

DeepCoMP: Self Learning Dynamic Multi Cell Selection for CoMP

EC354 Cellular Mobile Communication Project

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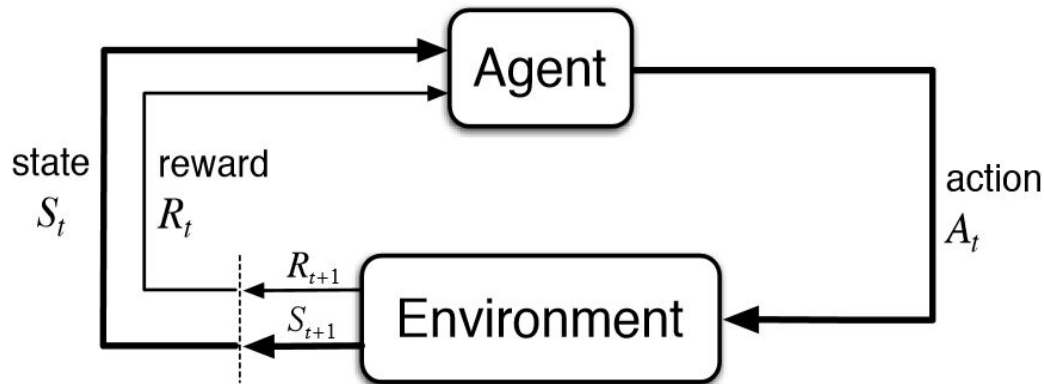
What is Reinforcement Learning?

-  Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions.
-  For each good action, the agent gets positive feedback or reward, and for each bad action, the agent gets negative feedback or penalty.
-  The agent interacts with the environment and explores it by itself. The primary goal of an agent in reinforcement learning is to improve the performance by getting the maximum positive rewards.

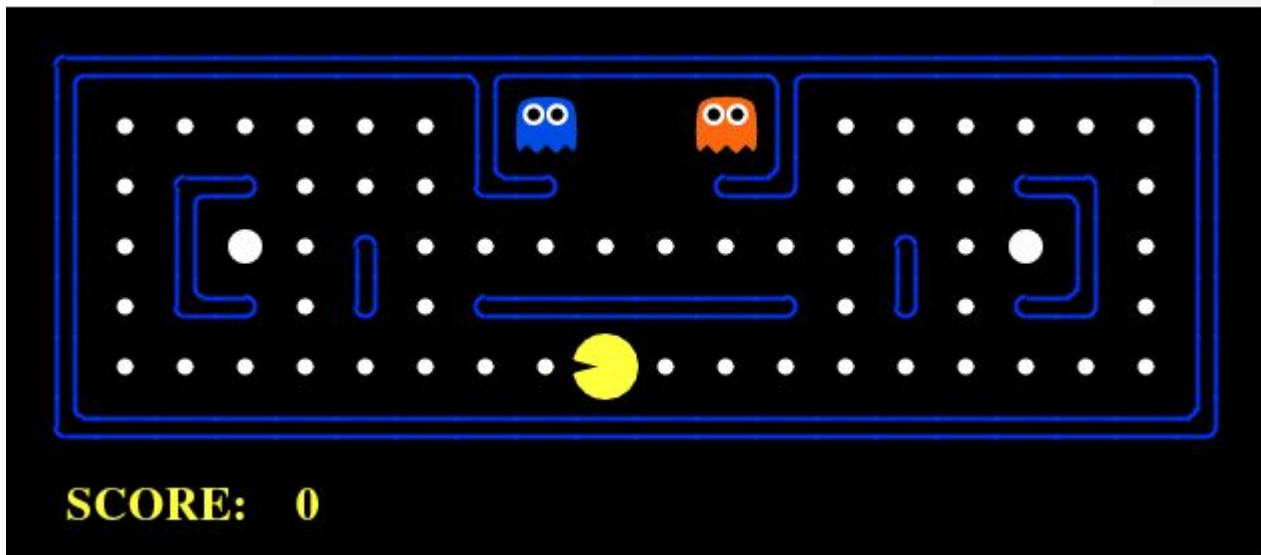
What is Reinforcement Learning?

We do not need to pre-program the agent, as it learns from its own experience without any human intervention.

- RL solves a specific type of problem where decision making is sequential, and the goal is long-term solution.
- Current use cases include the following:
 - resource management**
 - gaming
 - robotics



Example of Reinforcement Learning



Reinforcement Learning = Machine Learning + Control Theory



CoMP - Coordinated Multipoint

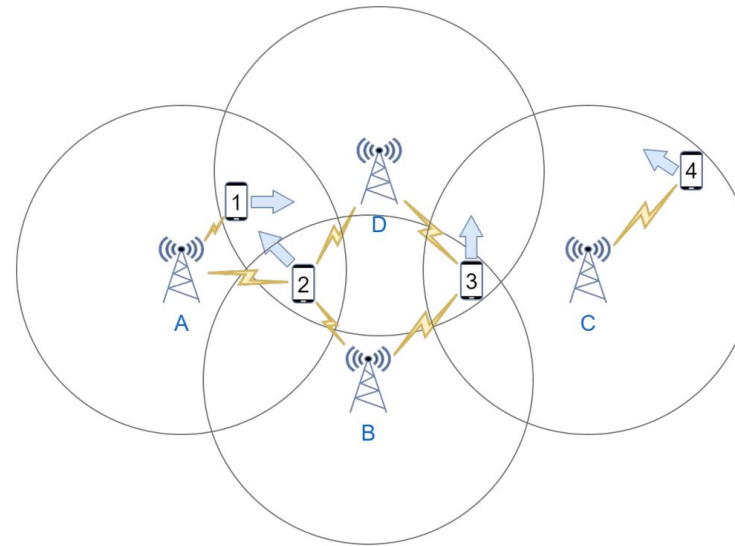
- Coordinated MultiPoint (CoMP) is based on transmission and reception at multiple separated sites with dynamic coordination among them.
- CoMP started to be used more aggressively in LTE Advanced, as a way of improving service at the cell edge.
- Makes better utilization of network by providing connections from several base stations at once.



Problem statement

Wireless mobile scenario

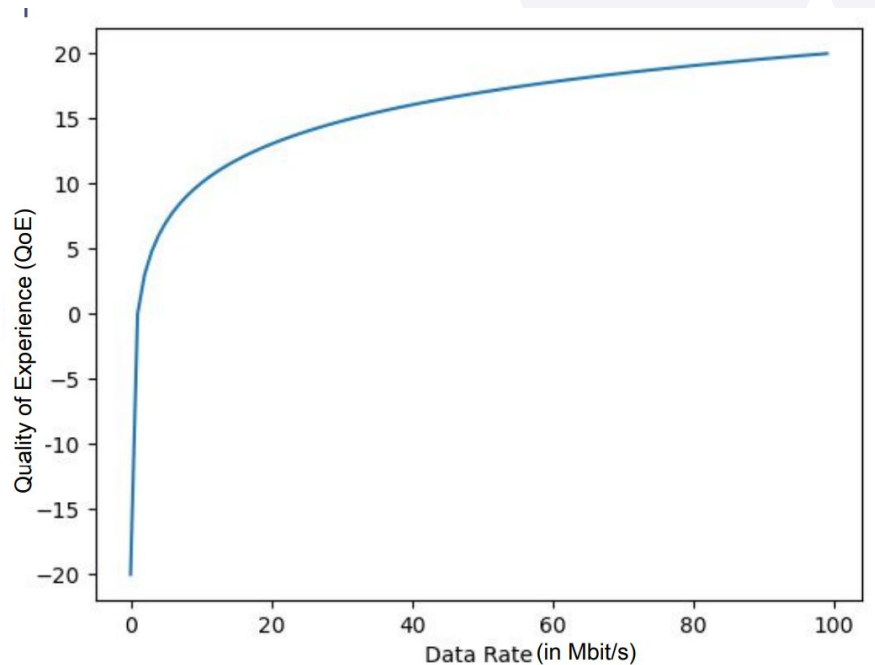
- dense cells, moving users
- requirement of high data rate
- Users compete for resources
- Heterogeneous resource allocation



Motivation and Approach

Parameter :
Quality of Experience
(QoE) = $\log(\text{data rate})$

Goal is to **Maximize QoE**
of all users





Types of self learning DRL Approaches:

| Training | Inference | Name |
|-------------|-------------|----------|
| Centralized | Centralized | DeepCoMP |
| Distributed | Distributed | D3-CoMP |
| Centralized | Distributed | DD-CoMP |

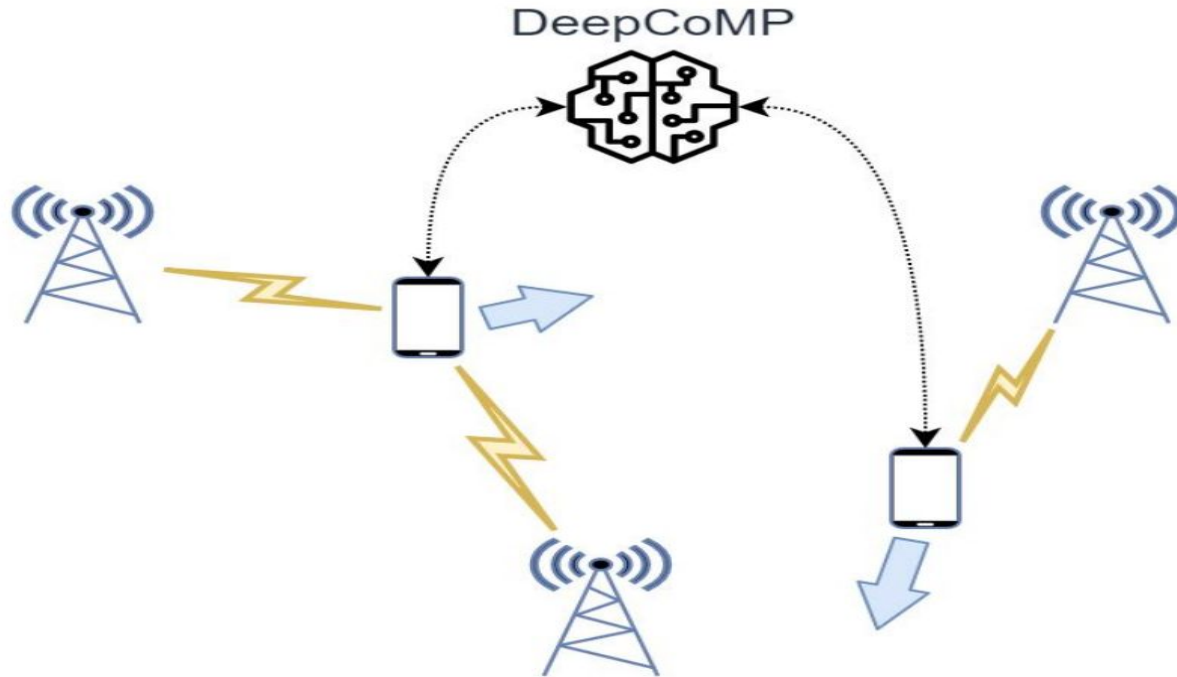


DeepCoMP : Central observation and control of all users

- Requires global view and control of all users
- Large action space
- Complex
- But allows fine grain cooperation between users



DeepCoMP





DeepCoMP

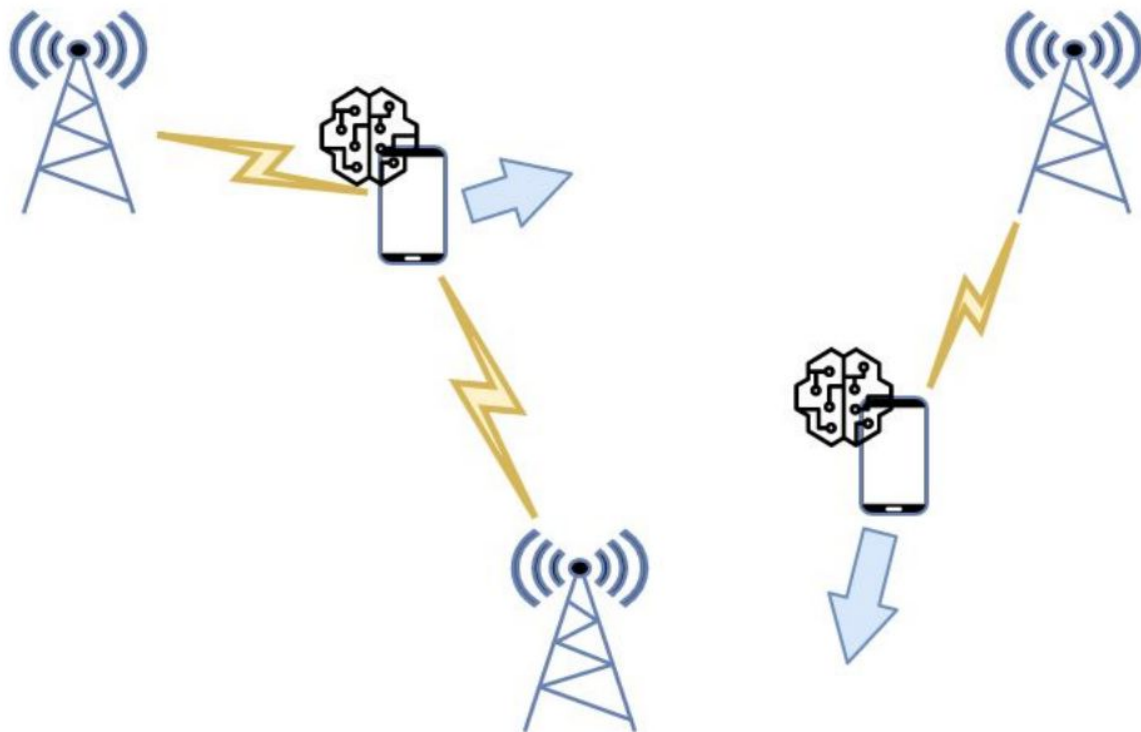
- ❖ Observations:
 - Current connections
 - Signal strength between all cells and users
 - Users' QoE
- ❖ Actions:
 - Either keep all current connections/disconnect
 - Or connect/disconnect a certain cell
- ❖ Reward:
 - Sum of users' QoE



Distributed DRL:

- Separate DRL agents for each user
- Local observations and control
- It is Simpler and Faster
- Prone to greedy behaviour

Distributed DRL:





D3-CoMP

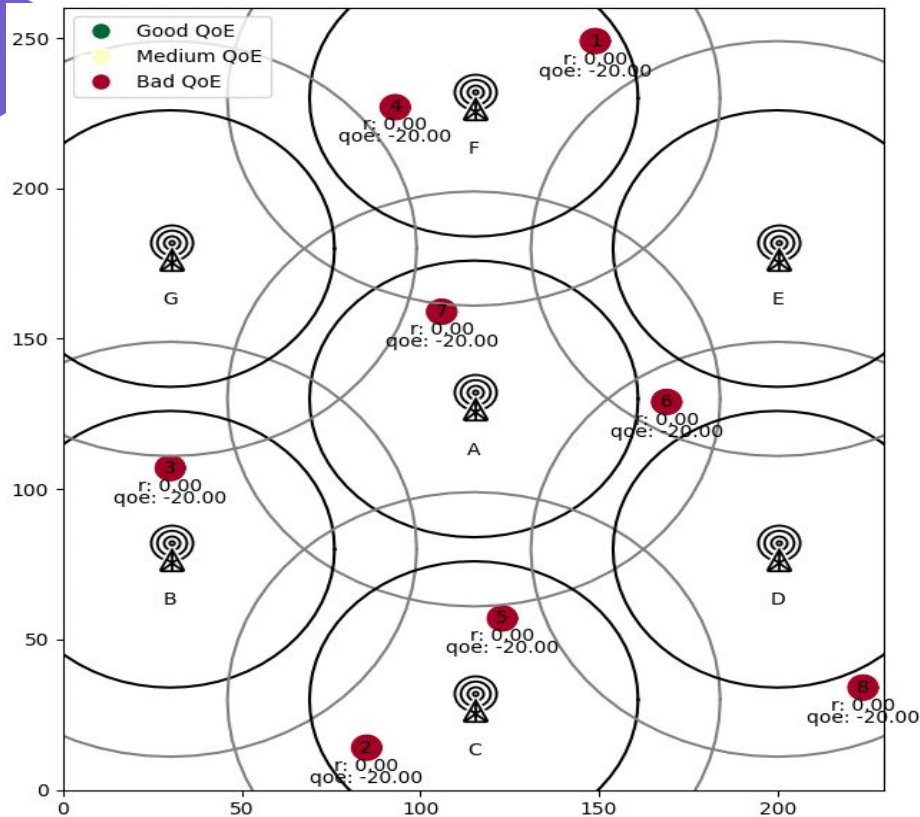
- Fully distributed
- independent DRL agents
- No communication between DRL agents for training
- Can learn heterogeneous cell selection policies per user



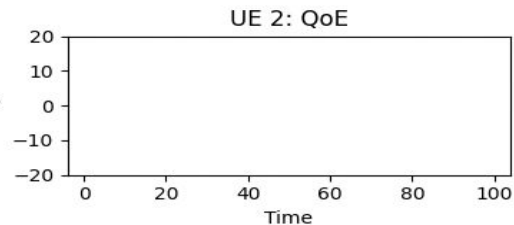
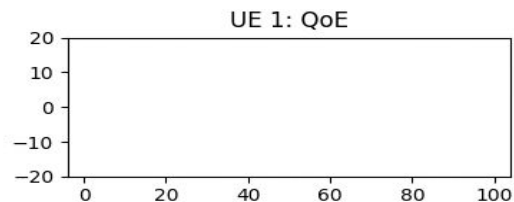
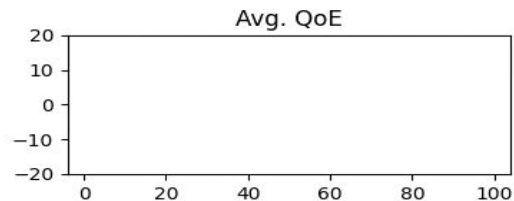
DD-CoMP

- Central policy and training, but distributed inference
- Distributed inference with local observations and actions
- But DRL agents share their experience
- Leverage data from other users
- Slightly better than D3-CoMP (more robust)

Outputs

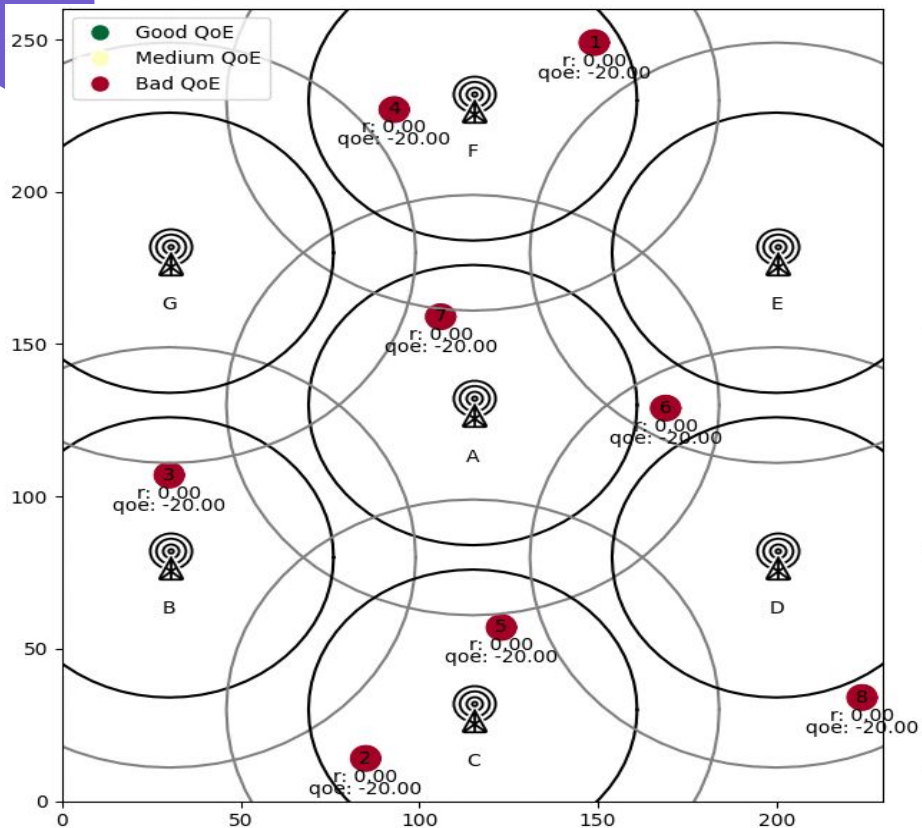


| | |
|-----------------|-----------|
| Agent | DeepCoMP |
| Training Steps | 4000 |
| Time Step | 0 |
| Curr. Avg. Rate | 0.00 GB/s |
| Curr. Avg. QoE | -20.00 |
| Total Avg. QoE | 0.00 |

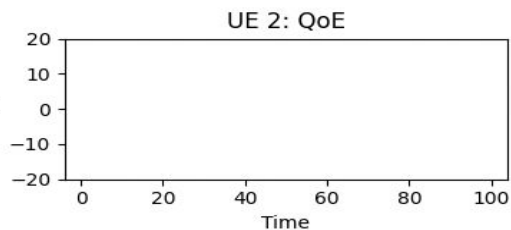
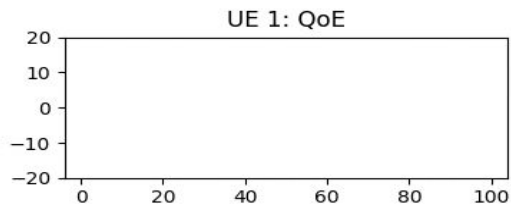
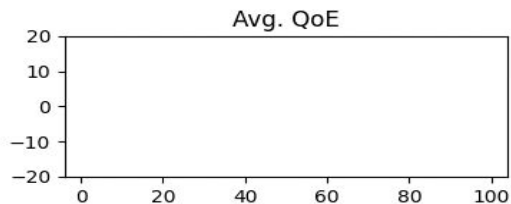


Name DeepCoMP:
Steps: 500
QoE: bad

Outputs

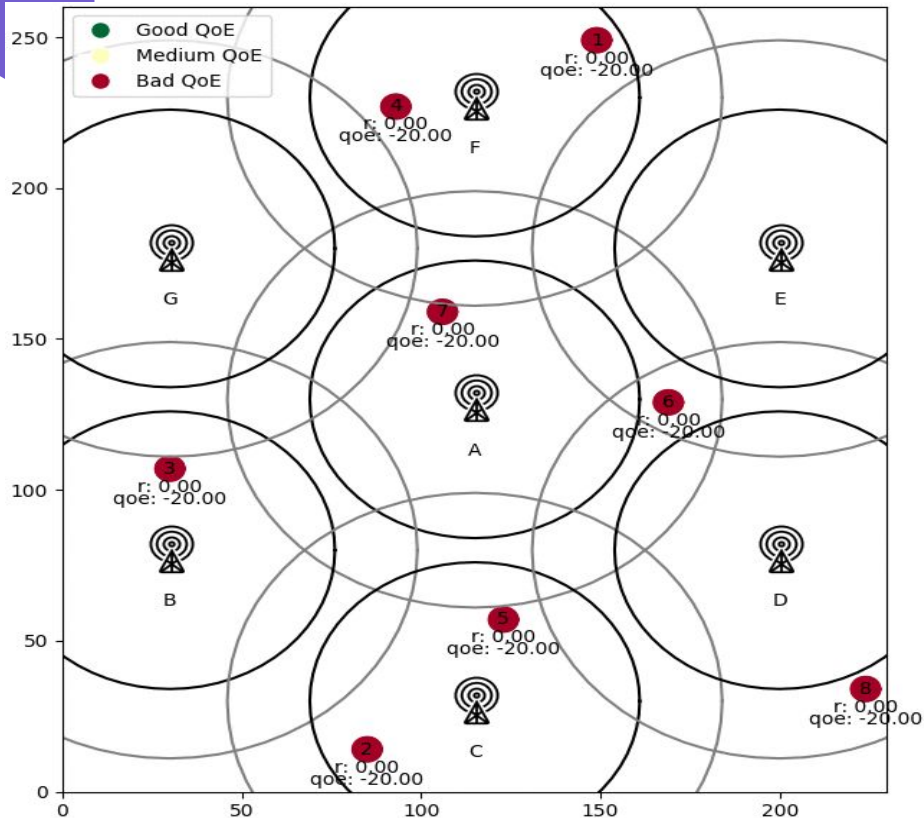


| | |
|-----------------|-----------|
| Agent | DeepCoMP |
| Training Steps | 52000 |
| Time Step | 0 |
| Curr. Avg. Rate | 0.00 GB/s |
| Curr. Avg. QoE | -20.00 |
| Total Avg. QoE | 0.00 |

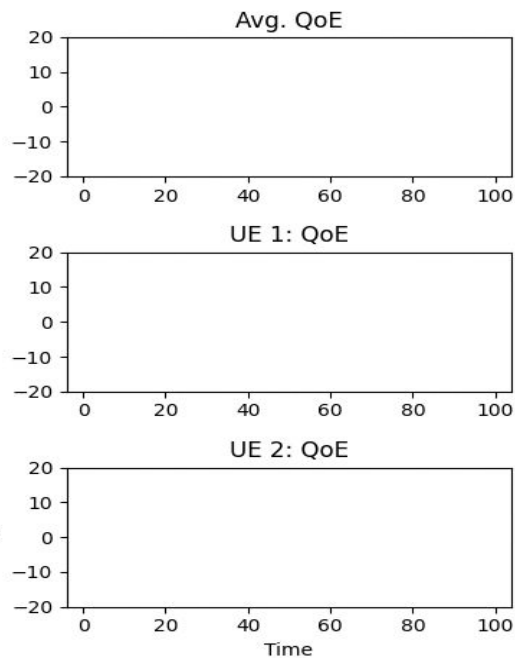


Name: DeepCoMP
Steps: 50,000
QoE: decent

Outputs

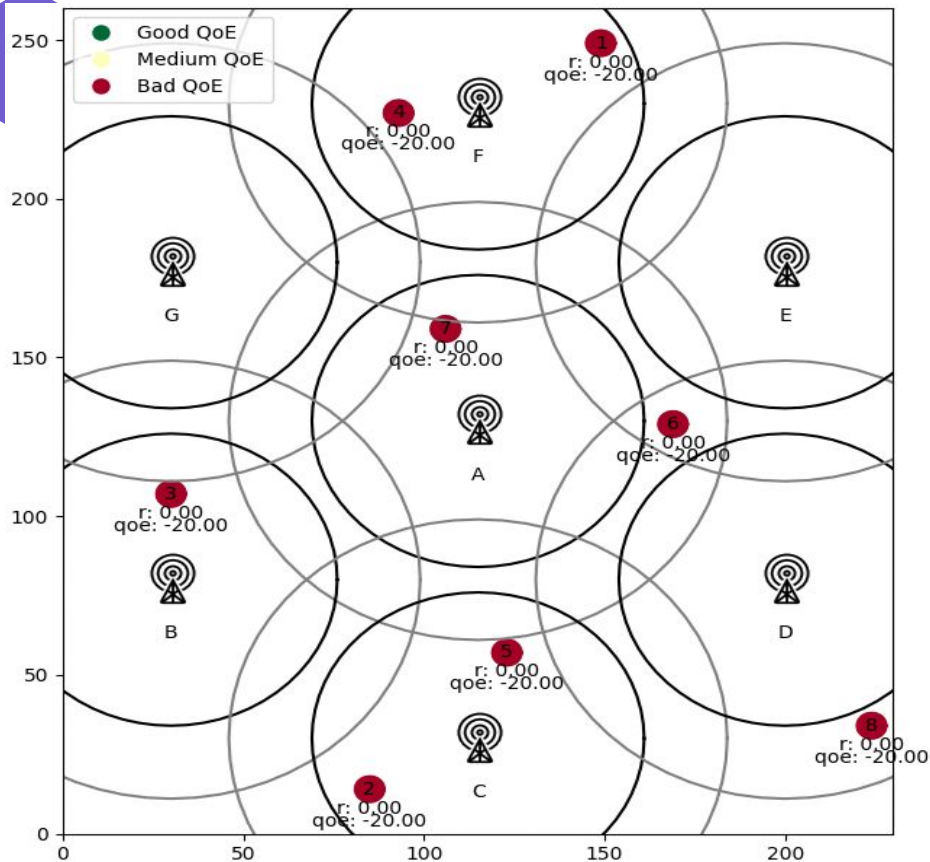


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| Agent | DeepCoMP |
| Training Steps | 200000 |
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| Curr. Avg. Rate | 0.00 GB/s |
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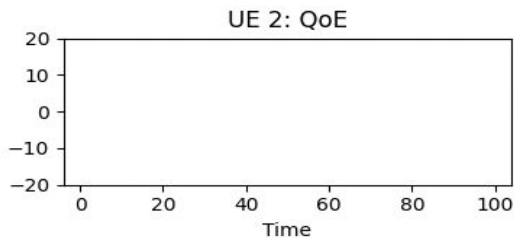
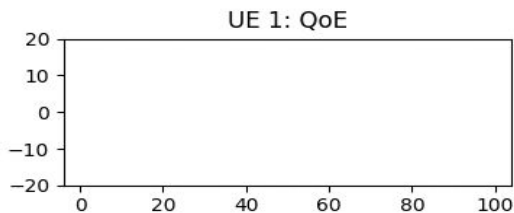
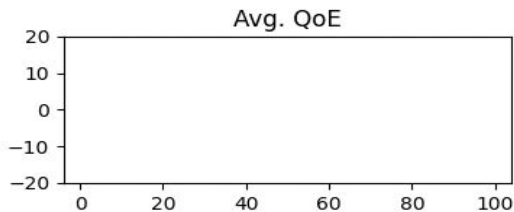


Name: DeepCoMP
Steps: 2,00,000
QoE: Good

Outputs

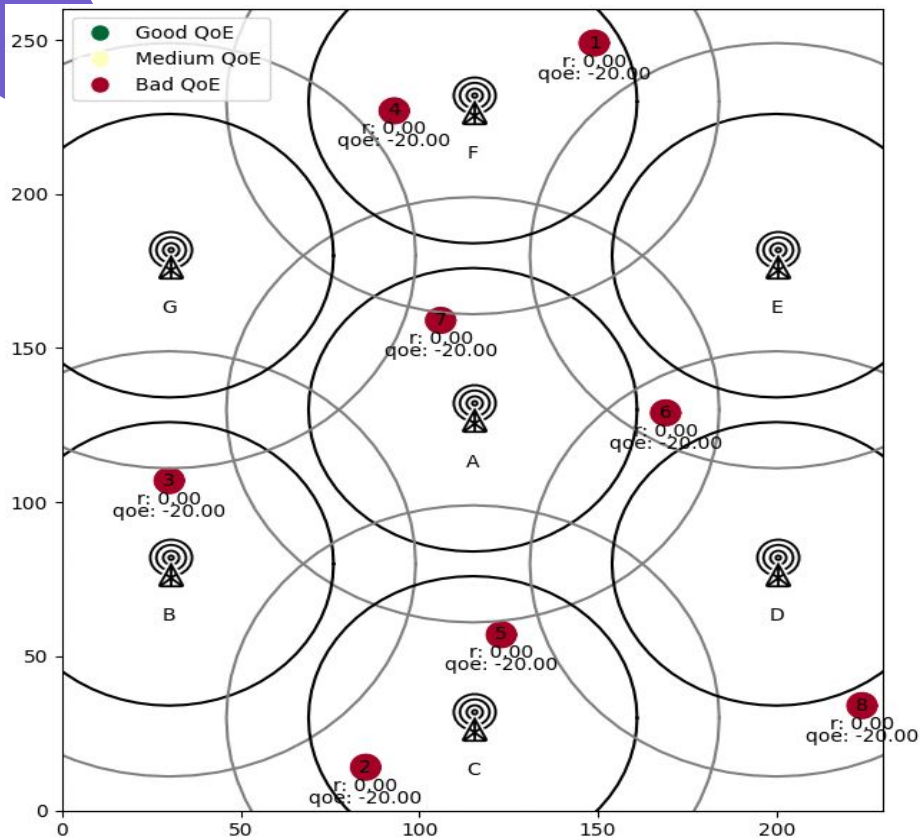


| | |
|-----------------|-----------|
| Agent | D3-CoMP |
| Training Steps | 4000 |
| Time Step | 0 |
| Curr. Avg. Rate | 0.00 GB/s |
| Curr. Avg. QoE | -20.00 |
| Total Avg. QoE | 0.00 |

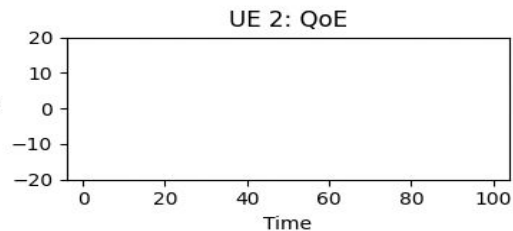
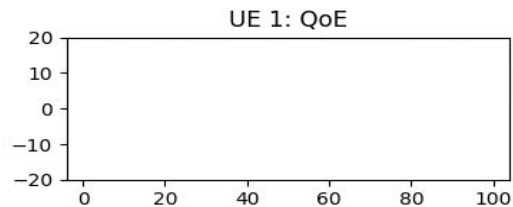
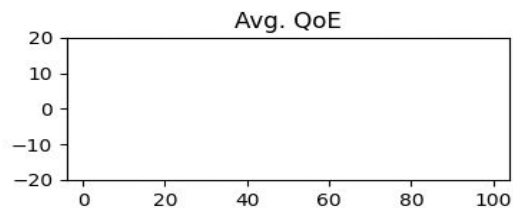


Name D3-CoMP:
Steps: 500
QoE: bad

Outputs

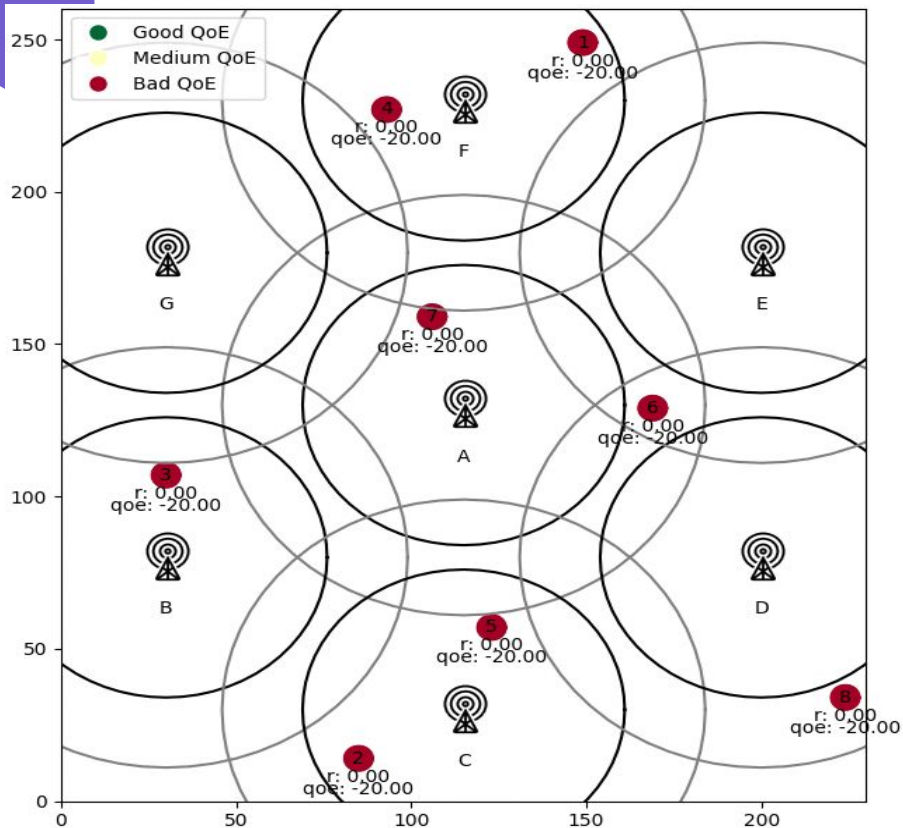


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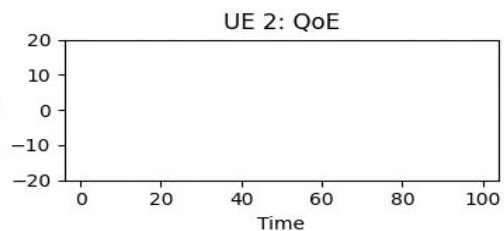
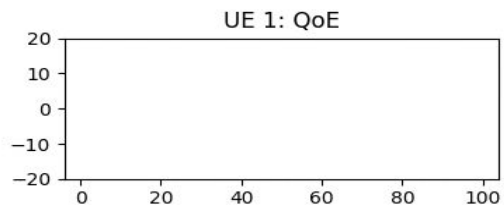
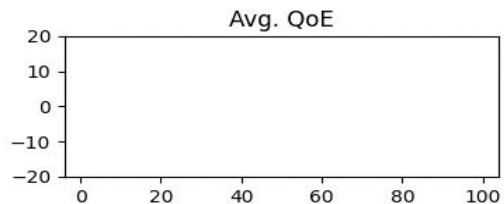


Name: D3-CoMP
Steps: 50,000
QoE: decent

Outputs

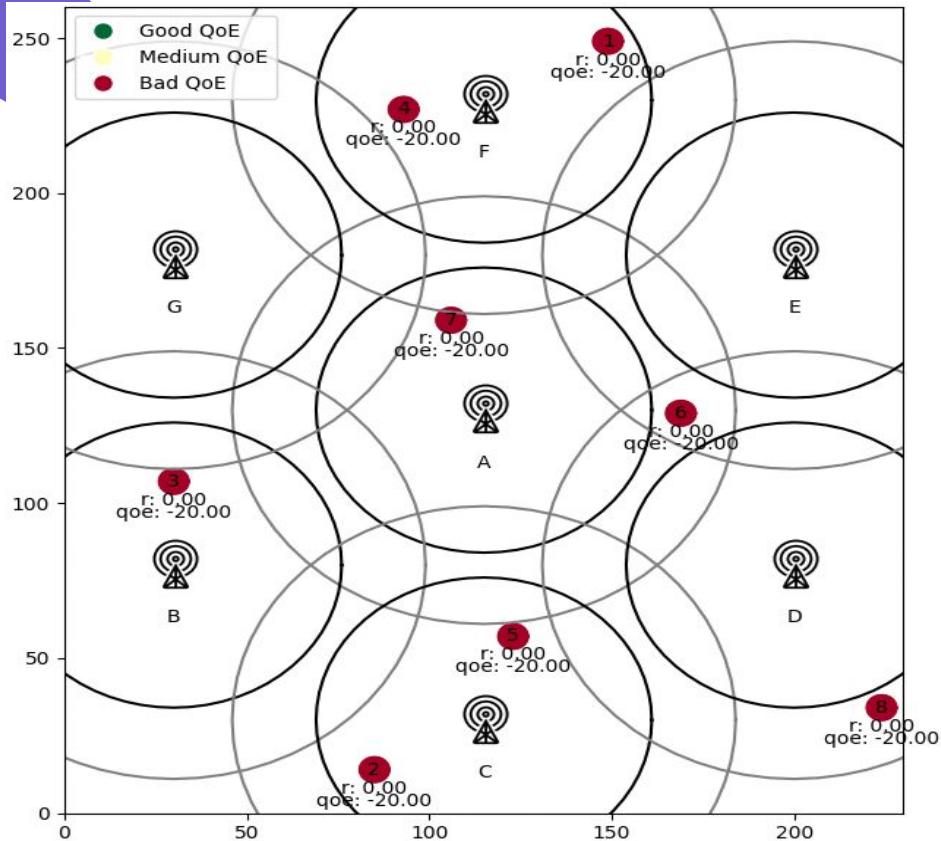


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| Agent | D3-CoMP |
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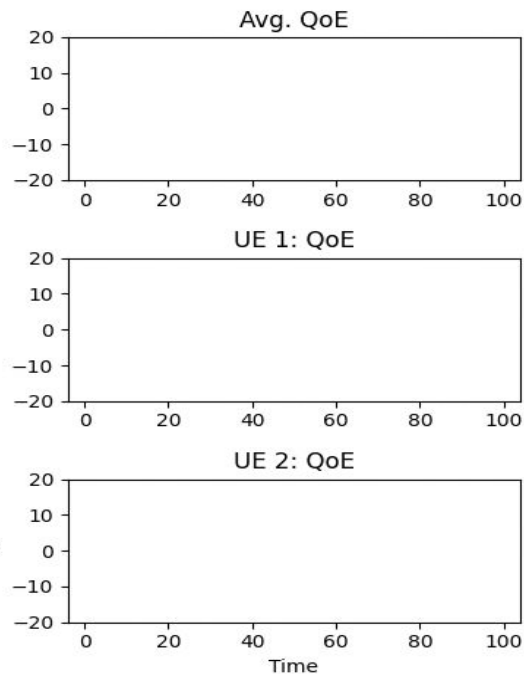


Name: D3-CoMP
Steps: 2,00,000
QoE: Good

Outputs

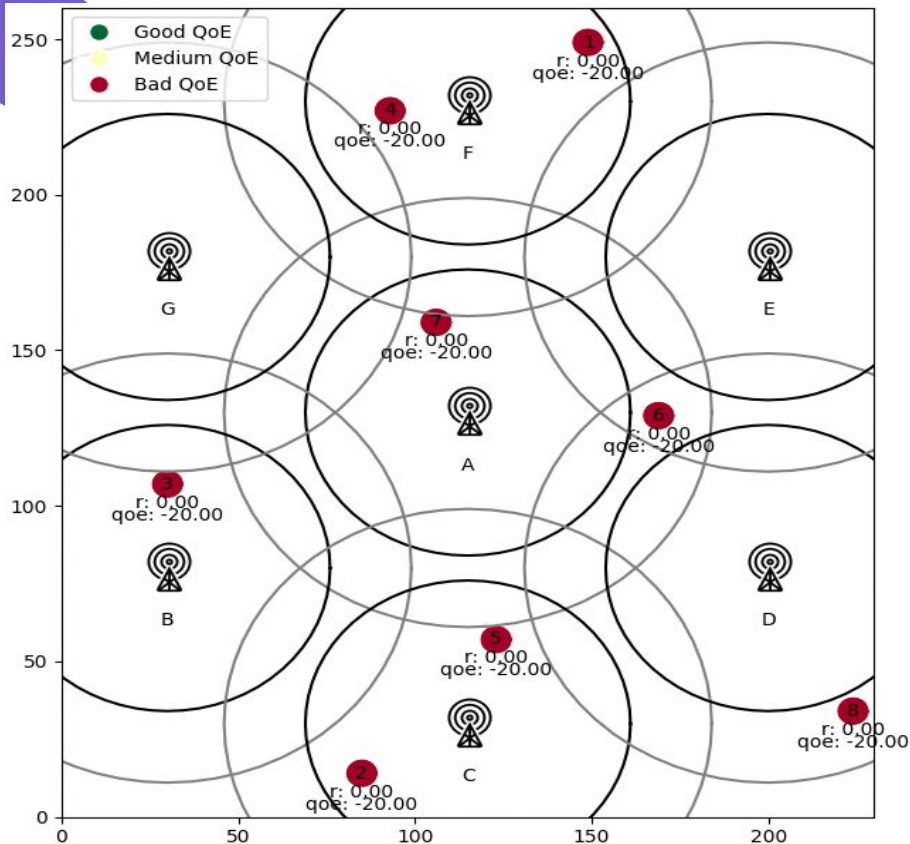


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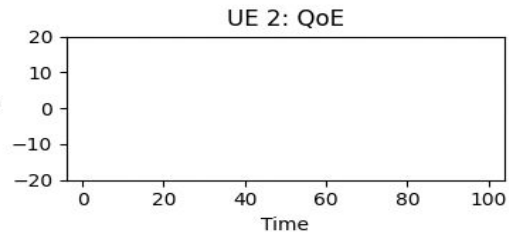
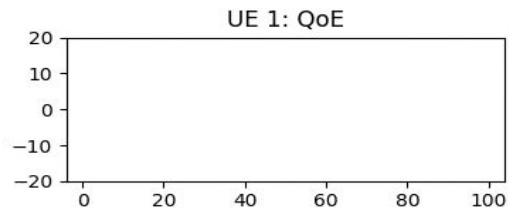
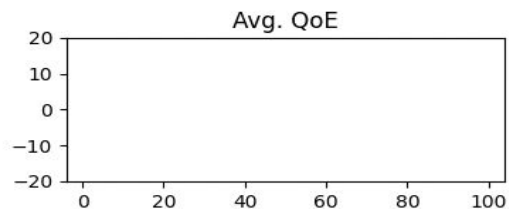


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Steps: 500
QoE: bad

Outputs

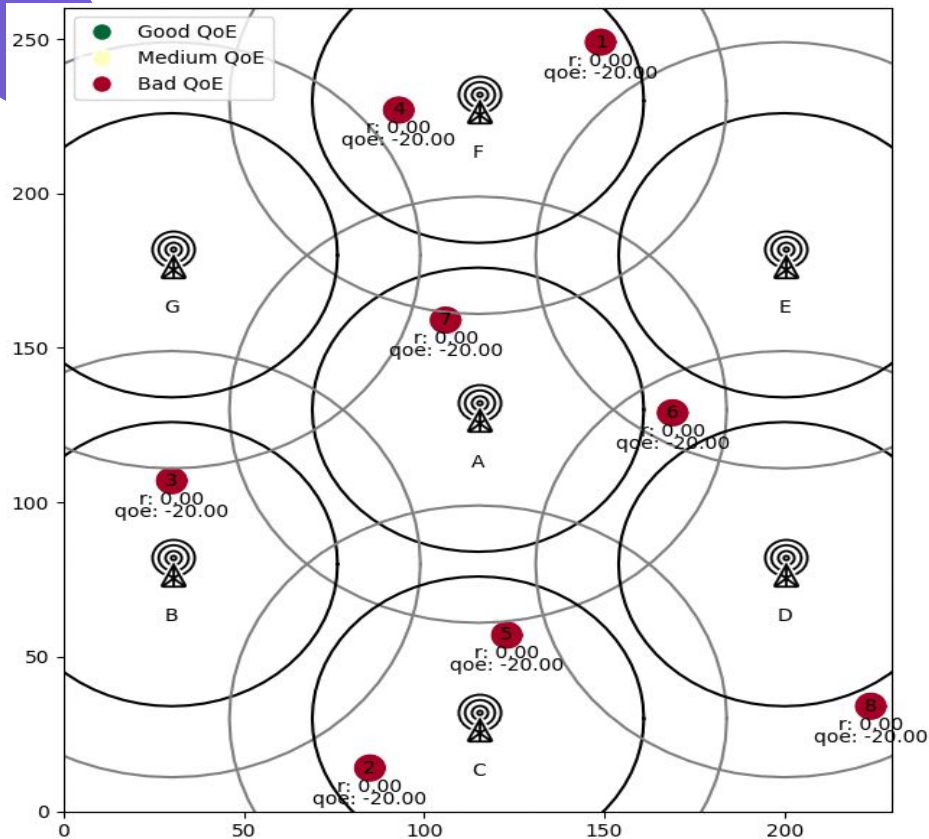


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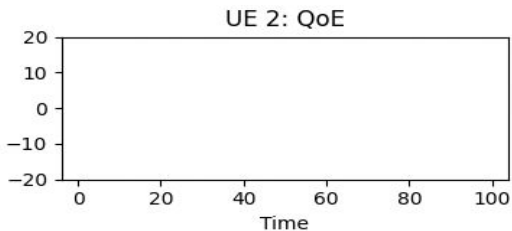
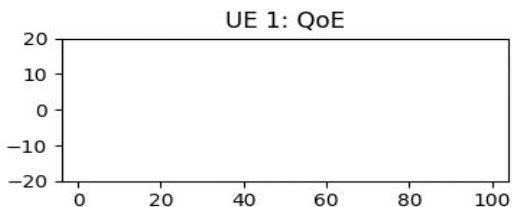
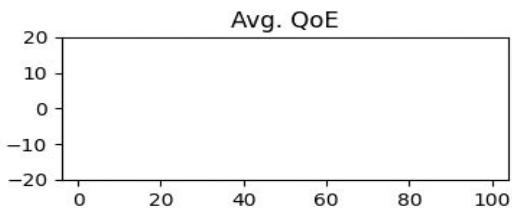


Name: DD-CoMP
Steps: 50,000
QoE: decent

Outputs



Agent DD-CoMP
Training Steps 200000
Time Step 0
Curr. Avg. Rate 0.00 GB/s
Curr. Avg. QoE -20.00
Total Avg. QoE 0.00



Name: DD-CoMP
Steps: 2,00,000
QoE: Good



Observation

- No need for human intervention or instructions
- DRL agents learn multi-cell selection effectively
- DRL agents self-adapt to each scenario
- DRL agents outperform existing approaches
- Distributed DRL learns good policy faster
- Central DRL ultimately learns better policy



Conclusion

- Three self-learning DRL approaches :
 - Central DeepCoMP: Slow but highly optimized multi-cell selection
 - Distributed DD-CoMP & D3-CoMP: Fast, local multi-cell selection
- Outperform existing approaches :
 - Work with minimal, realistically available information
 - Self-adapt to varying scenarios
 - Robust to sudden changes
 - Scale to large networks



THANK YOU!