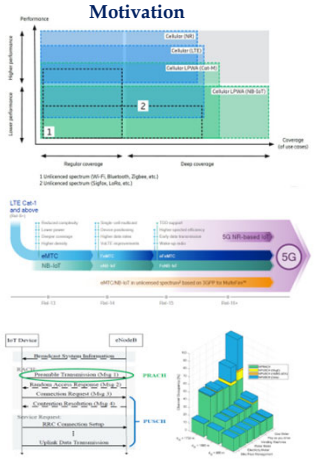
Machine Learning for 6G Wireless Communications

CSR Group

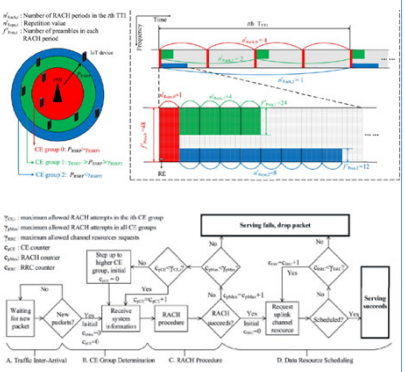
Machine Learning in 6G Massive Access [1, 2]

Motivation



Key Outage Events: *SINR Outage* and *Collision Outage*

NB-IoT Network

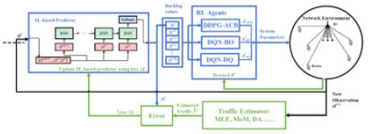


Challenges:
- How to adjust the repetition value, RACH frequency, the ACB factor, the back-off factor, etc..?
- Heterogeneous traffic.

Solution: *Dynamic Autonomous Optimization*

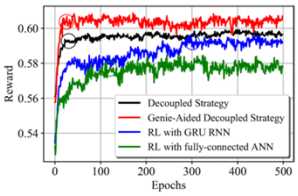
Solution

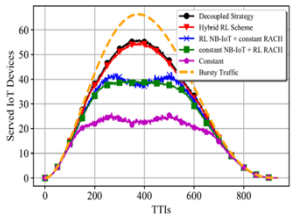
POMDP-Environment is partially observed:
- Unknown new traffic generation
- Unknown collision process (i.e., collided devices are 2, 3, or more?)
- Unknown packets dropping



DRL-aided Solution:
- Framed time
- BS organize devices' transmission and re-transmission in each frame
- BS receive feedback after each frame (number of successes/idles/collisions)

Numerical Results



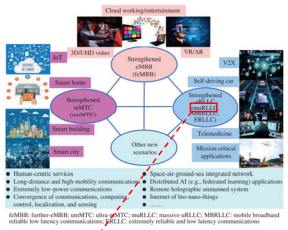


[1] N. Jiang, Y. Deng, **A. Nallanathan** and J.A Chambers, " Deep Reinforcement Learning for Real-Time Optimization in NB-IoT Networks", IEEE JSAC, 2019.

[2] N. Jiang, Y. Deng, **A. Nallanathan** and J. Yuan, " A Decoupled Learning Strategy for Massive Access Optimization in Cellular IoT Networks", IEEE JSAC, 2021.

Machine Learning in 6G Massive URLLC (mURLLC) [3]-[5]

Motivation



mURLLC Challenges:

Extreme Low Latency:
- E2E very low latency < 1ms
- Always low latency

Extreme High Reliability:
- Guaranteed QoS for wide range of use cases (upto 99.99999% reliability)
- Secure, private, safe, resilient, …

Extreme Massive Connectivity:
- Massive connected devices (10M/km^2)
- Sensing capabilities & high-precision positioning (cm-order)

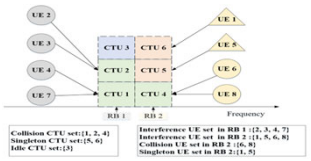
MCG-GF-NOMA

To Reduce Latency:
- GF provides low latency by removing scheduling request

To Increase Reliability:
- Advanced K-repetition and Proactive GF schemes provide high reliability

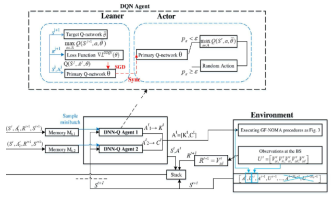
To Enhance Connectivity:
- NOMA provides additional connectivity in the same RB for massive access

Key Problem: CTU and Collision Detection:



Challenges:
- *CSI:* Set of active users and their respective channel conditions are unknown to the BS
- *Traffic:* Satisfy the reliability and latency requirements under random traffic
- *Detection:* CTU collision detection, blind UE activity detection, and data decoding
- *Environment:* Complex communication environment (lack of tractable mathematical formulations, non-convex optimization etc.)

Solution



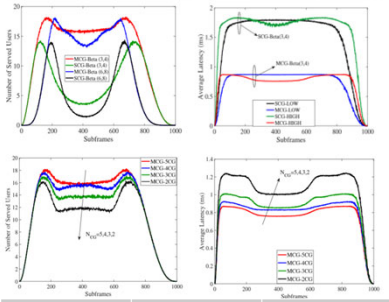
Observations from Environment:
- Number of the collision CTUs
- Number of the idle CTUs
- Number of the singleton CTUs
- Number of UEs that have been successfully detected and decoded under the latency constraint
- Number of UEs that have been successfully detected but not successfully decoded

Actions at DQN Agent:
- Number of CTUs
- Starting slot within a subframe
- Number of repetitions

Rewards for DRL Learning:
- Number of successfully served UEs under the latency constraint and CTU resources constraint

Numerical Results

Parameters	Value	Parameters	Value
Path-loss exponent η	4	Noise power σ^2	-132 dBm
Transmission power P	23 dBm	The received SINR threshold γ_{th}	-10 dB
Duration of traffic T	2 s	The set of the repetition value	$\{1, 2, 4, 6, 8\}$
The set of the CTU number	$\{12, 24, 36, 48\}$	Latency constraint	2 ms and 8 ms
Bursty traffic parameter Beta(α,β)	$(2, 4)$	The number of bursty UEs N	20000
Cell radius	10 km	Duration of one TTI	0.125 ms



Learning Rate	Minimum Exploration Rate	Discount Rate
0.0001	0.1	0.5
Minibatch Size	Replay Memory	Update Frequency
32	10000	1000

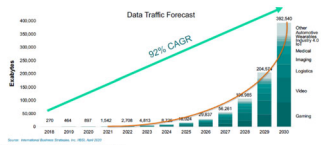
[3] Y. Liu, Y. Deng, M. Elkashlan, **A. Nallanathan**, and G. K. Karagiannidis, "Analyzing grant-free access for URLLC service," IEEE JSAC, 2021.

[4] Y. Liu, Y. Deng, M. Elkashlan, **A. Nallanathan**, and G. K. Karagiannidis, "Optimization of Grant-Free NOMA with Multiple Configured-Grants for mURLLC," IEEE JSAC, 2022.

[5] Y. Liu, Y. Deng, H. Zhou, M. Elkashlan and **A. Nallanathan**, 'Deep Reinforcement Learning-based Grant-Free NOMA Optimization for mURLLC', IEEE TCOM, 2023.

Federated Learning in 6G Mobile Edge Network [6], [7]

Motivation



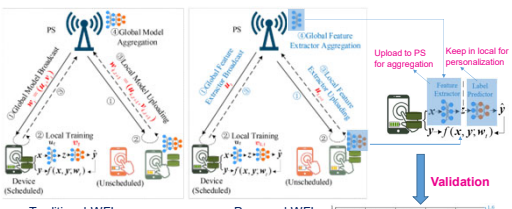
- Intelligence Interface (Deep learning driven)
- Energy Efficiency
- Huge Data Transmission
- Privacy Protection

Challenges and Solutions

- Limited Communication Resources
- Data Heterogeneity Across Devices
- Model Heterogeneity

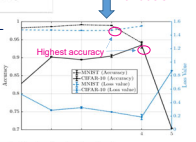
Joint designs from the following two research directions:
- **[Wireless+Data]:** How to jointly improve the communication and computation efficiency of WFL under non-IID data?
- **[Wirelss+Model]:** How to jointly improve the communication and computation efficiency of WFL with model heterogeneity?

Solution 1: A Partial Model Aggregation [6]



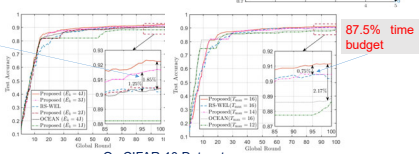
Traditional WFL Proposed WFL

- Convergence analysis to derive explicit upper bound of the loss function.
- Long-term optimisation to maximise the prediction accuracy via Lyapunov optimization framework, Convex optimization methods, and Greedy algorithms



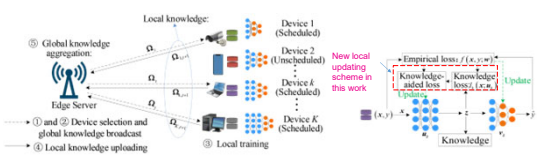
75% energy budget

87.5% time budget



On CIFAR-10 Dataset

Solution 2: Knowledge Aggregation [7]



Local networks can be different

Transfer output (knowledge) instead of model

Insight: Reducing over 99% communication overhead than model arregation-based algorithms without harming the performance.

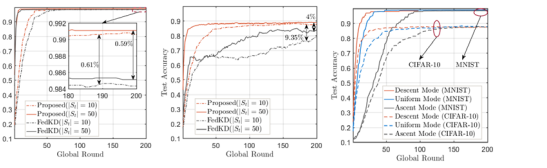


Figure: Comparison of learning performance under heterogeneous models (a) different algorithms on the MNIST dataset; (b) different algorithms on the CIFAR-10 dataset; (c) different scheduling patterns on MNIST and CIFAR-10 datasets.

[6] Z. Chen, W. Yi, **A. Nallanathan**, and G. Y. Li, "Efficient Wireless Federated Learning with Partial Model Aggregation," submitted to IEEE TCOM, 2023. [Available: https://arxiv.org/abs/2204.09746].

[7] Z. Chen, W. Yi, Y. Liu, and **A. Nallanathan**, "Knowledge-aided Federated Learning for Energy-limited Wireless Networks," IEEE TCOM, 2023. [Available: https://arxiv.org/abs/2209.12277].

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