Adaptive Bitrate Video Streaming for Wireless nodes: A Survey

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Abstract—In today’s Internet, video is the most dominant application and in addition to this, wireless networks such as WiFi, Cellular, and Bluetooth have become ubiquitous. Hence, most of the Internet traffic is video over wireless nodes. There is a plethora of research to improve video streaming to achieve high Quality of Experience (QoE) over the Internet. Many of them focus on wireless nodes. Recent measurement studies often show QoE of video suffers in many wireless clients over the Internet. Recently, many research papers have presented models and schemes to optimize the Adaptive BitRate (ABR) based video streaming for wireless and mobile users. In this survey, we present a comprehensive overview of recent work in the area of Internet video specially designed for wireless network. Recent research has suggested that there are some new challenges added by the connectivity of clients through wireless. Also these challenges become more difficult to handle when these nodes are mobile. This survey also discusses new potential areas of future research due to the increasing scarcity of wireless spectrum.

Index Terms—Video, Wireless, WiFi, Cellular, Spectrum Sharing.

I. INTRODUCTION

VIDEO is the most frequent type of traffic on today’s Internet [1][2]. It is important for services like Youtube, Netflix, and Facebook to deliver a high Quality of Experience (QoE) during video streaming to sustain revenues [3] and user engagement [4]. Most Internet video delivery services like Twitch, Vimeo, Youtube use Adaptive BitRate (ABR) to deliver high-quality video across diverse network conditions. Many different types of ABR are implemented in recent years [5][6] to optimize the quality of the video based on different inputs like available bandwidth and delay. Recently, Pensieve, a neural adaptive video streaming platform developed by MIT [5], it uses deep reinforcement learning (DRL) [7][8], and outperforms existing ABRs.

One of the major challenges will occur in the near future with 5G wide deployment when many devices share the unlicensed spectrum, such as [9][11]. Video stream applications can be optimized for these resource critical scenarios with the introduction of edge device based feedback to the Reinforcement Learning (RL) based ABR running on the server. These edge devices will collect data by spectrum sensing and then allocate the spectrum for the next time slot. This allocation will be transmitted to the ABR server in addition to the feedback from the mobile client.

A. Motivation: Why we need ABR solutions for Wireless Networks?

Video streaming over wireless/mobile nodes now accounts for more than 70% of Internet traffic, and it is still growing with a phenomenal rate [1]. Massive deployments of LTE based cellular networks has also played a vital role in this. LTE supports peak down-link bitrate of 300 Mbps, almost 10 times more than over 3G [12].
TABLE I
LIST OF COMMONLY USED ACRONYMS IN THIS PAPER

| Acronym | Explanation |
|---------|-------------|
| DASH    | Dynamic Adaptive Streaming over HTTP |
| ABR     | Adaptive BitRate |
| QoE     | Quality of Experience |
| DL      | Deep Learning |
| RL      | Reinforcement Learning |
| 5G      | 5th Generation mobile networks |
| LTE     | Long-Term Evolution |
| MIMO    | Multi-Input Multi-Output |
| IoT     | Internet of Things |
| HTTP    | HyperText Transfer Protocol |
| DRL     | Deep Reinforcement Learning |
| MAC     | Media Access Control |
| MDP     | Markov Decision Process |
| DQL     | Deep Q-Learning |
| CNN     | Convolutional Neural Networks |
| OFDMA   | Orthogonal Frequency-Division Multiple Access |
| OFDM    | Orthogonal Frequency-Division Multiplexing |
| HAS     | HTTP Adaptive Streaming |
| PoPs    | Point-of-Presence |
| CDN     | Content Delivery Network |
| MPTCP   | Multi-Path TCP |
| EC      | Edge Computing |
| SILP    | Stochastic Integer Linear Program |
| MEC     | Mobile Edge Computing |
| MNOs    | Mobile Network Operators |
| KPIs    | Key Performance Indicators |
| DNN     | Deep Neural Network |
| SDN     | Software Defined Networks |
| DRNN    | Deep Recurrent Neural Network |

However, most of the studies show QoE is still unsatisfactory \[13\].

New applications of video over mobile client are getting popular \[14\]. Exponential growth of IoT based networks will increase these innovative scenarios, with the applications like online object detection \[15\] \[16\] and energy efficient scheduling \[17\]. Many new applications apply machine learning algorithms like deep learning \[18\] on video streams on resource constraint mobile devices. These applications introduce new challenges and opportunities for Internet video ecosystem.

B. Prior Survey Articles

Having established the importance of ABR algorithms optimizing QoE for wireless and mobile clients in particular, in this paper, we are reviewing existing models and algorithms in this area. While, there exist previous surveys, in the area of Internet video and optimizing applications for wireless networks in our opinion there are none which focuses on mobile video streaming algorithms. Previous surveys like Seufert et al. \[19\] and Bentaleb et al. \[20\] discuss different ABR algorithms in general and related influence factors. In another survey by Juluri et al. \[21\], they discussed tools and measurement methodologies for predicting QoE of online video streaming services. Similarly in \[22\], authors provide a survey of QoE models for ABR applications. Kua et al. \[23\] focuses on rate adaptation methods for Internet video in general, provides a comprehensive review of video traffic measurement methods and a set of characterization studies for well-known commercial streaming providers like Netflix, YouTube, and Akamai. The survey in \[24\] discusses the growing popularity of deep...
learning (DL) based techniques to solve different wireless network problems. They discuss the applications of DL methods for different layers of the network, but do not include Internet video and its challenges in particular. Seufert et al. in [25] focused on video quality metrics and measurement approaches that are related to HTTP based adaptive streaming. Similarly, Barakabitze et al. [26] focused on techniques of maintaining QoE in emerging types of networks based on SDNs and NFVs. They do discuss QoE for multimedia application in LTE and 5G networks but more with the context and opportunities related to SDN/NFV.

Bentaleb et al. in their survey [27] describes a many recent paper related to ABR in detail. Their main focus is a scheme classification based on the unique features of the adaptation logic of ABR algorithms.

Our survey is unique from others in three key aspects: (1) It is focused on clients connected to the internet using wireless technologies like WiFi or cellular network. In all previous surveys none focused on different schemes and their challenges of designing ABR specifically for wireless networks. (2) We provide an indepth survey of schemes using machine learning in general and RL in particular to optimize QoE of video for wireless nodes. (3) We provide many open challenges in designing ABR for future wireless networks.

C. Contributions of This Survey Article

In this article, a comprehensive survey on the proposed ABR algorithms for wireless networks is presented. The contributions of this review paper are summarized as follows. Towards this end we present in this paper a review of the proposed ABR algorithms for wireless networks.

- We present and classify the existing works related to ABR for wireless networks. In this paper, we provide an overview of the current state of the art in the field of Internet video in wireless networks.
- We identify some important directions of future research. We present some area where upcoming new standards and their adaptations will create challenges for existing ABR algorithms. We discuss suggestions for future design of ABR algorithms.
- We review many open-source implementations of different ABR algorithms. And we present their differences and comparisons.

A list of acronyms used throughout the article is presented in Table I. The rest of this paper is organized as follows. Section II presents the overview of the Internet video delivery ecosystem. It also introduces basics of machine learning techniques used in the papers discussed in this survey. Section III surveys the bitrate adaptation algorithms for wireless networks. This section is divided in different subsection according to the type of algorithms. Section IV presents different open challenges in the area of ABR for wireless. In the section V discusses different open-source implementations of ABR algorithms and also different dataset available for experiments. Finally, Section VI provides concluding remarks.

II. Wireless ABR Video Streaming: An Overview

A. Why video on wireless is different?

Internet video systems are designed to cope with the inherent variability in network conditions. Media players at the client implement ABR algorithms [9, 25, 29]. There are a variety of protocols like MPEG-DASH [30], Apple HLS [31], Microsoft Smooth Streaming [32], Adobe HDS [33] etc. that adopt HTTP based adaptive video streaming. These protocols are called Dynamic Adaptive Streaming over HTTP (DASH). In these schemes, server splits each video into multiple segments with uniform playback time (typically 1 to 10 seconds). Afterwards, the server encodes these segments into multiple copies with different discrete encoding bitrate levels having different sizes. Before a DASH video session starts, a client obtains the available bitrate map from the server. To download each segment, the client needs to send
an HTTP request to the server, and specify the bitrate level it prefers for that segment.

Most of the content publishers in today’s Internet serve their videos from some popular content delivery networks (CDNs). These CDNs have point-of-presence (PoPs) in many different geographical and network domains. By using their PoPs and their peers, CDNs reduce the cost of serving videos and join times, each video is delivered over an ISP network. Most of these Internet service providers (ISPs) have two parts, the core network and the radio-access network (e.g., cellular network) as shown in Figure 1. User devices are connected with the ISP via wireless technology like WiFi or LTE. However, these solutions render unsatisfactory performance in WiFi or LTE networks.

ABR algorithms work by (a) chopping the video into chunks, each of which is available at a range of bit rates; then (b) choosing which bit rate to fetch a chunk at based on conditions such as the amount of video the client has buffered and the recent throughput of the network. These ABR algorithms are implemented in video clients. Hence, on a mobile client they must be energy efficient in addition to all other properties like computational efficiency and optimize QoE for the user.

One of the first ABR algorithms was designed in model predictive control (MPC) [34]. It predicts throughput of future chunk downloads using the historic data of recently downloaded chunks. The predicted value of throughput is used to select the bitrate for the future chunks such that optimizes the QoE function. MPC has a look-ahead window of 5 future chunks. There is an aggressive version of this algorithm called FastMPC which directly uses the throughput estimate obtained using a harmonic mean predictor.

On the other hand there are algorithms like Buffer Occupancy based Lyapunov Algorithm (BOLA) [35], which uses buffer occupancy to selects bitrate. BOLA solves an optimization problem to select optimal bitrate. BOLA is a buffer-based algorithm used in Dash.js [36]. In contrast to MPC, it does not employ throughput prediction in making decisions. It tries to avoid re-buffering by maintaining a minimum buffer threshold. This threshold can be used to make this algorithm conservative or optimistic about the future bitrates.

Recently, RL and other machine learning techniques are used to design ABR algorithms [37–39]. Using RL Pensieve [5] was able to outperform the state-of-the-art. Oboe [6] presented an ABR algorithm which performs an automatic tuning of configuration parameter values for each network state independently. This allows Oboe to give better QoE than Pensive.

B. Why Reinforcement Learning is popular for ABR design?

There are many schemes based on learning-based approach to solve problems in networks in general [40]. Some of them are focused towards applying RL. In the past, it has been noted that RL is very suitable to be applied to many computer network problems. RL is quite a natural way to model an optimization control problem [41].

There are two main entities in a RL problem Figure 2, Agent and Environment. Agent observes the state $s_i$ of the environment at each interval and then choose an action $a_i$. Agent receives a reward $r_i$ for his action which can be positive or negative. The goal of an agent in RL is to maximize the cumulative reward defined as follows:

$$V_\pi(s) = E\left[\sum_{t=0}^{\infty} \gamma^t r_i | s_0 = s \right]$$

Where $\pi$ is the policy function $\pi(s, a_i)$. It gives the probability distribution of the current state and action. While the $\gamma$ is the discount factor for the future reward. Hence, an RL agent learns optimal policy to maximize its rewards. To learn the optimal policy most of the RL applications use Q-learning.

In Q-Learning, each pair of state and action $(s, a)$ is mapped to a value under a policy $\pi$. This
value is the expected total reward of taking an action $a$ in a state $s$.

$$Q^\pi(s,a) = E \left[ \sum_{i=0}^{\infty} \gamma^i R(s_t, \pi(s_t))|s_0 = s, a_0 = a \right]$$

The goal of Q-learning algorithm is to find the policy to maximize this function. In DRL, an agent is learning this optimal policy using a deep neural network (DNN). So, in DRL approximate value functions called deep Q learning function is used. This function is learned by gradient method used in deep learning. Here the agent interacts with the environment like in RL and uses its reward as the training input for the deep neural network. The goal during training of this DNN is to optimize its parameters. Hence, it selects actions that can result in the best future return.

Pensive [5] was the first paper to use DRL in designing ABR. Pensive model it using DRL so it can be independent of the assumptions taken by the designer of ABR schemes. In Pensive algorithm, they defined the QoE as the reward of the ABR algorithm working as an agent in the DRL. They modeled their generic QoE based reward function as follows.

$$QoE = \sum_{i=1}^{n} q(R_i) - \mu \sum_{i=1}^{n} T_i - \sum_{i=1}^{n-1} |q(R_{i+1}) - q(R_i)|$$

Where the function $q$ is an increasing function of bitrate selected $R_i$ for the interval $i$ so, higher the bitrate higher the reward. The second term depends on the time taken to buffer that segment $T_i$. This will penalize the reward for any re-buffering required before playing the next segment. Last segment of the reward function is penalizing for lack of smoothness. If the bitrate of the video change from the previous segment,
then user will observe some lack in smoothness. Pensive [5] is used in many similar research for different variants of the problem. There are two main types of the RL based on the training. First is model based RL and the other is model free RL.

1) Model-free Reinforcement Learning: Model-free RL learns directly from the experiences while in training. The states and transition probabilities of the underlying Markov decision process (MDP) are unknown. In ABR, we have no prior model of QoE dependence on the different state variables. Model-free RL learns in more interaction with the environment as compared to the model-based RL Figure 3. It is free from the biases of the supervised training data.

2) Model-based Reinforcement Learning: In this type of RL we have a prior model of the system MDP. This will reduce the time of learning and cost in-terms of interactions with the environment, on the other hand, it require designer to provide or learn the model before the start of the training. RL training phase will only optimize or refine this model. In this case, if there are inaccuracies in the model, then this will lead to degradation in quality of final output.

In model-based RL, policy is learned through supervised learning. Then planning over the learned model is done in second phase. Consequently, model-based algorithm uses a reduced number of interactions with the real environment during the learning phase. So, learning can be much faster because there is no need to get the feedback from the environment. On the downside, however, if the model is inaccurate, we risk learning something completely different from the reality.

III. DIFFERENT TYPES OF ABR ALGORITHMS

There are different types of research in this area. Some have designed ABR algorithms for mobile nodes to incorporate the movement of the nodes, while others focused on the resource constraints like spectrum and energy of the video client.

Mobile Network Operators (MNOs) offer different packages to increase their number of users. In some packages, they offer not to count certain services like Facebook, WhatsApp and Netflix toward monthly data quota. But they limit the rate of the users toward those services. Traditional ABR based services does not account for this rate limiting. Here traditional throughput maximization based ABRs will not perform well. Zero-rated QoE [42] proposed a novel approach which uses the collaboration of the content provider and MNOs. They designed an ABR which focuses on improving QoE in these special scenarios. They implemented their approach in a simulated environment and performed evaluation with the baseline.

A. Machine Learning based ABR schemes

Comyco [43] is another study using the Learning-based ABR. They discuss a few weaknesses of previous RL-based ABR algorithms. Their measurement study shows that the quality of video presentations is not always maximized by QoE metrics based on only video bitrates, rebuffering times and video smoothness. They proposed Imitation Learning instead of supervised learning can address these weaknesses.

Reinforcement learning is also applied to make video streaming appear more smooth to the user.
| Paper        | Main Idea                                                                 | Is ABR? | For mobile? |
|--------------|---------------------------------------------------------------------------|---------|-------------|
| FESTIVE [34] | Stateful ABR with randomized chunk scheduling to avoid synchronization biases | ✓       | ✓           |
| Pensive [4]  | DRL is used to optimize the QoE                                            | ✓       | ✓           |
| Oboe [6]     | Combine offline and online tuning of the parameters                       | ✓       | ✓           |
| Pstream [12] | Improves the QoE by taking advantage of the PHY information of LTE networks | ✓       | ✓           |
| MP-DASH [43] | Use MPTCP to schedule                                                      | ✓       | ✓           |
| Wi-Fi Goes to Town [45] | Improves the QoE during high speed handovers                              | ✓       | ✓           |
| HotDASH [46] | Use DRL to detect user specific important part of video to improve their quality | ✓       | ✓           |
| Zero-rated QoE [42] | Collaboration of MNOs and content providers to improve QoE for rate limited users | ✓       | ✓           |
| QARC [47]    | Improve the perceptual quality of the video instead of traditional QoE metrics | ✓       | ✓           |
| Bursttracker [13] | Find the bottleneck in the video streaming over the LTE network | ✓       | ✓           |
| Qflow [48]   | Used both Model based and Model free DRL                                    | ✓       | ✓           |
| NAS [49]     | A deep neural network based ABR                                              | ✓       | ✓           |
| IncorpPred [49] | Incorporate cellular throughput prediction to improve ABR                   | ✓       | ✓           |
| Comyco [43]  | Proposed imitation based Learning instead of supervised learning           | ✓       | ✓           |
| Jigsaw [51]  | 4K video streaming                                                          | ✓       | ✓           |
| TransPi [52] | Introduced hardware-assisted video transcoding for Wireless                | ✓       | ✓           |
| CASTLE [53]  | Client scheduler to minimizes Load and Energy at the same time              | ✓       | ✓           |
| ALAA [54]    | Incorporate user’s subjective viewing information to improve ABR           | ✓       | ✓           |
| LinkForecast [55] | Bandwidth prediction for LTE network                                     | ✓       | ✓           |
| QUAD [56]    | Reduce the bandwidth usage while maintaining high QoE                       | ✓       | ✓           |
In [57], the authors design an optimization problem for ABR to exploit power control over multiple sub-channels at the transmitter in such a way that video quality remains smooth. It penalizes both for buffer underflow and overflow. Then, they mapped this constraint optimization problem into a MDP. The MDP is solved using reinforcement learning techniques.

It is challenging to implement heavyweight ARB techniques in resource constraint mobile devices. PiTree [58] introduced the idea of using lightweight decision trees to simplify the complex and heavyweight neural network based techniques. PiTree give a highly scalable framework to convert complex ABRs into decision trees. They also provide some theoretical upper bound on the optimization loss during the conversion.

Challenges of Video streams with high quality are increased in the case of remote drone piloting. The study in [59] discusses these challenges. It suggests decreasing the coupling of different functional blocks. They proposed to use edge-computing elements in addition to adapting for network conditions.

QFlow [60] paper used reinforcement learning to perform one-way adaptive flow prioritization at the edge network. QFlow argued current link are application agnostic in their scheduling. By making these links intelligently adapt for different type of traffic leads to a better QoE of the video streaming. QFlow borrowed concepts of network level priority queues from software defined networks (SDNs) and apply it to PHY/MAC layer using Software-Defined Radios.

QFlow uses RL to optimize the QoE for video by adapting configurations. QFlow uses both model-free and model-based RL approaches.

According to their evaluation, RL based approach not only improves the QoE but also results in better buffer state and lower stall duration. The survey [40] provides a comprehensive survey of deep learning-based techniques used in different wireless networking scenarios. It also highlights some potential applications of DL to networking, like in network security and user localization.

In QARC [47] they have designed a rate control algorithm that is focused on the perpetual quality of the video. The perpetual quality, of the video is defined as how many objects are in the image and how bright or dark it is. For low perceptual quality parts of the video we can save the bandwidth and delay by requesting video at the low quality. While for high perceptual quality, parts should be downloaded at a higher bitrate. This can be achieved by lower sending rate and latency. QARC also use DRL to train the neural network to predict the future video frames based on the perceptual quality of the previous frames. It employs two-fold training of DRL one for prediction of perceptual quality and the second one using A3C based asynchronous training technique to train the actual RL algorithm. They did trace driven analysis of their techniques and compare it with Google Hangout and compound TCP.

B. Edge computing based ABR systems

Increasing demands of lower network delay and higher data transmission rate are getting difficult meet from traditional ABR systems. Recently, edge computing (EC) Figure 4 based optimizations to ABR systems have been proposed to meet these challenges. In the paper [61], authors present some of the challenges and limitations of the current ABR applications. They proposed an edge computing based solution to address these challenges and limitations. QFlow [60] is an Edge computing based ABR system using ML based model to optimize QoE.

ShareAR [62] is a multi-user augmented reality (AR) system which uses edge nodes to optimize QoE for the user. The main challenge in multi-user AR is the communication between AR platforms. There are no prior work involving data transmission in between AR devices and their impact of the QoE. In multi-user AR, devices can have different fields-of-view. They need to render their respective FoVs. In their system, they overcome these challenges and implemented
Fig. 4. Introduction of MEC to improve the ABR based video streaming

a prototype of the system using two Android devices and an edge server.

In FlexStream [63] they leveraged the SDN functionality to get the benefits of centralized management of distributed components. Here they use wireless edge device like AP as SDN controller. They have implemented their system as a light weight controller. In there evaluation, they showed FlexStream can achieve appropriate bandwidth distribution.

Blockchain technology is used by decentralized peer-to-peer video streaming systems to monetize using smart contracts. In these new video streaming systems, content creators, consumers and advertisers can communicate with each other without the help of a trusted third party. There some challenges in designing these systems like processing and publishing of the video content in these systems. In [64], they propose using edge computing servers to offload these computationally intensive tasks. They proposed to employ edge servers through distributed block-chain based incentive mechanisms.

Mobile Edge Computing (MEC) is getting popular to provide low-latency ABR service. One way to decrease the latency of the system is to use MEC servers for video caching. Tran et al. [65] investigates a novel caching scheme using multi-server MEC systems. Their systems use two timescales. They formulated stochastic integer linear program (SILP) to integrate these two timescales of long-term caching and short-term video retrieval mode. By using simulations they showed the effectiveness of their system by reducing access delay and increasing cache hit ratio.

PrivacyGuard [66] is a system designed and developed to obfuscate the activities of sensitive IoT and mobile applications from attacks over WiFi network. They have implemented a prototype this systems on Android mobile devices that to apply application level traffic shaping and IP-sec tunneling schemes.

C. ABR with different optimization goals

In Wi-Fi Goes to Town [45], implement a WiFi based hotspot network using picocell size access point networks along the road to support vehicular communication over high speed. They implemented optimized version of IEEE 802.11k and 802.11r standards. Although their
main focus is not video streaming but most of their evaluation is done over video. Their scheme provides more reliable video stream for high speed mobile client. Also it improves the QoE metrics for the video like rebuffed ratio.

Sengupta et al. in HotDASH [46] focused on improving the video quality for the specific user requirements. In most of the video streaming situations there is some content of the video which is more important for the user. They use DRL to detect that part of the video and then the requirement, therefore, is for a video streaming strategy to into account the content preferences of the users. So, ABR will be aware of the high-priority temporal content. ABR try to pre-fetch those high priority parts of the video at much higher bitrate. HotDASH maximizes the content preferences of users, in addition to optimal use of bandwidth. They implemented their scheme in dash.js and compared it with the six baseline algorithms like FESTIVE, FastMPC and PENSIVE.

Most of the ABR algorithms are not designed with the consideration of data consumption. But most cellular customers have limited data in their monthly data plan. According to [67] average U.S. cellular customer has only 2.5 GB per month data plan, while one hour high definition (HD) video on mobile require 3 GB data. QUAD [56] focuses on reduce the bandwidth usage while maintaining high QoE for the user. Their scheme is also energy efficient because it requires to download less amount of data.

QUAD introduced a novel Chunk Based Filtering (CBF) approach which leverages two fundamental tradeoffs of video quality and bitrates. First, higher bitrate leads to diminishing return in terms of video quality. Second, different chunks have different impact on video quality. Their scheme selects chunks to maximize the QoE while keeping the data consumption minimal. QUAD implemented its scheme in both dash.js and ExoPlayer and perform evaluations. They compared their approach with RobustMPC and PANDA.

At the same time MP-DASH [44] take a different approach to optimize video quality over mobile devices. Their focus is on leveraging the availability of multi-path in many common mobile devices like cell phones. They have WiFi card and LTE modem at the same time. So, in many cases it is possible to use LTE opportunistically. They used Multi-Path TCP (MPTCP) to implement their approach. It prefers WiFi over LTE when at home. The evaluations were done in both controlled setting and in the wild. Trace of throughput and RTT of the WiFi networks at 33 locations in the US for the evaluation. MP-DASH is impelled using GPAC. FESTIVE and BBA is implemented over the multi-path scheduler. In [68] they implemented traffic offloading build on the MP-DASH approach for general application.

ACAA [54] is a scheme focused towards semantic information of video content. Recently ABR researchers are designing with user’s subjective viewing information to improve the QoE of the video specific to the user requirement. ACAA use the research on video affective content analysis. It incorporated individual user preferences into the bit-rate adaptation decisions to improve the QoE. Identify the user relevant parts of the video and then assign bit-rate budget according to it. They compared their scheme with BBA and buffer-based adaptation (BBA), and model predictive control (MPC). ACAA implemented their scheme with the DASH client in accordance with [69] to perform trace-driven evaluation platform with python 2.7.

D. Measurement of different ABR schemes

Many papers study performance of different ABR algorithms and make a comparative study. Some of them performed active measurement [70] [71] while other perform passive measurements [72]. There are others like [73] and Puffer [74] made a database of different ABRs. Duane et al. developed the Waterloo SQoE-III database [73]. This database provides a subjective evaluation of different QoE models and ABR algorithms. SQoE-III evaluated Rate-based, AIMD, Dynamic Adaptive Streaming algorithm, etc in
their paper. According to their evaluation 5 out of 6 models are quite close in terms of performance. In addition to the experimental evaluation of other ABR techniques, Puffer \[74\] developed a live TV streaming website. This prototype website has attracted over 100,000 users across the Internet. This system works as a randomized experiment; one set of ABR schemes is randomly assigned to each session.

Haung et al. \[71\] is the first study performed in this area. In their study, they perform a measurement study of three popular video services Hulu, Netflix, and Vudu. \[75\] studied and discussed the impact of QUIC on QoE of the popular ABR. It also discussed how can existing ABRs leverage the potential benefits of QUIC.

The study in \[76\] is a general measurement study of application performance in the rapid deployments of LTE networks. Data traces have been used from different major LTE providers. VideoNOC \[70\] is an passive measurement study of Video QoE for Mobile Network Operators (MNOs). VideoNOC presented an approach to assess the QoE for different MNOs using objective metrics for video quality. To get an objective estimate of QoE metric they collected HTTP/S traffic in the core of the LTE network. VideoNOC performed many efficient and scalable cross-layer analytics over these logs.

Recently, a third-party based system to is designed to evaluate and understand the behavior of different closed source ABR based streaming services \[77\]. Channel State Information (CSI) can also able to understand the behavior of ABRs in the presence of traffic encryption.

### E. 4K and 360-degree video streaming

4K videos are now getting increasingly common. New applications like virtual reality (VR) and augmented reality (AR) will make 4K extremely important in the coming future. These applications do not only require high resolution but also very low latency. In there raw form 4K video stream requires more than 2Gbps physical data rate. Currently, IEEE 802.11ad based WiGig card are commodity wireless cards supporting these data rates. These devices work in 60GHz spectrum. In this range, transmission is highly sensitive to mobility. There can be drastic change in the throughput for minor movement. In the case of blocking, the line of sight throughput might be affected and reaches to zero.

In the presence of these large throughput variations, traditional video codecs like H.264 and HEVC become infeasible. To overcome these limitations, layered video codecs are used by Jigsaw \[51\]. It uses scalable video coding (SVC) which is an extension of the H.264 standard. The study in \[51\] use fast encoding schemes and implement it using new layered video coding methods.

Panoramic video is another emerging application of video streaming, it is known as 360$^\circ$ video. Platforms like Facebook and YouTube also support them. Flare \[78\], presented a practical prototype of a 360$^\circ$ video streaming solution using commodity devices. This study predicts future behavior of the user to fetch only the relevant portions of the video to cover the view of the user, which enables Flare to reduce the bandwidth usage of the system significantly.

This viewport-adaptive 360$^\circ$ streaming is an establish technique. Flare is the first complete working implementation on commodity mobile phone. It uses a online machine learning (ML) algorithm to predict head movement of the user which changes the users’ future viewpoint.

Another 360$^\circ$ video streaming system is presented in Rubiks \[79\]. Rubiks discusses different challenges of implementing tile-based video streaming techniques used in different implementations to predict field of view (FoV) of the user. In resource constraints of commodity smartphones, it is not possible to meet with the requirements these tile-based systems.

Rubiks uses HEVC to implement tile-based streaming instead of H.264 \[80\] used by previous system. HEVC \[81\] has a built-in tiling scheme to encode video data. Their system can stream different parts of the video at different bitrates. This allows them to download tiles in different
quality according to their probability of viewing. Managing the amount of data downloaded at the client it can control the decoding time. Decoding time increases substantially for 8K videos on mobile device.

In the paper [82], DRL is used to implement a panoramic video streaming system. Their system used DRL to optimize QoE using a broad set of features. Here their focus is on two main challenges of 360-degree video. First, there is a large number of time-variant features which needed to be adapted to achieve a reasonable quality. Second, QoE metrics are also different for different scenarios. Zhang et al. uses DRL to find an optimization model. This model finds the best rate allocation scheme for different scenarios.

Tang et al. in [83] presented a promising approach to improve QoE for the user in a 360-degree video streaming system. Their focus is on streaming a newly generated 360-degree video. In this case, there is no historical viewing information available which can be used to predict user viewing behavior. In these scenarios, there are additional challenges of learning FoV patterns online and also the lengths of these FoV segments are also unknown in advance. The authors present OBS360 algorithm which is an online bitrate selection algorithm to optimize the user’s QoE in 360-degree video. OBS360 algorithm is able to learn user’s FoV preference and also the time-varying downloading capacity of the user.

Perfecto et al. [84] they discussed Immersive virtual reality (VR) applications. These applications require achieving motion-to-photon (MTP) delays, which are defined as end-to-end latency of 15-20 milliseconds. Providing 360° video with these delay guarantees is quite a challenge. They applied a deep recurrent neural network (DRNN) to predict the upcoming tiled FoV. In addition to that, they exploit millimeter wave (mmWave) multicast transmission at the physical layer to improve the efficiency of the system.

**F. Video stream in vehicular networks**

Video streaming in vehicular networks is even more challenging [85]. There are different types of communications in V2X networks. In recent years, many papers try to address these challenges [86,87]. Some of them use Edge network-based caching techniques and other explored learning-based approaches to optimize video streaming.

Recent papers explore the use of different machine learning-based approaches to optimize video streaming in wireless networks [88–91]. Some of them focus on the presence of IoT devices on the same spectrum, others optimize for energy-efficiency. In [82], they perform an experimental analysis of 10 widely deployed ABRs. Their measurement shows none of the deployed ABRs focus on available bandwidth and some leave a large fraction of available network capacity unused.

**G. Optimizing video during handovers**

Wi-Fi Goes to Town [45] was one of the first research approaches to implement a performance-tuned version of the IEEE 802.11r and 802.11k fast handover protocol. It try to use Picocells to increase the capacity of the network, which results in higher spectral efficiency and throughput. In [45] focus is not on video delivery. Focus of [45] is on maximizing throughput that can often lead to lower QoE for video clients. Wang et al. [93] propose a real-time handover protocol called mmHandover for a 5G network working in mmWave. In the past, there have been many efforts to design mechanisms to predict handovers [94,95]. These schemes try to predict handovers to improve the QoS of different traffic on mobile devices.

**H. Understand the network bottleneck to improve ABR**

In their paper BurstTracker [13] focused on LTE networks. BurstTracker identify issues affecting the QoE of the video streaming performance. BurstTracker is able to identify a sur-
Fig. 5. Resource Block and Resource Element in LTE networks

prisingly different bottleneck. BurstTracker understand the scheduling pattern of the LTE base station. Their focus is to identify the occupancy of each user’s download queue. If this queue is not empty for one scheduling cycle then access link the bottleneck link. It means that data was in the queue of LTE base station and was not being delivered in the next cycle. If there are so many cycles like that, they will decrease the QoE for the video.

One of the main challenges, is that user queue information is not available at the client. So, this approach designed a method to estimate this information. The approach observes that if a user is selected for transmission and its queue is full, then the LTE base station scheduler allocates the complete millisecond duration resource block (RB). As shown in the Figure 5, a RB is the smallest unit of resources that can be allocated to a user. It consists of 180 kHz in frequency while 6-7 OFDM symbols in time. In frequency it is further divided into 12 sub-carriers of 15 kHz each. Using these insights BurstTracker is able to find out most of times user queue becomes empty before the complete allocation of the user queue. This suggests that bottleneck is not at the base station radio link. According to BurstTracker, most of the large LTE network providers use split-TCP middle boxes. Due to TCP slow start used by middle boxes for TCP connections, these middle boxes introduce serious performance bottleneck.

PiStream [12] has determined total download resources allocated to the user on a LTE base station. BurstTracker is able to estimate it at the user and then use it to improve the estimation of bitrate. PiStream assumes in case of the bottleneck it is at the base station.

I. ABR algorithms with cross-layer optimizations

In the ground breaking paper [12] PiStream the first presented a challenge faced by DASH players in LTE. LTE bandwidth is very high, around 10x than its predecessor 3G. Despite this high bandwidth video clients does not perform well. PiStream motivated this problem with a measurement study which shows how a DASH client behaves in the LTE network. PiStream observes that in the LTE network this estimate is mostly an underestimate. This leads DASH selecting a lower quality for the future. PiStream observe that in the LTE networks all the bandwidth information for the access link is known to the LTE network. The approach takes advantage of the Physical layer information to get an accurate estimate of the bandwidth. PiStream implemented their scheme using SDRs at the Physical layer and using GPAC player as the open source client. In their evaluations, they compared their scheme with FESTIVE, BBA, and PANDA.

Recently, Raca et al. [97] designed a approach to address the challenges to ABR video in the challenging environment of cellular network. They observed in cellular network radio channel, conditions and load on the cell are continuously changing. In addition to that, there is gap in the time scale among different components of the system. Transport layer protocols react at the granularity of hundreds of milliseconds, while radio channel changes at the fraction of millisecond. One the other side, base station can allocate resource in a bursty manner. ML based approach is used to predict throughput
of the mobile devices in a LTE network. There ML model is learned on cellular trace data. Their approach shows the importance of radio level metrics in the video streaming applications [98]. Their technique is implemented in Android video player (ExoPlayer) and performed evaluation on a real testbed.

In [99], a dataset for 5G measurements is presented. These measurements are performed on a major Irish mobile operator. In this dataset all the key performance indicators (KPIs) for client-side cellular metrics and throughput are collected. Dataset is collected with two different mobility patterns of the user driving and static. Also, stream content is generated from Amazon Prime and Netflix streaming device. In this dataset, GPS based location information is also present. This data is generated from Android network monitoring application, G-NetTrack Pro. This application can run over a non-rooted Android phone.

In addition to the real dataset, a second synthetic dataset is also presented in [99]. This dataset is generated from ns-3 [100] using a large-scale multi-cell 5G/mmwave framework.

One of the first cross-layer ABR algorithm for wireless network was CrystalBall algorithm [101]. It is a two step algorithm to predict available bandwidth. Main ABR algorithm is based on it. In this study, the effects of the prediction quality on the accuracy of the ABR. CrystalBall shows with error mitigation techniques some level of prediction error can be tolerated.

Another similar technique is CQIC [102] to predict TCP throughput using Radio level information in smart phones.

Yue et al. [55] they showed even a trace of 500 data points can be used to develop an accurate model of LTE link level predictions using a ML model. LinkForecast presented an extensive measurement study to understand the bandwidth allocation algorithm of current cellular networks. Most of them allocate a fair proportion of the available bandwidth. Available bandwidth is calculated using the observations of the recent past throughput and link conditions. Using this measurement study as motivation which shows benefits of sharing application layer throughput to the lower-layer. LinkForecast explore the idea of sharing lower-layer link information to the application.

LinkForecast designs a ML based framework to predict link bandwidth in real time. This framework combine both upper and lower layers information for future prediction. According to their evaluation this technique is not only more precise but also lightweight and insensitive to the training data.

In [97] authors investigate further on the observation of high variability of network conditions in cellular radio access networks. Publicly available data sets [103] are used to learn a machine learning model. The data set is very rich in terms of parameters and different mobility patterns like static, walking, car and train etc. Random forest based technique is selected as their ML model. They used random forest (RF) as model for prediction. By increasing the number of trees and using mean of all trees in the RF as the predicted value avoid over-fitting.

Parameters used in [97] model are available through Android Debug Bridge (ADB) APIs. Implementation is done on ExoPlayer and performed evaluation on a real testbed. In there evaluation, they show the effectiveness of their system by improving all QoE metrics.

Chen et al. [107] authors proposed ABR can save energy during video stream if it consider the context of streaming. It means if user is watching a video in a room may have completely different QoE requirements as compared to a user on a moving vehicle. Using traces they have modeled the impact of vibration level in addition to video bitrate on the QoE and signal strength on power consumption. They designed an optimal algorithm using an optimization problem to minimize energy consumption.

Raca et al. in [106] presents the effects of the highly dynamic wireless communication on different application. Here they provide evidence of PHY layer metrics are used in assigning resources to the users in the cellular network. ABR
Adaptive Bitrate Streaming (ABR) is used as an example application to explain the advantages of using AI based techniques to learn accurate throughput prediction using PHY layer level metrics in cellular networks.

We classify the different ABR for wireless schemes into five main categories see Figure 6. These categories are based on techniques used to design ABR or different types of objectives used in the design of the algorithms. Similarly the reviewed major approaches are summarized along with the references in Table II.

IV. OPEN CHALLENGES AND OPPORTUNITIES

A. Improving video for developing world clients

Mobile phone adoption is even more explosive in developing countries. It has reached more than 98% recently [108]. But most of these devices are low end devices with slow network like 2G [109]. But video is the most dominant type of traffic in these parts of the world. This creates an even higher level challenge for Internet video providers [110].

B. Providing effective ABR for developing world

New services like Web Light and Facebook’s Free Basics service are introduced to improve the Internet quality and availability. Now, Free basics service is expanded to over 60 countries [111] across select cellular service providers. But these services do not handle video elegantly. Both of these services replacing videos with an image [112].
In future, demand for better quality Internet video will increase more for these low resource developing world clients. It is a challenge to provide even bare minimum service to these clients [108]. But one can use techniques like Oboe in [6]. There are some proposed schemes which incorporate device level characteristics to improve the selection of bitrate [113].

In the developing world, vast amount of data access and high speed both are a luxury. Most of the communication is through text-based media like posters and flyers. Most of the users in the developing regions are illiterate and resource-constraint in terms of poor connectivity and little exposure to the technology. Access to computer and laptops is also very limited. Most of the Internet access is through low-end cell-phone with a low-end camera. There has been many novel applications designed to solve different developing world specific problems. Many of these applications depends on video based solutions [114] [115]. Video streaming patterns of community health workers in Africa is studied in [116]. They demonstrated the effectiveness of health videos and also presented lessons for projects seeking to use multimedia content in rural setting.

AudioCanvas [117] is an application created for rural developing regions. It can be used by telephone as an audio information system. This system enable rural users to interact directly with their pictures and receive narration or description.

In a recent paper [113] authors have studied effects of memory pressure on video streaming applications. Their experiments suggest QoE of video streaming is significantly affected by the selecting higher nitrates in a low memory cell-phone. On the other hand [109] presents a comprehensive measurement study of cell phones used by users in developing world. Dataset used in [109] has less than 1% of the cellphone users in the developing world have more than 2GB memory in there devices. This creates a challenge of designing specialized ABRs for developing world.

In their measurements Nexus 5 phone with 2GB memory led to frequent video player crashes when it plays a 1080p video. To achieve high QoE under low-memory scenarios they proposed an new scheme DAVS which adapt the playback buffer size based on conditions based on device memory pressure.

C. Optimize the spectral efficiency for video traffic

The consistent exponential growth of video traffic will increase in the future with the advent of 5G based IoT devices. WiFi alliance has recently approved WiFi-6 [118] (802.11ax) with the focus of high density WLANs. These new changes will lead to even more congestion in the available spectrum specially in the unlicensed domain. There have been many recent studies to understand and optimize wireless spectrum sharing between different technologies like LTE or 5G based cellular networks and WiFi in unlicensed bands [9] [28] [29] [119]. Some of them used a machine learning-based approach to optimize spectrum sharing [10]. But most of these papers are optimizing at the network level. This leads to many lost opportunities specifically related to video streaming [88].

D. Improving the QoE in the presence of network handovers

Some recent measurement studies [105] shows that current policies of cellular carriers are not optimized, especially during handovers. These policies do not consider cell load information during handover resulting in degradation of application performance. In a 5G small cell, handovers will be more frequent. Figure 7 shows a typical scenario of small cell based network in 5G vehicles in these small cells will experience frequent hand-offs. It will be critical for video streaming applications to perform well during these handovers.
V. OPEN-SOURCE IMPLEMENTATIONS OF ABR ALGORITHMS AND DATASETS

There are many open-source video players available on the Internet. But dash.js and ExoPlayer are the most popular in the industry and research. ExoPlayer is developed by Google as the first Android-based mobile DASH player. Many research papers have used it as their reference to implement their ABR algorithm. The other popular implementation is dash.js. It is developed by DASH Industry Forum which is supported by most of the major players in Internet video industry like Akamai. Previously GPAC was also very popular in research for prototyping. It is now called MP4Client. Both GPAC and DASH are implemented in JavaScript. In comparison to all the open-source implementations, dash.js encapsulates the standard and best practices. It is easy to customize and there is an Akamai reference implementation also available online which makes it easy to test. There are libraries available to use this for trace-driven analysis. Video providers wishing to use DASH often use the reference client dash.js to build their own video players. Table III shows open-source implementation used in different papers. It is evident that most popular implementation in research is dash.js. Even in wireless network based evaluations it is more commonly used due to its flexibility and acceptance. There are hundreds of different ABR algorithms implemented using these open-source players. One of the popular one is of Pensive and their data traces. Recently NAS implementation is also available open-source.

There are two open-source data sets available for trace-based analysis and to train machine learning algorithms. They are available

\begin{table}[h]
\centering
\caption{SUMMARY OF OPEN-SOURCE ABR IMPLEMENTATIONS}
\begin{tabular}{|c|c|}
\hline
Implementation & Corresponding papers \\
\hline
Dash player & Pensive [9], Oboe [6], HotDASH [10], Bursttracker [13], QUAD [56] and NAS [49] \\
\hline
GPAC video player & Pstream [12] \\
\hline
ExoPlayer & IncorporPRED [50] and QUAD [56] \\
\hline
Trace driven & QARC [47], Comyco [43] and ACAA [54] \\
\hline
\end{tabular}
\end{table}
in multiple encoding. These encoding rates are comparative to the large CDN provider like Hulu, YouTube and Netflix.

The testbed used to collect measurements in [126] is based on “MP4Client”, a multimedia player based on GPAC [123]. They utilised very well known animated videos like Elephant Dreams, Big Buck Bunny etc. Their files are obtained as 920x1080 YUV files.

Similarly the second dataset [126] is a trace of 4G dataset which is composed of key performance indicators (KPIs) from two major Irish cellular providers. They are collected with different mobility patterns like static, car, bus and train. It has a very diverse range of throughput from 0 to 173 Mbit/sec. These traces are generated from a well-known Android network monitoring applications. There are few limitations of this dataset first all of its samples are of 1sec duration. Also, there is no GPS information in this dataset. To supplement the limitations of the real dataset there is repository of synthetic dataset.

VI. Conclusion

In this paper, we surveyed different key techniques in the area of Internet video for wireless networks. It was observed that many approaches used cross layer communications on the clients to improve the re-buffering, quality switching and encoding related impairments of the mobile video. It is important to note that with the upcoming deployments of WiFi-6 and 5G new challenges will arise which require us to rethink the implementation of ABR algorithms to address these challenges.

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