5G and Satellite Network Coexistence in FR3 Spectrum

RUTGERS
WINLAB | Wireless Information Network Laboratory

Aaditya Mittal, Arjun Prabhala, Nihal Shah
Advisors: Prof. Narayan Mandayam, Rifat Bin Rashid, Sreeram Mandava

Motivation

The Federal Communications Commission (FCC) is exploring the allocation of the FR3 band for 5G services necessitating sharing bandwitdith with satellite (SAT) communications. This will inevitably lead to co-channel interference and a deterioration of signal quality at satellite receiver (Rx) sites. To maintain Quality of Service (QOS), there is a critical need for dyanmic spectrum sharing.

Approach

Fig. 1. Orbit GRID at Rutgers WINLAB

- **GOAL**: Develop a dynamic radio network on the ORBIT testbed that optimizes signal parameters.
- Collect Signal-to-Interference -plus-Noise Ratio (SINR) and Packet Error Rate (PER) data for a given topology.
- Dynamically adjust normalised OFDM gains (amplification) from 0-1 and center frequency (3.49-3.51 GHz) to minimize interference and maximize quality.

$$SINR = \frac{Signal\ Power}{Noise + Interference\ Power}$$

$$PER = 1 - \frac{Recieved\ Packets}{Total\ Sent\ Packets}$$

ORBIT Emulation

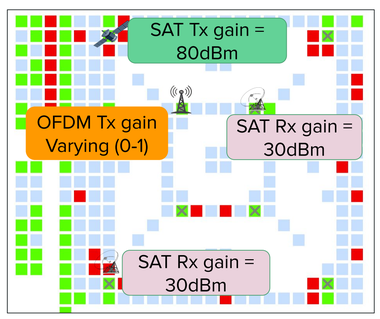

Fig. 2. Topology during data collection

- **SETUP:** One SAT Rx, one SAT transmitter (Tx), one OFDM Tx.
- Adjust OFDM gain and OFDM center frequency.
- Calculate PER and SNR.
- Automated through bash scripts and ssh protocol.

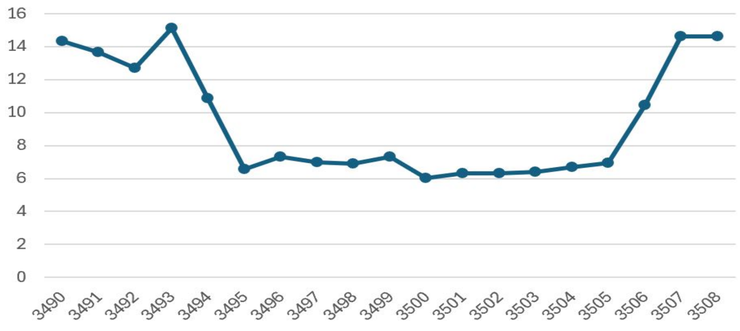

Fig. 3. Avg. SAT SNR v. OFDM Center Frequency when Gain = 1

Model Justification

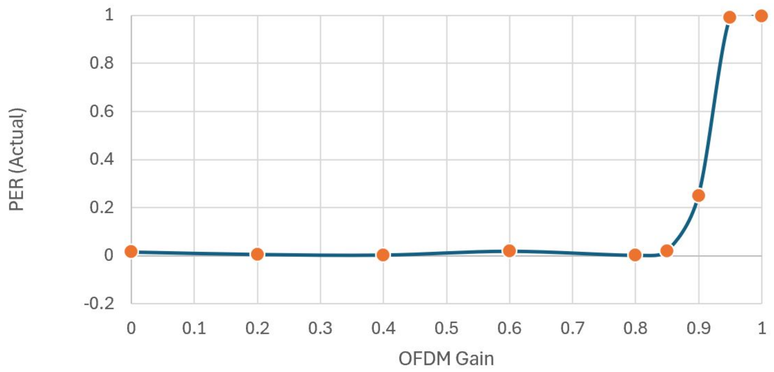

Fig. 4. SAT PER v. OFDM Gain

- A generally acceptable PER is below 5%.
- The large PER when 5G is running at high gain levels means that SAT and 5G cannot coexist at full power at the same time.
- Dynamic spectrum shaing is warranted to ensure maximum reception quality of both 5G and SAT simultaneously.

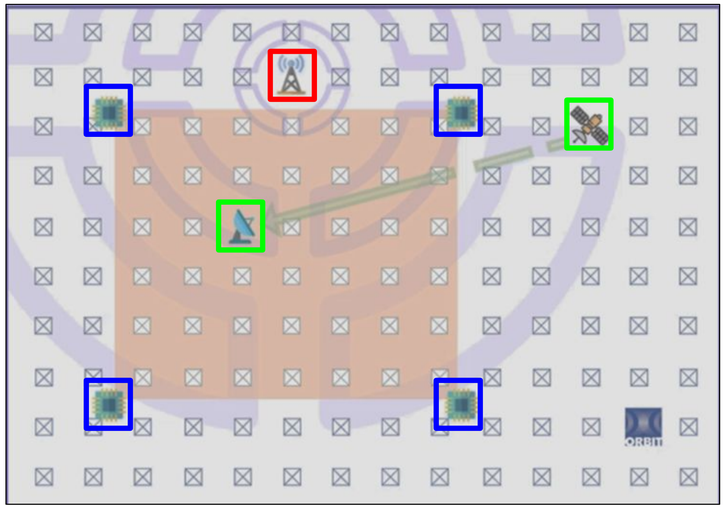

Fig. 5. Topology during reinforcement learning training

Reinforcement Learning

- Used **RL** to develop an autonomous agent to dynamically control OFDM gain and center frequency.
- **Tabular Q-Learning**: A model-free agent learns a Q-table that maps environment states to the long-term value of each action.

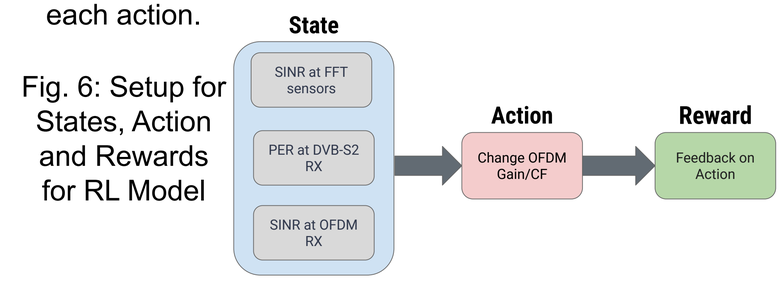

Fig. 6: Setup for States, Action and Rewards for RL Model

Agent Evaluation

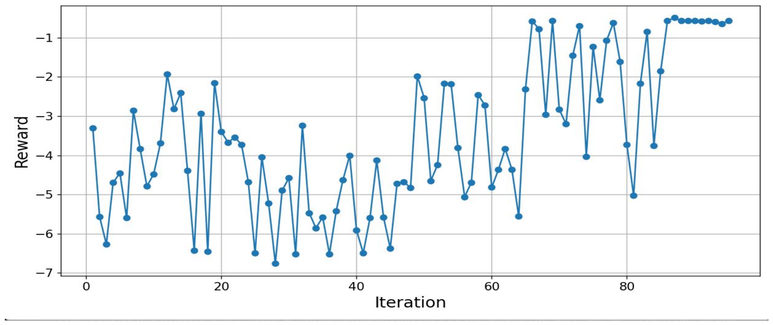

Fig. 6. Reward over Iterations

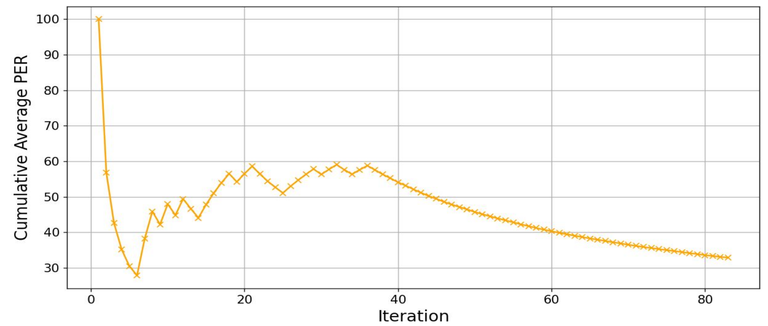

Fig. 7. Avg. SAT PER over Iterations

Conclusion

- Emulating the coexistence of DVBS2 and 5G OFDM signals on the ORBIT testbed showed a significant drop in DVBS2 signal quality
- Developed a reinforcement learning (RL) agent to implement Dynamic Spectrum Access, autonomously managing OFDM gain and center frequency based on real-time DVBS2 and 5G performance metrics
- While per-step rewards are variable (Fig. 6), the cumulative average DVB-S2 PER shows a clear downward trend (Fig. 7), confirming the agent is successfully learning to improve system stability.
- A longer training period is required for the policy to converge and to fully evaluate its peak performance.

Future Work

- Expirement with Deep Q-Networks using a policy and target network and replay buffer for stabilized training.
- Increase action space by adding SAT Rx locations and directional antenna changes.
- Use Bit Error Rate (BER) for more optimal performance metric.

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