

# Advancing RAN Slicing with Offline Reinforcement Learning



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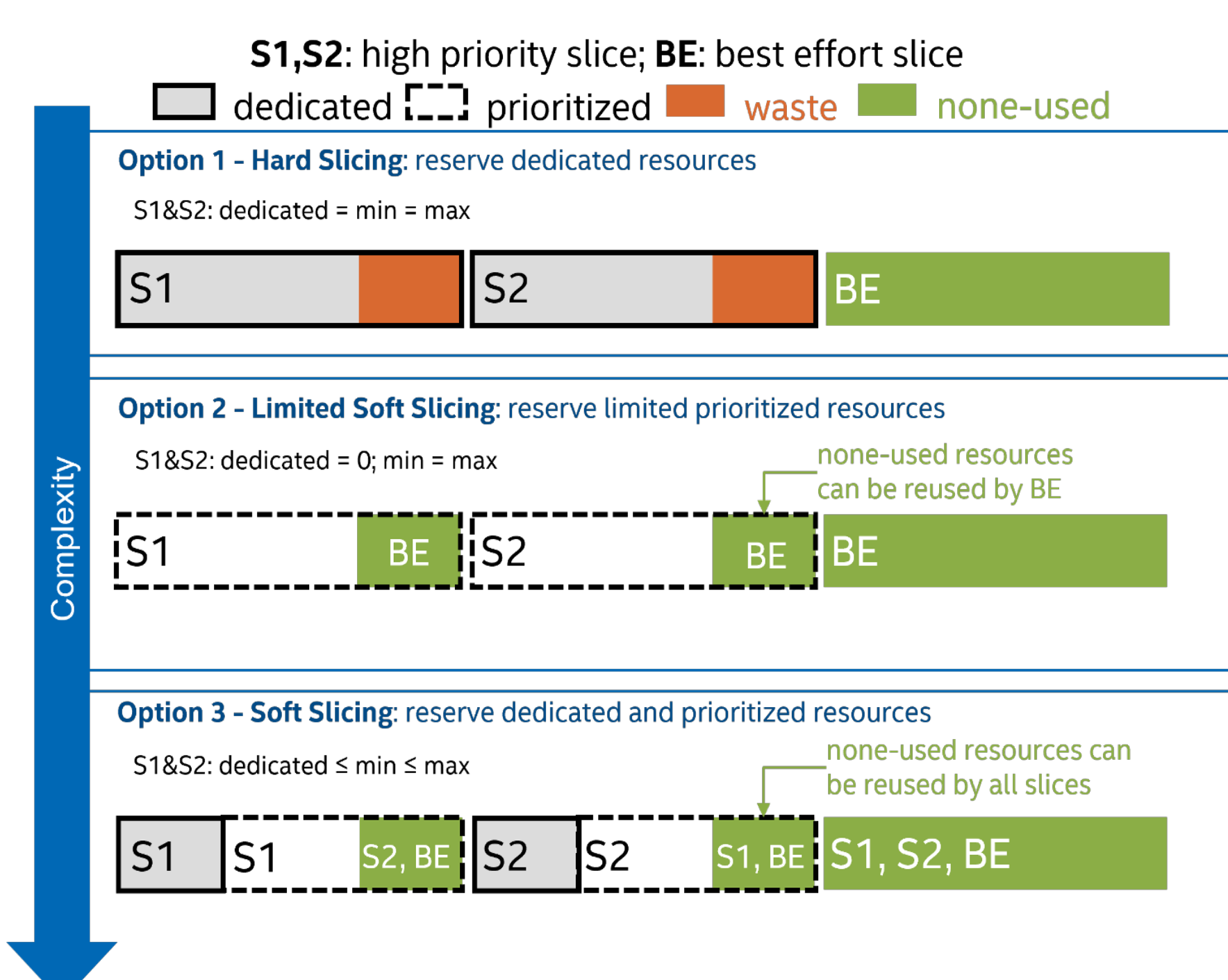


## Motivation

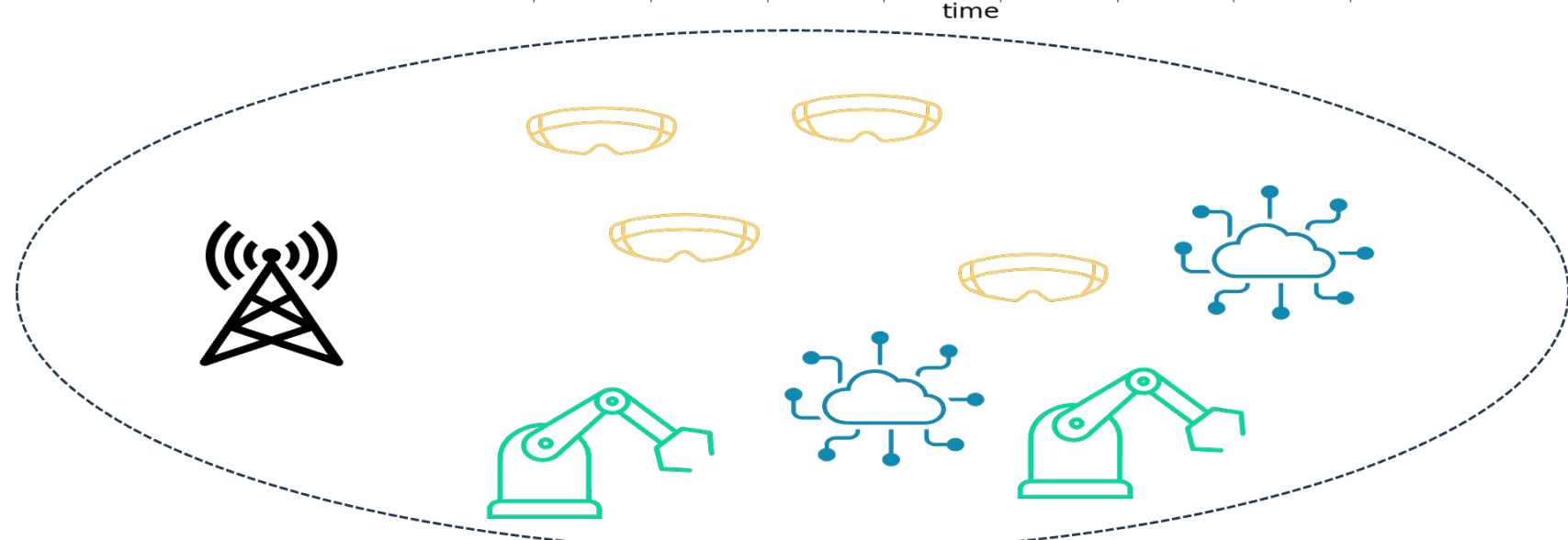
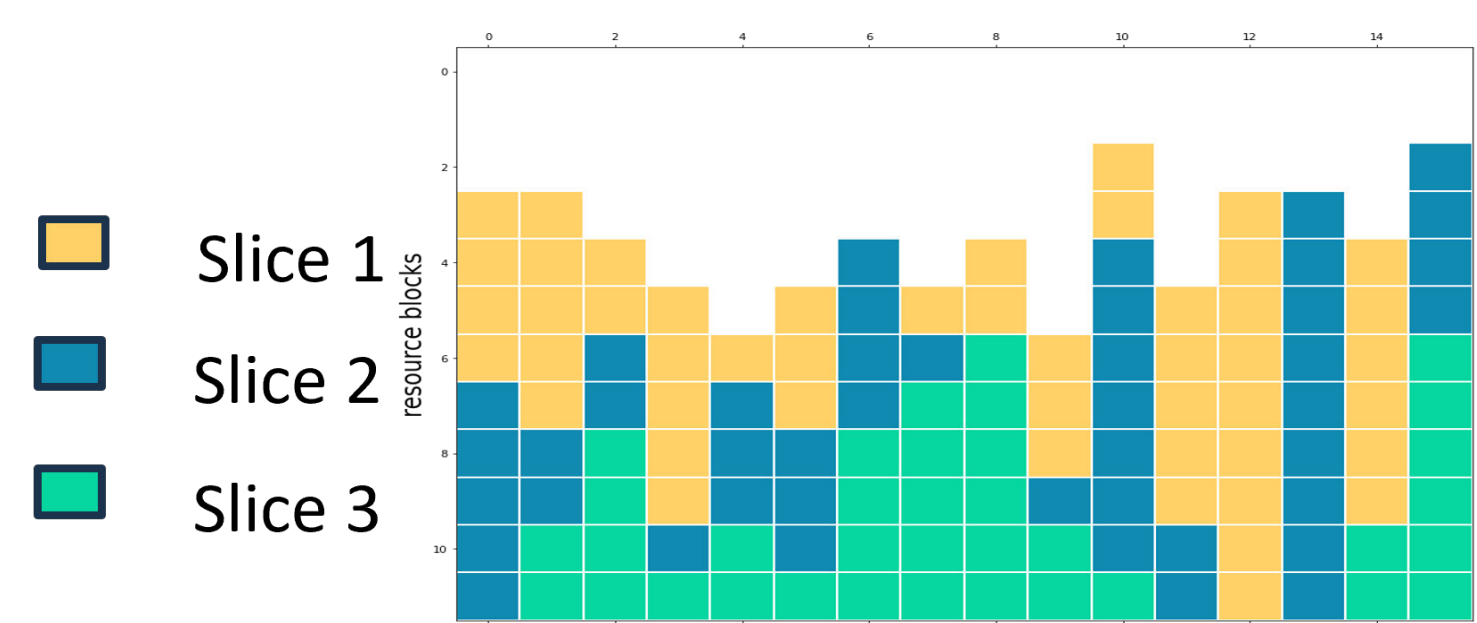
- RL can solve sequential decision-making problems like RRM
- Network slicing is designed to **handle different services** -> **create heterogenies data**.
- Traditional methods struggle **to adapt between distinct services**.
- Online RL needs **extra exploration and training** for a new environment/service requirement.
- Data with **good coverage (hetero data sources)** can help offline RL training.

Slice Type	Data Rate	Capacity	Latency
eMBB	<b>Very High</b>	High	Low
URLLC	Moderate	Moderate	<b>Ultra-low</b>
mMTC	Low	High	Moderate

## Environment Setting

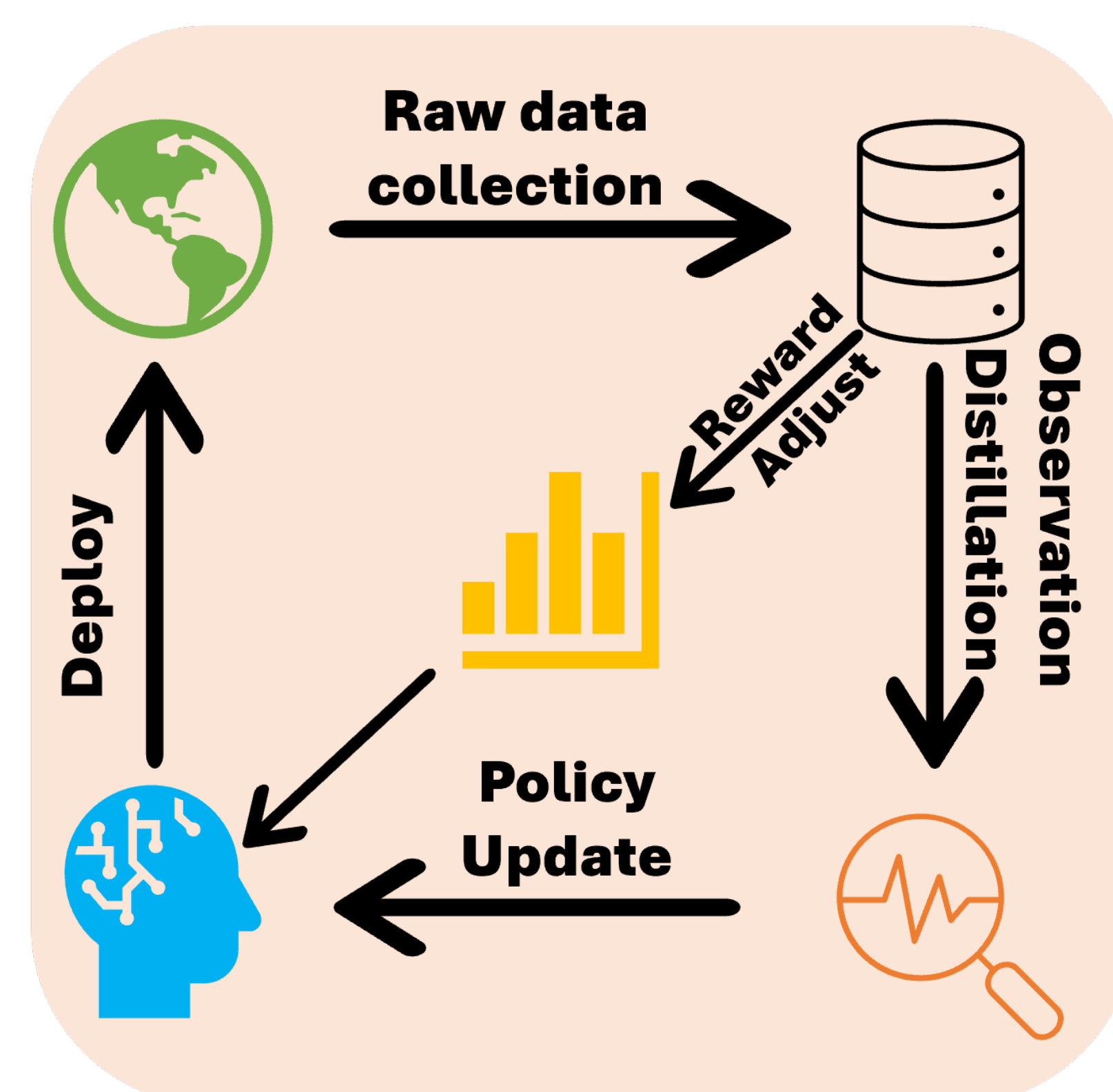


- Two prioritized slices**
- One best effort slice (Background)
- 1 Cell with 30 users:
- Service Level Agreement (SLA):**
  - Reduce delay violation rate
  - Maintain received (rx) traffic
- Objective:**
  - Allocate resource blocks for prioritized slices
  - Meet SLA**

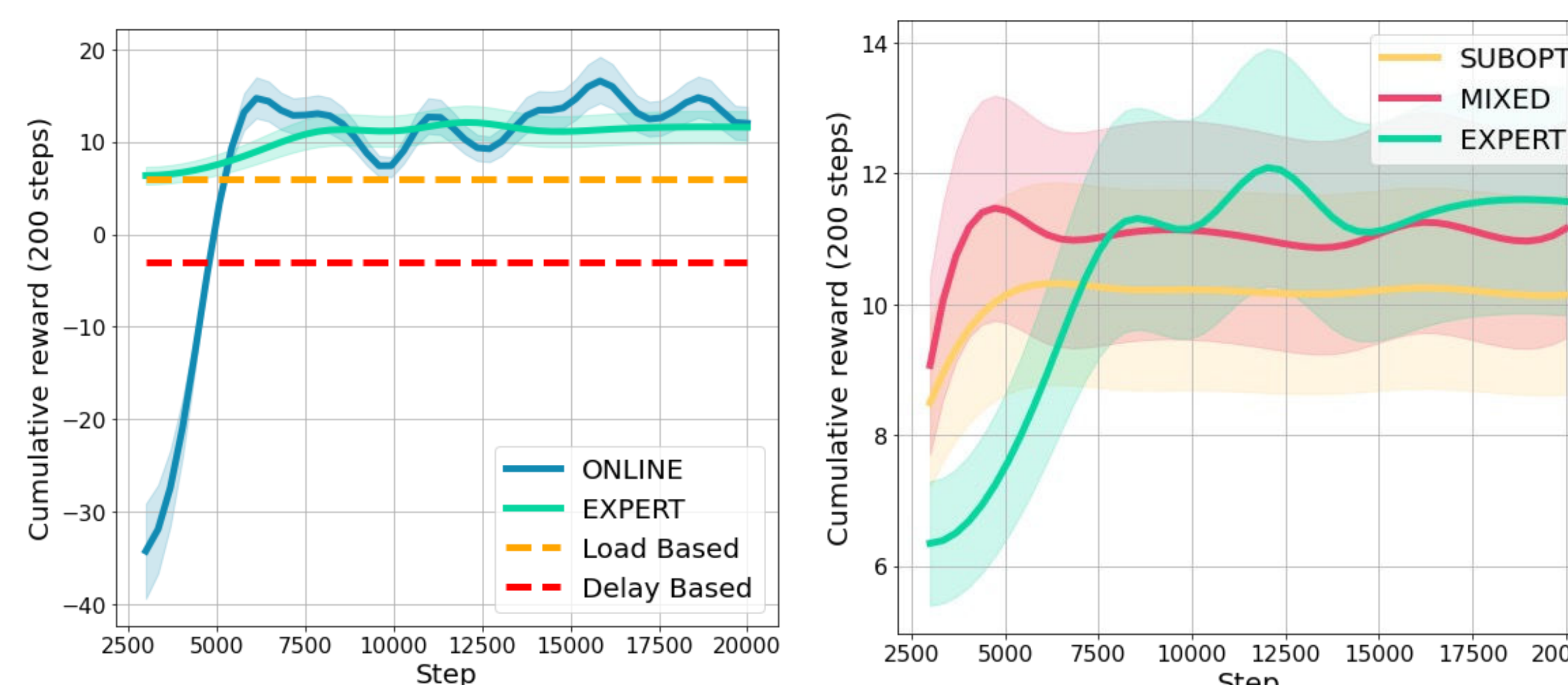


## Experiment Process & Result

\* **Observation distill & reward adjustment** enable **flexibility**

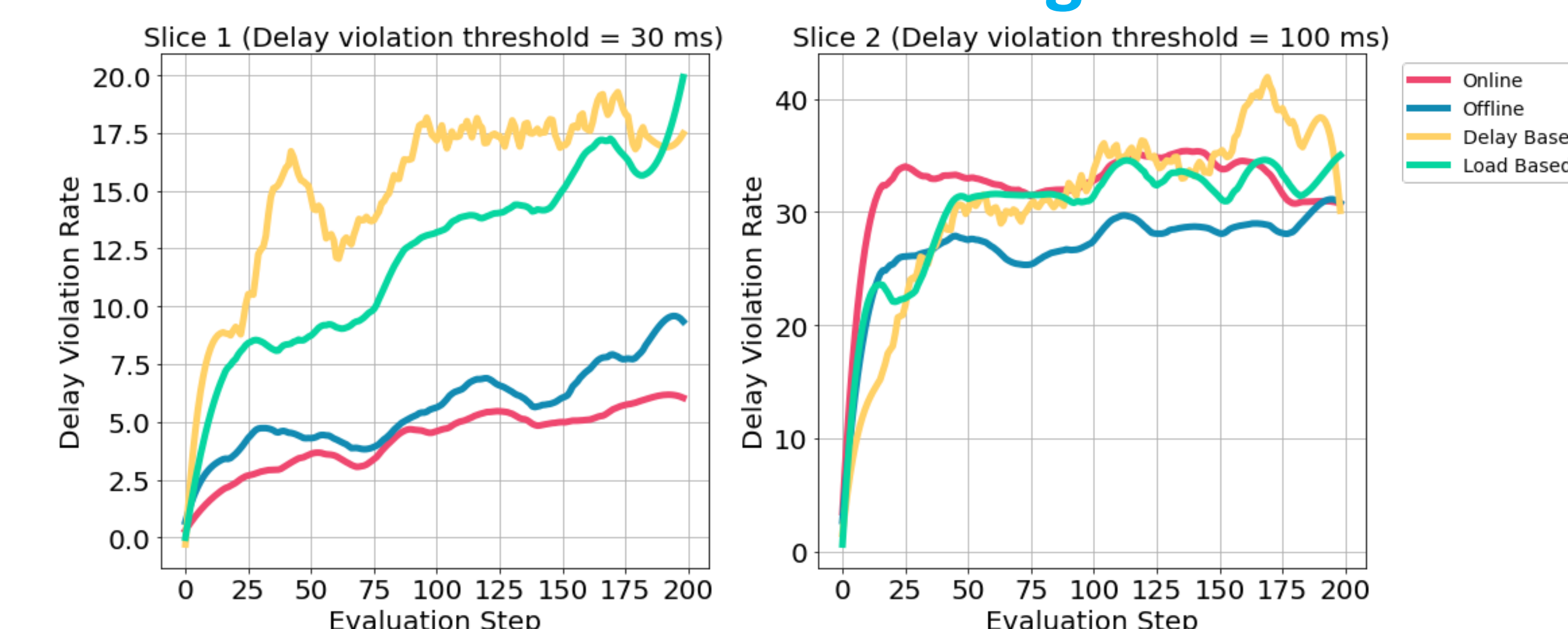


- Training from **pure expert data** can help offline RL outperform the online behavior policy.
- With **mixed suboptimal** datasets, the offline RL recovers online RL performance.



## Adjust SLA and Objective

- Offline RL can handle different SLAs **without retraining**.



- With **reward adjustment**, offline RL can **retrain policies** to handle different SLA requirements.

SLA requirement	Delay violation rate	Total Throughput	Resource Usage
Delay	<b>6.5 ± 3.5</b>	52.48 ± 13.65	49.15
Throughput	9.1 ± 4.4	<b>58.68 ± 11.23</b>	49.35
Resource	7.3 ± 4.1	51.44 ± 12.68	<b>48.89</b>

## Conclusion & Future work

- Offline RL is able to recover online-level policies with **mixed suboptimal dataset**.
- With **reward adjustment and observation distillation**, offline RL can adjust to different SLAs **without additional data collection**.
- Future question: Can offline RL algorithms handle different SLA **without retraining?**

## Acknowledgement

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