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Optimizing 5G Networks for Low-Latency Communication: A Reinforcement Learning-Based Approach

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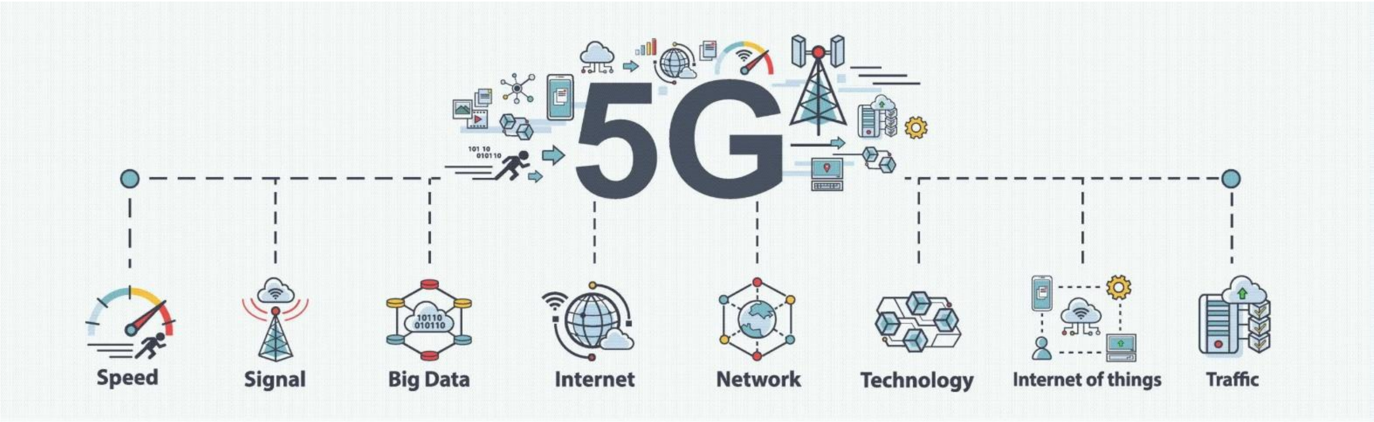
Introduction

- **Cyber-Physical Systems** (CPS) and **Industrial Internet of Things** (IIoT) are revolutionizing industrial automation by integrating real-time data sensing, transmission, and analytics.

- A key component enabling these technologies is the **Edge-Cloud continuum**, optimizing data processing between edge devices and cloud systems.

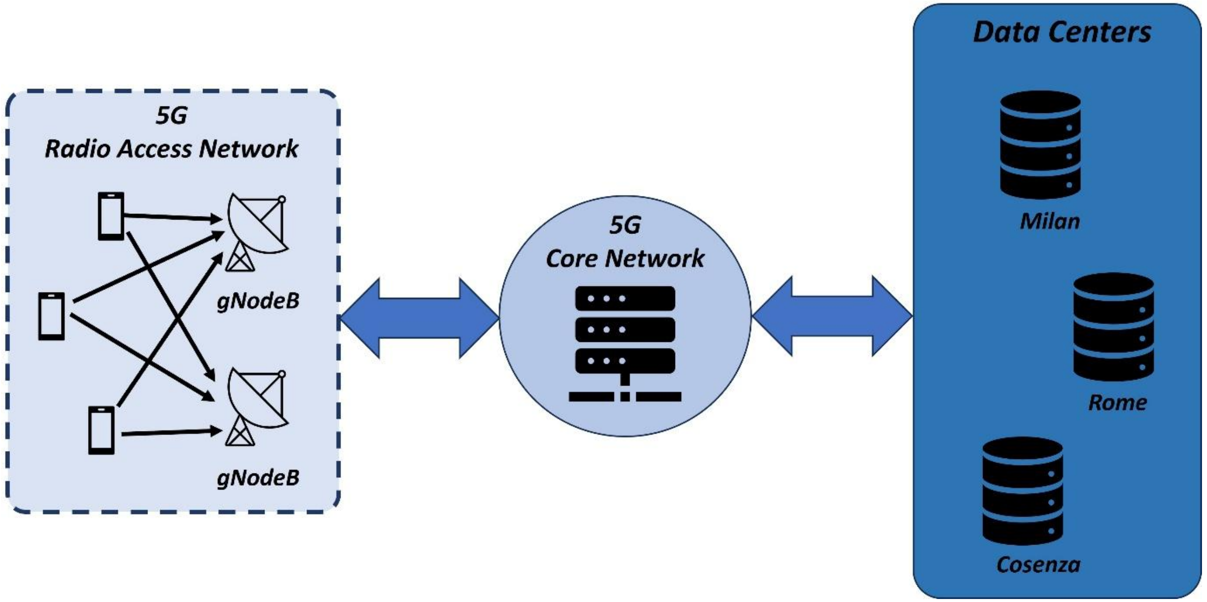
- **5G networks** serve as the backbone, providing high-speed connectivity essential for real-time industrial operations and smart manufacturing.



Problem Definition

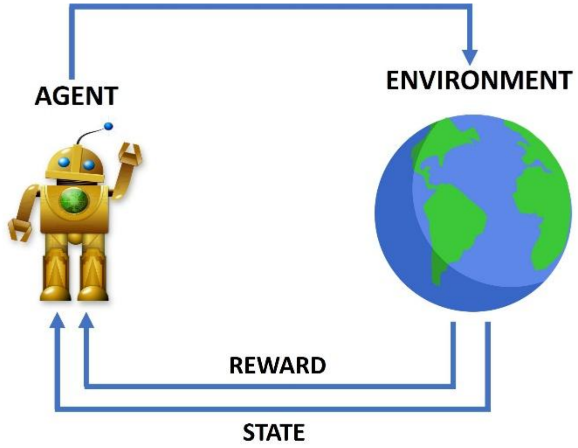
- Real-time data exchange is crucial for **Industry 4.0** applications, where delays can negatively impact automation and dynamic process adjustments.
- **Reducing latency** between the **gNodeB** Radio Access Network (RAN) and **User Plane Function** (UPF) is critical for effective operation in **5G networks**.
- This study focuses on developing methodologies for **optimizing 5G network performance**, with an emphasis on latency reduction through Reinforcement Learning (RL) techniques.

Network Architecture and Dataset Overview



- **Edge Nodes**: The key geographical sites for this study are the data centers in Milan, Rome, and Cosenza, representing diverse network conditions.
- **Dataset**: Data was collected from multiple data centers, simulating varied traffic profiles (e.g., Night, Busy Hour, Daytime) and introducing real-world constraints like bandwidth caps and packet loss.

Reinforcement Learning Methodology



CPU	Memory	Disk	Net in	Net out	Latency avg	Latency mdev	Packet loss
0.6	0.5	0.5	0.7	0.7	1	0.2	0.9

- **Goal**: To minimize latency while balancing other KPIs such as CPU and memory utilization across edge nodes.

- **RL Agent Design**: The agent's task is to select the optimal data center for minimizing latency, considering various network performance features:
  - Latency (average, mean deviation [ms])
  - CPU, memory, and disk usage [%]
  - Network traffic (net in, net out, packet loss [%])

$$\sum_{i=1}^{n} \frac{W(i)}{1+D(i)}$$

- **Reward Function**: The agent's reward is calculated based on a weighted sum of key KPIs, prioritizing latency and packet loss.

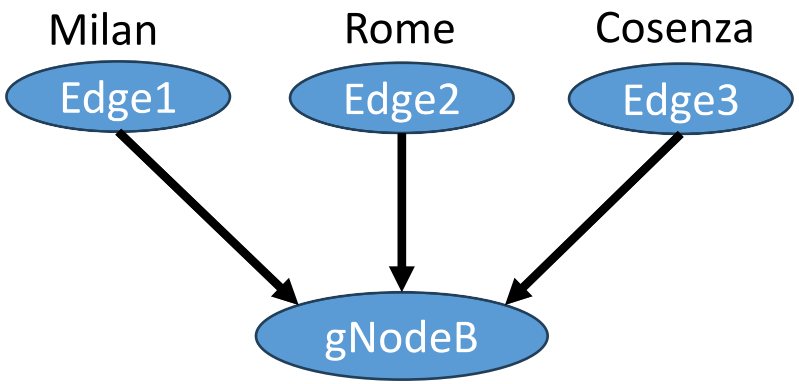
RL Environment

- **Framework**: Developed using Python’s Gymnasium library.

Gymnasium

- **Key Elements**:
  - Environment definition tries to follow the main rules of the 5G network.
  - Each of the three edges shares data with the gNodeB at the same time.

Our Network



Observation space

Real-time metrics from the dataset.

Each observation contains data from each edge, e.g. *Latency1, Latency2, Latency3, CPU1, CPU2, …, …, PacketLoss1, …*

Action space

Selection of an edge node (*Milan*, *Rome*, *Cosenza*).

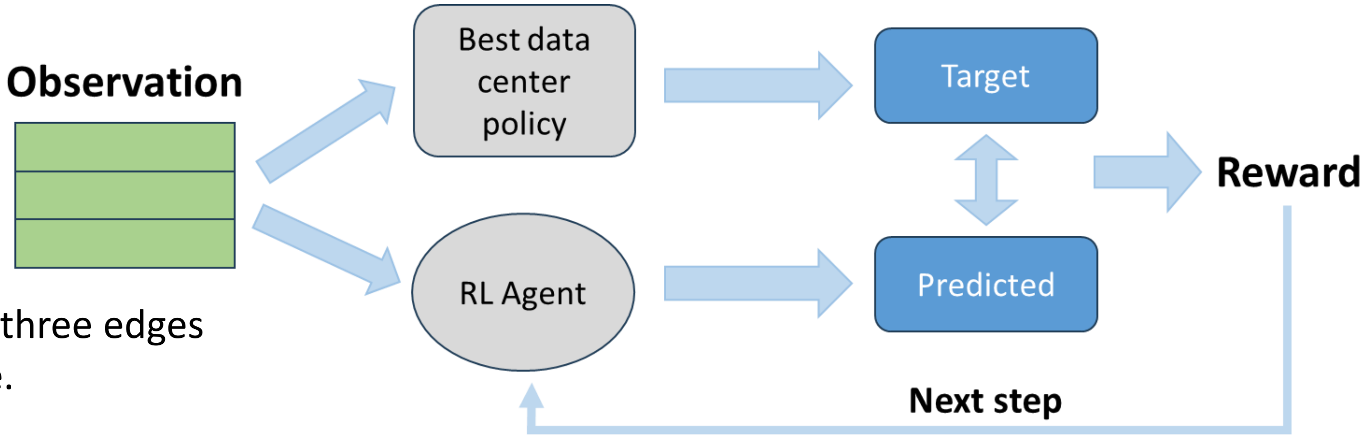
Reward function

Based on the efficiency of the selected edge node in minimizing latency and maintaining balance across KPIs.

RL Algorithms for 5G Network Optimization

- Three RL architectures were tested:
  - Deep Q-Network (**DQN**),
  - Proximal Policy Optimization (**PPO**),
  - Advantage Actor-Critic (**A2C**).

- Each model was trained using real-time data traffic and optimized through different hyperparameters:
  - Learning rate
  - Batch size
  - Discount factor (**γ**)

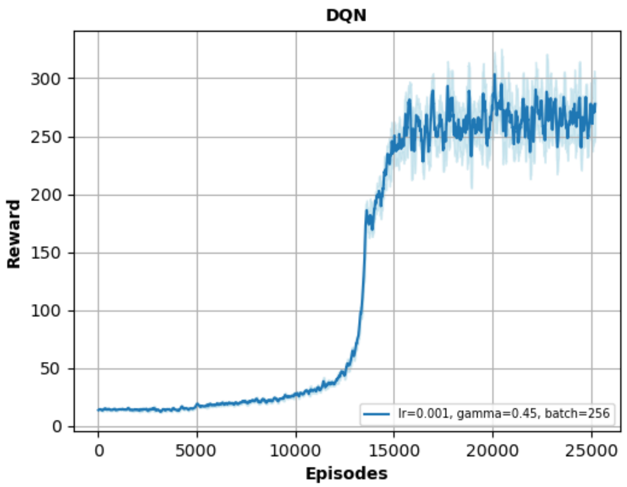


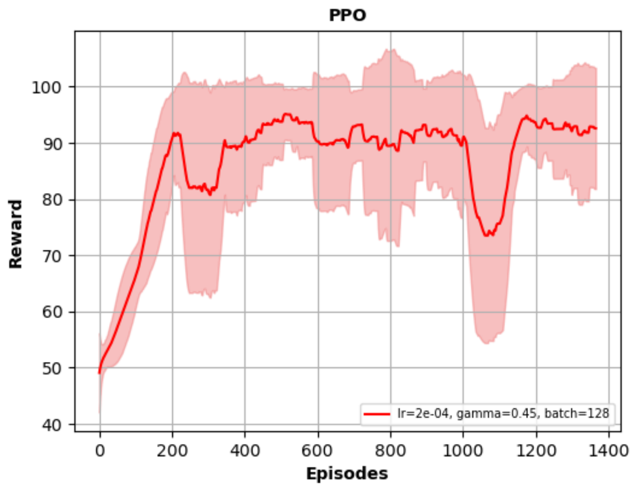
A matrix of three rows corresponding to the three edges measurements are used as observation state.

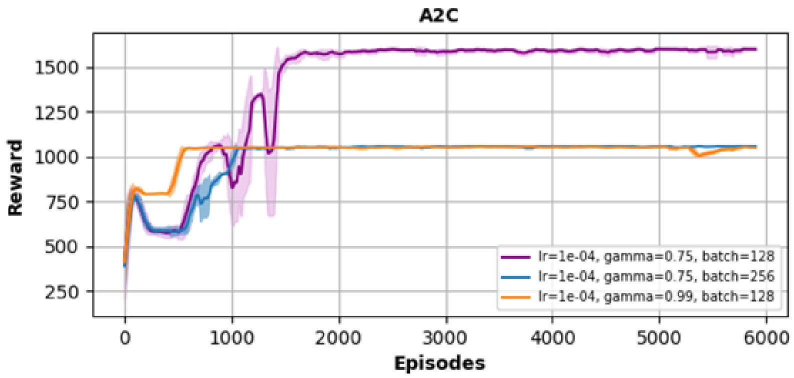
Results and Evaluation

- **DQN** emerged as the most effective algorithm, achieving the highest performance with a maximum reward of **338** and stable convergence.
  - Best configuration: **Learning rate** = **0.001**, **γ** = **0.45**, **Batch size** = **256**.

- **PPO** and **A2C** models demonstrated slower or unstable convergence, indicating they are less suited to the task compared to DQN.







Conclusion

- **DQN** is the preferred model for optimizing 5G network latency in CPS and IIoT environments, showing potential for real-time applications in smart manufacturing.
- **Future works** will focus on
  - **Refinements of the models**: exploring more diverse data center conditions and further reducing latency in edge-cloud interactions.
  - **Sustainability:** minimizing energy consumption and using green energy sources align with global sustainability goals and industry standards for low-carbon operations.

Takeaways

- The integration of **RL techniques** in 5G networks offers a robust solution for latency optimization, critical for the success of **Industry 4.0** applications.
- **DQN** provides the best balance between reward convergence and network performance in this study, proving its efficacy for low-latency, high-performance industrial operations.