

# Learning to Dynamically Allocate Radio Resources in Mobile 6G in-X Subnetworks

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# Learning to Dynamically Allocate RR in Mobile 6G in-X Subnetworks

## Outline

### Introduction

- 6G in-X subnetworks
  - Concept
  - Use-cases
  - Air-interface components

### Distributed dynamic channel allocation

- Existing algorithms
- Proposed DNN based method

### Performance Results

- Training and execution results
- Sensitivity analysis

### Summary and Conclusion

# Introduction

## 6G in-X Subnetworks

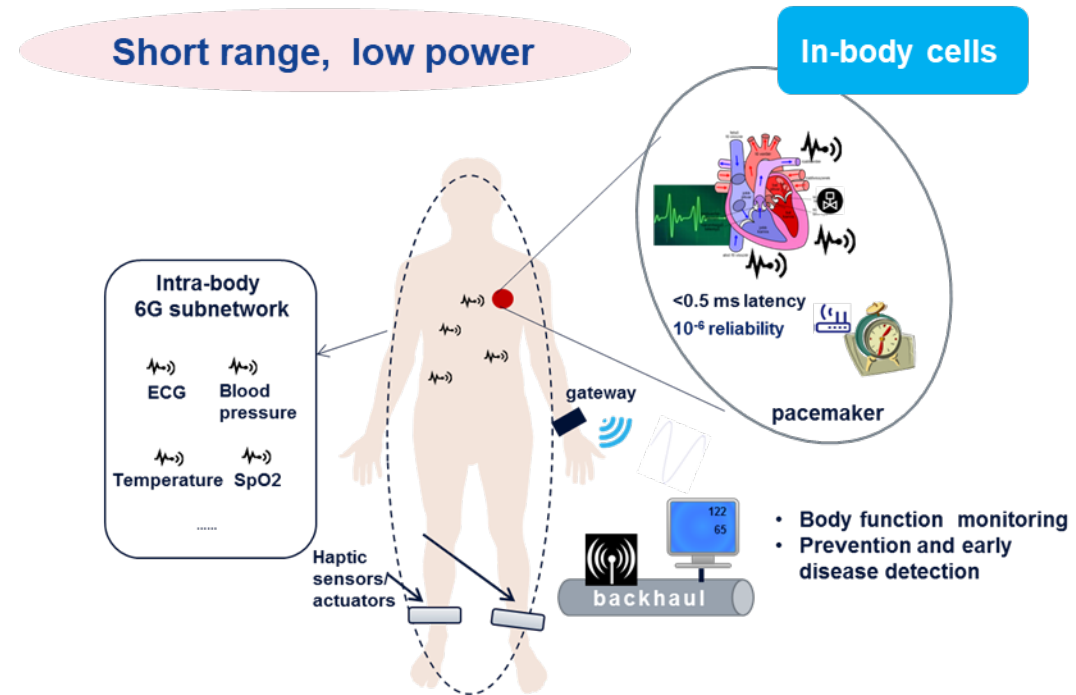
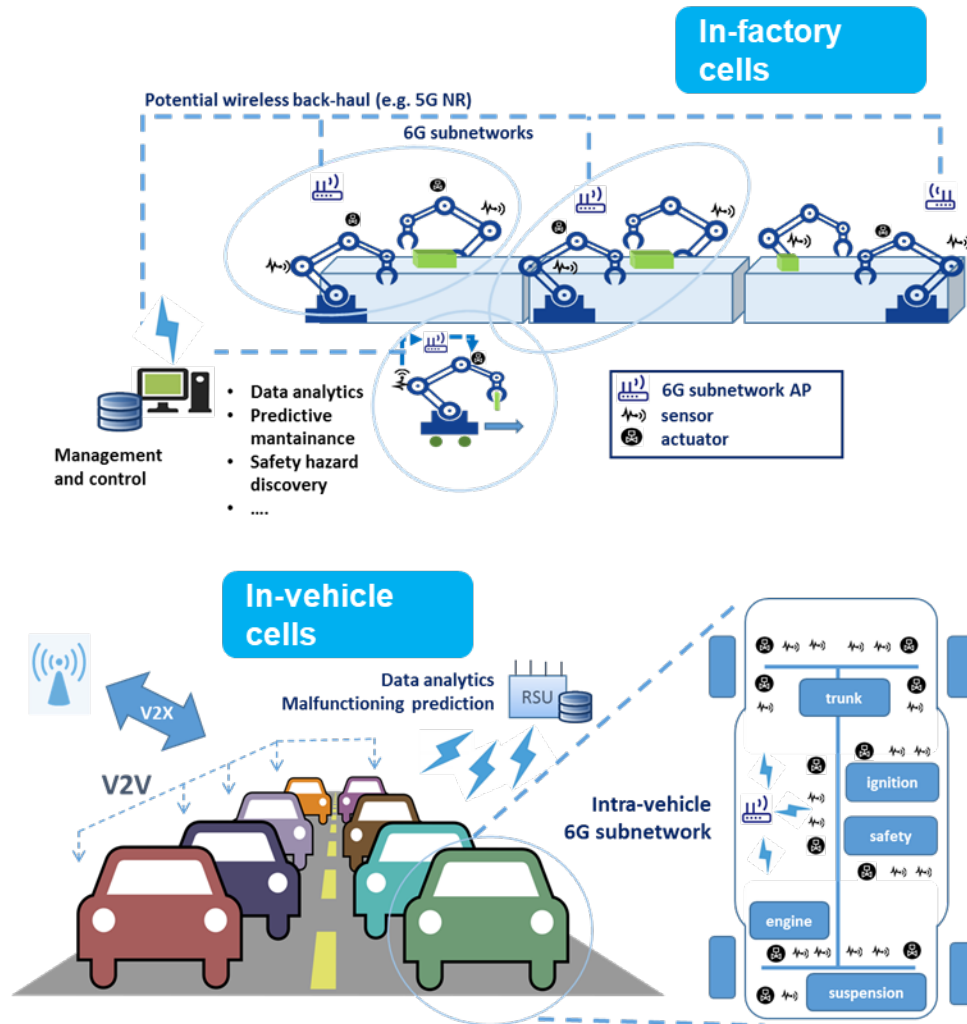
Short range low power cells with extreme performance requirements (e.g., below 0.1 ms communication loops with a wired-like reliability, or multi-Gbps data rates).

- Why 'in-X'?
  - We envision short range cells, to be installed in specific entities such as robots, production modules, vehicles, aircrafts, human bodies.
- Why short-range low power cells?
  - They offload micro/macro networks from the most demanding services, with extreme requirements
  - They enable aggressive spectrum reuse
  - Short range -> low delay spread -> limited system overhead (e.g., short Cyclic Prefix)

Life critical operations -> they should ensure the required service level everywhere, even when in motion (e.g., vehicles, mobile robots), and regardless of perceived channel and interference conditions

# Introduction

## 6G in-X Subnetworks: Envisioned Use-Cases<sup>[1,2]</sup>



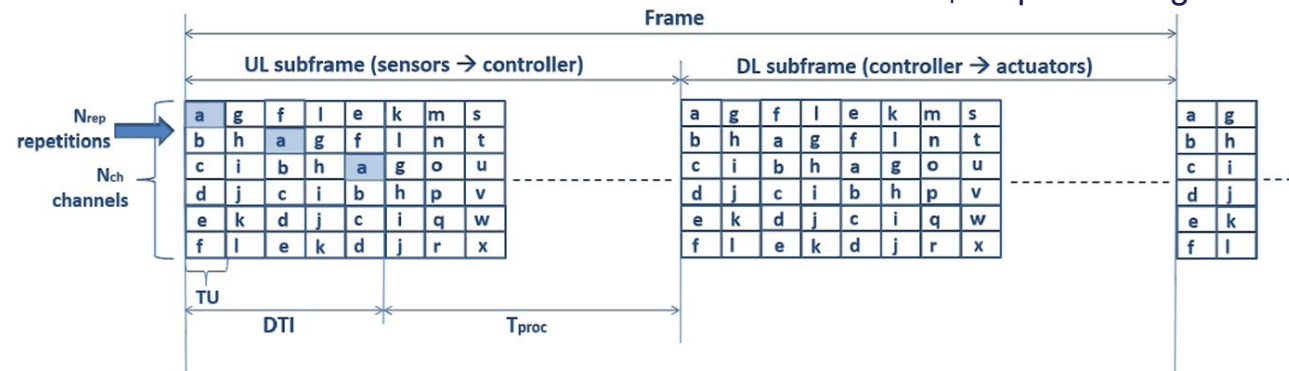
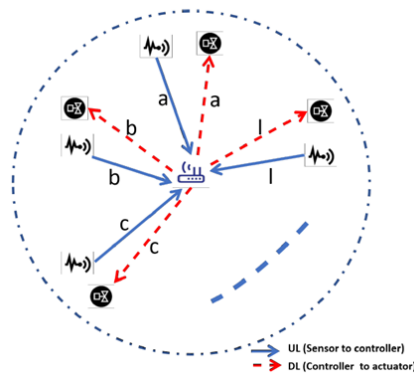
[1]. Adeogun, Ramoni, et al. "Towards 6G in-X subnetworks with sub-millisecond communication cycles and extreme reliability." *IEEE Access* 8 (2020): 110172-110188

[2]. Berardinelli, Gilberto, Preben Mogensen, and Ramoni O. Adeogun. "6G subnetworks for life-critical communication." *2020 2nd 6G Wireless Summit (6G SUMMIT)*. IEEE, 2020.

# Introduction

## 6G in-X subnetworks - Air interface components<sup>[1]</sup>

- 0.1 ms periodic traffic with wired-like reliability: large subcarrier spacings (>240 kHz), semi-persistent scheduling, blind repetitions (no HARQ) combined with channel hopping (frequency/interference diversity)
- Event-based ultra-low latency (e.g., alarm): large subcarrier spacings (>120 kHz), pre-emptive scheduling
- Multi- Gbps throughput: grant-based channel access, large spectrum, spatial multiplexing gain (though limited by small form factor)
- Battery-driven cells (e.g., in-body): grant-based channel access

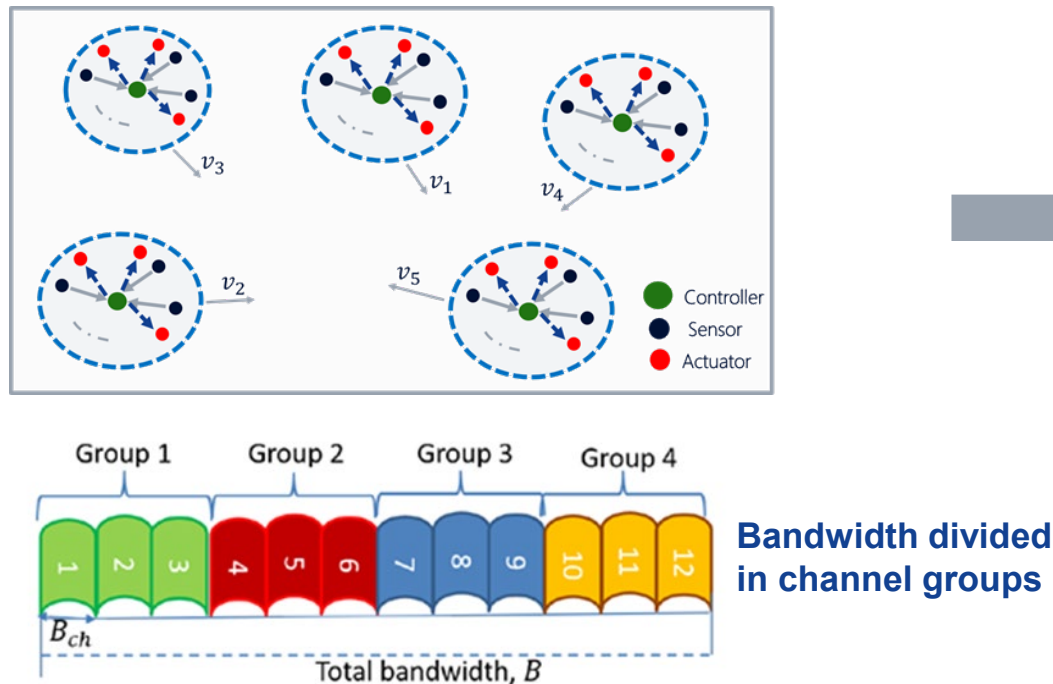


# 6G in-X Subnetworks for Life-Critical Communication

## Distributed implicit coordination – Existing Algorithms<sup>[3]</sup>

Extreme requirements in dense deployments -> smart interference coordination -> dynamic channel allocation

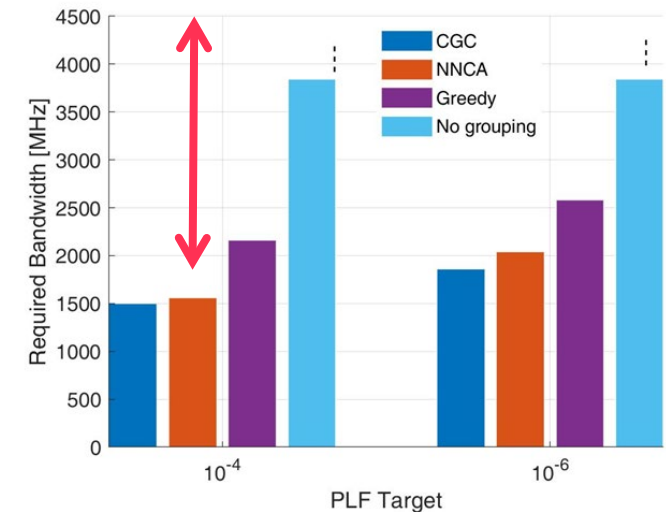
- Fully distributed implicit coordination (e.g., no explicit signaling among cells)



- 16 independent mobile subnetworks each with 18 sensor-actuator pairs in a 30m x 30m area
- Random movement with fixed speed of 2m/s and minimum inter-controller distance of 1.5m

Dynamic channel allocation algorithms:

- Centralized Graph Coloring (CGC);
- Nearest Neighbor Conflict Avoidance (NNCA)
- Greedy channel selection



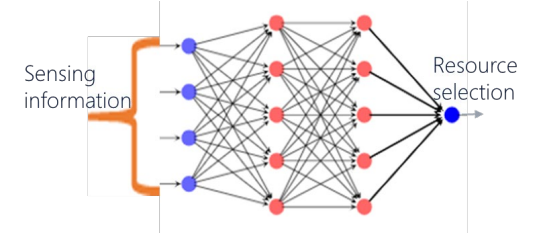
**Large improvement in spectral efficiency possible with appropriate sensing and dynamic channel group selection**

# Learning to Dynamically Allocate Radio Resources in 6G in-X Subnetworks

## Proposed Method

Current heuristic methods for resource allocation leads to **high spectrum usage** in dense networks, or **high complexity**

- ✓ NNCA requires identification of neighbor cells -> complex receiver processing!!



**Hypothesis:** ML can lead to a significantly lower complexity and/or a significantly higher spectral efficiency than heuristic resource allocation methods 😊

**Solution:** A supervised learning for dynamic channel allocation based on **local aggregate interference measurements only**.

**Assumption:** Offline generation of sufficiently large representative examples, i.e., interference power vector – channel selection pairs.



# Learning to Dynamically Allocate Radio Resources in 6G in-X Subnetworks

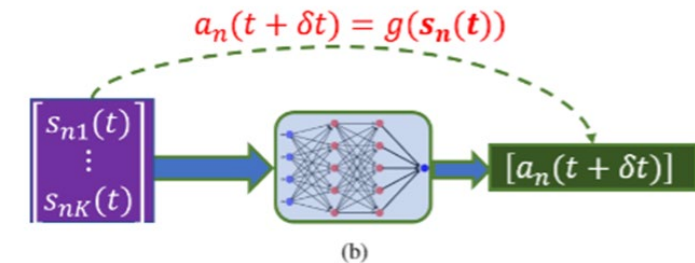
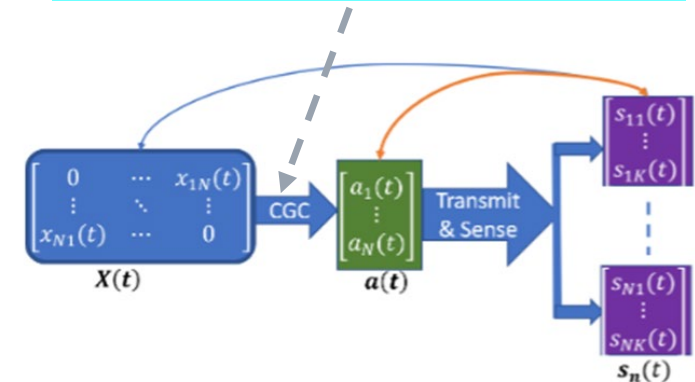
## Proposed Method (2)

- Centralized dataset generation + distributed execution
  - Data generation: simulated environment with centralized graph coloring (CGC) applied to interference coupling matrix
  - Data transformation: collect measurements of aggregate power vector at each subnetwork
  - Network design and training
    - A single DNN trained with data from all subnetworks
  - Centralized execution
    - Trained DNN deployed at each subnetwork for fully distributed channel selection

### Algorithm 1 Improper Graph Coloring Procedure

```

1: Input: Interference matrix,  $\mathbf{X}(t)$ , number of channel groups,  $K$ 
2: Create conflict graph,  $G_t$ 
3: Apply greedy coloring,  $C \leftarrow \text{GreedyColor}(G_t, K)$ 
4: while  $\max(C) > K$  do
5:   Remove edge with lowest interference power in  $G_t$ 
6:   Re-apply greedy coloring,  $C \leftarrow \text{GreedyColor}(G_t, K)$ 
7: end while
8: Output: Assigned colors,  $C$ 
    
```





# Supervised Learning for Distributed Channel Allocation

## Simulation settings and DNN Training Results

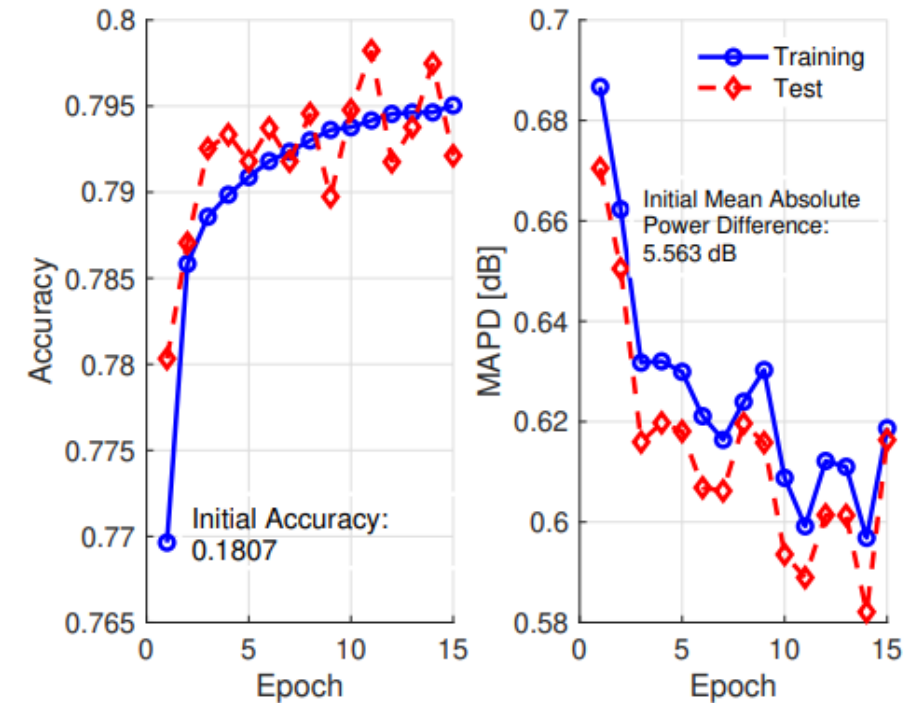
- Simulation parameters

Deployment and system parameters	
Parameter	Value
Deployment area [m <sup>2</sup> ]	30 × 30
Number of controllers/subnetworks, $N$	16
Number of devices per subnetwork, $M$	18
Cell radius [m]	2.5
Velocity, $v$ [m/s]	2.0
Minimum inter-subnetwork distance [m]	1.5
Number of channels, $N_{ch}$	12
Number of groups, $N_{gr}$	6
Number of receive antenna	2

Propagation and radio parameters	
Pathloss exponent, $\epsilon$	1.8/2.2
Shadowing standard deviation, $\sigma_s$ [dB]	3/5
De-correlation distance, $d_c$ [m]	4
Lowest frequency [GHz]	6
Transmit power per channel [dBm]	-10
Noise figure [dB]	10
Subcarrier spacing [kHz]	480
Payload size [bytes]	50
Per channel bandwidth [MHz]	40 - 320

DNN and simulation settings	
Number of hidden layers	2
Number of neurons per layer	30
Optimizer	Adam
Learning rate	0.01
Batch size	32
Training duration [s]	600
Simulation time [s]	2000
Snapshot duration [s]	20
Measurement update interval [ms]	5

- Network training performance



# Learning to Dynamically Allocate Radio Resources in 6G in-X Subnetworks

## Performance Metrics

- **Failure:** A control loop is said to fail if the achieved SINR on either or both the UL and DL is below  $P_{outage,T} = 10^{-6}$
- **Probability of Loop Failure (PLF):** The probability that the system does not meet the outage target of  $10^{-6}$  within the  $100\mu s$  latency

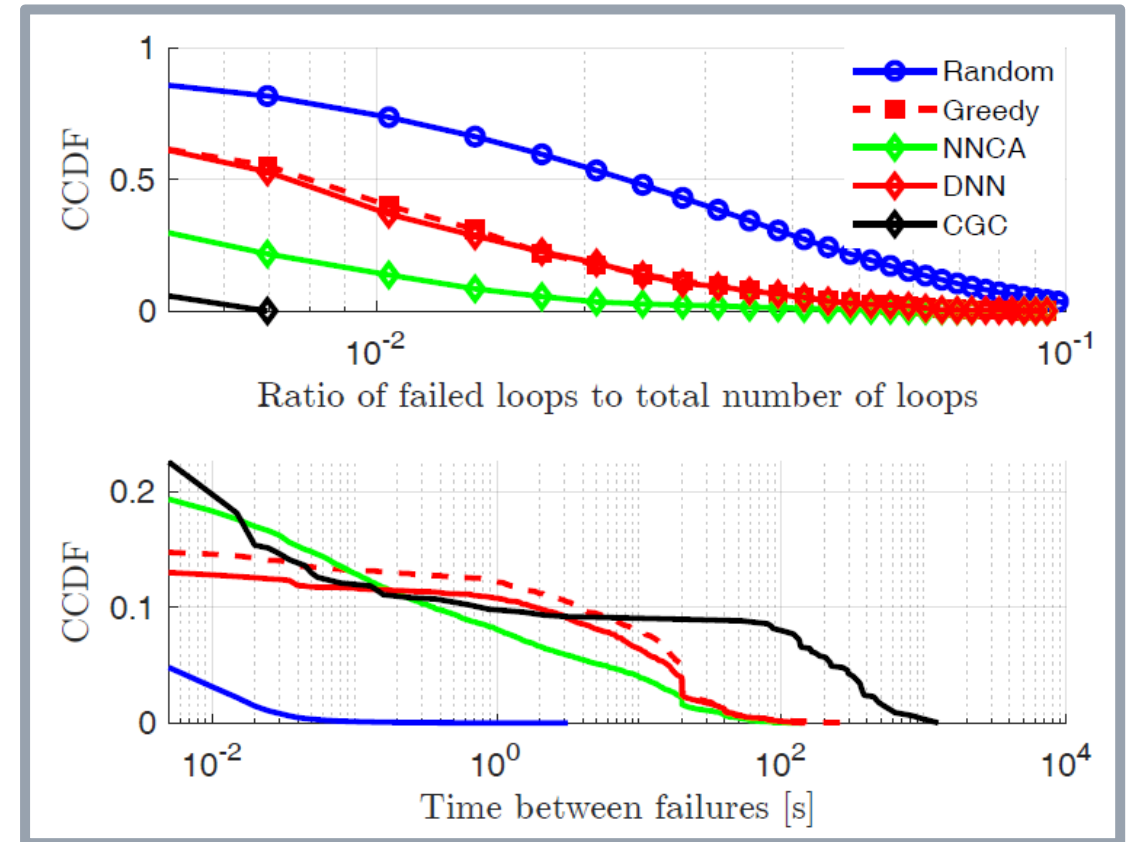
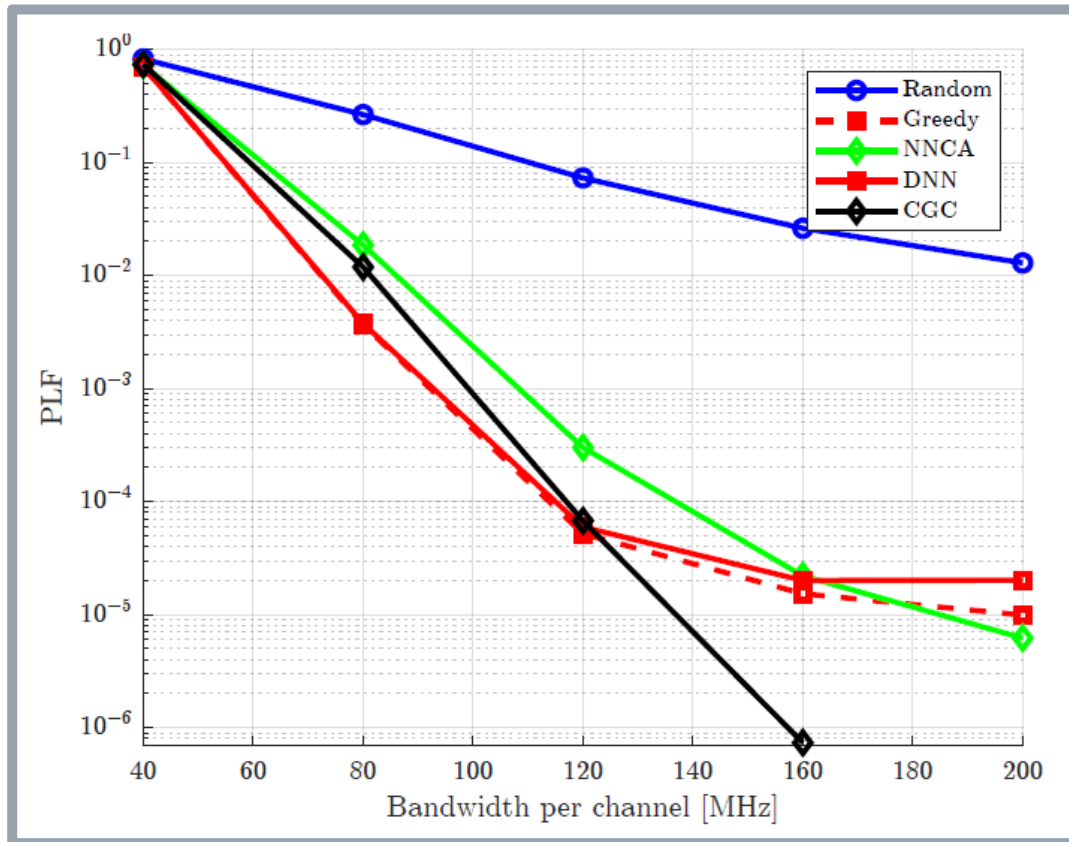
$$PLF = \frac{1}{N_{sim}} \sum_{n=1}^{N_{sim}} R_n$$

Ratio of number of failed loops (UL and/or DL) to the total number of loops at instant  $n$

- **Time between failures:** Time between simulation instants where the achieved SINR is below that required to achieve  $10^{-6}$  outage probability.
- **Average time between channel switching:** A measure of the overhead associated with each dynamic selection algorithm

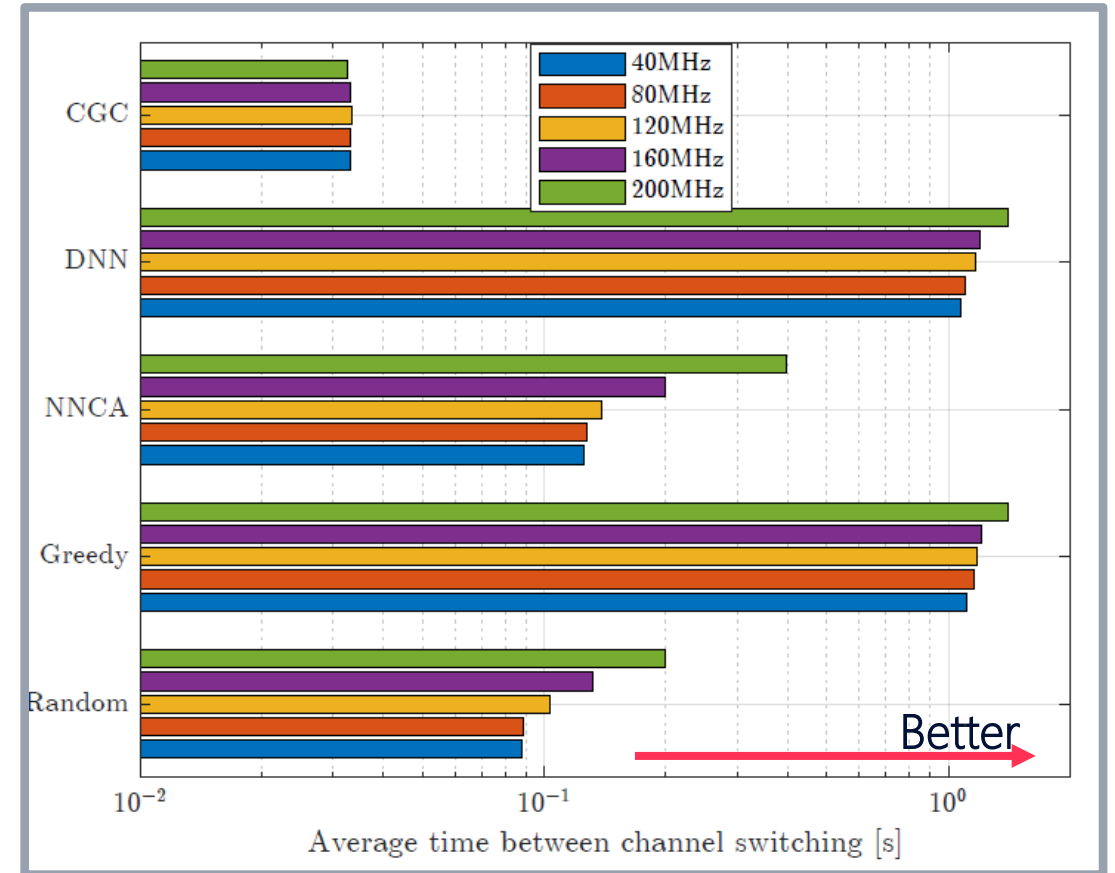
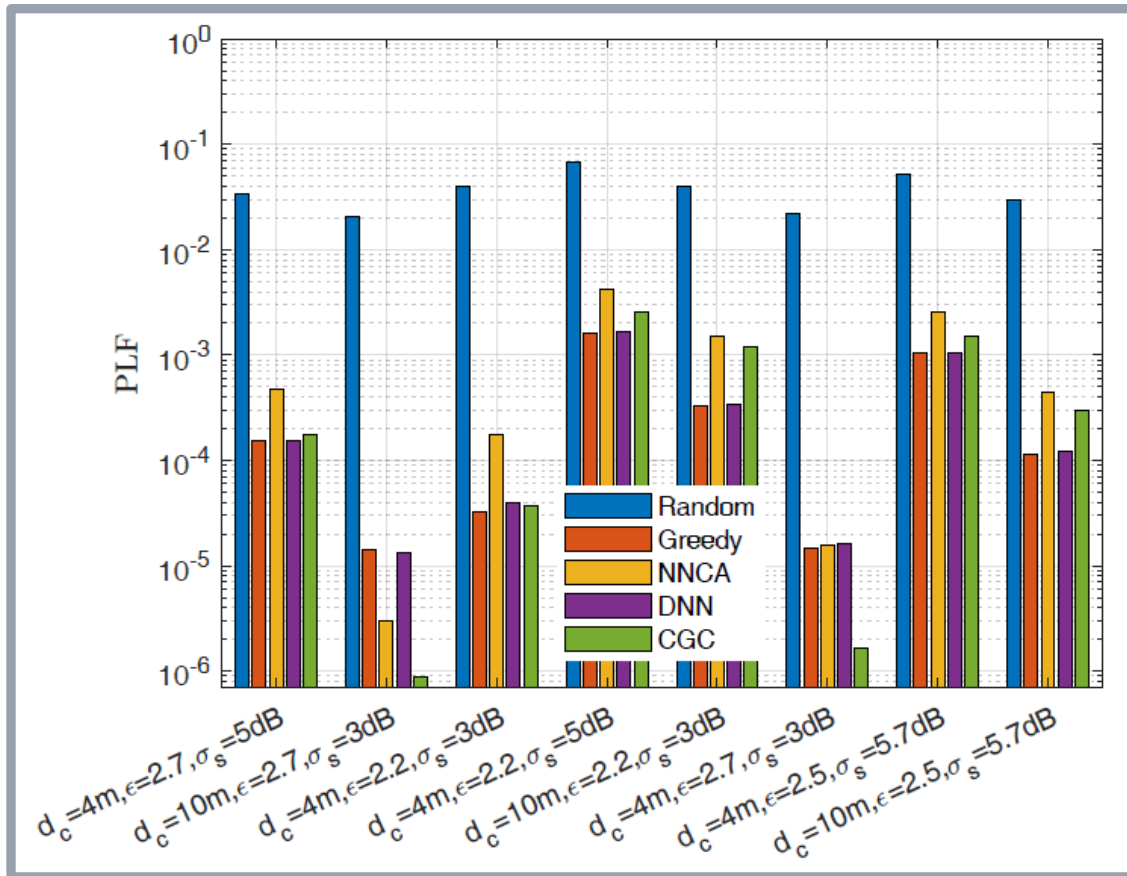
# Learning to Dynamically Allocate Radio Resources in 6G in-X Subnetworks

## Performance Evaluation Results



# Learning to Dynamically Allocate Radio Resources in 6G in-X Subnetworks

## Performance evaluation results – sensitivity analysis and switching overhead



# 6G in-X cells for Life-Critical Communication

## Summary

- 6G in-X cells are short range low power cells meant to support extreme requirements in terms of latency/reliability or data rates
  - In-robot, in-vehicle, in-body cells, etc.
- A supervised learning for distributed channel selection is proposed
  - DNN classifier designed and trained using data generated with CGC
  - The DNN based method can achieve similar performance up to a PLF of  $6 \times 10^{-5}$  as the centralized baseline even in environments with propagation conditions different from the ones used for generating the training data.
- Achieving low PLF at similar bandwidth with centralized algorithms requires more proactive mechanisms, e.g.,
  - Recurrent neural network to learn patterns in sensing data
  - Context-information aware techniques
  - Enabling signaling among in-X cells