OSCAR: An Optimized Stall-Cautious Adaptive Bitrate Streaming Algorithm For Mobile Networks

Ahmed H. Zahran
Jason Quinlan
Darijo Raca
Cormac J. Sreenan

Emir Halepovic
Rakesh K Sinha
Rittwik Jana
Vijay Gopalakrishnan

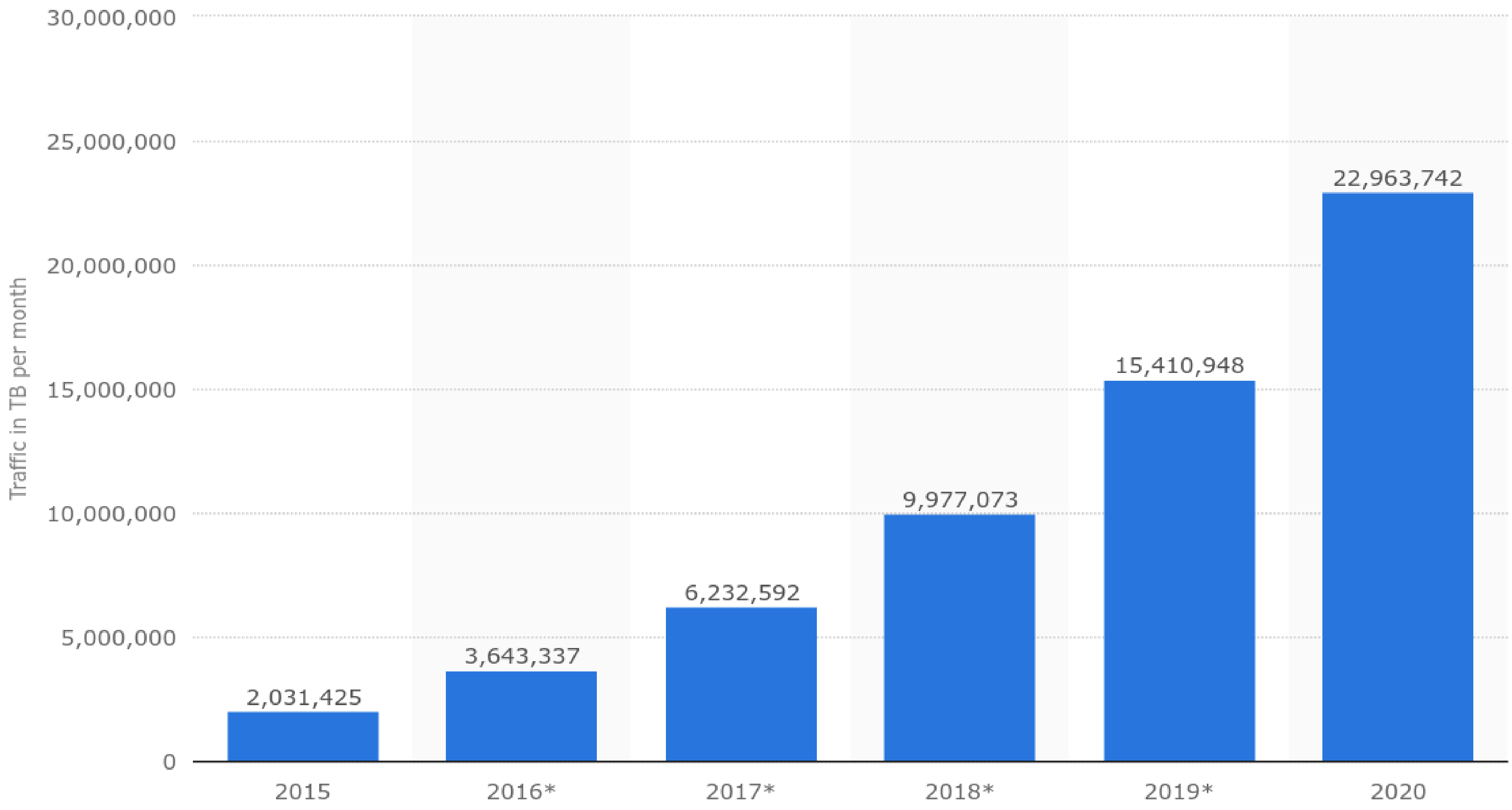
MoVid @ MMSYS 2016

This publication has emanated from research conducted with the financial support of Science Foundation Ireland (SFI) under Grant Number 13/IA/1892.

Outline

- ***Motivation & Challenges***
- Background & Related Work
- OSCAR Design
- Performance Evaluation
- Conclusions

Global Mobile Video Traffic

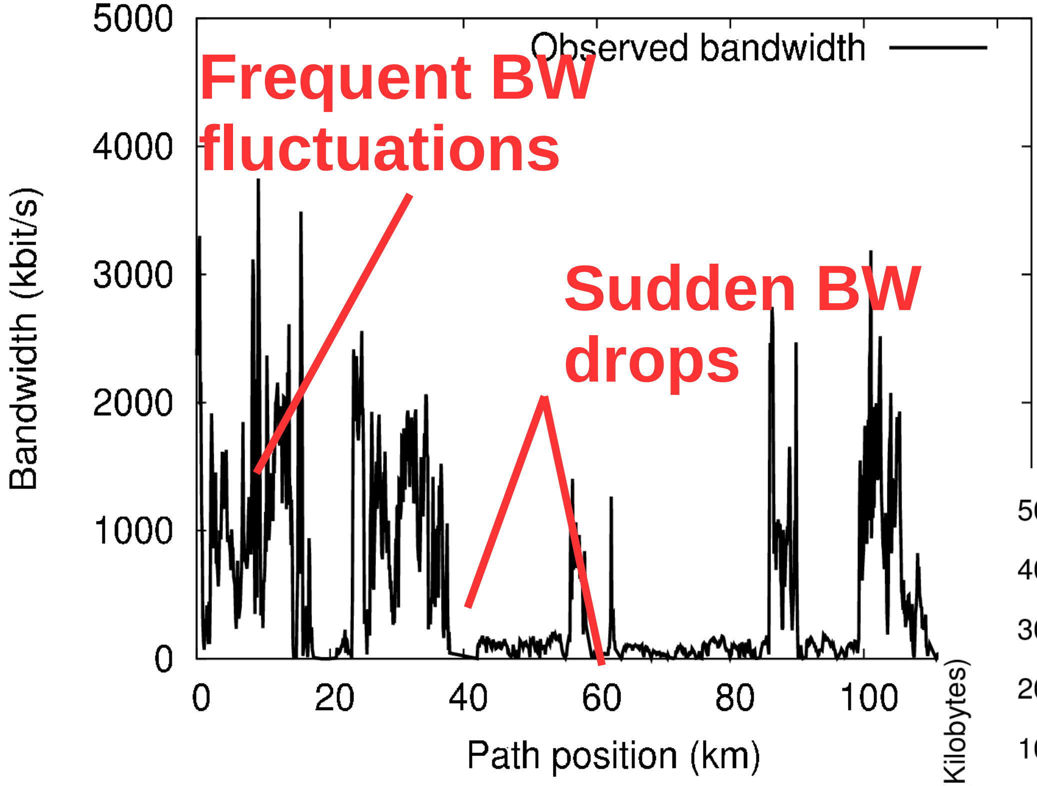


http://www.statista.com/statistics/252853/global-mobile-video-traffic-forecast/

Inherent System Challenge

MISL

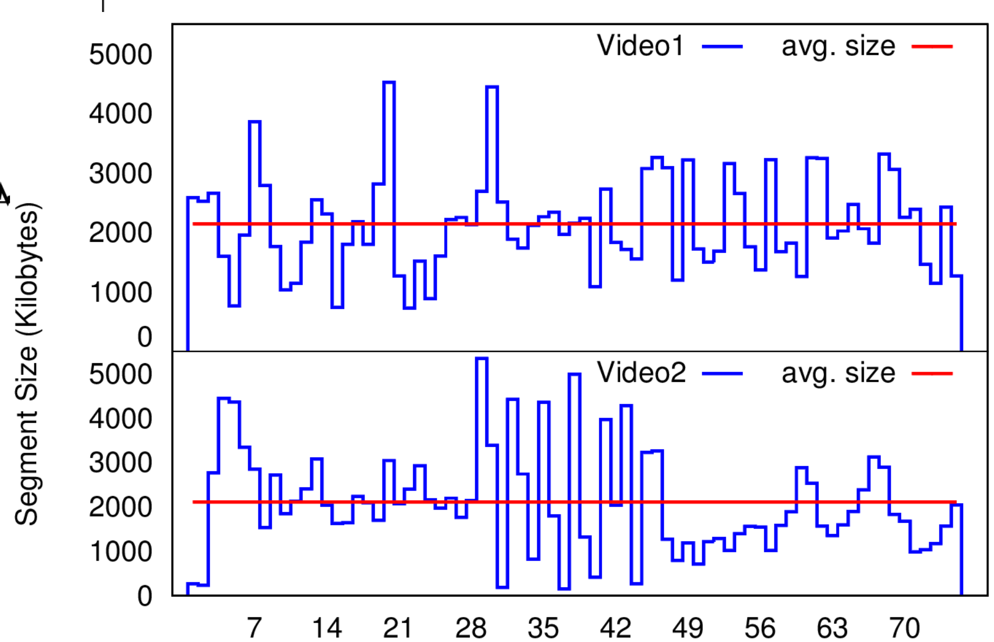
Highly Variable Bandwidth



http://home.ifi.uio.no/paalh/dataset/hsdpa-tcp-logs/

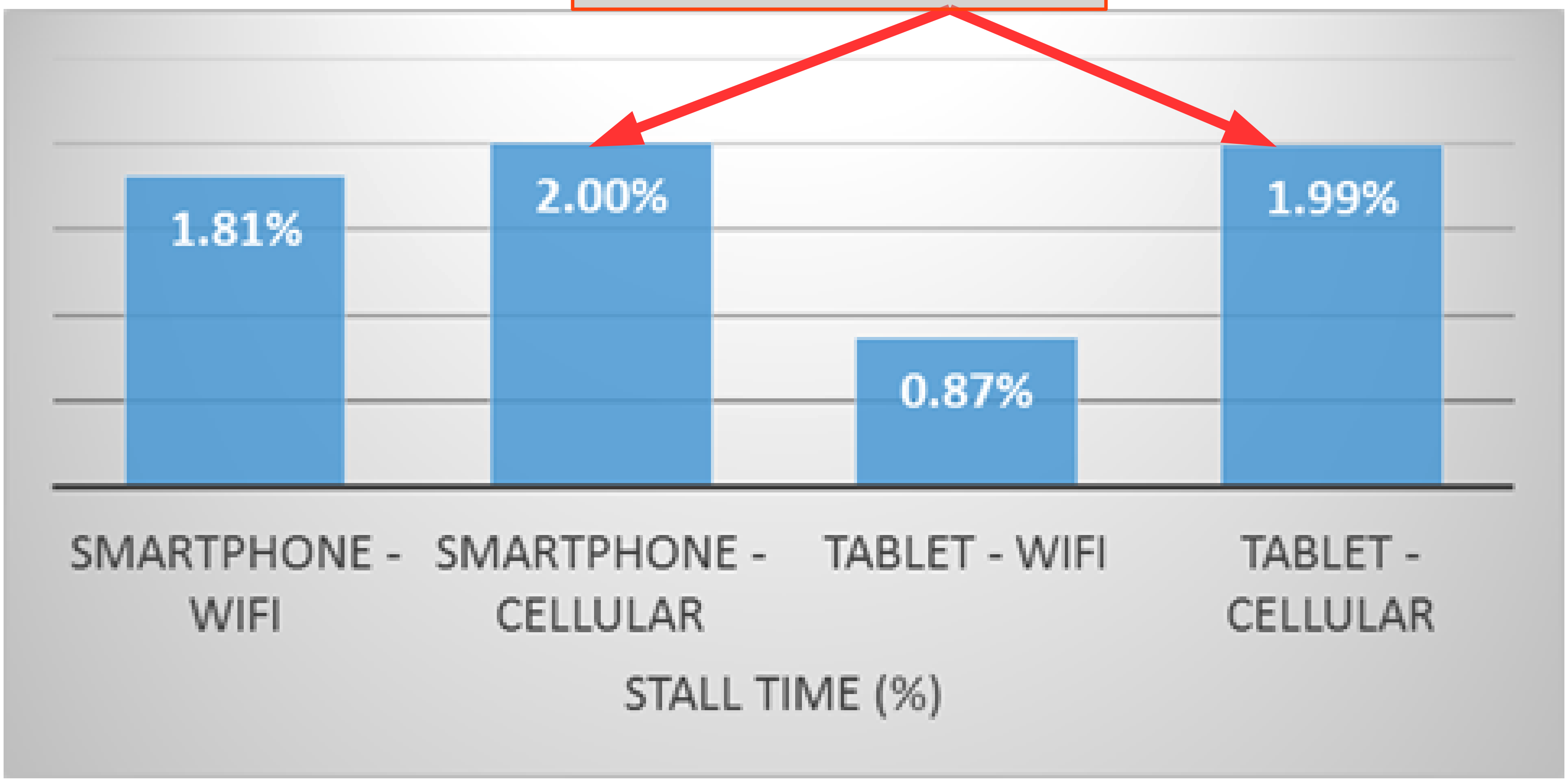
High Variability is an inherent feature

High Variable bitrate



Mobile Video Quality

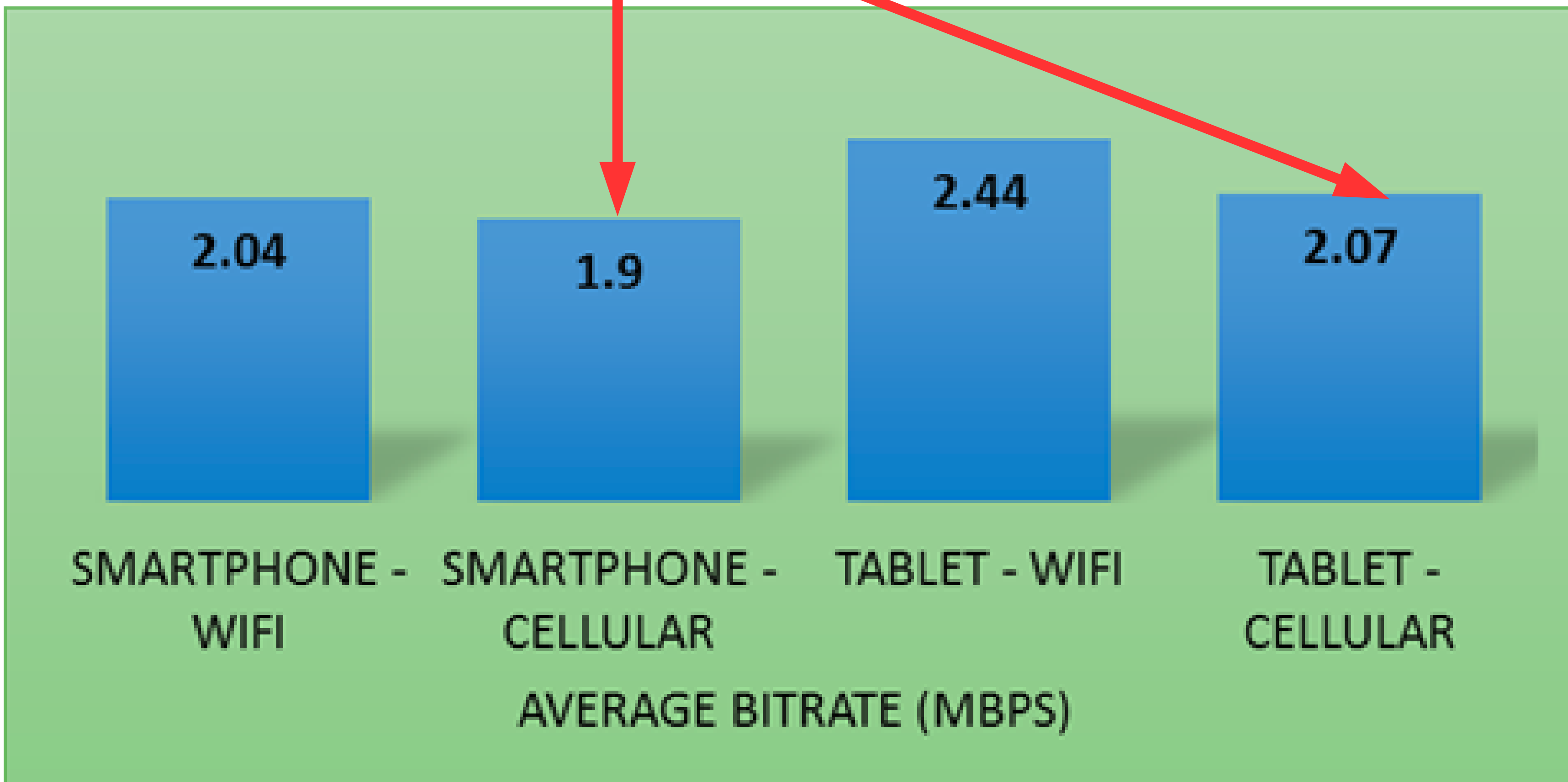
Video clients stall more in mobile networks



Source: Conviva Streaming Industry Data, Q1 2016 Report, http://www.conviva.com/streaming-industry-data/

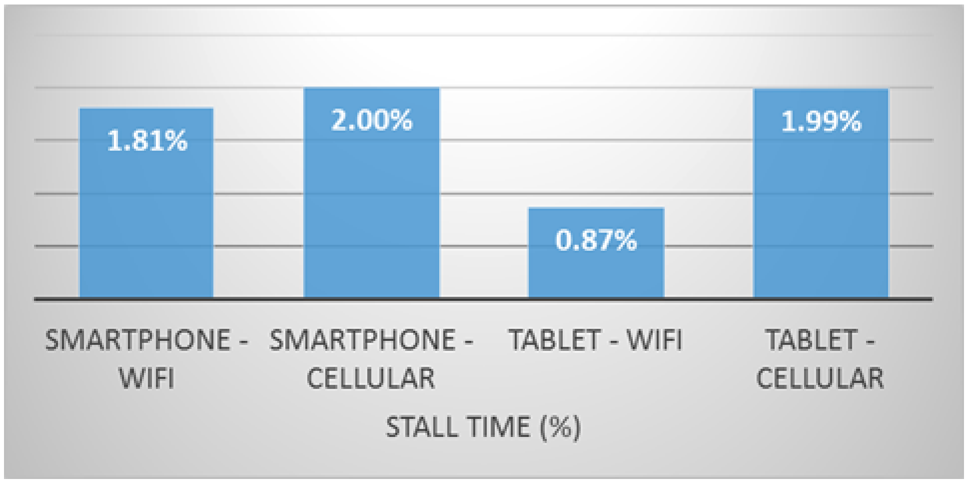
Mobile Video Quality

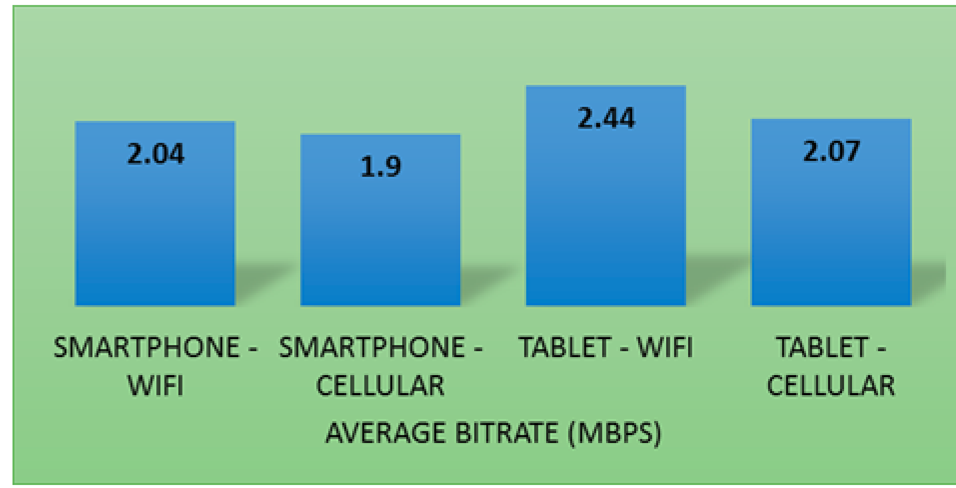
Video clients stream lower quality in mobile networks



Source: Conviva Streaming Industry Data, Q1 2016 Report, http://www.conviva.com/streaming-industry-data/

Mobile Video Quality



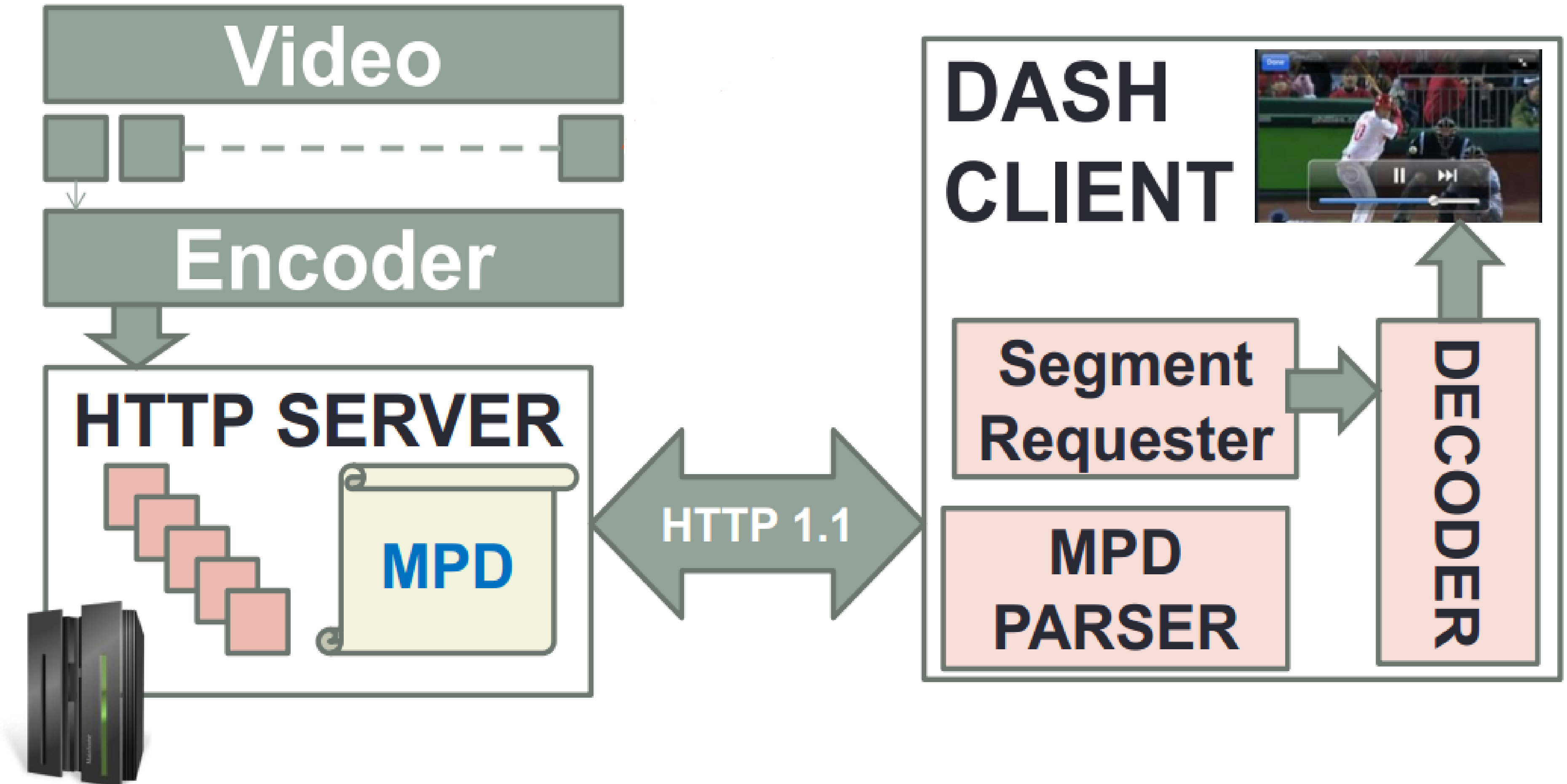


There is a need for advanced mobile video clients that optimally adapt to underlying operating conditions

Outline

- Motivation & Challenges
- ***Background & Related Work***
- OSCAR Design
- Performance Evaluation
- Conclusions

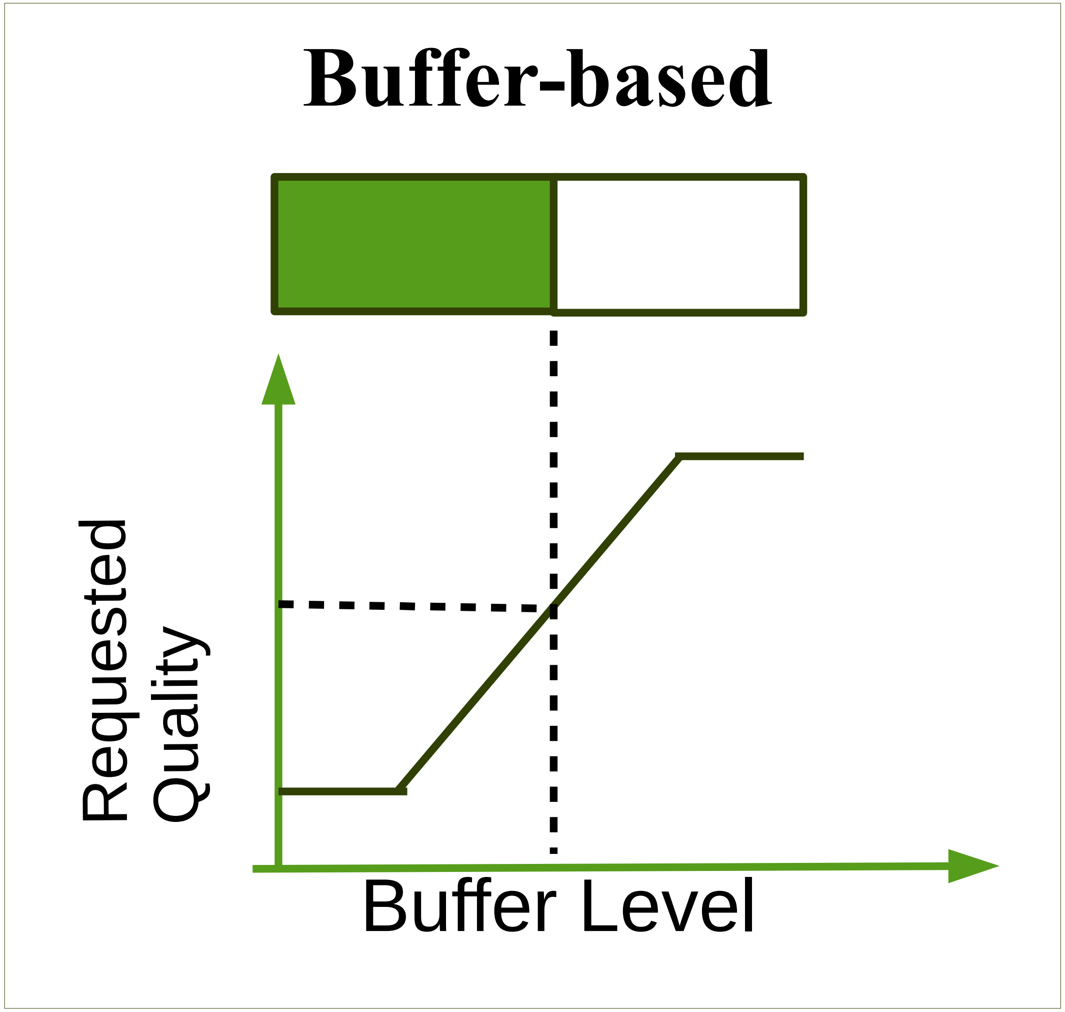
DASH Architecture



DASH client changes the video quality at segment border to adapt to changes in the operating conditions

DASH Adaptation Strategies(1/3)

MISL

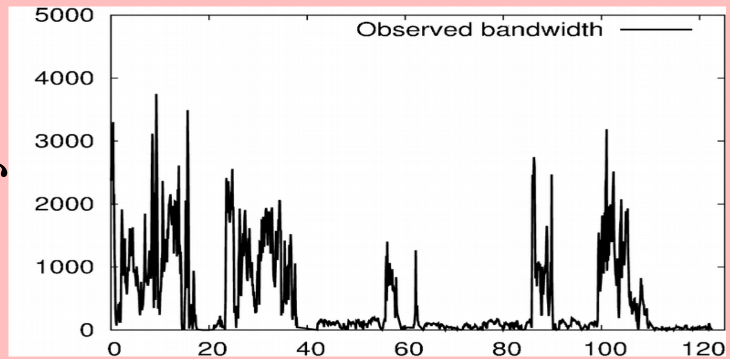


Example: BBA [9], Sigcomm 2014

DASH Adaptation Strategies(2/3)

Rate-based

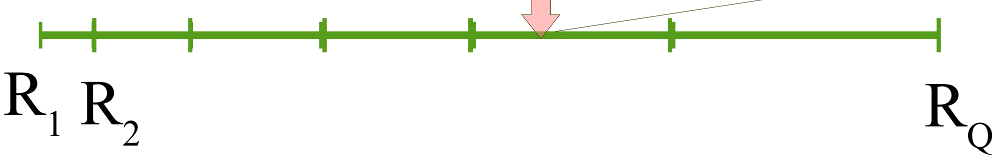
Delivery Rate



Time

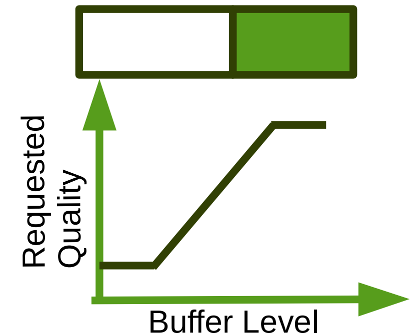
Throughput Estimator

Rate upper bound



Example: FESTIVE [9], CoNext'12

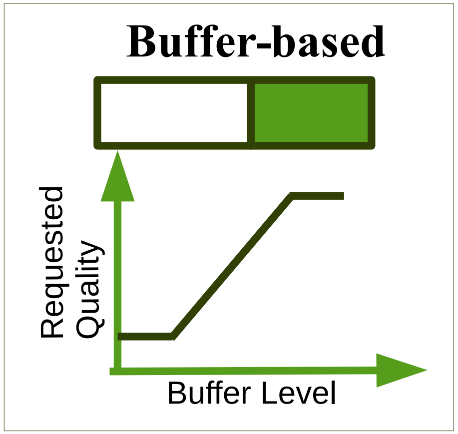
Buffer-based

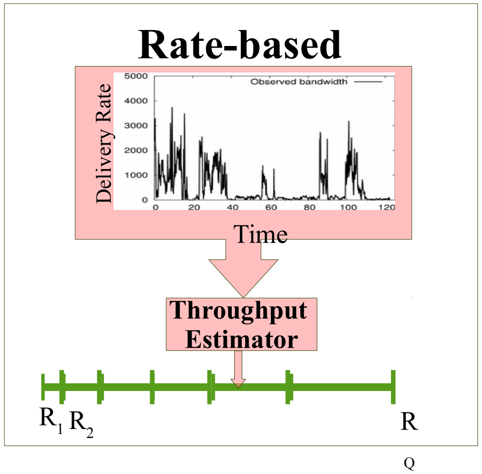


DASH Adaptation Strategies(3/3)

Hybrid Algorithms

- Integrates application and network states in their decision using different approaches
  - [5] uses Markov decision process for adaptation decision with the bandwidth modeled using a normal distribution whose parameters are estimated using Q-learning
  - [17] (Sigcomm 2015) formulates an optimization framework to maximise a QoE objective





Outline

- Motivation & Challenges
- Background & Related Work
- ***OSCAR Design***
- Performance Evaluation
- Conclusions

OSCAR Overview

- ***OSCAR optimizes the streaming visual quality subject to a constraint on the stall***
- ***OSCAR accommodates throughput variability by***
  - *Modeling the network throughput as a RV*
  - *Mandating a probabilistic constraint on the stall*
- ***OSCAR accommodates video rate variability by***
  - *Optimizing adaptation decision over a look-ahead window of future segments*

OSCAR Throughput Modeling

- We model throughput using Kumaraswamy distribution
  - A doubly-bounded generic two-parameter RV
  - Has an invertible cumulative distribution function (CDF)

$$F_{\varrho}(\rho) = 1 - (1 - \rho^{\kappa_1})^{\kappa_2}$$

Two shape parameters

- On the reception of every segment, throughput sample window is updated and new throughput parameters are estimated.
- Measured segment throughput samples are assigned exponentially decaying weights with the most recent sample having the highest weight.
- The parameters of Kumaraswamy distribution are estimated using the maximum likelihood method.

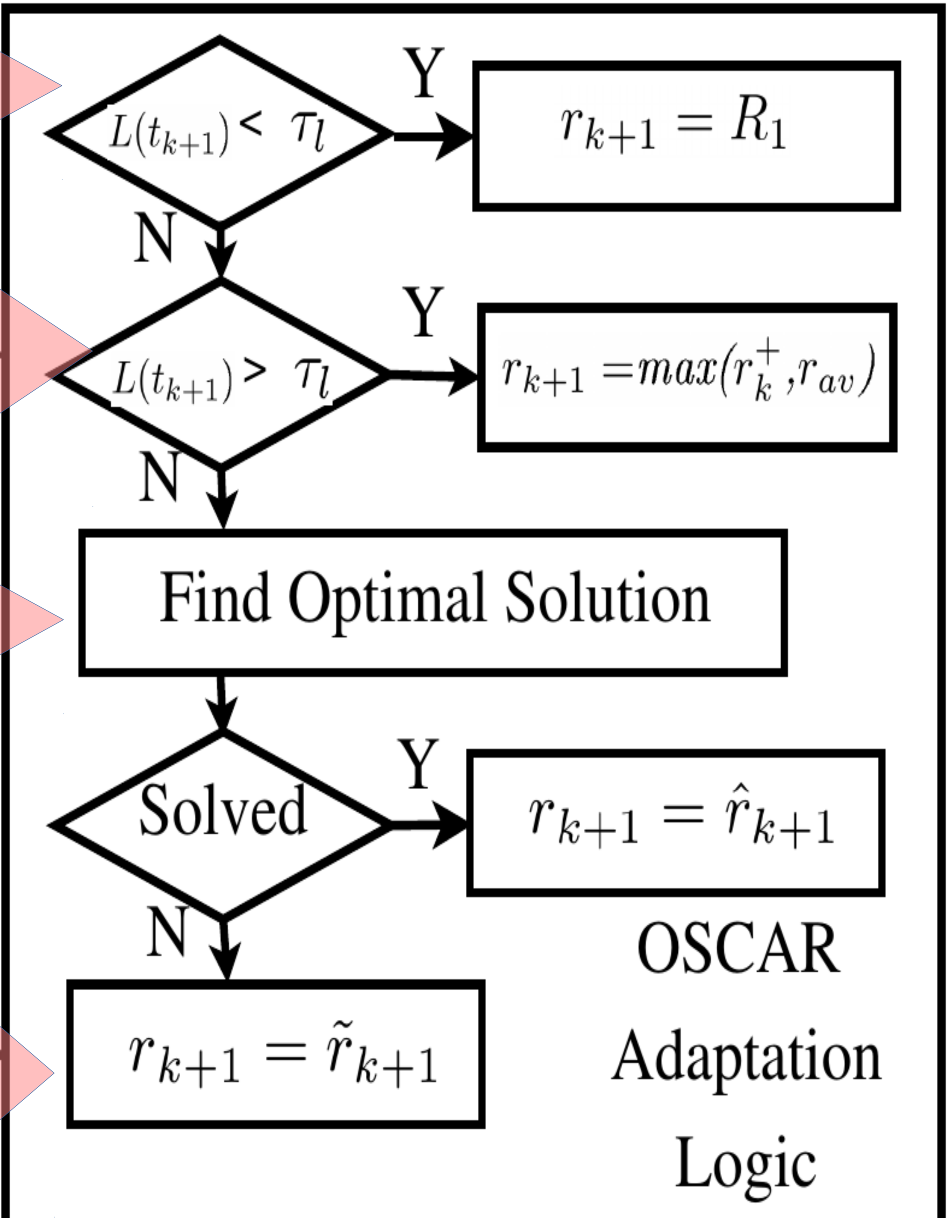
OSCAR Adaptation Logic

At low buffer levels, request the lowest quality

At high buffer levels, request the higher of next better quality or the highest quality bounded By the average throughput

Optimize quality selection in the intermediate region

If the problem is infeasible, select a fallback quality rate



OSCAR Optimization Model

Look-ahead window
Next W_V segments

Exponential video quality utility

Switching penalty encouraging incremental changes

$$\max_{r_n} \sum_{n=k+1}^{k+W_V} U(r_n) - \alpha P(r_n)$$

St.

C1: Prob (segment stall) < γ , $\forall$ look-ahead segments

C2: No quality oscillations in the look-ahead window

OSCAR Fallback Policy

- Identify a ***rate bound*** as the minimum rate in the throughput samples
- Select a best quality rate that is
  - Lower than the rate bound
  - At most n_b levels higher than the current quality

Outline

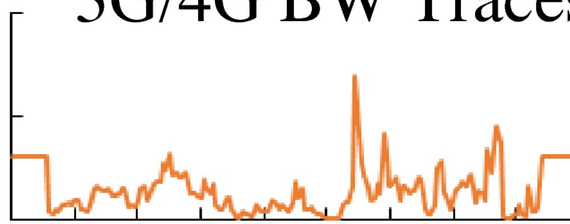
- Motivation & Challenges
- Background & Related Work
- OSCAR Design
- ***Performance Evaluation***
- Conclusions

Evaluation Setup

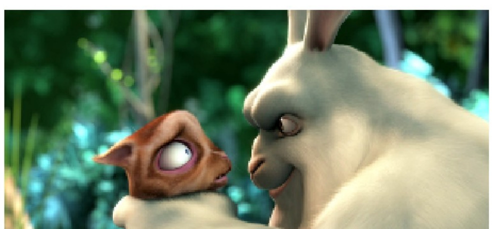
- Performance evaluation is performed using NS3
- A client connects to the server using a single TCP [new Reno] connection

DASH Client Module

3G/4G BW Traces



DASH Server Module



(c) copyright 2008, Blender Foundation
www.bigbuckbunny.org

GET Request

GET Response

Video traces

- 60 Sec buffer
- 8 sec initial buffering
- 4 sec rebuffering

- 54 3G traces [15]
- 23 4G traces [18]

- data set [14]
- 6 movies
- 4-sec segments

Performance Evaluation

OSCAR performance is compared against

ELASTIC [6]	**BBA** [8]	**MPC** [17]
PI controller with a harmonic mean throughput estimator.	buffer-based algorithm	Adaptation decision is based on optimizing a QoE objective

– OSCAR and MPC optimization programs are solved using Lindo Solver, tuned to provide global optimal solution.

- **Key performance metrics**

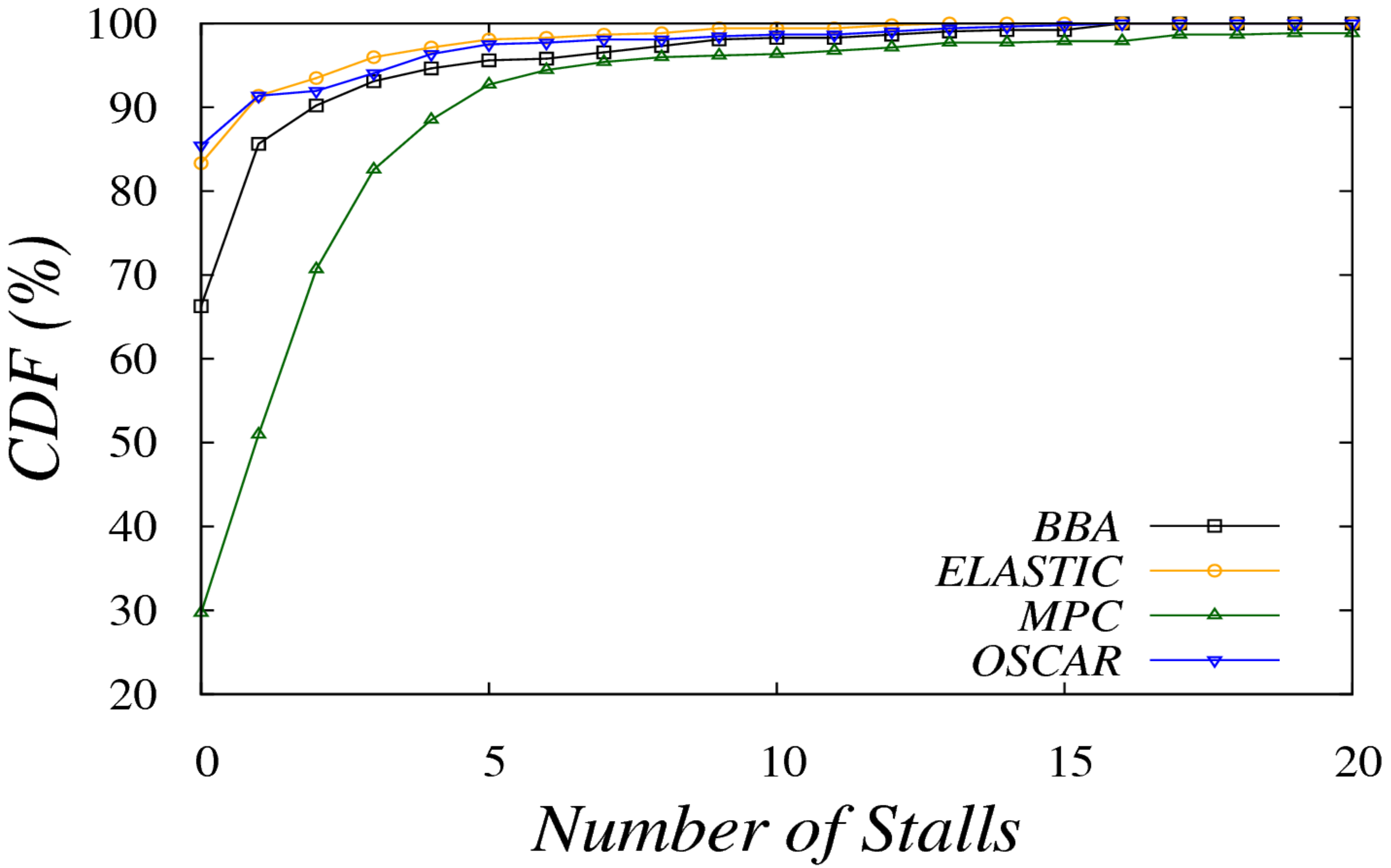
- r_{av} The average received quality rate per session
- n_{st} :The average number of stalls per session
- t_{st} The average stall duration per session
- n_{sw} The average number of switches per session
- l_{sw}: The average switching level
- ζ: The average network bandwidth utilization per session.

Average performance metrics

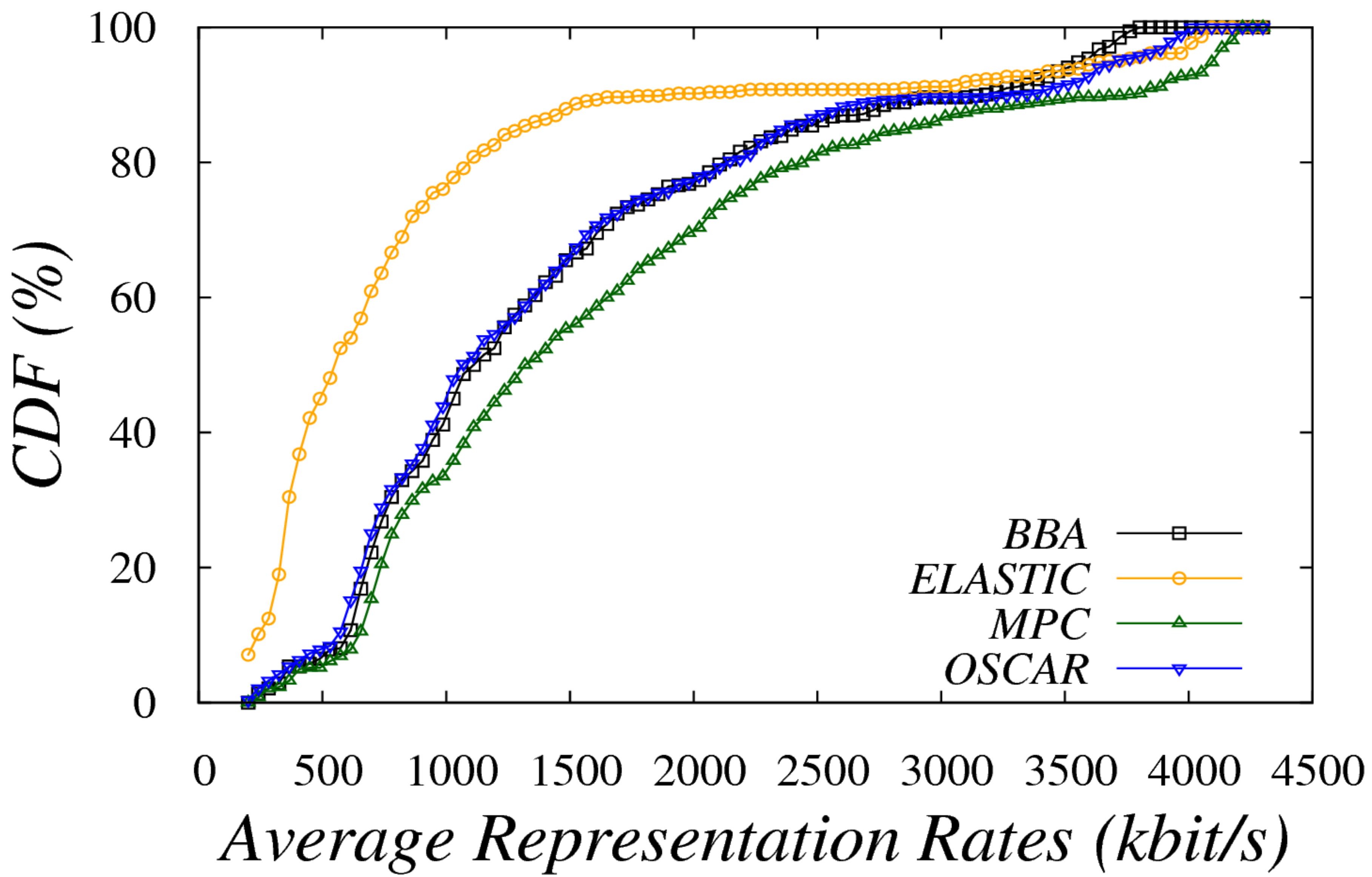
- **OSCAR strikes a good balance between achieving high video quality and low number of stalls**
  - OSCAR achieves close average rate to BBA with 40% less stalls.
  - OSCAR achieves 1.6x average rate of ELASTIC with only 16% stalls
  - OSCAR attain these gains through performing agile switching.

Algorithm	n_{st}	t_{st}	r_{av}	n_{sw}	l_{sw}	ζ
BBA	0.95	5.59	1467	24.74	1.71	0.64
ELASTIC	0.47	2.25	935	13.21	1.24	0.44
MPC	2.30	14.16	1699	22.93	2.07	0.68
OSCAR	0.56	4.33	1461	27.7	1.67	0.65

Stall Dynamics CDF



Quality Rate CDF



Impact of Variability (1/2)

- Split traces into low variability and high variability traces based on the coefficient of variation of the throughput trace (0.5 threshold)
  - 25 traces (150 video trace combination) with low variability
  - 62 traces (372 video trace combination) with high variability
- **For highly variable link conditions, OSCAR maintains its high quality performance and low number of stalls**

Algorithm	n_{st}	t_{st}	r_{av}	n_{sw}	l_{sw}	ζ
BBA	1.07	7.136	1419	24.89	1.73	0.69
ELASTIC	0.47	2.62	851	13.84	1.24	0.46
MPC	2.74	18.20	1656	23.81	1.83	0.73
OSCAR	0.61	5.54	1398	29.36	1.66	0.69

Impact of Variability (1/2)

For more stable link conditions, OSCAR achieves the least stalls while providing high quality rate

Algorithm	n_{st}	t_{st}	r_{av}	n_{sw}	l_{sw}	ζ
BBA	0.63	1.77	1588	24.37	1.66	0.55
ELASTIC	0.46	1.35	1145	11.65	1.23	0.42
MPC	1.34	4.46	1814	20.00	2.67	0.59
OSCAR	0.44	1.35	1620	23.7	1.71	0.58

Outline

- Motivation & Challenges
- Background & Related Work
- OSCAR Design
- Performance Evaluation
- ***Conclusions***

Conclusions

- The design of advanced adaptation algorithms is crucial for the success of mobile video
- OSCAR represents a novel optimized stall cautious algorithm that optimises the visual quality subject to constraint on stalls
- OSCAR accommodates throughput variability by modeling the throughput as a random variable
- OSCAR accommodates video variability by optimizing over a short-term look-ahead window
- OSCAR achieves high average quality rate with a small number of stalls while performing agile switching
- We are currently developing light weight heuristics that are based on OSCAR

Questions

Ahmed H. Zahran

a.zahran@cs.ucc.ie

OSCAR Optimization Model

$$\max_{r_n} \sum_{n=k+1}^{k+W_V} U(r_n) - \alpha P(r_n)$$

$$U(r_n) = 1 - exp(-r_n/(R_Q\overline{r}))$$

Exponential utility to capture the quality improvement saturation towards high quality rates

$$P(r_n) = \left(\frac{r_n - r_{n-1}}{R_Q}\right)^2$$

Prefers multiple smaller quality shifts in comparison to fewer large changes

OSCAR Optimization Model

$$\max_{r_n} \sum_{n=k+1}^{k+W_V} U(r_n) - \alpha P(r_n)$$

$$\text{s.t.} \sum_{i=k+1}^{n} S_{r_n}/D_n < F_{\varrho}^{-1}(1\text{-}\gamma)\ \forall \text{n=k+1,...,k+}W_V$$

Mandates an upper bound on stall probability for all segments in the look ahead window

AT&T

OSCAR Optimization Model

$$\max_{r_n} \sum_{n=k+1}^{k+W_V} U(r_n) - \alpha P(r_n)$$

$$\text{s.t.} \sum_{i=k+1}^{n} S_{r_n}/D_n < F_{\varrho}^{-1}(1\text{-}\gamma) \ \forall \text{n=k+1,...,k+}W_V$$

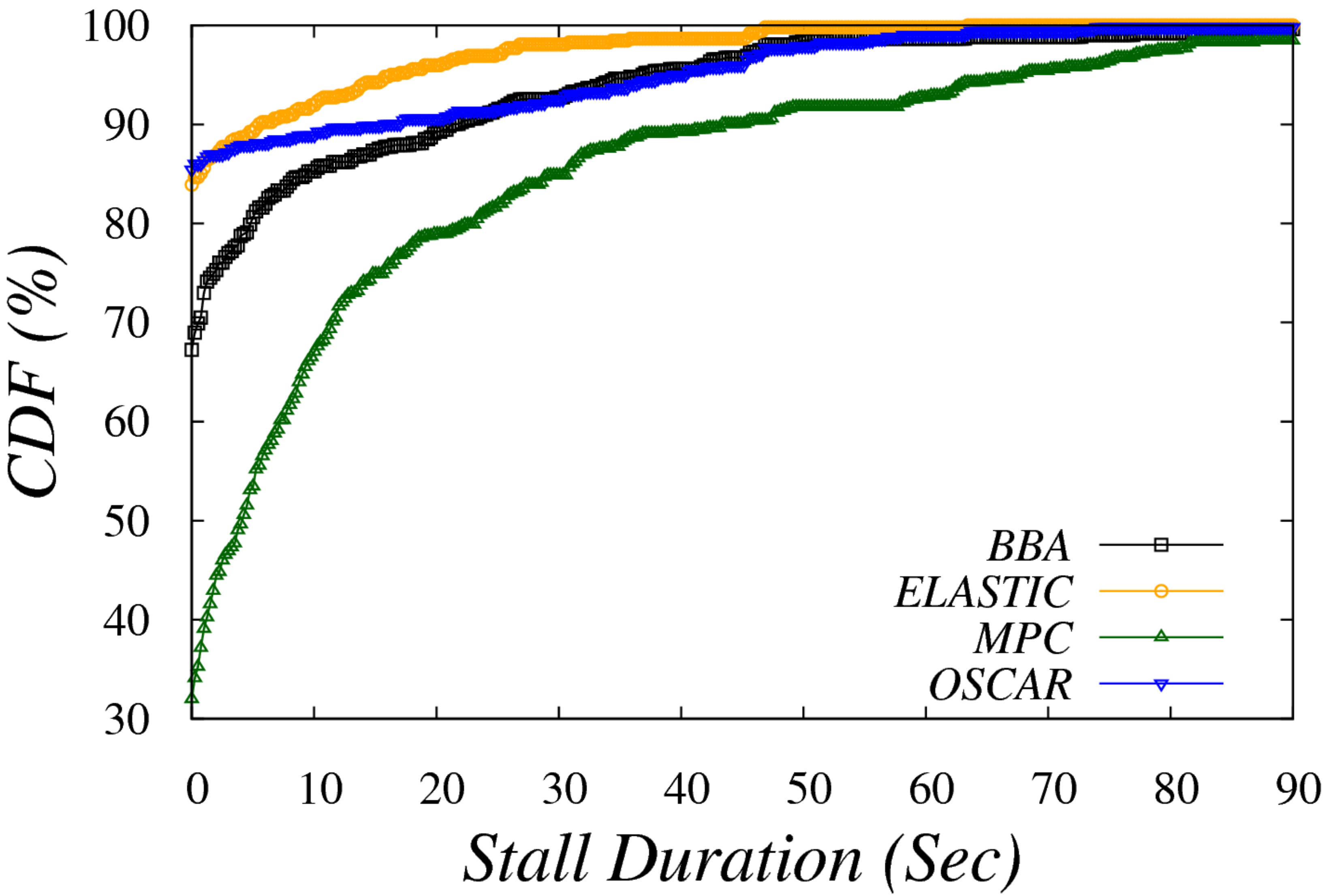
$$\sum_{n=k+1}^{k+W_V} | \, r_n - r_{n-1} \, | = |r_{k+N} - r_k|$$

$$r_n \in \{R_1, ..., R_Q\} \ \forall n \in \{k+1, .., k+W_V\}$$

Mandates monotonic quality changes in the look ahead window

AT&T

Stall Duration CDF



Switching Dynamics