in bandwidth consumption and latency [36]. The design applies a higher compression ratio to I-frames in the camera and trains an SR model online to reconstruct the I-frames in the server. Guided by the estimated uplink bandwidth, SR-model processing time, and model accuracy, *LiveSRVC* adopts MPC to select the I-frame compression ratio and chunk bitrates.

5.2.3 Machine-learning methods. *Dynamic adaptive video encoding (DAVE)* is a real-time P2P video streaming protocol that avoids transcoding in intermediate nodes so as to reduce end-to-end latency, increase perceptual video quality, and improve QoE [76]. *DAVE* adopts an SR model and applies Q-learning (QL) to adjust the frame rate, encoding speed, compression ratio, and resolution in the H.264 encoder. [32, 96, 200] design codecs for perceptual compression and

Table 1. Designs at the ingestion stage of the end-to-end streaming pipeline (*u* abbreviates *unspecified*).

	Name [reference]	Technique of the core contribution	Codec	QoE model	Transport-layer information	Edge infrastructure	Bandwidth efficiency evaluation	Year
Intuition	[179]	switch between upload protocols	<i>u</i>	✗	✗	✗	✗	2016
	[118]	dynamic encoding ladder	H.264	✗	✓	✗	✗	2015
	[139]	AIMD encoding-rate control	H.264	✗	✗	✗	✗	2017
	NeuroScaler [188]	zero-inference selection of anchors	VP9	✗	✗	✗	✗	2022
Theory	DDS [52]	adaptive feedback control	H.264	✗	✗	✗	✓	2020
	[160]	dynamic programming, greedy heuristics	SVC	✓	✗	✗	✗	2017
	Vantage [151]	mixed-integer program, regression heuristic	VP8	✓	✓	✗	✗	2019
	CHN [136]	knapsack-like problem, greedy rounding heuristic	<i>u</i>	✗	✓	✓	✗	2019
	[34]	relaxation-based heuristic	<i>u</i>	✓	✗	✓	✗	2019
	LiveNAS [100]	concave optimization problem, gradient ascent	<i>u</i>	✗	✓	✗	✓	2020
	LiveSRVC [36]	MPC	H.264	✓	✗	✗	✓	2021
ML	DAVE [76]	RL, QL	H.264	✓	✗	✗	✗	2021
	[200]	SL, CNNs	H.265-based	✗	✗	✗	✗	2017
	[32]	SL, CNNs	ROI-based	✗	✗	✗	✗	2020
	DeepFovea [96]	UL, Wasserstein GAN	DeepFovea	✗	✗	✗	✗	2019
	CrowdSR [119]	SL, unspecified DNNs	<i>u</i>	✗	✗	✗	✗	2021
	DIVA [183]	SL, AlexNet variants (CNNs)	H.264	✗	✗	✗	✓	2021
	Reducto [113]	UL, <i>k</i> -means clustering	H.264	✗	✗	✗	✓	2020

share the ambition to enhance coding efficiency. Compared to the standard codecs, these designs increase video quality and decrease storage requirements with reductions in the encoding speed. [200] extends the H.265 codec by introducing a hybrid compression algorithm that initially employs a CNN for spatial saliency computation, followed by temporal saliency extraction from compressed-domain motion information. [32] proposes an ROI codec that integrates CNNs with an entropy codec to achieve higher encoding efficiency than with previous ROI codecs. However, its decoding performance is weaker. [96] exemplifies foveated coding and improves compression of the image areas not covered by the fovea. The proposed codec uses a GAN to reconstruct a realistic peripheral video from a minimal set of frame pixels. The design is sufficiently fast for HMDs and demonstrates superior perceptual quality in subjective evaluations. *CrowdSR* enhances live streaming from low-end devices via SR-based video uploading [119]. The design periodically trains an SR model on high-quality video patches from similar content broadcasters. *CrowdSR* outperforms existing counterparts in regard to the peak signal-to-noise ratio (PSNR) [85] and structural similarity (SSIM) [177] metrics.

DIVA and *Reducto* refer to advanced systems for video analytics that reduce the bandwidth consumption by camera-to-server communications while retaining accuracy and speed. *DIVA* processes sparse video frames on the camera, avoiding unnecessary uploads [183]. The server trains CNNs, variants of AlexNet [105], on the provided sparse analytical results and sends the CNNs back to the camera to identify I-frames for upload. The iterative design improves analytics performance and operates 100 times faster than real-time video. In contrast, *Reducto* tracks basic features such as pixel

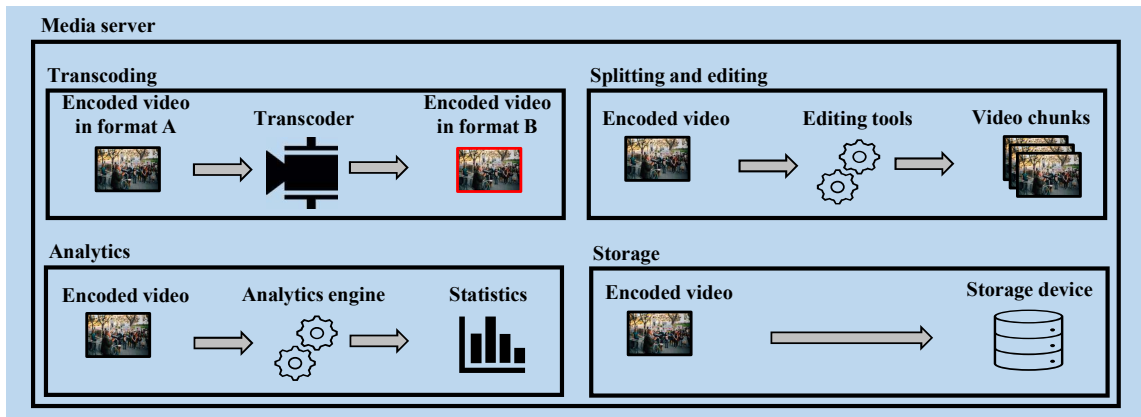


Fig. 5. Processing stage for VoD.

or edge differences [113]. It considers a feature relevant to the specific query and uses k-means clustering to set a dynamic threshold for frame filtering at the camera. By filtering out frames of low importance, the design reduces upload traffic without sacrificing analytics accuracy.

Table 1 sums up the above recent designs at the ingestion stage. The table classifies the designs with respect to the main technique of the core contribution, codec, reliance on a well-defined QoE model, usage of transport-layer information, leverage of edge infrastructure, evaluation of bandwidth efficiency, and publication year.

5.3 Main takeaways

The above review of recent research at the ingestion stage reveals a heavy emphasis on live streaming. The outcome arises due to both growing importance of this steaming mode and serious technical challenges presented by it. The tight timing constraints of live streaming affect the ingestion stage too and back a trend toward integrated solutions for the entire end-to-end pipeline. Another trend is toward a larger computational role of cameras. New streaming designs exploit the increasing capabilities of camera-equipped devices to offload computation from servers. The offload enables video analytics with fast query response and low consumption of upload bandwidth. ML methods continue gaining traction in video streaming, with reliance on ML in either main algorithm or supporting elements of a streaming solution. In particular, ML-based SR models receive significant attention and enjoy notable success. The major focus is not on designing new ML techniques or SR models but on adoption of existing designs for the needs of video streaming, as well as on effective training strategies.

6 PROCESSING

6.1 Background

The processing stage occupies an intermediate position between ingestion and distribution in the end-to-end streaming pipeline. This stage operates in dedicated or cloud servers, involves no communication component of its own, and provides a number of services to support communications at the adjacent stages. Figure 5 depicts the tasks of transcoding, splitting, editing, storage, analytics, and storage common on the processing stage for VoD.

Transcoding refers to conversion of one encoding to another [4]. Because transcoding produces compressed videos, it bears many similarities with video compression on the ingestion stage, and the respective background presented in Section 5.1.1 remains largely relevant. There are also important differences. While the main purpose of encoding in the camera is to efficiently utilize the ingestion bandwidth, transcoding leverages the superior computation and storage resources in media servers to create compressed videos suitable for distribution to large populations of diverse user devices. In particular, construction of the encoding ladder typically occurs at the processing stage and produces the compressed video in multiple representations with different combinations of the bitrate and resolution. After the introduction of the first major ladder in 2004, encoding ladders keep evolving, e.g., due to frame-by-frame optimization techniques such as the constant rate factor that adjusts the bitrate to maintain a targeted level of video quality. Per-title encoding seeks the best ladder for a specific video [1]. Shot-based encoding detects scenes in a video and considers the scene boundaries to encode the video in differently sized chunks [98]. Context-aware encoding constructs ladders by accounting for delivery and playback statistics [152]. Transrating and transsizing refer to the kinds of transcoding that convert the bitrate and resolution of the input video respectively. *Video splitting* partitions the video into smaller chunks for HTTP compatibility. The chunk size usually lies between 2 and 10 seconds, and the size variation significantly affects quality of video streaming [195].

Whereas transcoding is intrinsic to the end-to-end pipeline and directly impacts streaming performance, other important tasks at the processing stage play auxiliary roles. *Video editing* changes the video content, e.g., to add ads or remove censored material. The process often involves video decoding followed by encoding of the altered content. Traditionally executed at the processing stage, *video analytics* employs techniques from computer vision to detect objects and segment, classify, and recognize images. *Video storage* in media servers is especially relevant for VoD where videos need to be stored over long periods. Performance, energy, and security issues dominate the research agenda for this task [172].

6.2 Recent results

Our discussion of recent research at the processing stage focuses on the tasks of ladder construction and transcoding.

6.2.1 *Intuition-based methods.* To reduce the energy consumption by mobile devices, the *environment-aware video streaming optimization (EVSO)* accounts for the battery status of the mobile device and generates encoding ladders that adjust the frame rate for different chunks of a video in accordance with a new metric of perceptual similarity [138]. To support fast low-complexity transcoding from H.264 to H.265, [191] proposes a method that, for different types of coding units (CUs), employs statistics-driven heuristics for early termination of the CU partition and prediction unit mode selection. [157] deals with transcoding of encrypted video streams for both H.264 and H.265. Because the decryption and re-encryption of such streams introduces significant latency, [157] develops a joint crypto-transcoding scheme that transcodes an encrypted video stream without decrypting it or exposing the decryption key at intermediate devices.

6.2.2 *Theory-based methods.* [33] represents context-aware encoding methods and formulates the construction of the encoding ladder as an optimization problem that models the player's bandwidth estimates and viewport sizes as stationary random processes. [104] proposes online just-in-time transcoding by a CDN that strives to transcode a video chunk into a bitrate level only when a user needs the segment at this bitrate level. The design relies on a Markov model to predict the bitrate level of the next requested chunk so that the CDN can start delivering the transcoded chunk immediately upon receiving the request for it. To minimize storage and processing requirements, the edge

Table 2. Transcoding designs at the processing stage of the end-to-end streaming pipeline (*u* abbreviates *unspecified*).

	Name [reference]	Technique of the core contribution	Codec	Type	Performance	Infrastructure	Year
Intuition	EVSO [138]	frame-rate adjustment	H.264	offline	energy	<i>u</i>	2018
	[191]	statistics-driven early termination	H.264 → H.265	<i>u</i>	processing	<i>u</i>	2017
	[157]	joint crypto-transcoding	H.264, H.265	<i>u</i>	processing	<i>u</i>	2018
Theory	[33]	context-aware ladder optimization	H.264	offline	bandwidth	<i>u</i>	2018
	[104]	Markov model	H.264	hybrid	processing	CDN	2015
	LwTE [55]	MILP, binary search	H.265	hybrid	storage and processing	edge	2021
	[110]	knapsack-like optimization problem	H.264	hybrid	energy	<i>u</i>	2020
	ARTEMIS [171]	MILP	<i>u</i>	online	processing and bandwidth	CDN	2023
ML	DeepLadder [79]	RL, dual-clip PPO	H.264	online	bandwidth and storage	<i>u</i>	2021
	MAMUT [44]	RL, multi-agent QL	H.265	online	processing and energy	<i>u</i>	2018
	FastTTPS [3]	SL, MLP	H.264	<i>u</i>	processing	<i>u</i>	2020
	HEQUS [63]	SL, NB classifiers	H.265 → VVC	<i>u</i>	processing	<i>u</i>	2021
	[31]	SL, DTs	H.265	online	processing and energy	<i>u</i>	2018
	[67]	SL, RFs	H.265	<i>u</i>	processing	<i>u</i>	2018

server in *light-weight transcoding at the edge (LwTE)* performs partial transcoding based on the optimal CU partitioning structure received from the origin server [55]. By formulating a mixed-integer linear program (MILP) and solving it heuristically via binary search, LwTE differentiates between unpopular and popular chunks and, for unpopular chunks, stores only the highest bitrate level and generates lower requested bitrate levels on the fly via metadata-accelerated transcoding. To support energy-efficient transcoding, [110] selects between the three options of offline transcoding, online transcoding, and serving the chunk at a lower than requested bitrate level. The selection seeks to maximize video quality within a limit imposed on the total transcoding time, formulates a knapsack-like problem, and solves the problem via a greedy heuristic. *Adaptive bitrate ladder optimization for live video streaming (ARTEMIS)* [171] builds the encoding ladder for a live streaming session dynamically by considering content complexity, network conditions, and fine-grained feedback from the clients in the common media client data (CMCD) format. ARTEMIS advertises a large number of representations via a mega-manifest file and solves a MILP to select a small subset of them for the encoding ladder [171].

6.2.3 ML methods. *DeepLadder* and *MAMUT* represent RL designs that increase real-time transcoding efficiency. Based on content features, available bandwidth, and storage costs, *DeepLadder* transcodes each chunk according to an optimal encoding ladder constructed via a dual-clipped version of proximal policy optimization (PPO) [79]. On the other hand, *MAMUT* uses multi-agent QL in an environment with multiple users where three agents cooperatively tune the QP, number of encoding threads, and processor frequency to optimize a reward function that combines the frame rate, bitrate, power consumption, and PSNR [44]. *Fast video transcoding time prediction and scheduling (FastTTPS)* considers features of source videos, trains an MLP to predict transcoding time, and leverages the predictions to schedule transcoding tasks on a parallel computer [3].

[31, 63, 67] exemplify techniques that limit searching parameters of the encoder to reduce transcoding time. *HEVC-based quadtree splitting (HEQUS)* transcodes H.265 to VVC. It trains NB classifiers to partition the first QT level in 128×128 blocks and derives the QT splitting decisions on the 64×64 and lower levels from the CU partitioning of

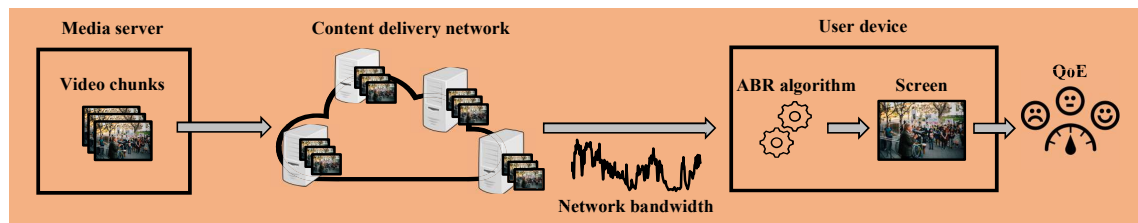


Fig. 6. Distribution stage for VoD.

H.265 [63]. [31] employs DTs to limit the maximum CTU depth while achieving desired trade-offs between transcoding time, energy consumption, and video quality. [67] speeds up cascaded pixel-domain transcoding by using two RF classifiers to set upper and lower limits on the depth of CTUs.

Table 2 compares the aforementioned transcoding designs. For each of them, the table identifies the main technique of the core contribution, involved codecs, transcoding type (offline, online, or hybrid), performance improvement focus (processing, energy, storage, or bandwidth), specifically targeted distribution infrastructure (CDN or edge), and publication year.

6.3 Main takeaways

The objectives of faster processing and lower power consumption dominate the recent research agenda on the processing stage. In particular, the transcoding acceleration seeks to enable on-the-fly construction of encoding ladders, which reduces storage requirements and aligns well with the overall trend toward live streaming. A trend toward targeting specific, e.g., CDN or edge, infrastructure used on the distribution stage is another sign of closer integration across the pipeline stages. Compared to the ingestion stage, ML techniques similarly play a prominent role with the main difference in the reliance on simple models rather than deep networks. Also, most of the designs involve H.264 or H.265 rather than more advanced codecs.

7 DISTRIBUTION

7.1 Background

The end-to-end streaming pipeline concludes with the distribution stage that delivers the requested video to the user device and plays back the video on the device screen. Figure 6 illustrates the distribution stage for VoD. The media server, which stores video chunks in multiple representations, distributes the requested chunks to the user device via the CDN. The CDN provides scalable low-latency distribution by leveraging its extensive footprint of cache servers located in many geographical regions. The ABR algorithm in the user device dynamically chooses the representation for the next requested chunk. Dependent on predictions of the network bandwidth during the chunk download, the representation choice strives for a good balance between uninterrupted playback and high representation quality and, more generally, for high QoE which captures the user satisfaction with the streaming service. Live streaming employs shorter chunks, downloads them from the camera to the user device in real time, and imposes more stringent requirements on the distribution stage, prompting different approaches to CDN support and QoE improvement. In this section, our survey focuses on the key ABR, CDN, and QoE aspects of the distribution process.

7.1.1 ABR algorithms. In selecting the representation for the next requested chunk, the ABR algorithm seeks to provide the highest QoE possible under the changing network conditions. HAS protocols dominate the distribution stage and, in order of decreasing popularity, include HLS, dynamic adaptive streaming over HTTP (DASH) [165], Microsoft's smooth streaming (MSS), and Adobe's HTTP dynamic streaming (HDS). The proprietary HLS protocol works with the H.264 or H.265 codecs, employs transport stream containers, and sets the chunk duration to 6 s (10 s originally). On the other hand, DASH is codec-agnostic, uses MP4 containers, has typical chunk duration between 2 and 10 s, and stands out by being an open-source international standard. Introduced in 2018 to make HLS and DASH more compatible, the common media application format (CMAF) is a container format embraced by both protocols and represents an industry-wide effort to support low-latency streaming of segmented videos [86].

Within the HAS paradigm, we focus on the prevailing approach that deploys the ABR logic on the client side rather than on the server side or in the network. When the client requests a video, the media server provides the client with the manifest file that specifies the encoding ladder. The client requests chunks one after another in the representations chosen by the ABR algorithm. After downloading the requested chunk in its entirety, the user device renders the chunk on the screen. The dynamic representation selection is challenging due to a priori unknown network conditions, mismatches between the manifest-file descriptions and actual chunk bitrates, large gaps between the bitrates of adjacent representations, and conflicts between individual QoE metrics. While optimal ABR control is an NP-hard problem [82], practical ABR algorithms adopt various heuristics, e.g., for prediction of the available network bandwidth from the client's measurements of the playback-buffer occupancy or throughput.

7.1.2 CDN support. A CDN refers to a system of cache servers distributed across wide geographical areas to improve the performance of content delivery from CPs to end users [141]. The CDN stores the videos and other content collected from the CPs' origin servers in the cache servers placed near the users. The content caching enables the CDN to reduce network traffic and serve the users' requests for the content with low latency [121]. Being in principle an optional element of end-to-end delivery, CDNs become indispensable in the modern Internet ecosystem. The estimated shares of all Internet traffic that crosses CDNs are 56% and 72% in 2017 and 2022, respectively [39]. One can classify CDNs as public, private, or hybrid depending on the economic relationships between them and CPs. A public CDN, such as Akamai [48], acts as a third party and charges the CPs for its content-delivery services. A private CDN belongs to the same organization as the CPs utilizing the CDN. A hybrid CDN serves CPs both inside and outside its organization. Because CDNs differ in their scalability, pricing, and QoE provided across regions and time [175], it is common for a CP to deliver its content over multiple CDNs. CMCD and common media server data (CMSD), introduced in 2020 and 2022 respectively, support information exchange between a CDN and clients for such purposes as data analysis and QoE monitoring [14, 21]. Edge infrastructure extends the original CDN concept through involvement of network operators into content caching and offers new options for video streaming [28].

7.1.3 QoE. In contrast to the earlier notion of QoS which considers individual network-level metrics such as packet loss, latency, and throughput, QoE captures the user's subjective satisfaction with the overall performance of the streaming service [88]. QoE is highly relevant for streaming platforms because the user satisfaction strongly correlates with the attraction and retention of customers and, more generally, with the provider revenues. On the other hand, the user perception of the service performance is complex and depends on many diverse influence factors [161].

Because QoE is a complex subjective concept, QoE assessment poses major challenges. Direct QoE measurement relies on subjective tests where the user of the streaming session provides a score for the experience. Whereas such subjective tests typically take place in a tightly controlled lab environment and follow well-established protocols [199], online

crowdsourcing increases the testing scalability at the expense of looser control over the experimental settings [73]. Still, the predominant approach to QoE evaluation is indirect and involves subjective tests only to construct a QoE model which expresses QoE as a function of objectively measurable influence factors. Typical modeling methods represent QoE in terms of the mean opinion score (MOS), which refers to the average of the scores given to the streaming experience by the users in a subjective study [89]. Once constructed, a QoE model does not require human feedback and enables QoE assessment at scale by automatically measuring the influence factors of the model. Existing QoE models are greatly diverse with respect to the considered influence factors and construction methods [149]. Despite the importance of QoE and QoE models, their usage lacks in standards and rigor, creating pitfalls and opportunities for improvement [142].

7.2 Recent results

7.2.1 ABR algorithms. *Intuition-based methods:* A series of *buffer-based algorithms (BBA)* maps the occupancy level of the playback buffer to a control parameter [83]. BBA-0 employs piecewise linear mapping of the buffer occupancy to the bitrate. BBA-1 performs the mapping to the chunk size. BBA-2 extends BBA-1 by estimating the available network bandwidth and increasing the bitrate more aggressively during a startup phase. *Segment-aware rate adaptation (SARA)* enhances the manifest file with chunk sizes and switches between its four adaptation modes depending on the buffer occupancy [94]. Aspiring to eliminate video stalls, the *adaptation and buffer management algorithm (ABMA+)* relies on buffer-occupancy mapping to characterize the rebuffering probability.

The *fair, efficient, and stable adaptive (FESTIVE)* algorithm combines a number of mechanisms to support fairness, efficiency, and stability in ABR streaming to multiple clients [92]. These mechanisms include randomized scheduling of chunk requests, harmonic-mean estimation of the network bandwidth, and stateful bitrate selection with delayed updates. Pursuing similar goals, the *probe and adapt (PANDA)* algorithm incorporates estimation, smoothing, quantization, and scheduling techniques and, in particular, applies AIMD to estimate the network bandwidth [115]. *Playback rate and priority adaptive bitrate selection (PREPARE)* modifies PANDA by considering the client priority and playback speed and by involving the server into prediction of the network bandwidth [162]. Compared to PANDA, PREPARE improves fairness, achieves a higher average bitrate, and enhances stability.

Developed for streaming over mobile networks, the *adaptive rate-based intelligent HTTP streaming (ARBITER+)* algorithm addresses the variability in the bitrates and network conditions by such techniques as tunable smoothing and hybrid throughput sampling [193]. To support effective ABR streaming over a wireless link from an access point (AP) to the client, [51] caches video chunks in the AP. While the AP selects chunks for prefetching into the cache, the client determines which chunks to request from either AP or remote server.

After analyzing interactions between DASH and TCP, [176] leverages its analytical findings to design *spectrum-based quality adaptation (SQUAD)*. SQUAD tries to maximize QoE by minimizing the spectrum, a metric that captures the bitrate variation. *Low-latency prediction-based adaptation (LOLYPOP)* targets live streaming and strives to maximize QoE through optimization of the operating point, a metric that combines the frequency of stalls, frequency of bitrate changes, and latency [127]. LOLYPOP predicts TCP throughput over period from 1 to 10 s and assesses the prediction error. [127] surprisingly finds that the simple method of using the last sample as the prediction is the most accurate. Designed for live streaming, *standard low-latency video control (STALLION)* uses a sliding window to measure the mean and standard deviation of both bandwidth and latency [72]. The implementation of STALLION in dash.js, a popular streaming client, outperforms the client's built-in ABR algorithm by significantly increasing the bitrate and decreasing the number of stalls.

Table 3. Intuition-based ABR algorithms at the distribution stage of the end-to-end streaming pipeline (*u* abbreviates *unspecified*).

	Name [reference]	Technique of the core contribution	Mode	Codec	SR	QoE model	Bandwidth efficiency evalua- tion	Bandwidth fairness evalua- tion	Year
Intuition-based methods	BBA [83]	buffer-occupancy mapping	VoD	<i>u</i>	✗	✗	✗	✗	2014
	SARA [94]	buffer-occupancy mapping	VoD	<i>u</i>	✗	✗	✗	✗	2015
	ABMA+ [18]	buffer-occupancy mapping	VoD	<i>u</i>	✗	✗	✓	✗	2016
	FESTIVE [92]	stateful delayed bitrate update	VoD	<i>u</i>	✗	✗	✓	✓	2014
	PANDA [115]	AIMD bandwidth estimation	VoD	<i>u</i>	✗	✗	✓	✓	2014
	PREPARE [162]	server-client cooperation	VoD	<i>u</i>	✗	✗	✓	✓	2019
	ARBITER+ [193]	hybrid throughput sampling	VoD	H.264, H.265	✗	✗	✗	✓	2018
	[51]	proxy caching	VoD	<i>u</i>	✗	✗	✗	✗	2015
	SQUAD [176]	spectrum minimization	VoD	<i>u</i>	✗	✗	✗	✓	2016
	LOLYPOP [127]	stall-probability prediction	live	H.264	✗	✗	✗	✗	2016
	STALLION [72]	sliding-window measurement	live	<i>u</i>	✗	✗	✗	✗	2020
	BANQUET [101]	brute-force search	VoD	H.264	✗	✓	✓	✗	2021
	Oboe [6]	offline parameter optimization	VoD	<i>u</i>	✗	✗	✗	✗	2018

For a given ABR algorithm, *Oboe* computes offline a map from network conditions to an optimal configuration of the algorithm parameters and automatically tunes the parameters online in accordance with the current network conditions [6]. The *balancing quality of experience (BANQUET)* algorithm strives to minimize the traffic volume while providing the QoE level specified by the user or streaming provider [101]. To estimate the impact of bitrate choices on the traffic and QoE, BANQUET employs brute-force search across all possible bitrate patterns for the next several chunks via predictions of the buffer transitions and throughput.

Table 3 classifies the intuition-based ABR algorithms with respect to the main technique of the core contribution, streaming mode (VoD or live), codec, usage of SR, publication year, and other aspects. In particular, the table reports whether the ABR design leverages a well-defined QoE model that combines multiple influence factors. Also, the classification discloses whether the work evaluates efficiency and fairness of bandwidth utilization.

Theory-based methods: Contributing a number of firsts to the ABR topic, [190] advocates MPC as a basis for chunk selection and designs two MPC-guided algorithms *RobustMPC* and *FastMPC*. While *RobustMPC* performs better, *FastMPC* incurs significantly lower overhead. Also, the QoE function proposed in [190] acts as the QoE model in many subsequent QoE-based ABR algorithms. As an enhancement of MPC to improve QoE, the *interest-aware approach (IAA)* adjusts the bitrate by considering the user’s interest in video scenes [61]. IAA embeds content properties into the manifest file, and the client analyzes these properties to quantify the user’s interest in the content. *LDM* applies MPC to live streaming and drops frames to provide low latency [114]. Toward the same goal of low latency, *iLQR based MPC streaming (iMPC)* combines MPC and iLQR by using MPC to predict the available network bandwidth and iteratively linearizing the control system around its operation point to determine the bitrate via iLQR [168]. While relying on MPC to select the bitrate, *Fugu* predicts the bandwidth via a DNN trained via supervised learning in situ, i.e., in the actual deployment environment [186].

The optimization objective in the *buffer occupancy based Lyapunov algorithm (BOLA)* is to jointly maximize the playback utility (of the bitrate) and smoothness (lack of rebuffering) under a rate stability constraint [163]. BOLA applies

Table 4. Theory-based ABR algorithms on the distribution stage of the pipeline (*u* abbreviates *unspecified*).

	Name [reference]	Technique of the core contribution	Mode	Codec	SR	QoE model	Bandwidth efficiency evaluation	Bandwidth fairness evaluation	Year
Theory-based methods	RobustMPC and FastMPC [190]	MPC	VoD	<i>u</i>	✗	✓	✗	✗	2015
	IAA [61]	MPC	VoD	<i>u</i>	✗	✓	✗	✗	2018
	LDM [114]	MPC	live	H.264	✗	✓	✗	✗	2020
	iMPC [168]	MPC, iLQR	live	H.264	✗	✓	✗	✗	2021
	Fugu [186]	MPC	VoD	H.264	✗	✓	✗	✗	2020
	BOLA [163]	Lyapunov optimization	VoD	<i>u</i>	✗	✓	✗	✗	2020
	Elephanta [146]	Lyapunov optimization	VoD	<i>u</i>	✓	✓	✗	✗	2020
	ACAA [75]	dynamic programming	VoD	<i>u</i>	✗	✓	✗	✗	2019
	PIA [147]	PID	VoD	<i>u</i>	✗	✓	✗	✗	2017
	QUAD [148]	PID	VoD	H.264, H.265	✗	✓	✓	✗	2019
	ERUDITE [46]	Bayesian optimization	VoD	<i>u</i>	✗	✓	✗	✗	2019
	[102]	Bayesian optimization	VoD	<i>u</i>	✗	✓	✗	✗	2021
	QUETRA [185]	M/D/1/K queuing	VoD	<i>u</i>	✗	✓	✗	✓	2017
	OSCAR [192]	MINLP	VoD	H.264	✗	✓	✓	✗	2016

Lyapunov optimization, provides theoretical guarantees on the achieved utility, and performs among the best ABR schemes in the buffer-based category. *Elephanta* uses Lyapunov optimization to address diversity of QoE perception by different users [146]. *Elephanta* provides the users with an interface for adjustment of QoE perception parameters, models video streaming as a renewal system, and selects the bitrate by minimizing a user-specific function that combines penalties and drift. Pursuing a similar goal as *Elephanta*, the *affective content-aware adaptation (ACAA)* algorithm considers affective relevancy of content for different users [75]. *ACAA* characterizes video chunks and users with confidence levels for six basic emotions, formulates a QoE maximization problem based on this affection information, and solves the formulated problem via dynamic programming.

PID-control based ABR streaming (PIA) removes the derivative (D) component of the standard PID controller to linearize the closed-loop control system and maintain the buffer occupancy at a targeted level [147]. *PIA* equips this PI controller with mechanisms for faster initial ramp-up, reduction of bitrate fluctuation, and avoidance of bitrate saturation. Using the same PI controller as *PIA*, the *quality-aware data-efficient streaming (QUAD)* algorithm strives to maintain video quality at an intended level in order to prevent stalls, enhance playback smoothness, and reduce bandwidth consumption [148].

The *deep neural network for optimal tuning of adaptive video streaming controllers (ERUDITE)* relies on Bayesian optimization to configure offline parameters for the ABR controller so that to jointly optimize QoE and control robustness [46]. At runtime, *ERUDITE* uses a CNN to tune the controller parameters in accordance with real-time bandwidth measurements and video features. [102] develops a context-aware ABR system to maintain QoE at the minimum level acceptable for the user. The system applies Bayesian optimization to determine the target QoE level and selects a corresponding bitrate via *BANQUET*.

The *queuing theory approach to DASH rate adaptation (QUETRA)* [185] uses the M/D/1/K queuing model to assess the buffer occupancy based on the bitrate, network bandwidth, and buffer capacity and adjusts the bitrate to keep the

buffer half-full. Due to its consistent performance across different buffer sizes and in other heterogeneous scenarios, QUETRA compares favorably with other ABR algorithms that require parameter tuning. For a transient range of the buffer occupancy, the *optimized stall-cautious adaptive bitrate (OSCAR)* algorithm models the available network bandwidth via the Kumaraswamy distribution and formulates the bitrate adaptation as a mixed-integer nonlinear program (MINLP) over a sliding look-ahead window, where the optimization objective combines a switching penalty and bitrate utility [192].

Table 4 categorizes the above theory-based ABR algorithms. The considered categories are the same as in Table 3, i.e., the main contribution technique, streaming mode, codec, SR, QoE model, evaluation of bandwidth efficiency and fairness, and publication year.

ML methods: *Pensieve* represents the pioneering work that ushers deep reinforcement learning (DRL) into ABR streaming [122]. *Pensieve* formulates the bitrate selection as a DRL problem and solves it by asynchronous advantage actor critic (A3C) [70] where the function approximator combines one-dimensional (1D) CNNs and fully connected layers. The DNN structure supports different encoding ladders. To speed up state transitions, *Pensieve* trains the DNN by means of a chunk-level simulator, bequeathing this trait to many subsequent DRL-based ABR approaches.

NAS leverages content-aware DNNs and anytime prediction to improve QoE via SR [187]. For each video, the server trains multiple DNNs with different sizes and performance levels. The client picks the largest DNN that runs in real time. Furthermore, each DNN is scalable and consists of multiple layers, enabling the client to progressively download the entire DNN, immediately benefit from the DNN layers downloaded so far, and dynamically select the DNN configuration for SR of the current frames. *NAS* uses A3C to balance the bitrate selection with the progressive DNN download. *Super-resolution based adaptive video streaming (SRAVS)* is another DRL A3C approach that involves SR [198]. Using the super-resolution convolutional neural network [50] for video reconstruction, *SRAVS* maintains separate downloading and playback buffers to decouple its bitrate selection from reconstruction decisions.

Grad applies DRL to design ABR algorithms for SVC-encoded videos [116]. *Grad* mitigates the SVC-related coding overhead and improves QoE through such generation of enhancement layers that a single layer enhances the video quality by multiple levels. [11] jointly maximizes QoE and fairness of video streaming to multiple clients over a shared bottleneck link. In the proposed ABR algorithm, the actor of A3C incorporates a long short-term memory (LSTM) layer, and the server dynamically configures the manifest file in response to transport-layer signals about the loss rate. With throughput measurements underlying many ABR algorithms, *accurate network throughput (ANT)* seeks to precisely model the full spectrum of the available network bandwidth [189]. *ANT* performs k -means clustering of throughput traces over short periods, trains a CNN for cluster-specific prediction of the bandwidth over the next period, and utilizes the prediction to select the bitrate via an A3C-based algorithm. Also based on DRL with A3C, *FedABR* provides faster training and preserves data privacy via federated learning [184]. After receiving from multiple clients their locally trained ABR policies, the *FedABR* server produces a global aggregate ABR policy and disseminates it back to the clients for further refinement of their ABR algorithms based on local data.

The *short-form video streaming and recommendation (SSR)* framework targets short videos and employs advantage actor critic (A2C) to jointly optimize the effectiveness of video recommendation and bitrate adaptation [150]. The optimized QoE metric combines the recommendation efficiency, bitrate, and rebuffering. The transformer-based recommendation module of *SSR* encodes the user's watching preferences into a recurrent neural network. *Ahaggar* uses A2C with distributed PPO to perform server-side bitrate adaptation for multiple clients [22]. *Ahaggar* exploits CMCD and CMSD for communication with the clients and enables quicker learning in new network conditions via meta-RL. To support fast training of DRL-based bitrate adaptation, *Fastconv* prepends to its simple actor critic (AC) network an

Table 5. ML-based ABR algorithms on the distribution stage of the pipeline (*u* abbreviates *unspecified*).

	Name [reference]	Technique of the core contribution	Mode	Codec	SR	QoE model	Bandwidth efficiency evaluation	Bandwidth fairness evaluation	Year
ML methods	Pensieve [122]	DRL, A3C	VoD	<i>u</i>	✗	✓	✗	✗	2017
	NAS [187]	DRL, A3C	VoD	H.264	✓	✓	✓	✗	2018
	SRAVS [198]	DRL, A3C	VoD	<i>u</i>	✓	✓	✗	✗	2020
	Grad [116]	DRL, A3C	VoD	SVC	✗	✓	✓	✗	2020
	[11]	DRL, A3C	VoD	H.264	✗	✓	✗	✓	2020
	ANT [189]	DRL, A3C	VoD	<i>u</i>	✗	✓	✗	✗	2021
	FedABR [184]	DRL, A3C	VoD	H.264	✗	✓	✗	✗	2023
	SSR [150]	DRL, A2C	VoD	<i>u</i>	✗	✓	✗	✗	2020
	Ahaggar [22]	DRL, A2C, PPO	VoD	H.264	✗	✓	✓	✗	2023
	Fastconv [125]	DRL, AC	VoD	H.264	✗	✓	✗	✗	2019
	Vabis [60]	DRL, ACKTR	live	<i>u</i>	✗	✓	✗	✗	2020
	Stick [81]	DRL, DDPG	VoD	H.264	✗	✓	✗	✗	2020
	MLMP [84]	multi-task DRL, PPO	VoD	<i>u</i>	✗	✓	✗	✗	2020
	Ruyi [203]	DRL, DQL	VoD	H.264	✗	✓	✗	✗	2022
	Tiyuntsong [78]	self-play RL, GAN	VoD	<i>u</i>	✗	✗	✗	✗	2019
	Comyco [77]	IL, DNN	VoD	H.264	✗	✓	✗	✗	2020
	PiTree [126]	IL, DTs	VoD	<i>u</i>	✗	✗	✗	✗	2021
	[71]	IL, DTs	VoD	<i>u</i>	✗	✗	✗	✗	2020
	SMASH [154]	SL, RFs	VoD	H.264	✗	✗	✗	✗	2020
	Karma [182]	SL, GPT	VoD	H.264	✗	✓	✗	✗	2023
Swift [45]	UL, AE	VoD	neural layered codecs	✗	✓	✓	✗	2022	

adapter that converts highly fluctuating input features into a more stable signal [125]. Designated for low-latency live streaming, the *video adaptation bitrate system (Vabis)* relies on AC using Kronecker-factored trust region (ACKTR) in its server-side ABR algorithm and operates at the granularity of frames to synchronize the state information on the training and testing stages [60]. Vabis also incorporates three playback modes in the client and special ABR regime for poor network conditions.

Stick combines the deep deterministic policy gradient (DDPG) and BBA to improve performance and reduce computational cost [81]. *Stick* uses DDPG to train a neural network that controls the boundaries for the buffer occupancy in BBA. The *meta-learning framework for multi-user preferences (MLMP)* relies on multi-task DRL with PPO for policy updates so that the bitrate adaptation for different users accounts for user-specific sensitivities to three QoE metrics [84]. Pursuing the same goal, *Ruyi* integrates user preferences into its QoE model and uses the model to train a deep QL algorithm [203]. *Ruyi* enables the users to provide their preferences in real time, and the model adapts to the dynamic user preferences without retraining. *Tiyuntsong* is a self-play RL approach where two ABR algorithms compete against each other in the same streaming environment [78]. Wins and losses from this continuous competition, rather than a QoE metric, serve as the reward for the two RL agents. In addition, each of the RL agents in *Tiyuntsong* employs a GAN to extract hidden features from the unlimited past.

In a significant deviation from the above RL-based ABR approaches, *Comyco* relies on IL [77]. *Comyco* incorporates a solver to generate expert ABR policies aimed at QoE maximization and trains a DNN by cloning the behavior of the expert policies. *Comyco* embraces lifelong learning through continuous updates of the DNN on freshly collected traces. Based on the IL approach of teacher-student learning in a simulated video player, *PiTree* converts DNN-based and other sophisticated ABR algorithms into faithful DT representations to support efficient online operation of the algorithms [126]. Inspired by *PiTree*, [71] uses DTs to reconstruct proprietary ABR algorithms in a human-interpretable manner for enabling a domain expert to inspect, understand, and modify the DT representations of the algorithms. The reconstruction relies on small sets of rules that express decisions as upgrades or downgrades of video quality. [154] applies SL to bitrate adaptation and develops the *supervised machine learning approach to adaptive video streaming over HTTP (SMASH)* as an RF classifier trained in a wide variety of streaming settings on outputs of nine existing ABR algorithms. *Karma* [182] employs causal sequence modeling on a multidimensional time series and trains a generative pre-trained transformer (GPT) via SL to improve the generalizability of ABR decisions [182]. Relying on UL to address the problems of coding overhead and latency in layered coding, *Swift* incorporates a chain of autoencoders to create residual-based layered codes on the server side, a single-shot decoder on the client side, and a Pensieve-like ABR algorithm that accommodates layered neural codecs [45].

Following the same classification as in Tables 3 and 4, we describe and compare the aforementioned ML-based ABR algorithms in Table 5. Again, the main contribution technique, streaming mode (VoD or live), codec, usage of SR, well-defined QoE model, evaluation of bandwidth efficiency and fairness, and publication year comprise the considered categorizes.

7.2.2 CDN support. Recent research on CDN support for video streaming aligns well with the trend toward greater integration of various functionalities across the end-to-end pipeline. [64] measures video streaming from two popular CPs over three major CDNs and leverages intuition to design a CDN-aware RobustMPC variant that tangibly improves the ABR performance. To jointly handle caching and transcoding in radio access networks, [27] formulates an integer linear program (ILP) to minimize the CDN cost and solves the ILP with a greedy heuristic.

Video-specific optimizations of CDNs constitute an active research area. The *video delivery network (VDN)* is a centralized control-plane design that enables a CDN to operate at scale and with high responsiveness [130]. VDN constructs distribution trees for videos by formulating an integer program and approximating the program through initial solutions and early termination. *FastTrack* minimizes the probability that the stall duration in CDN-assisted video streaming exceeds a predefined threshold [7]. *FastTrack* formulates a non-convex optimization problem, partitions it into four subproblems, and iteratively solves them via an algorithm that replaces a non-convex objective function with convex approximations. *Intelligent network flow (INFLOW)* dynamically selects a CDN among multiple CDN options [174]. Based on measurements provided by video players, *INFLOW* predicts the available network bandwidth and latency via LSTM. By considering both predictions and business constraints, *INFLOW* chooses the CDN for each player and implements the choice by updating the manifest file accordingly.

Recent work also seeks general CDN improvements that benefit both video streaming and other traffic classes. To outperform traditional intuition-based caching heuristics such as least recently used, *AdaptSize* utilizes a Markov model for content admission into a CDN cache [24]. Representing ML-based alternatives, *RL-Cache* uses a feedforward neural network to perform cache admission and trains this DNN with a new DRL method that relies on direct policy search [103].

Edge-computing enhancements of the CDN paradigm include the *video super-resolution and caching (VISCA)* system that combines SR and edge computing to improve QoE [194]. The system caches low-resolution chunks at the edge with a new intuition-based eviction policy that accounts for chunk quality and request frequency. VISCA increases the chunk resolution via SR and streams videos to players via a new edge-based ABR algorithm. *Learning-based edge with caching and prefetching (LEAP)* prefetches and caches chunks at the edge by leveraging a DNN that predicts QoE under a cache hit vs. cache miss [159]. [167] proposes an intuition-based *sequential auction mechanism (SAM)* for a crowdsourced CDN where third-party edge devices supplement CDN servers and charge CPs for the leased cache space.

7.2.3 QoE. Recent research on QoE in video streaming advocates new influence factors, modeling methodologies, and QoE models. [144] studies the utility of facial expression and gaze direction for QoE prediction. Contributing a new technique for QoE modeling, [201] develops a *YouQ* application to conduct subjective tests on Facebook’s social-media platform. Also, user engagement as a proxy for QoE keeps attracting significant research attention. [129] analyzes a queuing-theoretic model and shows strong correlation between user engagement and QoE. [107] considers DT, RF, and k-nearest neighbors algorithms to predict QoE from user engagement and other factors.

The work on QoE modeling includes modifications of existing QoE models. Whereas the QoE model of [190] employs a video-quality factor, [163] alters the model by setting this factor to the logarithm of the ratio between the bitrate and lowest bitrate in the encoding ladder. In contrast, [77] assesses the video-quality factor via video multi-method assessment fusion. *SENSEI* enhances its QoE model with dynamic sensitivity to the video content [196]. *P.1203* is a standard QoE model that relies on RFs to predict the MOS on a five-point scale [87]. As the name suggests, *LSTM-QoE* refers to a QoE model that computes QoE via an LSTM network [56]. *Video assessment of temporal artifacts and stalls (Video ATLAS)* expresses QoE based on the support vector regressor and features related to perceptual quality, rebuffering, and memory effects [15].

Personalization of QoE models forms a prominent research direction striving to accommodate diverse preferences of individual users. To personalize QoE models, [62] performs federated learning on sparse data and accounts for changes in influence factors over time. On the other hand, *individualized QoE (iQoE)* engages a user in a short series of subjective assessments and iteratively builds an accurate personalized QoE model for the user by means of active learning [143]. *Jade* relies on DRL with PPO to train a QoE model based on relative ranks, rather than absolute values, of subjective scores [80]. *VidHoc* considers user engagement as a proxy for QoE and dynamically restrains the available network bandwidth so as to construct a personalized QoE model for a new user via regret minimization [197].

7.3 Main takeaways

The recent research on the ABR, CDN, and QoE aspects of the distribution stage pays the strongest attention to ABR algorithms and, especially, those for VoD. These foci of interest transpire because ABR algorithms are essential for scalable video dissemination to heterogeneous user devices, with VoD remaining the prevalent streaming mode. The ABR algorithms leverage mostly DRL and, in particular, actor-critic methods. The ABR work for live streaming is less extensive, partly because the ABR paradigm offers smaller opportunities for latency reduction necessary for live streaming. Similarly, adoption of DRL-based ABR algorithms is more challenging in live streaming due to their high computational requirements. For the same reason, usage of SR at the distribution stage is relatively rare compared to the ingestion stage. In regard to codecs, the research efforts resemble the situation at the processing stage and predominantly rely on H.264 or H.265 as opposed to cutting-edge alternatives, again because the advanced codecs tend to be proprietary. Yet, the recent work with new layered codecs produces promising results. The general trend

towards integrated designs reveals itself at the distribution stage as well and, in particular, in the research on the CDN and QoE aspects. ABR designs that are CDN-aware or utilize a well-defined QoE model become increasingly common. Also, personalized QoE modeling constitutes an active research area. On the other hand, coordinated operation on the application and lower layers struggles to gain traction, and application-layer ABR algorithms tackle mostly efficiency of bandwidth usage, with fairness of network sharing delegated fully to the transport layer.

8 TRENDS AND FUTURE DIRECTIONS

Based on the materials presented in Sections 5 through 7, we now distill prominent trends and discuss directions for future research on video streaming.

8.1 Trends

8.1.1 Continued emergence of live streaming. Live streaming keeps gaining in not only traffic volume but also attention from researchers. The research efforts at the ingestion stage transform its tasks of video capture, analysis, compression, and upload to support live streaming with low latency. To a smaller extent, live streaming also has important implications at the processing stage, e.g., in the tasks of on-the-fly transcoding and ladder construction. The distribution stage also sees limited work on improved support for live streaming.

8.1.2 Increasing diversity of devices. The end-to-end streaming pipeline involves different kinds of equipment, including cameras, servers, and viewing devices. The infrastructure becomes more heterogeneous in both type and capabilities. New high-performance devices appear and complement legacy equipment. In their turn, the changing capabilities redistribute functionalities across the pipeline. For example, smart cameras support deep learning and play a growingly salient role in the tasks of video analytics and ladder construction executed traditionally in servers. On the other hand, servers play a bigger part in ABR algorithms in a deviation from the classic client-side ABR paradigm. The server infrastructure also experiences diversification of economic models, with the distribution stage engaging CDN, edge, and cloud operators. The device heterogeneity is the largest at both ends of the pipeline and expands due to the interest in new streaming modes and QoE improvement.

8.1.3 Integration across the end-to-end pipeline. Live streaming and more capable devices constitute major drivers of the trend towards unified solutions across the streaming pipeline. The integration promises more efficient designs with better end-to-end performance. For instance, boundaries between initial compression in the camera and transcoding in the media server start to blur, and emerging designs split the coding functionality between the camera and server dynamically in order to support low latency while saving energy, storage, and communication resources. Similarly, video analytics benefits from joint designs operating at both ingestion and processing stages. SR methods are of transversal relevance and hold a significant potential for coping with low network bandwidth during video ingestion and distribution. Awareness of the CDN, edge, or other distribution infrastructure proves useful for ABR algorithms and at the processing stage, e.g., in the transcoding task. QoE and, in particular, well-defined QoE models gain stronger traction not only at the distribution stage which faces the users directly but also elsewhere in the streaming pipeline.

8.1.4 Shift toward ML methodologies. The availability of devices with larger memory and processing capabilities also drives the greater reliance of streaming designs on ML methods. The recent results across all three stages of the streaming pipeline consistently show that ML techniques gain in popularity and dominate the more traditional approaches based on intuition or theory. Because the cheaper memory and processing justify using more resources to

achieve performance gains, the trend toward heavier data-driven methodologies is rather expected. More surprisingly, our survey unveils that the ML-based research on each stage differs dramatically with respect to the used ML models and training approaches. Ingestion-stage designs tend to rely on UL or SL with DNNs, e.g., CNNs. Processing-stage solutions predominantly apply SL to train simple models, such as DTs and RFs. On the distribution stage, DRL clearly constitutes the prevalent training approach, with actor-critic methods becoming most prominent. The above differences indicate challenges for the integration trend as designing a unified ML-based solution that works effectively across pipeline stages does not appear to be straightforward.

8.1.5 Design for better trade-offs. Because video streaming is a complex problem with conflicting objectives in regard to performance and resource consumption, it is infeasible to simultaneously optimize all metrics of interest, and practical solutions instead seek to offer attractive trade-offs. Whereas settling for a trade-off is unavoidable, technological advances affect which trade-offs are achievable. Changes in the availability and relative cost of network bandwidth, memory, processing, and energy enable new streaming designs with better trade-offs. The shift toward ML methodologies, which we discuss in Section 8.1.4, exemplifies such new desirable trade-offs. The integration trend also enhances the choice of achievable trade-offs, as the placement of functionalities across the pipeline becomes more flexible. The search for better trade-offs in video streaming clearly manifests in the adoption of SR which consumes less network bandwidth at the expense of more processing.

8.2 Future directions

Based on the current trends reported in Section 8.1, we now project future developments in the field and discuss their potential and challenges.

8.2.1 ML-based streaming. The shift toward ML methodology is likely to continue because its main driving force remains strong, as cheaper memory and processing keep becoming more available. Another key enabler for this research direction is the wealth of unexplored opportunities since many of the existing ML techniques have not been applied yet to streaming problems. For instance, application of transformers to streaming certainly deserves wider investigation. Furthermore, the ongoing rapid advances in DNN architectures and training strategies keep producing novel ML methods that might form additional bases for innovative streaming designs. The abundance of research opportunities in ML-based streaming also presents a challenge since there is no clarity which courses of investigation are most promising. In particular, as discussed in Section 8.1.4, it remains unclear which ML methods support effective operation across multiple stages of the streaming pipeline. The proliferation of ML-based designs on different stages of the pipeline also opens research questions about interoperability and mutual impact of the designs. The increasing maturity of ML-based streaming will likely bring larger development of ML methods specifically for video streaming, as opposed to application of existing generic ML techniques.

8.2.2 Pipeline-wide designs. The two current trends of integration across pipeline stages and design for better trade-offs merge to form a future direction toward pipeline-wide solutions. The recent marked increase in the research on the ingestion stage contributes to a more balanced consideration of the three stages and their traditional tasks. Cross-stage designs benefit from the newly acquired capability of moving a task to a different stage or splitting the task among stages in order to utilize resources more efficiently or improve performance. For example, shift of some analytics functionalities from media servers to smart cameras allows a streaming system to save network bandwidth and reduce upload latency. Whereas pipeline-wide designs represent a highly promising direction with many uncharted possibilities, the unified

solutions should realize their advantages without sacrificing their flexibility and preferably rely on loose coupling. SR is likely to feature prominently in pipeline-wide designs due to its ability to operate on top of codecs across all three stages of the end-to-end pipeline.

8.2.3 Streaming personalization. The greater storage and processing capabilities of devices create exciting opportunities for service personalization. Personalized services already enjoy recognition in such application domains as video recommendation [12], music recommendation [90], web browsing [128], and wireless networking [8]. The perception of QoE in video streaming also varies dramatically among users [84]. Because MOS-based and other one-size-fits-all QoE models are unable to capture QoE accurately for each user, a streaming service cannot fully satisfy all its users if conditioned by a one-size-fits-all QoE model. Hence, personalization of QoE models carries immense promise for empowerment of personalized streaming services. The construction of personalized QoE models faces challenges with ample avenues for research. An attractive approach of inferring the QoE perception of the user in a nonintrusive manner is difficult to realize due to the complexity of human actions, cognition, and emotions. If the creation of a personalized QoE model for the user involves explicit feedback about the subjective QoE perception, this feedback should be expressible, actionable, and small in amount so that to support accurate QoE modeling without overburdening the user. Staying closer to the status quo, another direction is to build multiple MOS-based QoE models for different reference groups and associate the user with the QoE model of the most representative group. This alternative also needs to overcome concerns about its accuracy and overhead.

8.2.4 Bigger emphases on newer modes. Compared to VoD, live streaming is poised to stir greater interest among users, service providers, and researchers. The public appeal stems from the ease of creating diverse content affordably and the allure of consuming the fresh content. Live streaming presents service providers and researchers with, respectively, new opportunities to raise revenues and additional technical challenges to solve, e.g., to make end-to-end latency ever smaller. Because specialized 360-degree video equipment, such as omnidirectional cameras and HMDs, becomes widely available, the industry pays growing attention to 360-degree streaming and AR/VR applications. The vision of metaverse epitomizes this attention [53]. Due to the burgeoning practical interest in 360-degree streaming, the already sizable body of research results on the topic is likely expand rapidly.

8.2.5 More ABR research with different foci. While the surveyed recent results on ABR algorithms are extensive, research efforts in this important area are likely to persevere and pursue different focal points. As expected for a thoroughly explored topic, existing ABR proposals vary dramatically in their complexity and performance properties. Although the recent research focuses mostly on highly performant ABR algorithms that leverage complex DNNs, deployed streaming systems tend to use simple intuition-based ABR algorithms that lag in performance. This dichotomy calls for new ABR designs that strike a practically acceptable balance between complexity and performance. A potential approach for addressing the problem is to improve interpretability of DNN-based solutions so that the better understanding of the decision logic augments confidence in the algorithm robustness. Whereas interpretability of deep learning has been studied in various application domains [58], the work that improves understanding of black-box ABR algorithms [47] or converts DNN-based ABR solutions into simpler interpretable counterparts [126] remains fairly limited and requires heightened investigation. Another angle for anticipated ABR research attends to automatic tuning of algorithms. Whereas ABR designs typically come with a number of parameters, the operator of an ABR streaming system manually tunes the parameters to ensure effective execution in each environment. [6] and [46] exemplify early efforts on automatic parameter tuning and exhaustively explore the parameter spaces via simulations. Design of more efficient techniques

for automatic tuning and their application to advanced DNN-based ABR algorithms are appealing directions for future work.

8.2.6 Streaming with advanced codecs. Whereas the surveyed research mostly adopts the widely available H.264 or H.265 codecs, a future direction with a high potential impact is to build streaming systems around state-of-the-art codecs such as VVC, EVC, and LCEVC. Because the cutting-edge codecs tend to be proprietary, the research progress in this area is likely to involve reverse-engineering efforts, open-source initiatives, and collaborations with the codec owners.

8.2.7 Application-network interaction. Video streaming in its mainstream HAS paradigm is an application that runs on top of the Internet, with TCP acting as a standard transport protocol. The application-layer ABR logic and transport-layer congestion control form two concurrent control loops that independently allocate network bandwidth to streaming sessions. The uncoordinated adjustments by the two control loops cause efficiency, fairness, and stability problems for the bandwidth utilization [5]. Whereas our survey already covers ABR designs that tackle the above problems by exploiting transport-layer information, there are also proposals addressing these problems via transport-layer or network-layer modifications [20, 132]. Due to the prominent emergence of the QUIC transport protocol [108], interactions between video streaming and underlying transport functionalities attract a strengthened interest from researchers. While some studies find QUIC beneficial for video streaming [13, 25], others dispute the advantages of switching from TCP to QUIC [26, 156]. Besides, proposed modifications of QUIC seek to improve its support of video streaming [135]. The topic of interactions between application-layer video streaming and underlying transport/network functionalities is still insufficiently explored and contains new research opportunities for both understanding the interactions and developing new integrated solutions.

9 RELATED SURVEYS

A large number of earlier surveys covers the important topic of video streaming. Due to the complexity of the end-to-end streaming pipeline, the prior surveys focus on individual stages of the pipeline or even individual elements of a stage. For example, [23], [106], and [153] limit their scopes to ABR algorithms at the distribution stage. While [153] reviews only client-side ABR algorithms in regard to their resource availability estimation, chunk request scheduling, and bitrate selection logic, [23] and [106] expand the scope to consider also server-side and network-assisted ABR algorithms. [17], [95], and [199] address QoE in video streaming, with emphases on subjective testing methods, influence factors, and QoE models. [16] deals with QoE management and investigates video streaming in software-defined, information-centric, and other novel network architectures. [2] surveys video streaming over multiple wireless paths. [202] discusses CDN support for video streaming and other traffic classes. [112] covers cloud-based video streaming. In contrast to the previous surveys, our work offers a holistic coverage of video streaming across the entire end-to-end pipeline. In addition to CDN support, QoE, and ABR algorithms at the distribution stage, our survey also reports advances in video streaming at the ingestion and processing stages. Besides, we provide an up-to-date perspective on the field by emphasizing the most recent research results.

10 CONCLUSION

The real-world importance and technological sophistication of Internet video streaming attract substantial research efforts. This paper surveys recent work that aligns closely with the currently prevalent practice of using HAS protocols with client-side ABR logic to stream 2D videos over CDN-assisted best-effort networks. To make the survey more

accessible for newcomers to the field, we also provide substantial tutorial materials. Our paper offers a holistic perspective on the end-to-end streaming pipeline that consists of the ingestion, processing, and distribution stages. At each stage, we report prominent research results for its individual tasks, such as upload protocols at the ingestion stage, transcoding at the processing stage, and ABR algorithms at the distribution stage. We also consider interactions between stages and review, among others, relevant results in the areas of SR and QoE that span multiple stages of the streaming pipeline. The survey covers more than 200 papers and classifies their designs with respect to their underlying methodology and, in particular, whether intuition, theory, or ML forms their methodological foundation. We further categorize the surveyed designs in regard to their streaming mode, usage of codecs, QoE models, SR, distribution infrastructure, transport-layer information, evaluation of bandwidth efficiency and fairness, and other factors. The prominent current trends distilled by our survey include shift toward ML methodology, continued emergence of live streaming, increasing diversity of devices, integration across the end-to-end pipeline, and design for better trade-offs. By analyzing and extrapolating the current trends, we argue that ML-based streaming, pipeline-wide designs, streaming personalization, bigger emphases on newer modes, more ABR research with different foci, streaming with advanced codecs, and application-network interaction constitute promising directions for future research.

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