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Evaluation of Reinforcement-Learning Queue Management Algorithm for Undersea Acoustic Networks Using ns-3

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Workshop on ns-3

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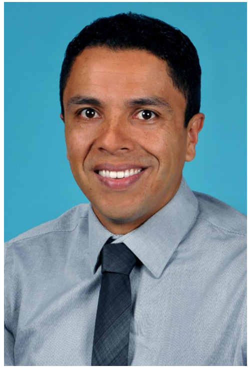
Authors introduction

- Mr. Peng Zhang
  - § Machine learning engineer and algorithm developer

- Mr. Daniel Yap
  - § Software and networking engineer

- Dr. Pedro Forero
  - § Signal Processing, machine learning and communication systems



- Mr. Dusan Radosevic
  - § Physical layer integration and experimentation lead

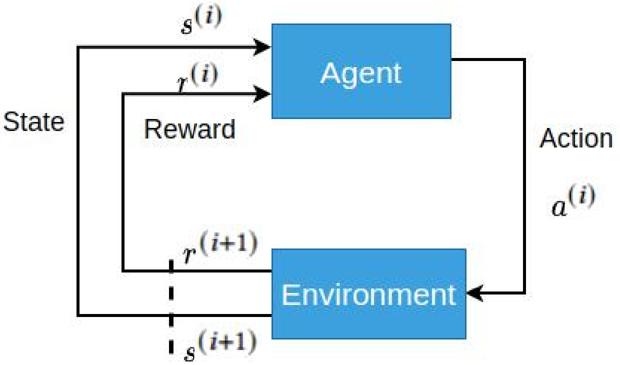
Undersea Acoustic Networking

- Characterized by limited and variable bandwidth availability
- Need to provide quality-of-service (QoS) guarantees to different traffic types
- Queue management enables 'shaping' traffic based on QoS requirements and bandwidth availability
- Some known queue management policies:
  - Priority scheduling
    - Does not guarantee that all traffic types are served
  - Fair queuing (FQ) scheduling
    - suboptimal since it does not adapt to the data traffic requirements and dynamics
  - Weighted-fair queuing (WFQ)
    - using fixed weights can be problematic as the traffic pattern and the state of the links changes

Our approach

- Learn WFQ weights via reinforcement learning (RL)
  - Agent aquires state information and acts on the environment according to RL-based policy at each decision epoch.
    - Point in time when agent makes decision.
  - RL agent seeks a policy to select WFQ weights that maximizes network throughput and minimize packet delay.

States (S):
- queue size
- queue size delta
- violation (v)
- # of marked packets (λ)
- mean delay
- mean delay delta



Action:
- WFQ weights (w)

$$r^{(i+1)} = \sum_{d=1}^{D} \kappa_d \left[C_0 w_d^{(i)} B^{(i)} - C_1 \mathbb{1}\left(|v_d^{(i)}| > 0 \right) - C_2 \lambda_d^{(i)} \right]$$

where κ_d is the priority of the d-th queue, $B^{(i)}$ is total bandwidth, C_0, C_1, and C_2 are hyperparameters.

Our approach (Cont.)

- RL agent is trained using OpenAI Gym environment in Python
  - Compatible with external training algorithm libraries, such as RLLlib and Stable-Baselines 3
  - Trained with Soft Actor-Critic (SAC) algorithm
- The WFQ policy is deployed using ns3gym
  - enables communications between ns-3 simulation and Python applicaiton

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WFQ module in ns-3

- We developed two modules
  - WfqQueueDisc - Enqueue(), Dequeue()
    - Modified CoDel (mCoDel) is used as child class for congestion identification
  - ProtocolPacketFilter - Classify()

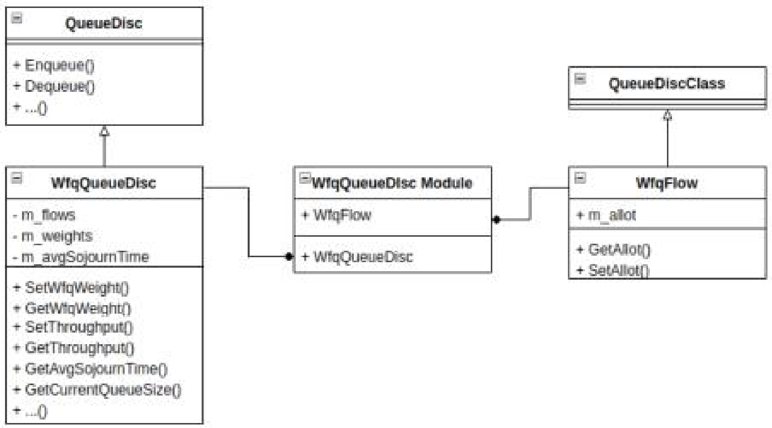

Figure 1: UML diagram of the WfqQueueDisc module

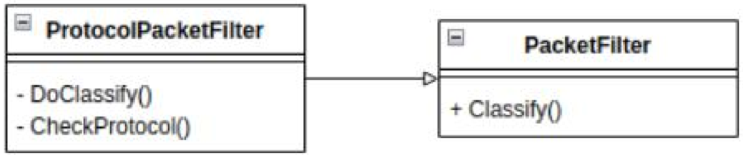

Figure 2: UML diagram of the ProtocolPacketFilter module

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ns-3 simulation

- Aquasim-NG is an ns-3 library that provides several underwater acoustic networking protocols and acoustic propagation models
- Packets start with source node application and are consumed in destination routing layer
- WFQ queuedisc in TrafficControlLayer dequeues a portion of packet based on queue weight allocation at each decision epoch
- mCoDel (as part of WFQ queuedisc) marks packets that may cause delay and notifies application to reduce data rate

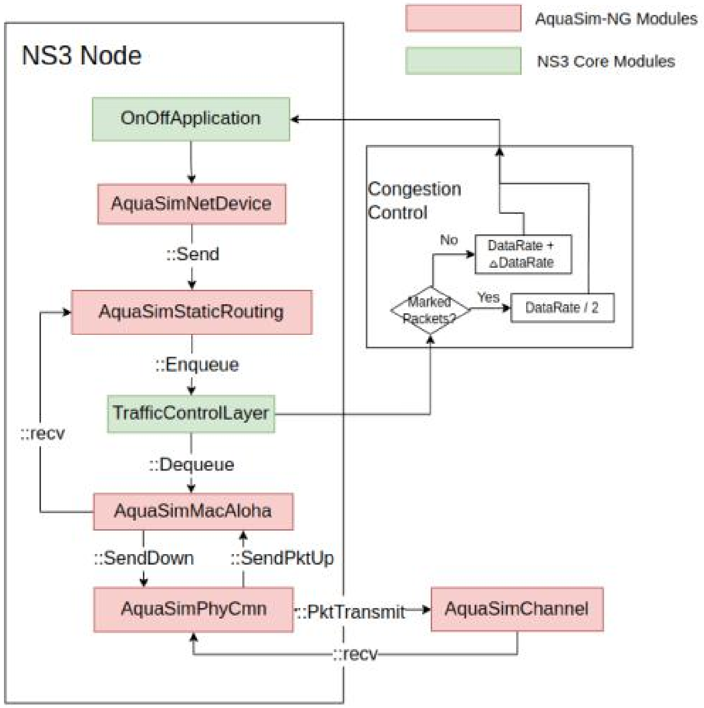

Figure 3: ns-3 node structure

WFQ agent training

- Trained in OpenAI Gym environment
  - Parameters are identical to ns-3 simulation
    - Data rate
    - Delay requirement
    - Queue priority
    - Modified CoDel parameters
  - Trained with Stable-Baselines3 SAC algorithm with entropy term $\alpha = 20$
  - Used 4 hidden layers with 64 neurons per layer for actor network and 128 neurons per layer for critic network

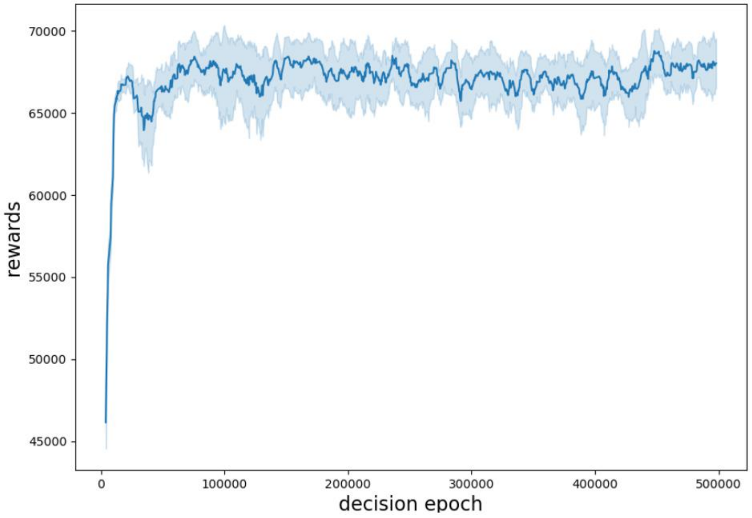

Figure 4: Training result. Shaded region represents 95% confidence interval

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Model deployment

- WFQ policy model is loaded in Python
- We use ns3gym library to connect the WFQ policy to the ns-3 simulation, enabling data exchange
  - ns-3 callback in C++
  - OpenAI Gym API in Python
- WfqQueueDisc public functions to set weight and obtain state information for WFQ policy
- Action synchronization to avoid dequeuing more packets than policy assigns
  - ReleasePackets()
    - Calls Wake() in NetDeviceQueue
  - StopPackets()
    - Calls Stop() in NetDeviceQueue

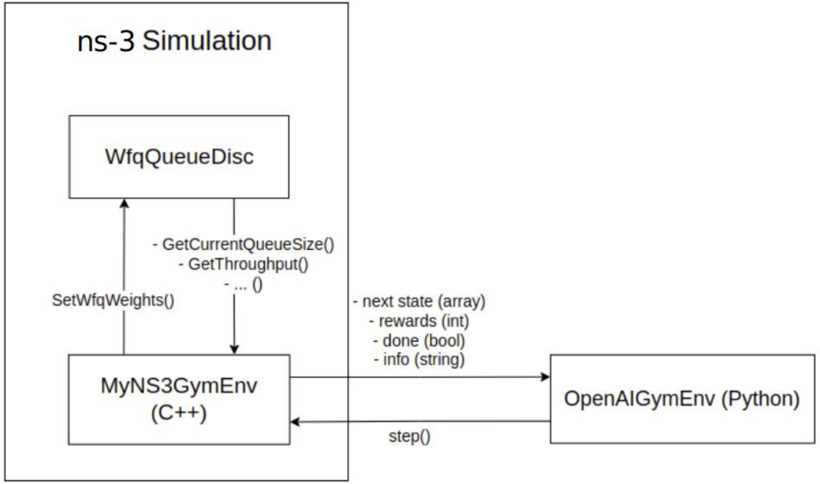
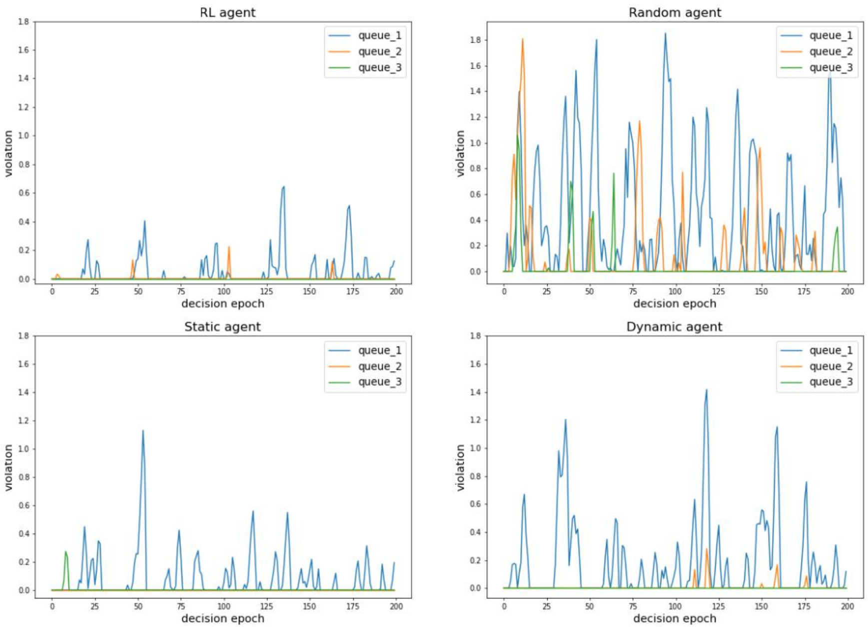


Figure 5: ns-3 and OpenAI Gym interaction

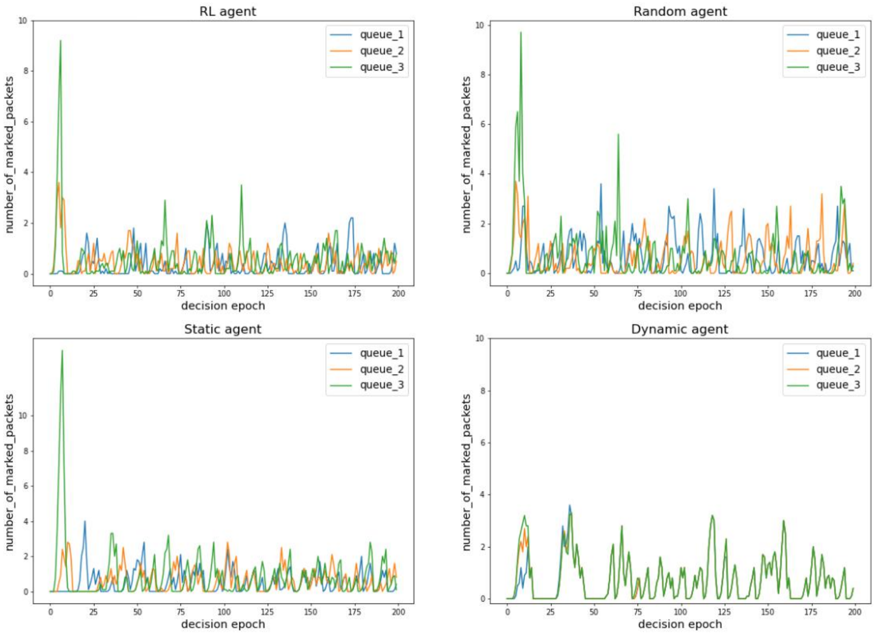
Queue management tests

- Conducted 10 tests
  - each test runs 200 decision epochs, or 1100 simulation second with 5.5 seconds per decision epoch interval
- 2-node setup
  - Source node with 3 OnOffApplication - 800 bps, 1600 bps, 2400 bps
    - Each application corresponds to one type of traffic
  - OnOffApplication always on (OnTime = 1.0)
- Three queue management strategies
  - Static WFQ algorithm
  - Random WFQ algorithm
  - Dynamic WFQ algorithm
    - Proportional to queue size at each decision epoch
  - Our RL WFQ algorithm

Queue management tests



(a) Delay violation



(b) Number of marked packets

Figure 6: RL agent evaluation against three other WFQ policies: random action (top right), static weights (bottom left), and dynamic weights (bottom right) in each subfigure.

Summary

- Developed RL-based algorithm that maximizes queue data throughput while satisfying QoS requirements
  - State: queue size, mean queue delay, bandwidth, etc
  - Action: WFQ weights
- Learned policy for dynamically choosing WFQ policy weights
  - Update actor network through SAC
- Developed new ns-3 modules: WfqQueueDisc, ProtocolPacketFilter
- ns3gym enables data exchange between RL model in Python and ns-3 simulation in C++
- Plan to train RL agent directly in ns-3

Questions?