

# EnDASH-A Mobility Adapted Energy Efficient ABR Video Streaming for Cellular Networks

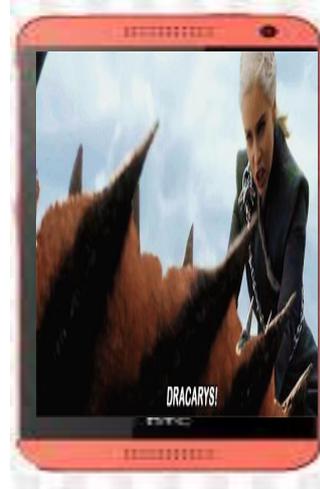
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# A Typical Scenario





# Pretext

- Online video streaming - most popular mode of entertainment
- Online mobile video traffic - 71% in total mobile traffic volume
- Video experience over mobile Internet negatively affected by
  - Poor mobile connection quality
  - Fall back to legacy networks
  - Excessive Battery Drainage - increases under mobility
    - Incessant network scanning
    - Handovers

**Our proposed solution: EnDASH - A mobility adapted energy efficient video streaming algorithm for cellular networks**

# UE Energy Consumption Model - 4G LTE

- Understanding the energy/power consumption model and RRC state machine of 4G LTE
- Radio Resource Control (RRC) – Radio Resources are time-frequency resources in LTE

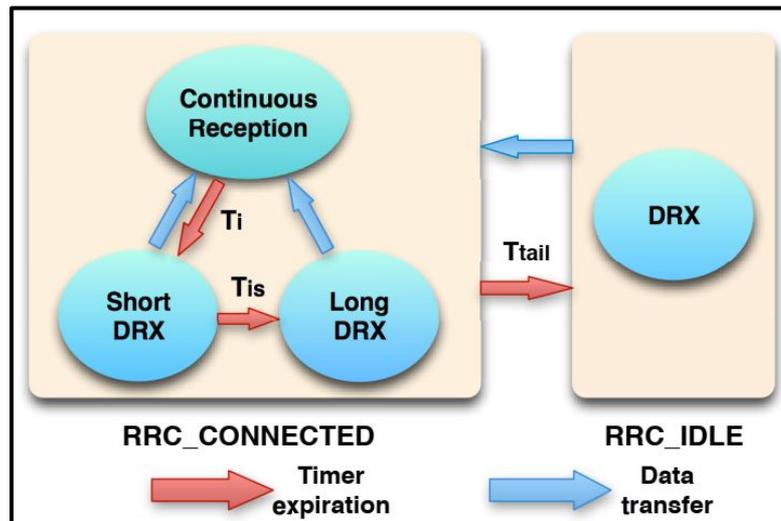


Fig: RRC state machine of 4G LTE<sup>1</sup>

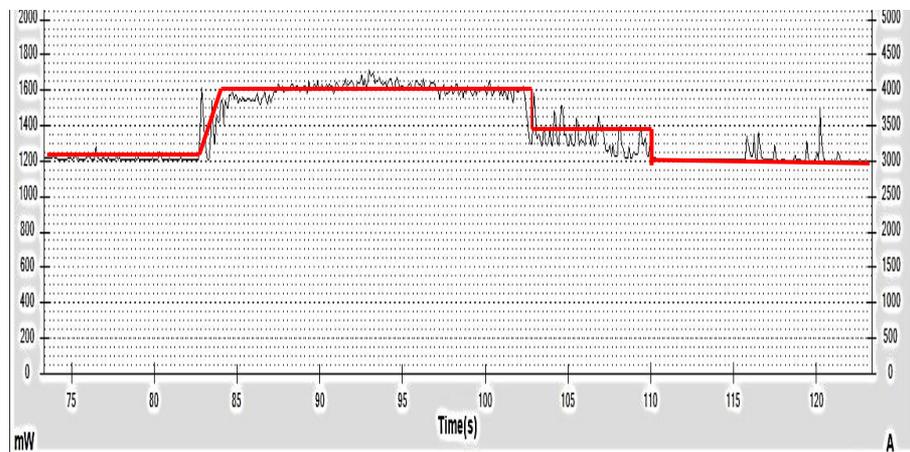


Fig: Measured Power data for downloading a 1Mb file

## **Our Goal :** Energy optimization at end devices based on Intelligent Traffic Scheduling

1. Profiling the end user device energy consumption as a function of fluctuations in the network conditions
2. Understanding the correlation between traffic generation pattern and energy consumption

PILOT STUDY: Extensive throughput and energy measurements based carried out

- In different mobility conditions - Stationary, slow-moving electric vehicle, cars in the highway, cities,
- In different geographic locations - Kharagpur, Kolkata, Guwahati, Bangalore, Malda

# Experimental Set-up



*A total of 39662 seconds of valid data point, collected over a period of 11 months*

- **Equipment Used:**

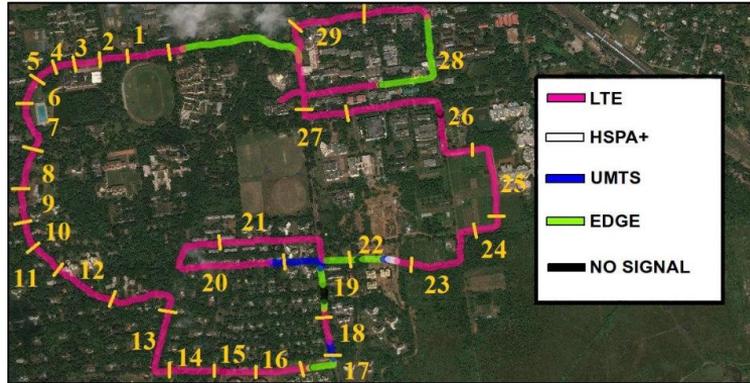
- Monsoon Solutions Power Monitors
- Smartphones - Moto G5, Micromax Canvas Infinity

- **Service Providers** - Airtel, JIO, Vodafone

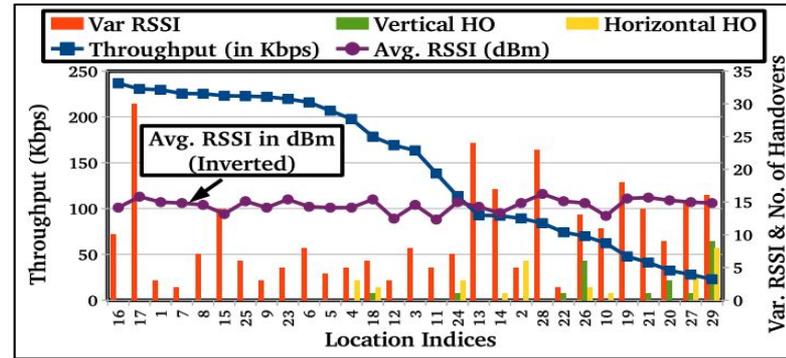
- **Software Set-up:**

- Network data collected - NetMonitor Lite app
- GPS location and Speed - GPS logger
- File download throughput - tcpdump
- HTTP client-server program set up using smartphone and Amazon Web server
- Video Streaming Apps - YouTube, Netflix, Amazon Prime, SonyLiv

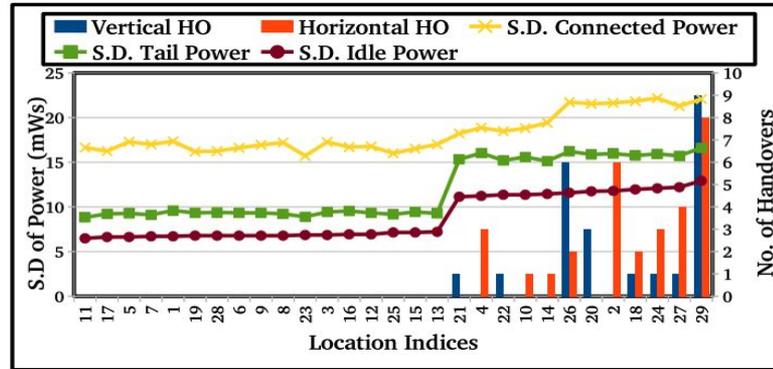
# Observations



**Fig: Trajectory of Moto G5 connected to Airtel inside IIT Kharagpur campus. Networks : 4G, HSPA, UMTS, EDGE.**



**Fig: Sorted thpt across 29 stretches. Variations with RSSI, Vertical and Horizontal Handovers**



**Fig: Variance of Power Consumption with RSSI, and Vertical and Horizontal Handovers**

*Takeaway 1: The wireless network condition is best quantified by throughput which depends significantly on phenomena such as handovers and not on received signal quality alone.*

# Observations

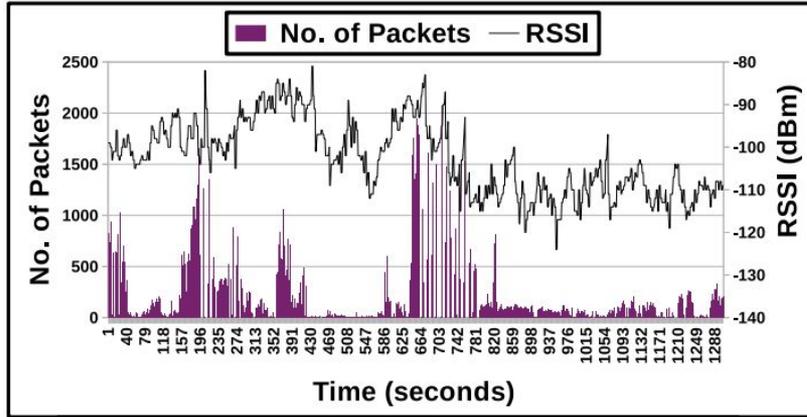


Fig: Packet trace of a 360p Youtube video download with the temporal variation in the RSSI during the download

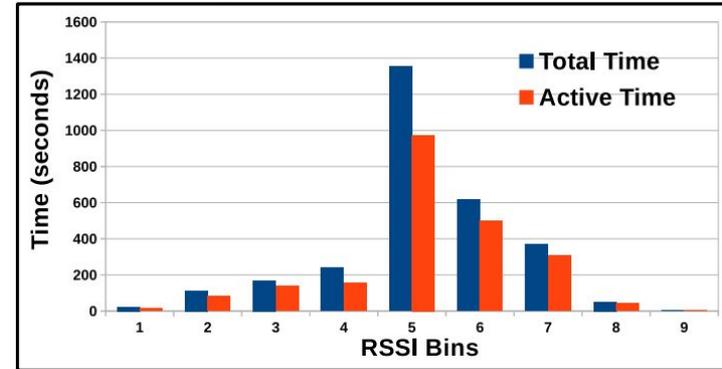


Fig: Total time spent in each RSSI bin and the active time in each bin

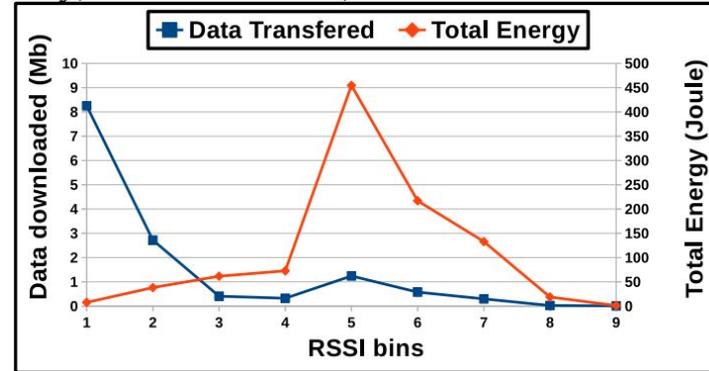


Fig: Amount of data downloaded and Power Consumption in each RSSI Bin

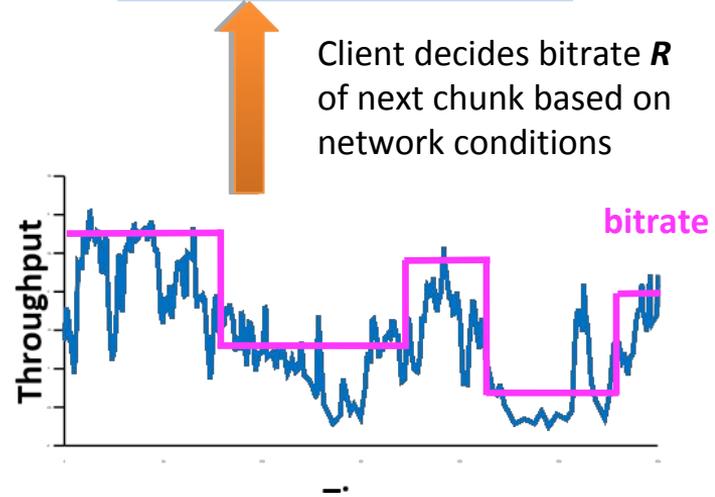
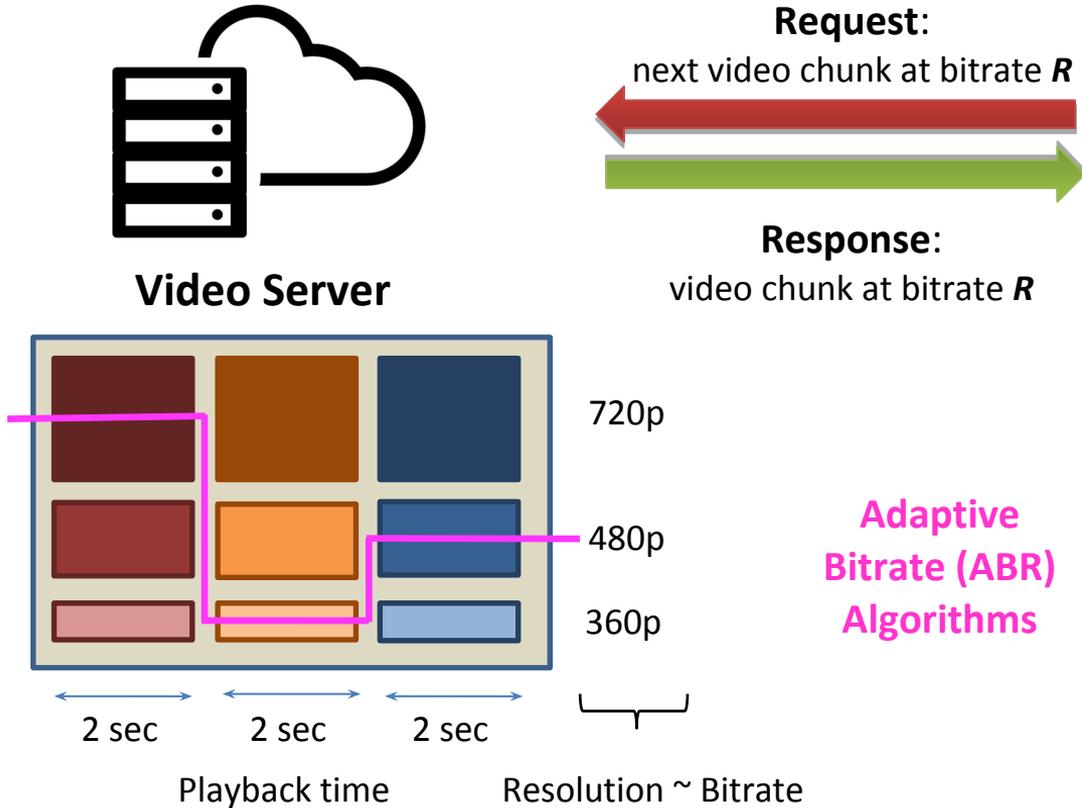
Takeaway 2: The current protocol of video download attributes higher weightage to the playback-buffer length than the user's instantaneous received signal strength or throughput.

# EnDASH - To improve energy efficiency



- Fetching data during good channel conditions can reduce total download time
- Reduced dwell time in CONNECTED RRC state - less power consumed.

# DASH - Bitrate Adaptation





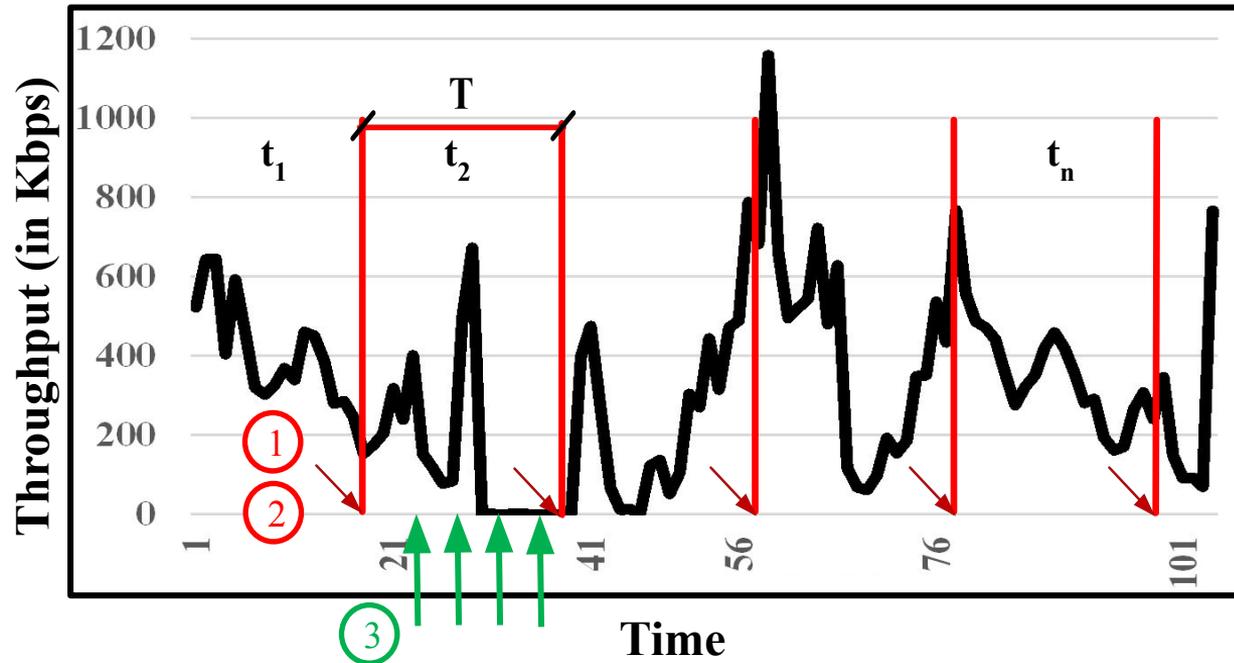
- Fetching data during good channel conditions can reduce total download time
- Reduced dwell time in CONNECTED RRC state - less power consumed.

To be achieved through the following:

- Tuning buffer length to the perceived throughput
  - **Advantage:** Allows downloading higher volume of video chunks during good channel conditions while in motion
- Adapting the bitrate to the perceived throughput
  - **Advantage:** Unhindered Quality of Experience (QoE)

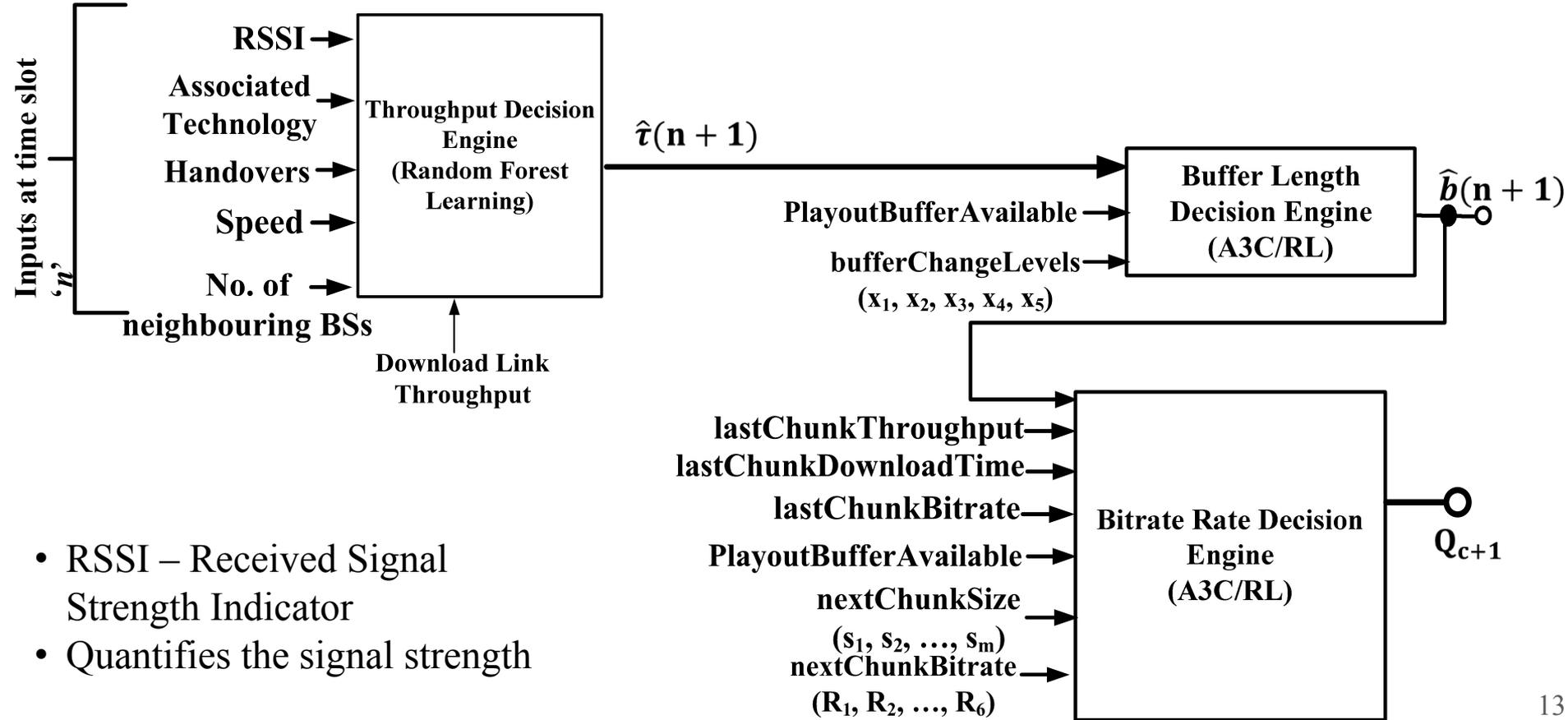
**USP of EnDASH: accounts for vertical handovers or connection to different network technologies.**

# How EnDASH works?



- ① Predict average throughput at time slot  $n+1$ ,  $\hat{\tau}(n+1) = \mathcal{F}(\tau(n))$
- ② Predict play-out buffer length at time slot  $n+1$ ,  $\hat{b}(n+1) = \mathcal{F}(\hat{\tau}(n+1))$
- ③ Predict Next Chunk Quality as a function of  $\hat{b}(n+1)$

# The EnDASH flow



- RSSI – Received Signal Strength Indicator
- Quantifies the signal strength

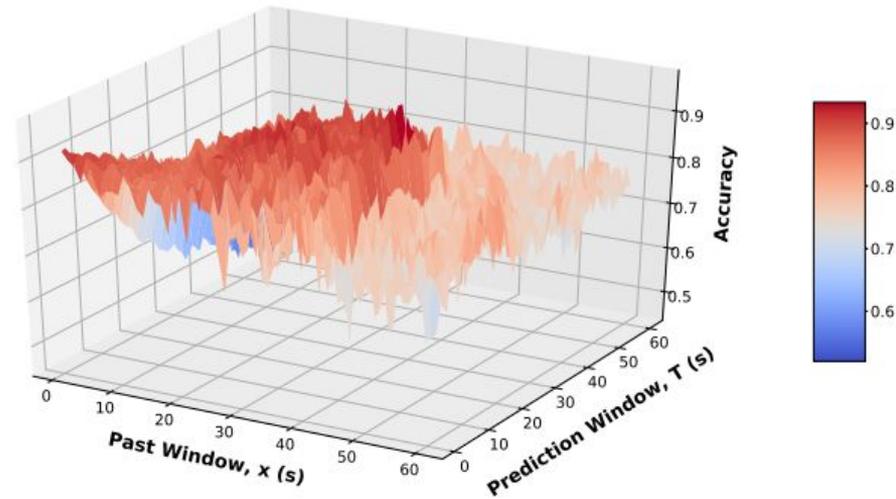


# Throughput Prediction Algorithm

- A supervised learning algorithm - Random Forest Learning
  - Two phases: Training and Test
  - Train-Test split: 70-30
- Historical information of previous 'x' seconds of various radio related parameters used to predict the average throughput experienced by a user in the next T seconds.
  - Represented as  $P_x F_T$ .
- Data Processing:
  - Each parameter a random quantity;
  - Instead of feeding entire data statistically important metrics fed
  - Derive quantities like Mean, median, 25<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup> percentiles
- Random Forest Regressor: 100 Estimators
- Features: RSSI, Network Type, Base Station Id, Number and Type of neighbouring BSs

# Throughput Prediction - Results

Dataset	Accuracy	Mean cross-validation accuracy	Variance	Feature with maximum feature importance	Value of maximum feature importance
Kharagpur	95.96 % (8780 training samples & 2196 test samples)	0.96	5.39E-05	Past 90 <sup>th</sup> percentile throughput	0.6



# Buffer Length Selection RL Model



Agent

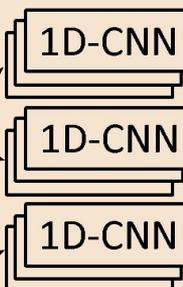
Reward

$$\bar{E}_{\text{bufflen}} = w_1 \cdot (|E_{\text{EnDASH}_t} - E_{\text{old}_t}|) + w_2 \cdot QoE$$

State  $s_t$

Predicted Throughput  $\hat{b}_n$

Current Available Buffer  $b_t$



+2  
+1  
0  
-1  
-2

Action  $a_t$

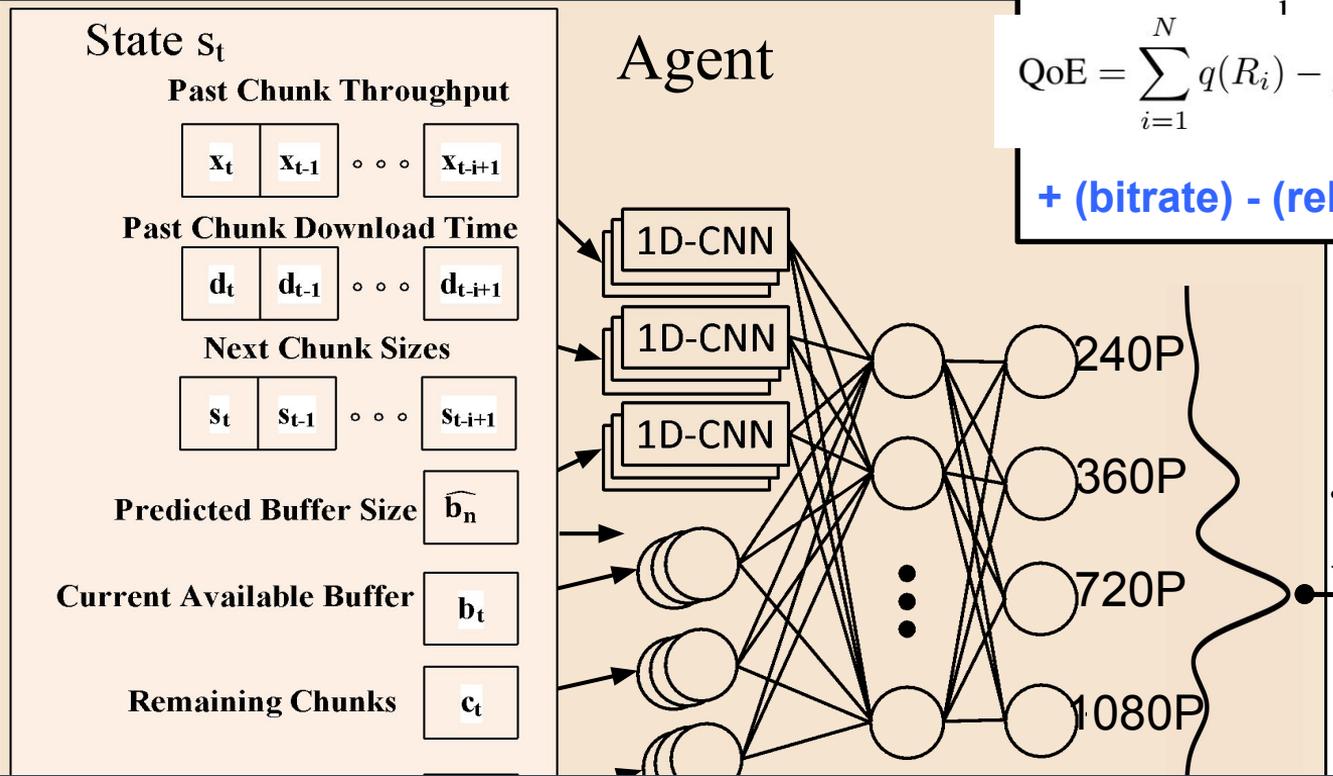


# Bitrate Selection RL Model

**Reward  $r_i$**

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

**+ (bitrate) - (rebuffering) - (smoothness)**



**We Leverage Pensieve [SIGCOMM'17] for the Bitrate Selection Model**



## Trace Driven Evaluation: For Throughput Prediction

- **Dataset:** Dataset consisting of 148 traces on throughput and power consumption
- **Duration:** Trace length varies between 34 seconds to 3298 seconds
- **Formatting:** Formatted to be compatible with MahiMahi Network Emulation Tool

## Training the buffer length and bitrate selection models

- **57 DASH-ified videos used, with a total duration of 45 hours**

## Throughput Prediction

- **Historical Window Size – 30 seconds**
- **Future Window Size – 30 seconds**

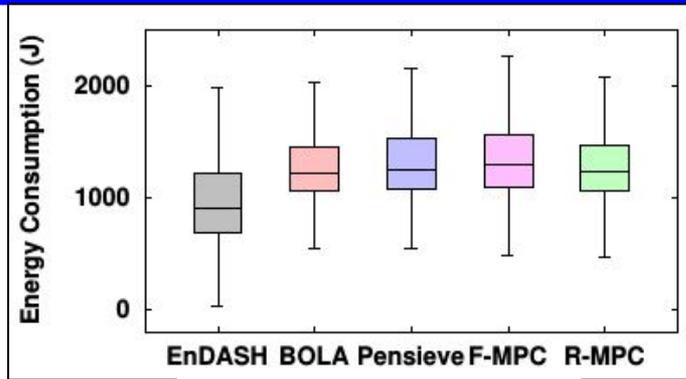
**How Does EnDASH Perform?**



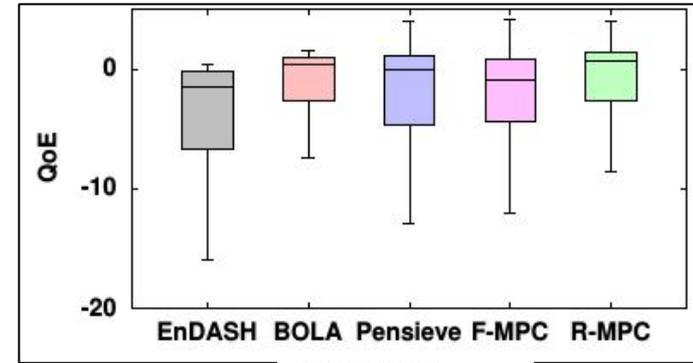
- **Rate-based:** pick bitrate based on predicted throughput  
**FESTIVE** [CoNEXT'12], **PANDA** [JSAC'14], **CS2P** [SIGCOMM'16]
- **Buffer-based:** pick bitrate based on buffer occupancy  
**BBA** [SIGCOMM'14], **BOLA** [INFOCOM'16]
- **Hybrid:** use both throughput prediction & buffer occupancy  
**PBA** [HotMobile'15]
- **QoE-metric based:** optimization problem to maximize QoE metric  
**MPC** [SIGCOMM'15], **Pensieve** [SIGCOMM'17]

The Baseline Algorithms used in the work highlighted.

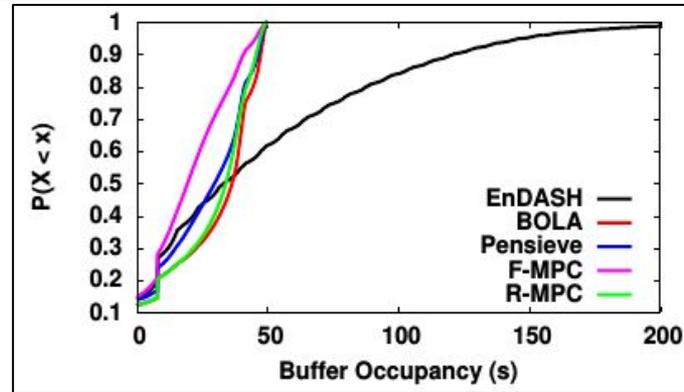
# Energy Consumption and QoE



(a) Energy Consumption



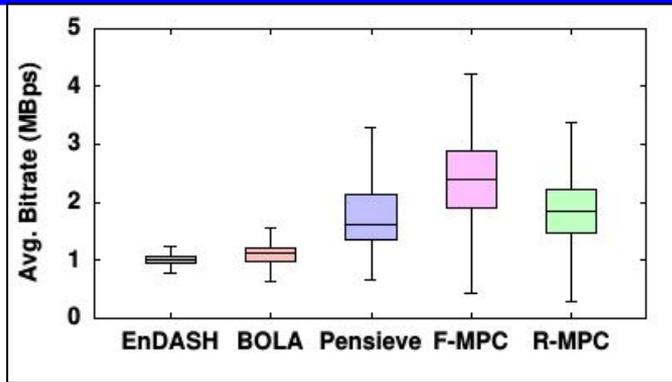
(b) QoE score



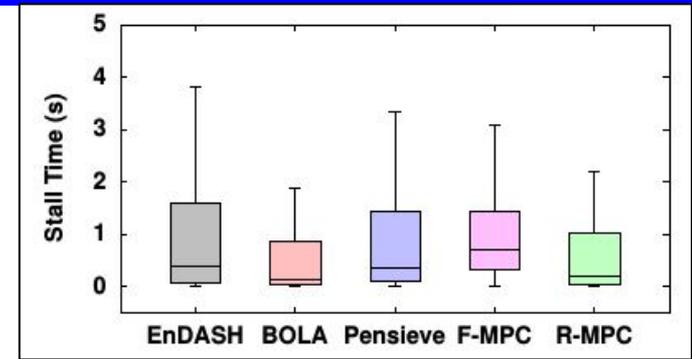
(c) CDF of buffer length of different algorithms

Fig: Performance comparison of EnDASH with baseline ABR streaming algorithms, BOLA [11], Pensieve [10], Fast MPC [13], Robust MPC [13]

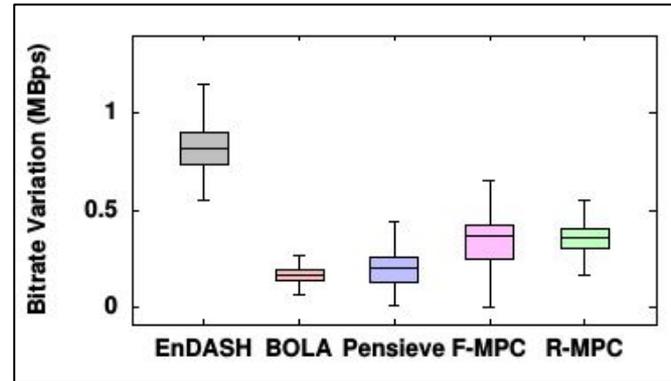
# Individual QoE components



(a) Avg. Bitrates in Kbps



(b) Stall Time per segment (in secs)



(c) Bitrate Variation

Fig: Comparison of different components of QoE score (average bitrate, stall time, smoothness) of EnDASH with baseline ABR streaming algorithms, BOLA [11], Pensieve [10], Fast MPC [13], Robust MPC [13]

# Results

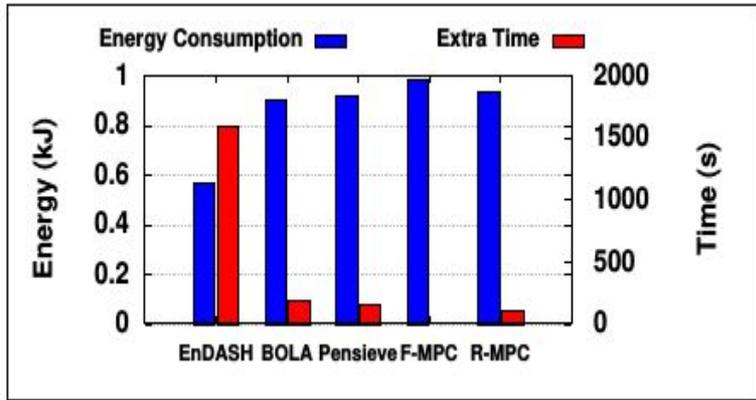
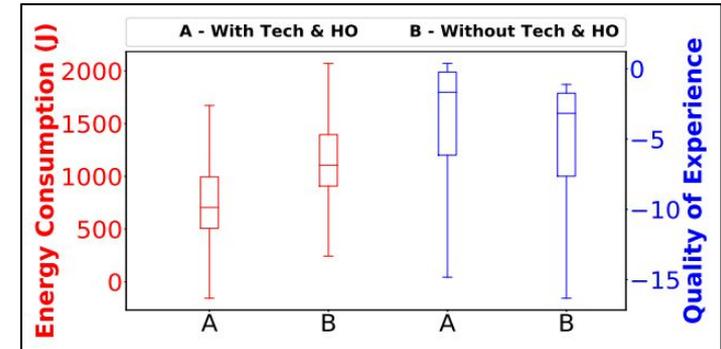


Fig. Energy Consumption and Extra Playtime obtained w.r.t. Fast MPC, which has the highest energy consumption

Fig: Impact of considering associated technology and vertical handovers (HOs) on EnDASH; for  $P_{30} F_{30}$





- What we have:
  - An energy efficient mobility adapted video streaming algorithm - EnDASH
  - Saves energy with some compromise in QoE and also in memory usage in terms of increased buffer length.
  - Offers nearly 29% increase in video viewing time
- Look Ahead
  - Work in progress for app development
  - Implementation of EnDASH for base-station assisted energy management in smartphones



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Thank you

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# Impact of features on throughput prediction

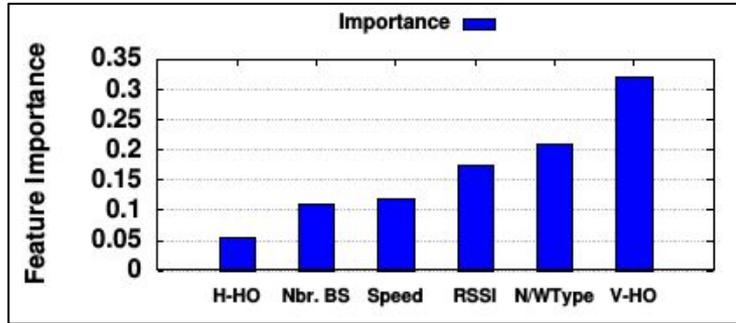


Fig: Feature Importance

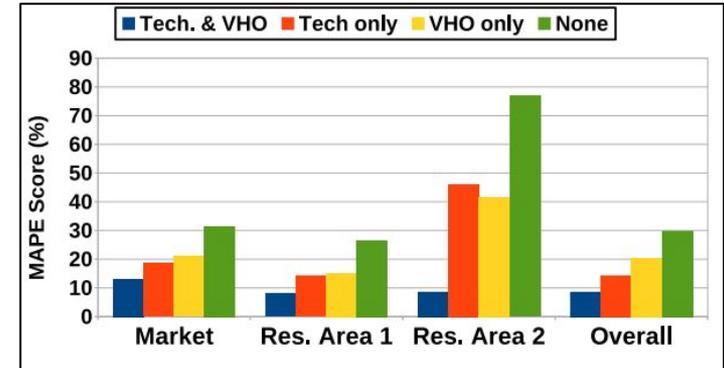


Fig: MAPE score measuring error of thpt prediction in different regions for P30F30

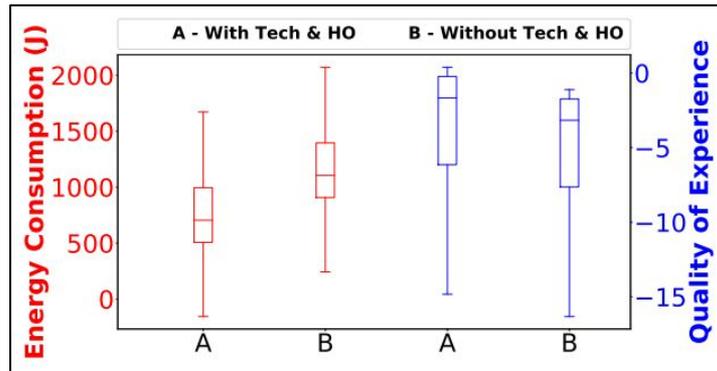


Fig: Impact of considering associated technology and vertical handovers (HOs) on performance metrics of EnDASH; for P30F30