NAP

Network Architectures and Protocols

Dynamic Dual-Reinforcement-Learning Routing Strategies for Quality of Experience-aware Wireless Mesh Networking

Nuno Coutinho
nunocoutinho@ua.pt

Ricardo Matos
ricardo.matos@ua.pt

Carlos Marques
car.manuel@ua.pt

Susana Sargento
susana@ua.pt

André Reis
abreis@cmu.edu

Andreas Kassler
andreas.kassler@kau.se

Jacob Chakareski
jakov@jakov.org

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universidade de aveiro

instituto de telecomunicações

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- Wireless Mesh Networks
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- Learning Method
- QoE-Aware Source Rate Control
- Evaluation
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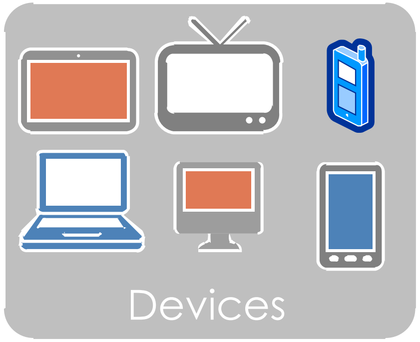
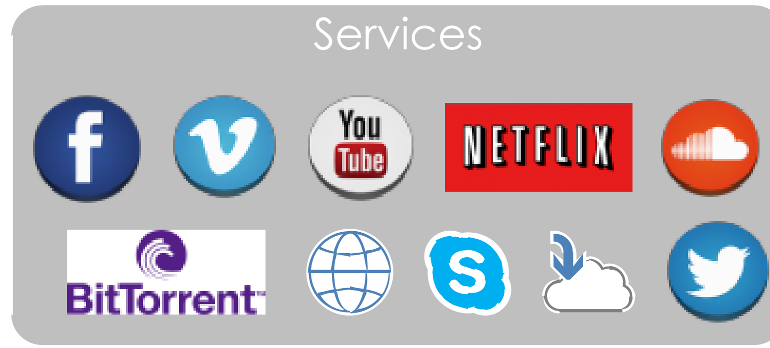
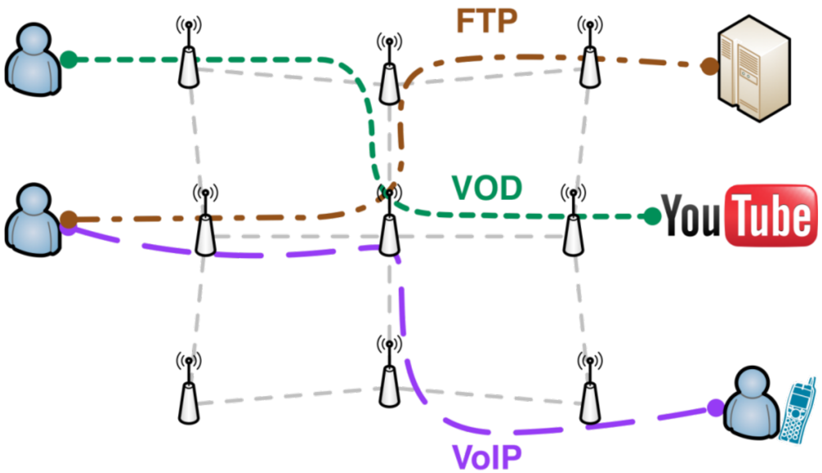
Motivation



- Fast-growing number connected devices
- Different features and capabilities

- A wide variety of available services
- Very distinct requirements

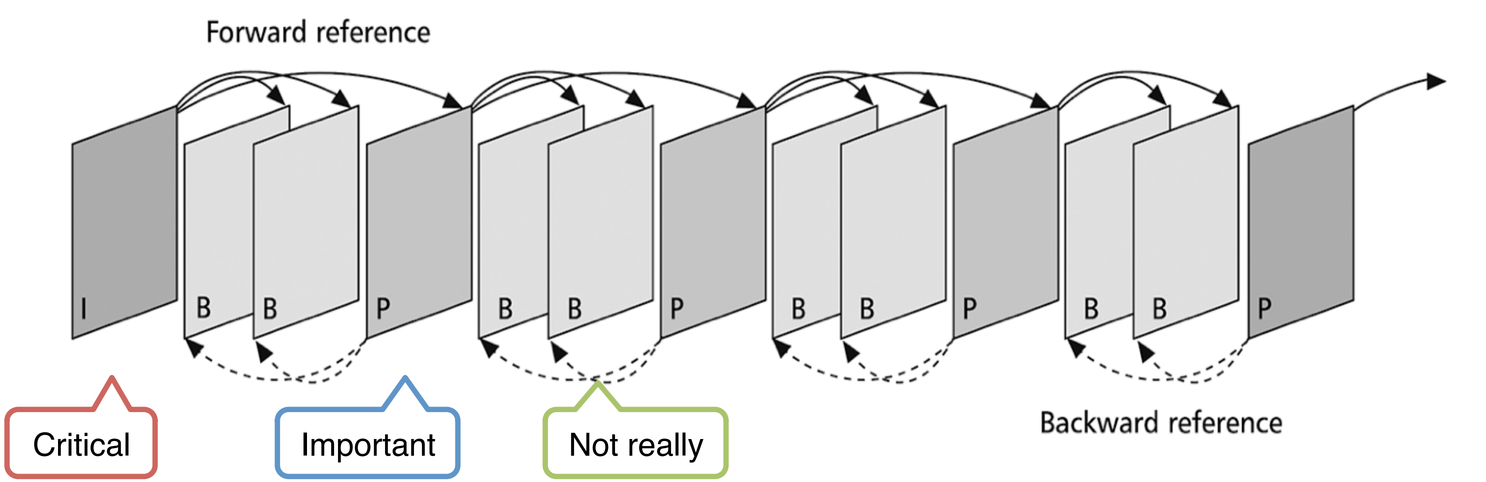




- Communication under resource constraints
- QoS metrics do not translate the service experience
- QoE-based Network Optimization

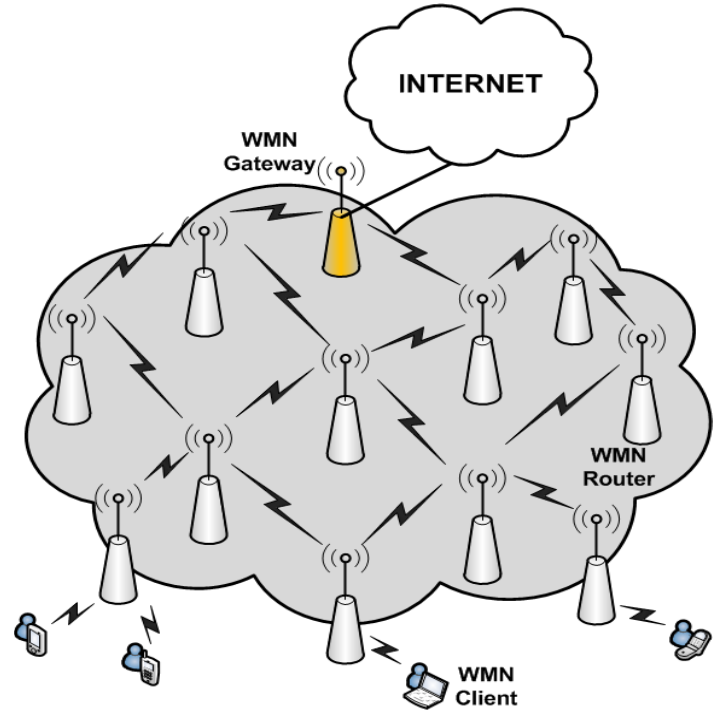
Quality of Experience

- QoS metrics are focused on network performance metrics
  - Regardless the packet's content and its impact
- QoS metrics are meaningless to users, they have their subjective service perception
- Despite a good QoS, QoE could be improved

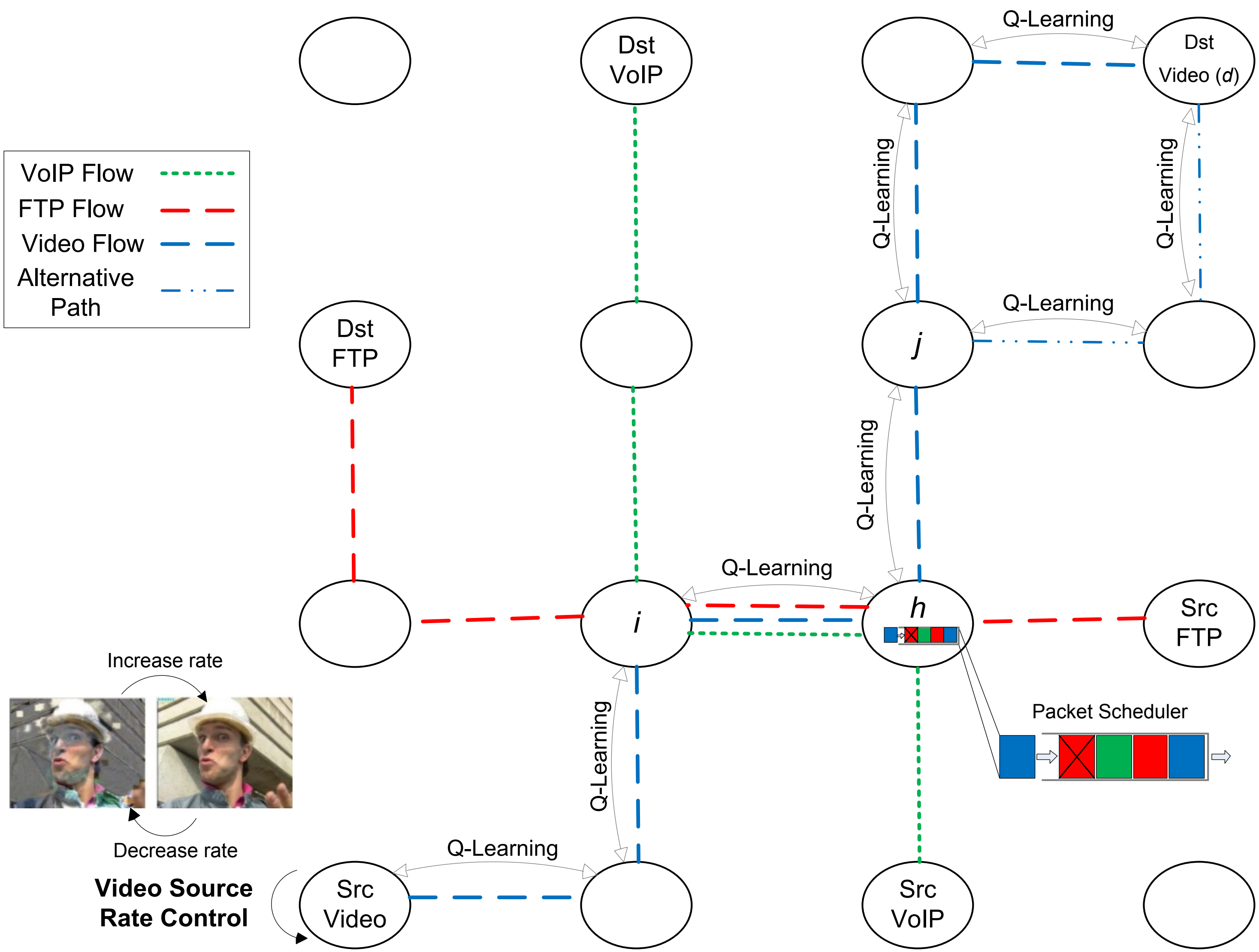


Wireless Mesh Networks (WMNs)

- Routing in WMNs is typically done in a proactive or reactive way (e.g. OLSR or AODV)
  - The path is used even if congested → bad QoS/QoE
- QoS-aware routing approach for WMNs
  - Select paths that meet throughput and/or delay requirements, ignoring packet content → bad QoE
- QoE-aware routing approach for WMNs
  - Select paths that lead to a better user QoE
- Traditonal packet schedulers are unaware of the packets' content



QoE-Aware WMN Framework



Learning Function

- **Q-learning method** → Each node within the path of a service flow determines the expected QoE of the remaining path towards the destination

  - Expected QoE of reaching *d* in the new state *t* of node i, when using the next hop h (new action)
  - Learning rate
  - Discount factor

$$QoE_{i \to d,h}^{t} = QoE_{i \to d,h}^{t-1} + \alpha \left[\left(QoE_{i \to h}^{t} + QoE_{h \to d}^{aux} \right) - QoE_{i \to d,h}^{t-1} \right]$$

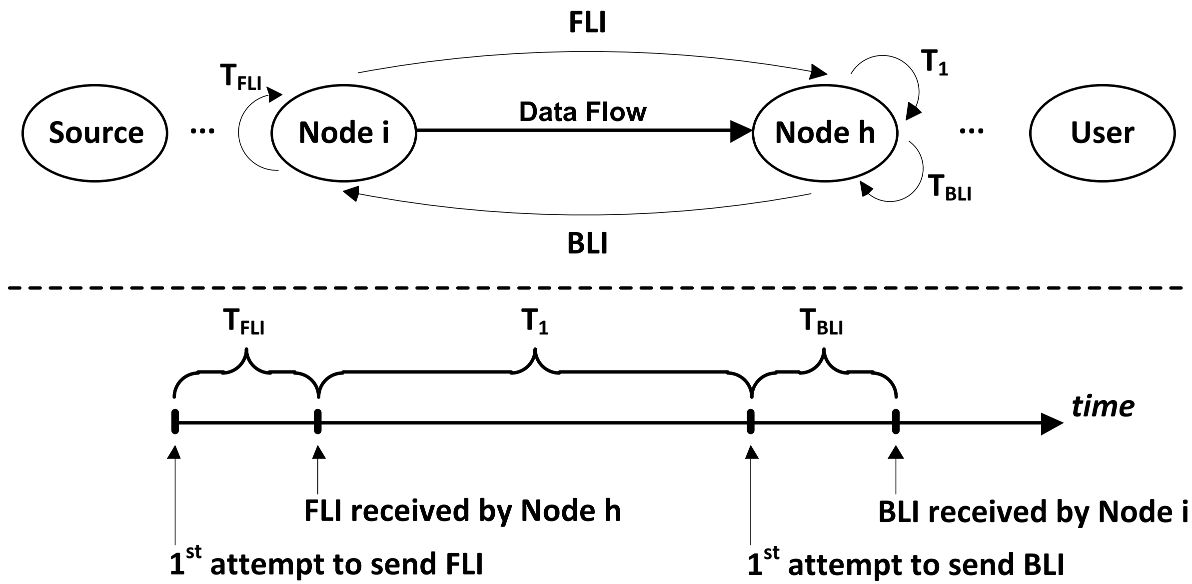
  - Expected QoE of reaching *d* in the previous state *t-1,* when using the next hop *h*
  - Local QoE of the connection between node *i* and the next hop *h*, for the current state *t* (reward)

- Each node of a flow path selects the best next hop to reach a specific destination

$$QoE_{i \to d}^{t} = \underset{h \in H_{i \to d}}{\arg\max} \{ QoE_{i \to d,h}^{t} \}$$

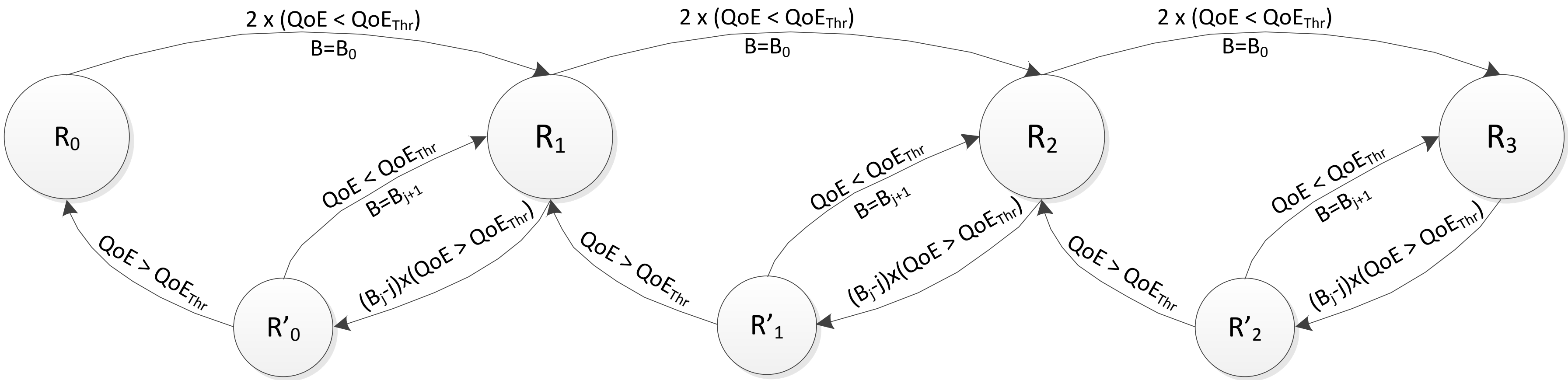
Learning Scheme

- Backward Learning Mechanism
  - Each node informs the previous one about the expected QoE to reach a destination
  - Information carried in MAC-ACK headers



- Forward Learning Mechanism
  - Every node informs the selected next hop about the expected QoE towards the source
  - Extra data packet header

QoE-Aware Source Rate Control



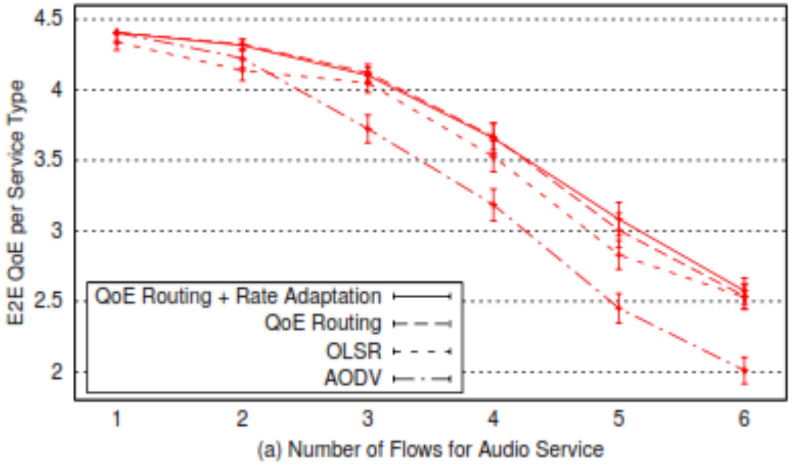
- Deal with networking scenarios with scarce resources
- Take advantage of the QoE knowledge at the content's source
- Goal: Maximize the QoE perceived by avoiding frequent rate changes
- Strategy: Additive Increase / Multiplicative Increase
  - Fast source rate switch down when the QoE is below a threshold
  - Slow and controlled source rate switch up only after a few good QoE feedbacks

Evaluation – Simulation Details

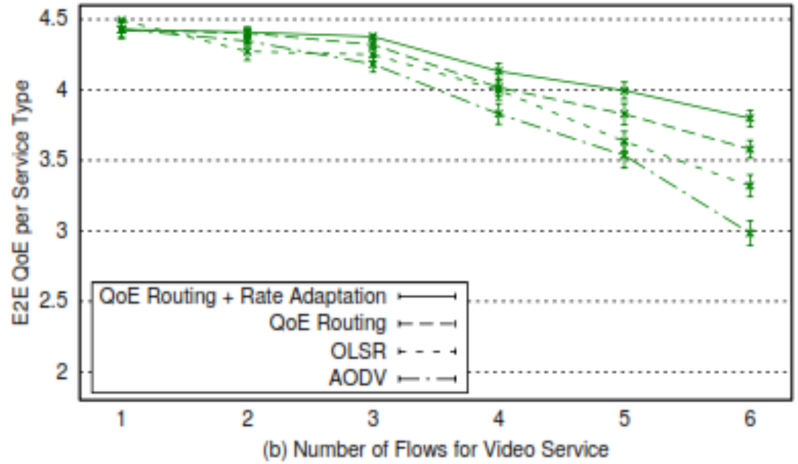
Variable	Value
Network	8×8 Grid 802.11-based WMN
WMN Node Interface Range	$100m$
User Terminal Interface Range	$40m$
WMN Node Interface Capacity	$54Mbps$
WMN Node Buffer Size(packets)	500
Service Types	{Audio, Video, and Data Transfer}
Number of User Flows per Service Type	$\{1, 2, 3, 4, 5, 6\}$
Source and Destination of Service Flow	Nodes randomly chosen with a shortest path between them less than 7 hops
Lifetime of User Service Flow	$20sec$
User Mobility Type	Each user randomly moves 1 to 6 times to a random 1-hop neighbor
Simulation Runs	50 with confidence interval of 95%

- Audio is configured for 64Kbps with payload size of 160Bytes
- Video uses H.264 codec sampled at 30 frames per GoP (10 of which are P-frames)
- Data returns a maximum MOS for 450Kbps, and a minimum for 10Kbps

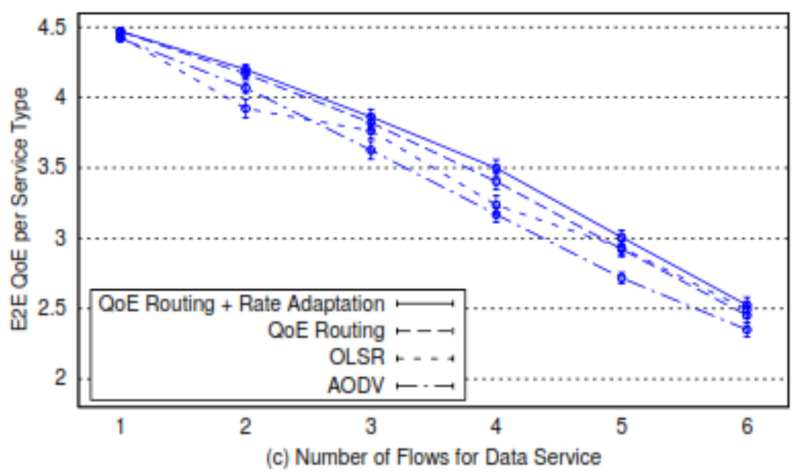
Evaluation – Grid Topology



(a) E2E QoE of Audio Service

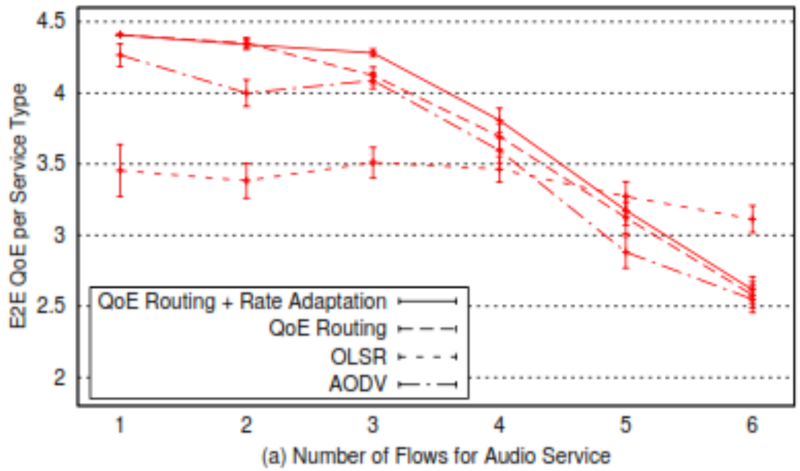


(b) E2E QoE of Video Service

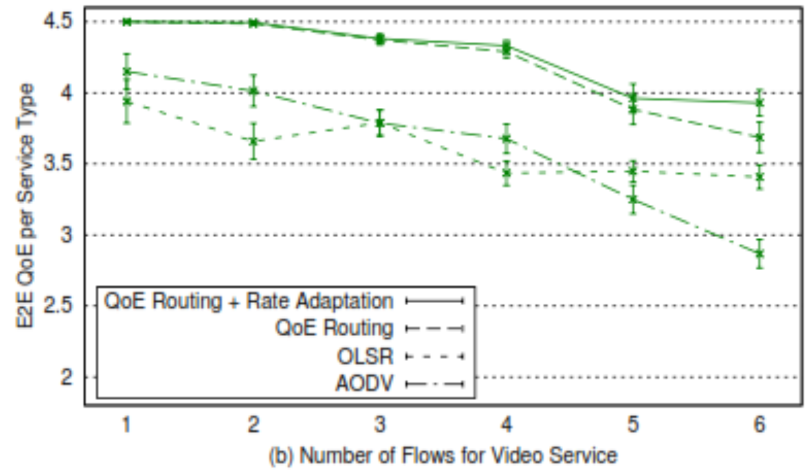


(c) E2E QoE of Data Service

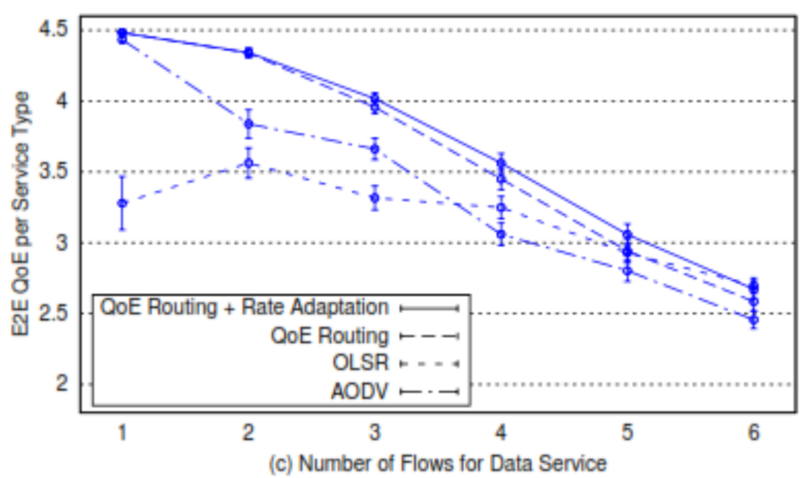
Evaluation – Random Topology



(a) E2E QoE of Audio Service

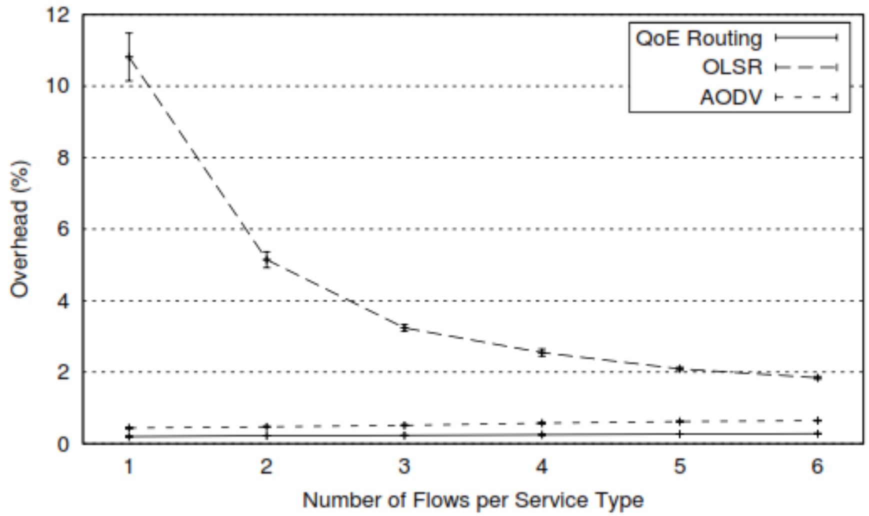


(b) E2E QoE of Video Service



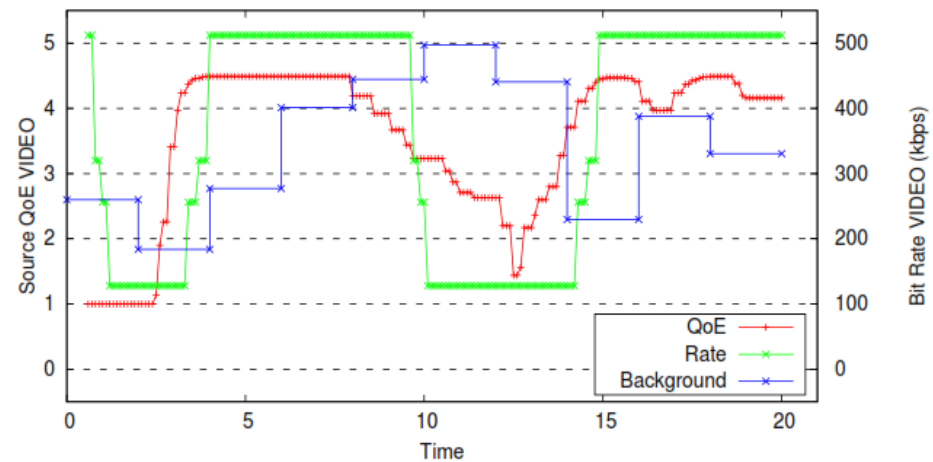
(c) E2E QoE of Data Service

Evaluation – Results



- Our approach requires less overhead while improving the overall QoE
- The periodic topology updates of OLSR require a considerable amount of overhead

- Source rate control behavior when applying a dynamic background load
- The impact of mobility level was also addressed
  - Our approach outperformed the AODV and OLSR protocols



Conclusions & Future Work

- Novel QoE-driven optimization framework for multi-service WMNs
- Approach relying on a double reinforcement learning scheme
- WMN nodes autonomously learn the paths that maximize the QoE of distinct services delivered over the WMN
- QoE-aware source rate control is able to gradually adapt the video rate to the network conditions
- The combination of the different QoE-aware schemes significantly improves the overall user perceived QoE
  - Decreases the control overhead comparing to the current standards

NAP

Thank You!

Nuno Coutinho

nunocoutinho@ua.pt