Rate Adaptation Aware Positioning for Flying Gateways using Reinforcement Learning

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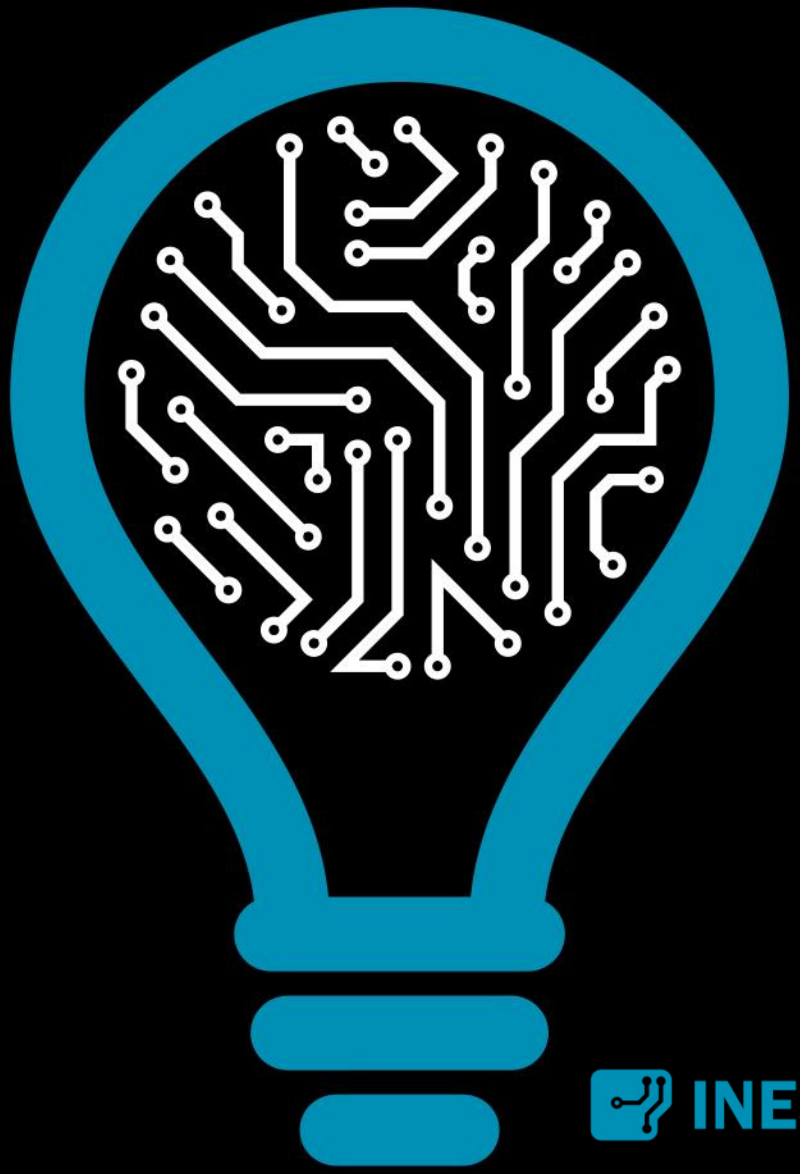

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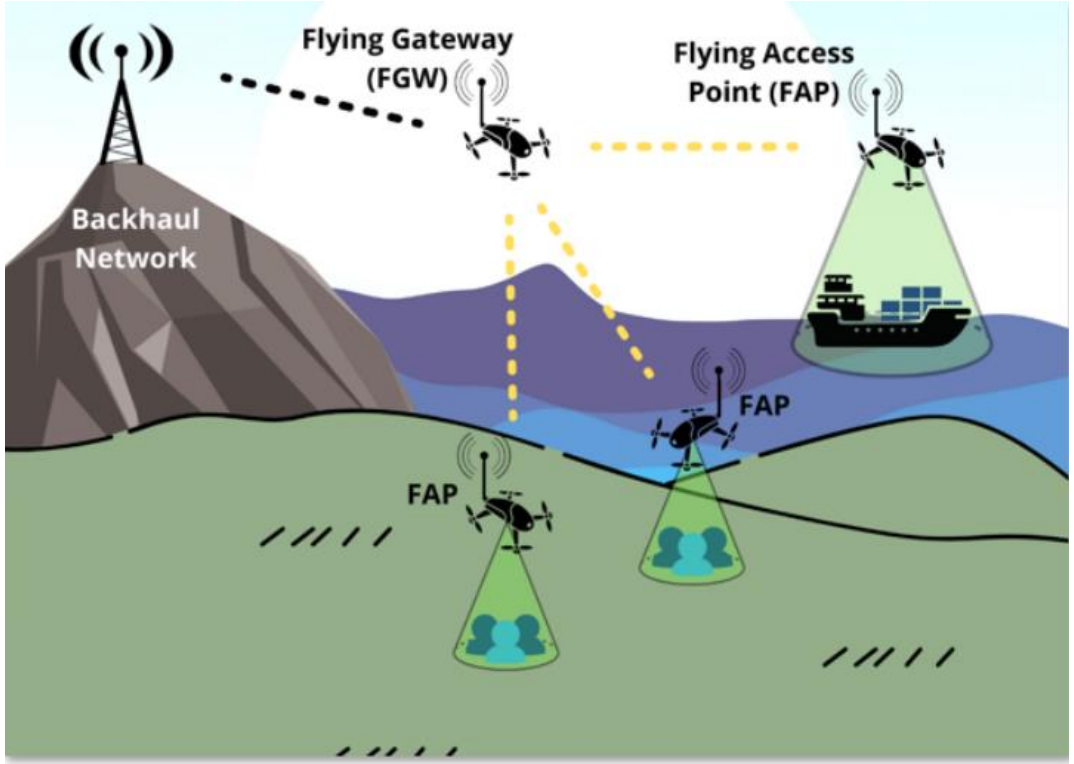
1. Introduction

- Scope
- Contributions

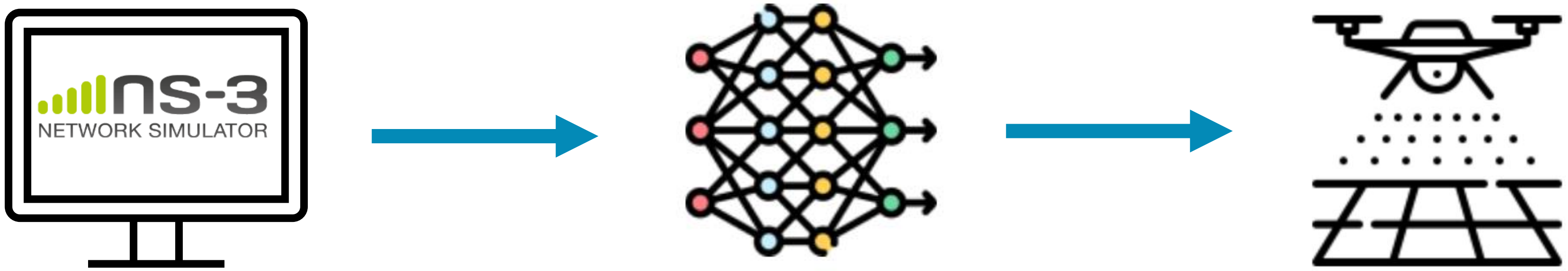
Scope

- Aerial networks’ diverse range of applications
- Unmanned Aerial Vehicles (UAVs) as **nodes of the Aerial network**
  - Flying Access Points (FAPs)
  - Flying Gateways (FGWs)
- **Positioning of the FGW** as a core element of the aerial networks



Contributions

- The **R**ate **A**daptation aware **RL**-based Flying Gateway Positioning **(RARL)** algorithm enables the **FGW to find a final position**, considering the
  - Effect of **realistic** Rate Adaptation (RA) algorithms
  - Impact of the **Backhaul** network **configuration**
  - **Continuous evaluation** of the network state
- The algorithm is meant to be **trained in the simulation environment of ns-3** and posteriorly the model should be used by FGWs through **transfer learning**



2. State-of-the-Art and Relevant Concepts

- State-of-the-Art
- Rate Adaptation
- Reinforcement Learning
- ns-3 Simulation Environment

State-of-the-Art

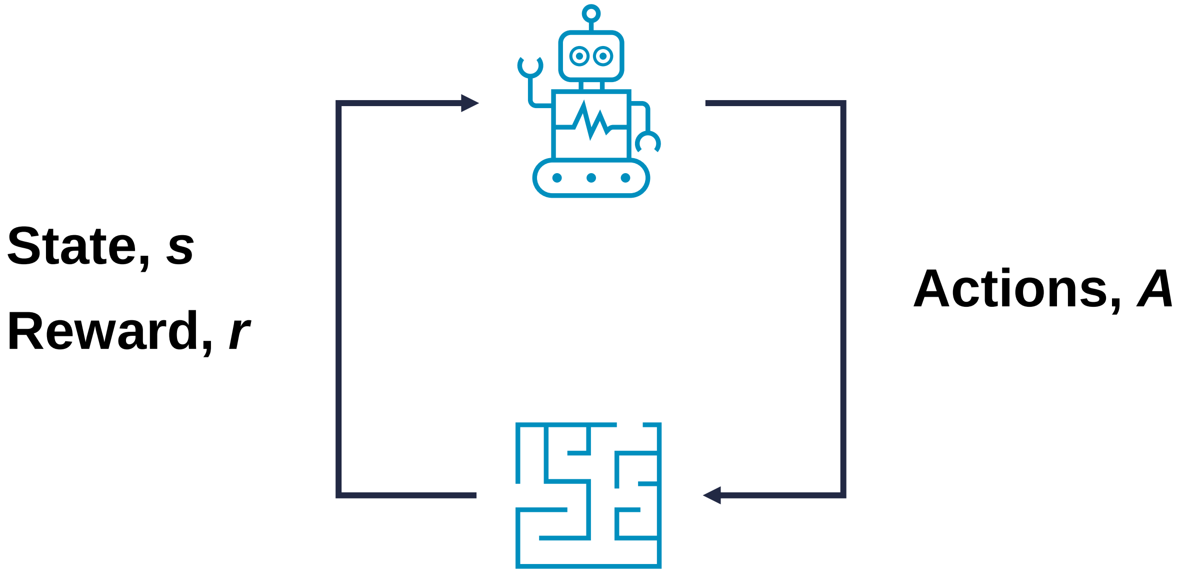
- State-of-the-art solutions for drone positioning in aerial networks **overlooks the impact of Rate Adaptation algorithms**
  - Use of **fixed Modulation and Coding Schemes**
  - Use of **ideal RA algorithms**
- Deep Reinforcement Learning (DRL) emerges as a promising approach for UAV positioning
  - Supports choice of the Deep Q-Learning approach in the implementation of the RARL algorithm

Rate Adaptation

- RA algorithms are a **core feature** of wireless systems
- Techniques employed to **enhance** the **reliability** and **robustness** of wireless transmissions
  - Data rate control methods find a **trade-off** between the **transmission rate** and the network **performance**
- In this study, the **Minstrel-High Throughput (HT)** algorithm was analysed

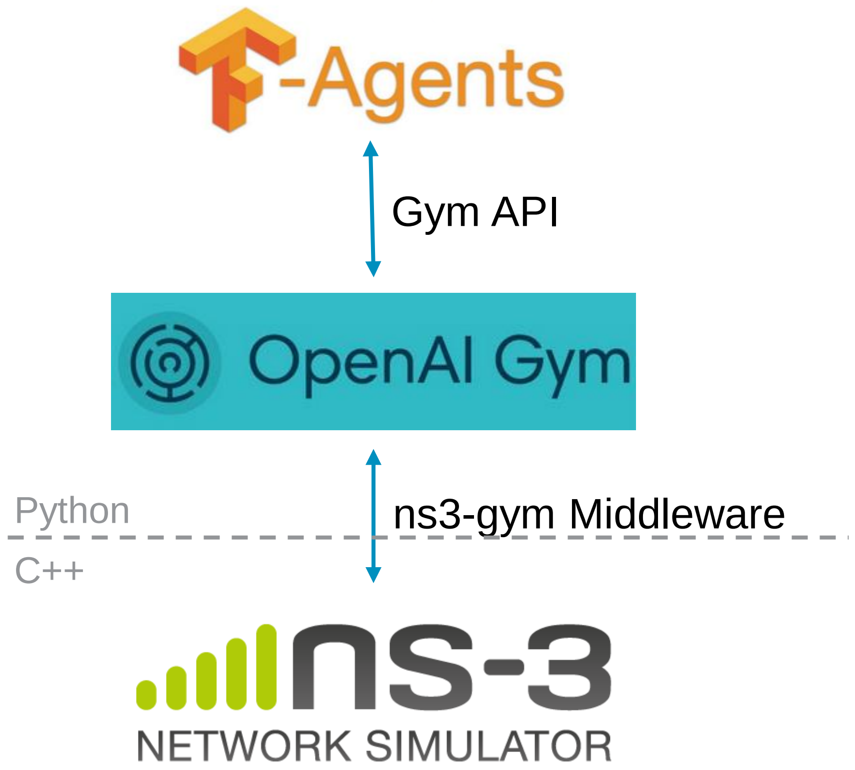
Reinforcement Learning - Overview

- Through the feedback obtained to the actions it takes, the agent learns how to interact with the environment
- The rewards come as incentive or punishment, measuring how the actions impact the environment towards the defined goal



ns-3 Simulation Environment

- ns-3 is a discrete-event network simulator
- ns3-gym integrates both OpenAI Gym and ns-3 to allow the development of RL-based algorithms in networking research



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3. Rate Adaptation aware RL-based Flying Gateway Positioning Algorithm

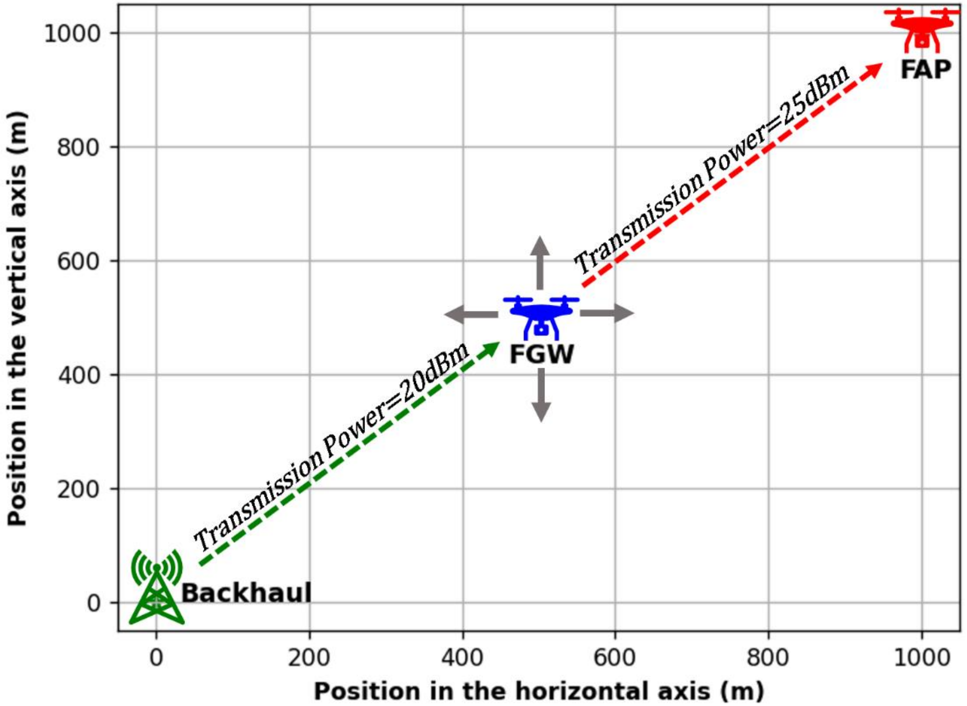
- Rate Adaptation aware RL-based Flying Gateway Positioning Algorithm Design
- Scenarios Studied
- Algorithm Design for Asymmetric Links and Moving FAP Scenarios

Rate Adaptation aware RL-based Flying Gateway Positioning Algorithm Design

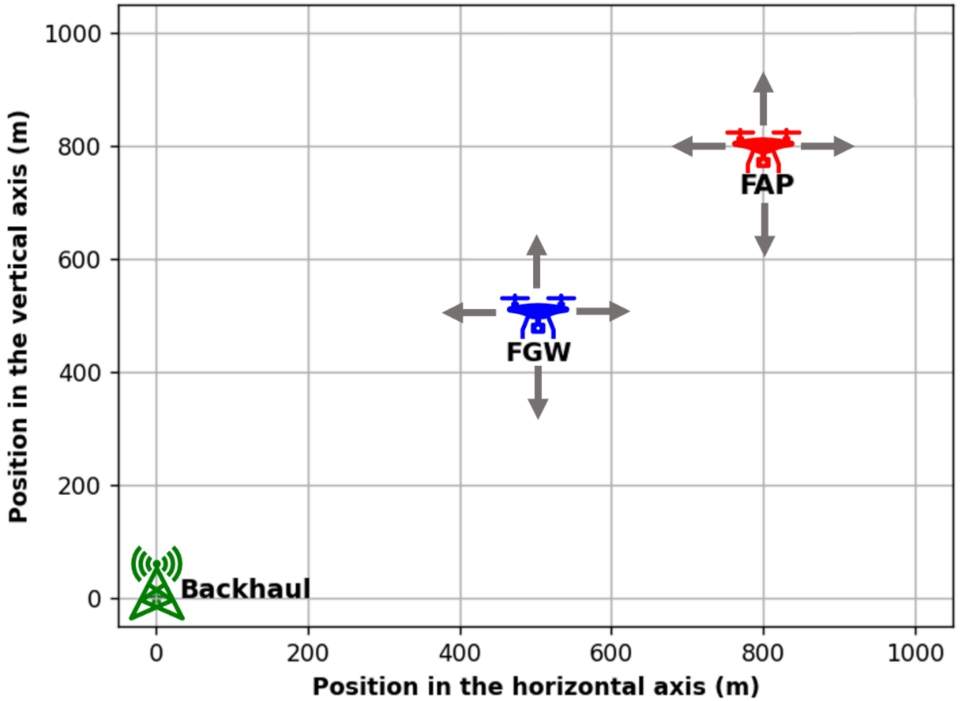
- The algorithm was formulated to find a **final position**, given the current network state and nodes‘ positions
  - **Maximizes the throughput** in the FGW and the FAP
  - **Minimizes imbalances** between links
- For **each scenario** studied, the RARL algorithm **was trained independently**, under **diverse conditions**
- The simulations were carried with
  - the Wi-fi Standard IEEE 802.11n
  - Friis Propagation Loss Model
  - Minstrel-HT as RA algorithm
  - Downstream traffic
  - Saturated links
  - Independent Wi-Fi channels for each link
  - UDP traffic

Scenarios Studied

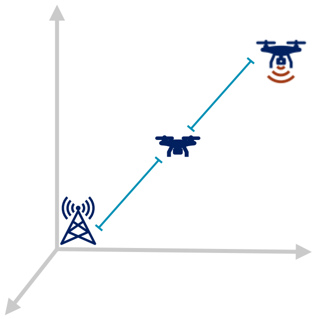
Asymmetric Links



Moving FAP



Algorithm Structure for Asymmetric Links and Moving FAP Scenarios



Observations:

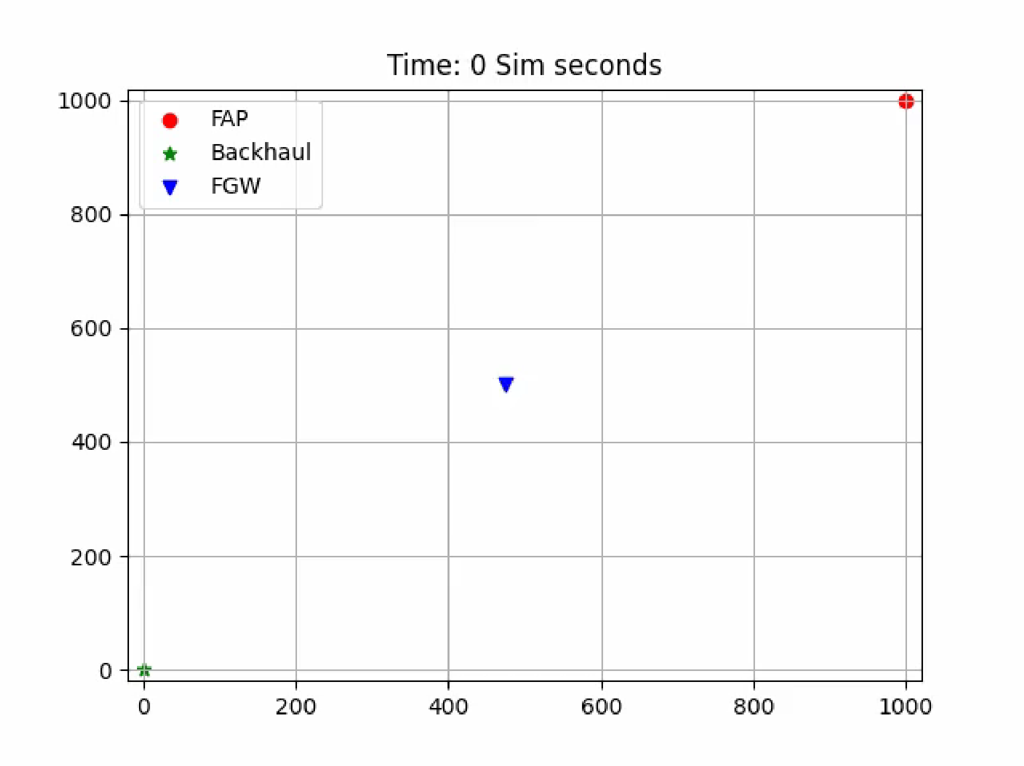
- FGW's coordinates
- Distances Backhaul-FGW and FGW-FAP
- Throughputs in FGW and FAP

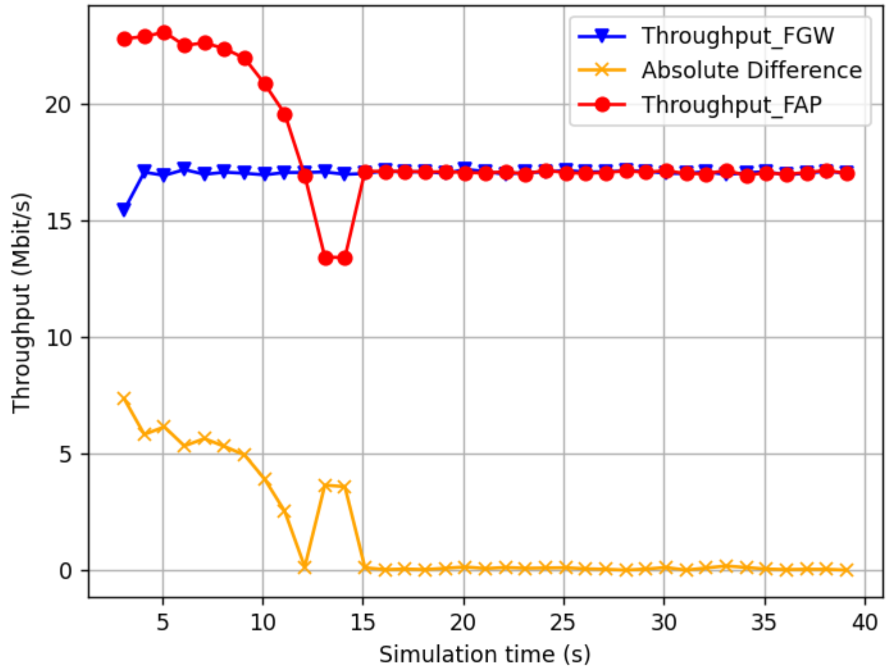
$$\boldsymbol{{}^{*}Reward} = SNR_{FGW} + SNR_{FAP} - 2|SNR_{FGW} - SNR_{FAP}|$$

4. Performance Evaluation

- Asymmetric Links Scenario
- Moving FAP Scenario
- Two FAPs Scenario

Asymmetric Links Scenario

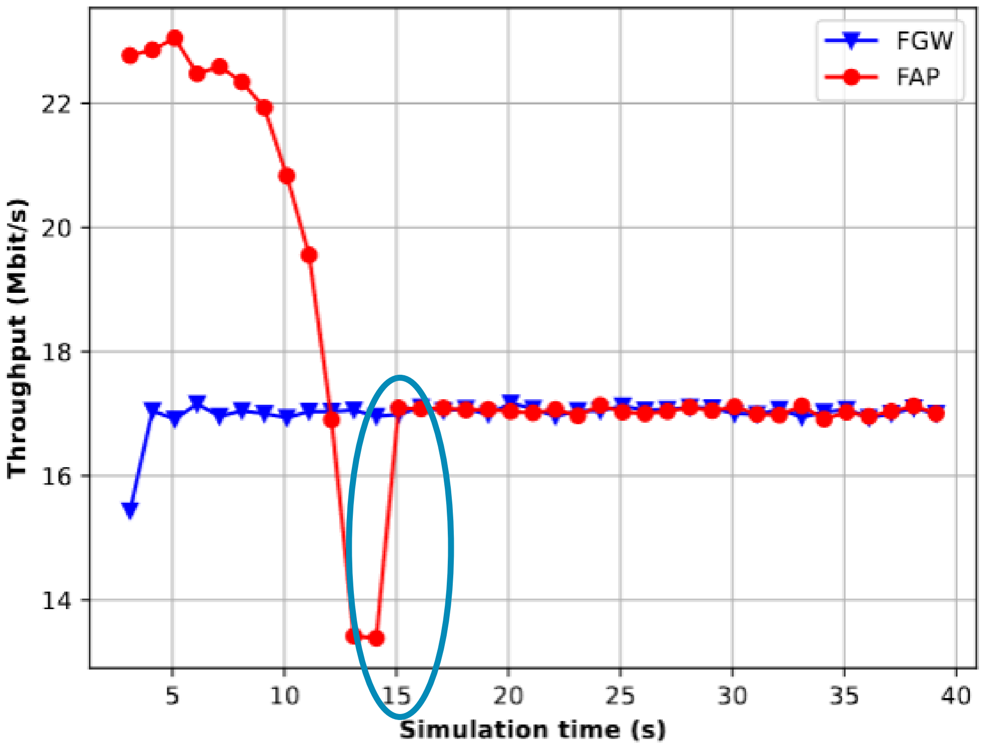




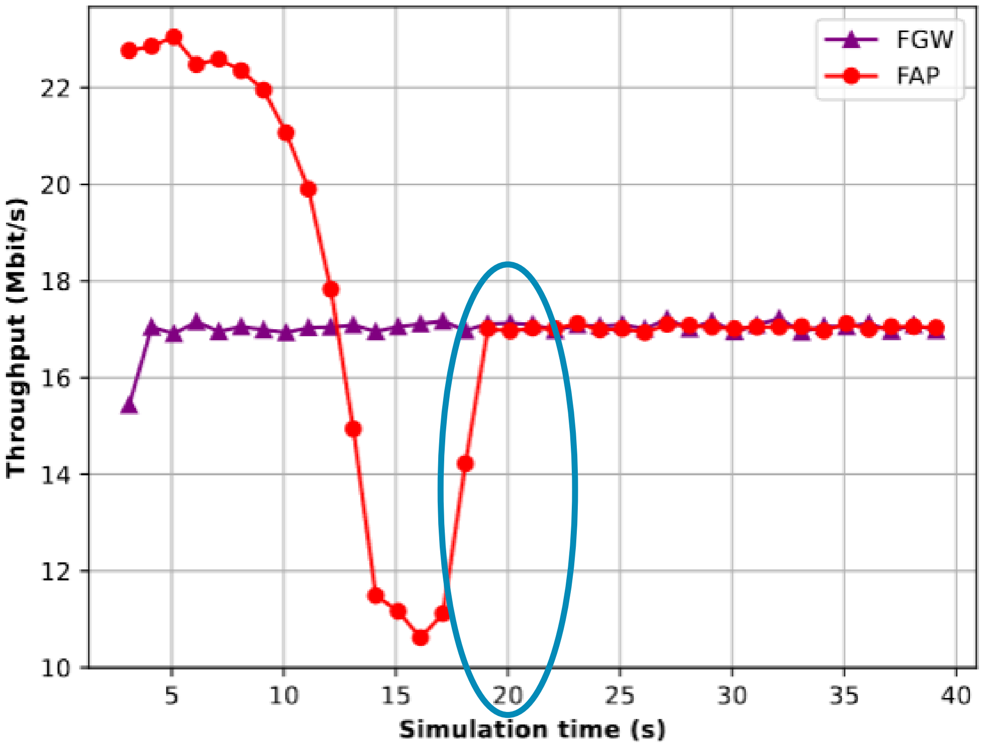
- Final Position: (175, 525) ↔ (175, 550)
  - Evidence of the detection of imbalance of transmission power
- Throughput in both links converge to around 17 Mbit/s

Asymmetric Links Scenario – RARL vs Baseline

RARL

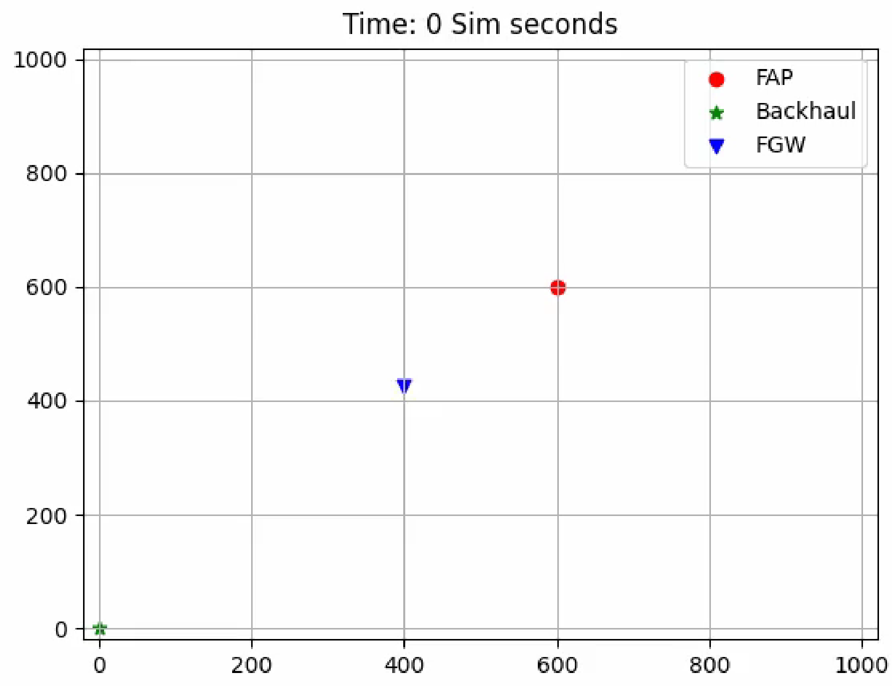


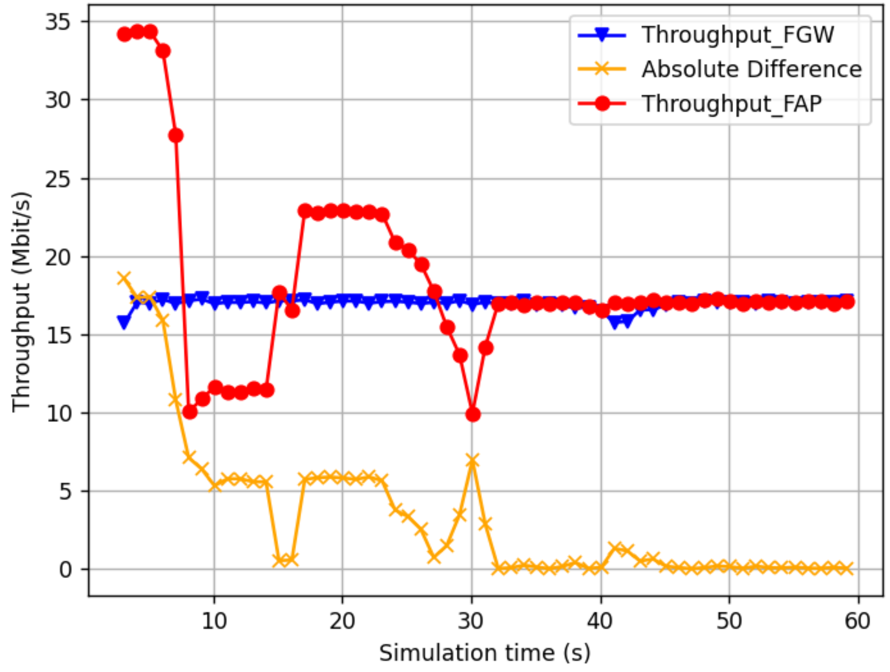
Baseline



- Baseline defined as optimal trajectory from the initial position to the position that ensures the SNR in both links were the same
- RARL algorithm achieves faster convergence

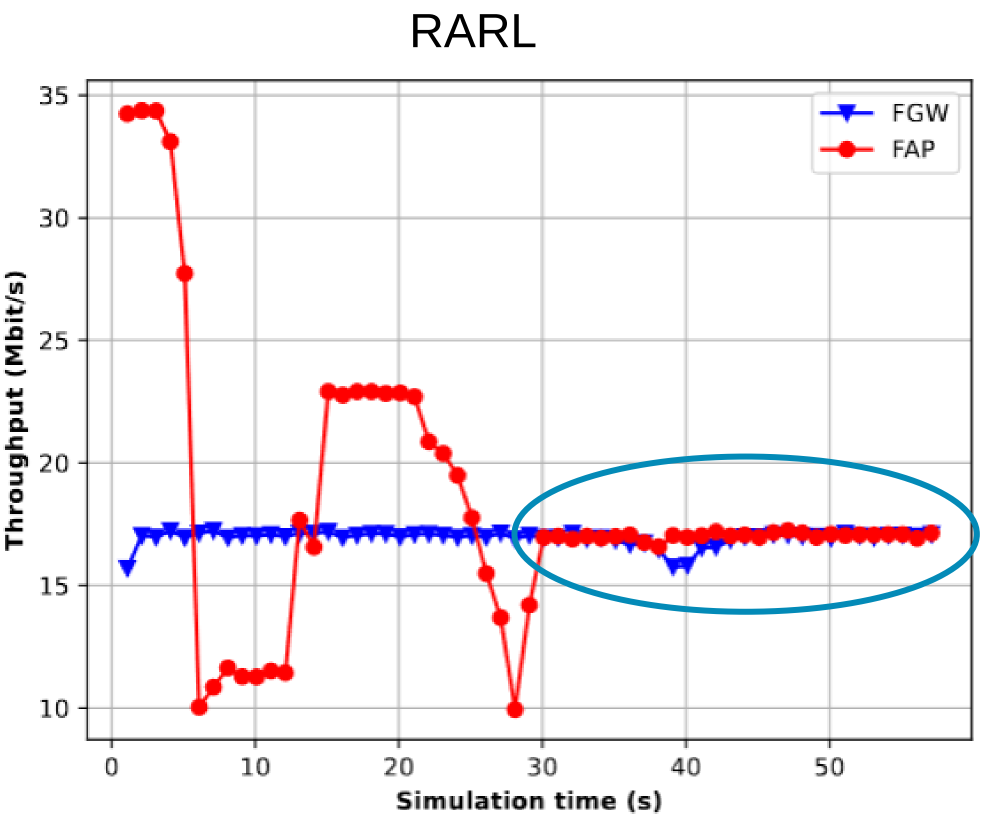
Moving FAP Scenario

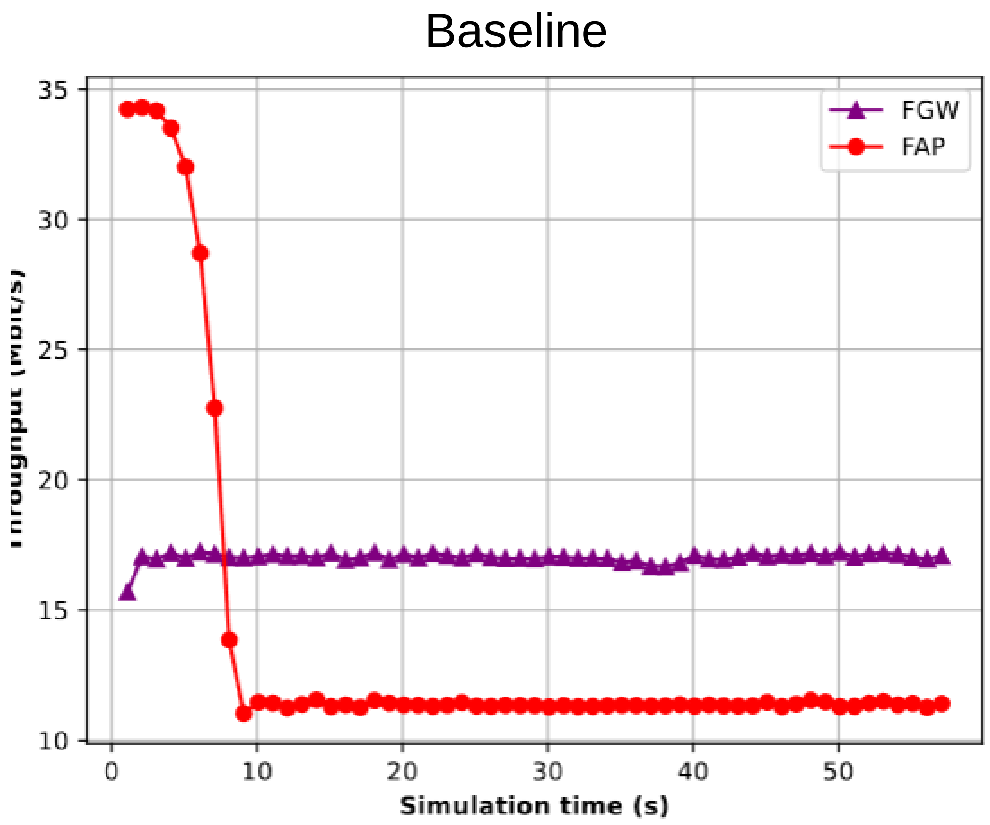




- The FGW moves mainly in the horizontal direction → maintains the balance of the throughput in the links
- Throughput in both links converge to around 17 Mbit/s

RARL vs Baseline





- Baseline defined as central position between Backhaul and FAP
- RARL algorithm outperforms baseline solution, achieving the throughput convergence

5. Conclusions

- Conclusions
- Future Work

Conclusions

- The RARL algorithm enables the FGW to find the final position that
  - Maximizes the throughput in both links
  - Minimizes imbalances
- The comparisons of the RARL algorithm with the baseline validate the implementation
  - Supports an RA aware positioning algorithm for real-world deployments
- Need to overcome interference caused by the underlying RA
  - Fluctuations when transitioning data rates
  - Poor performance when an improvement of channel quality is observed

Future Work

- Consider a more realistic simulation
  - Stochastic propagation models that account for fading effects (e.g., Rician Propagation Model)
  - Non-ideal directional antennas
- Test more complex scenarios, adding
  - More non-stationary FAPs
  - Varying traffic demands
- The trajectory should be improved

Thank you!