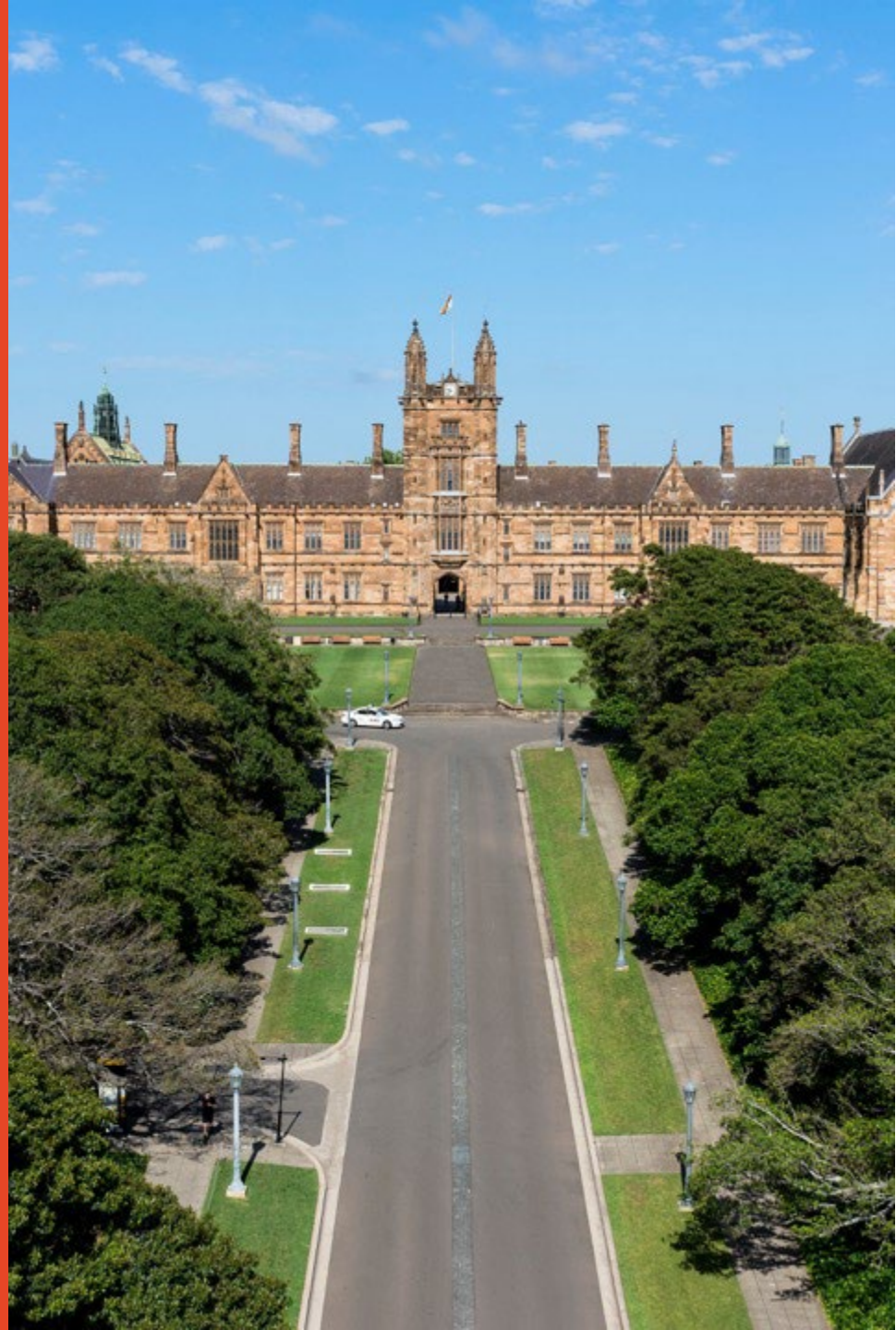
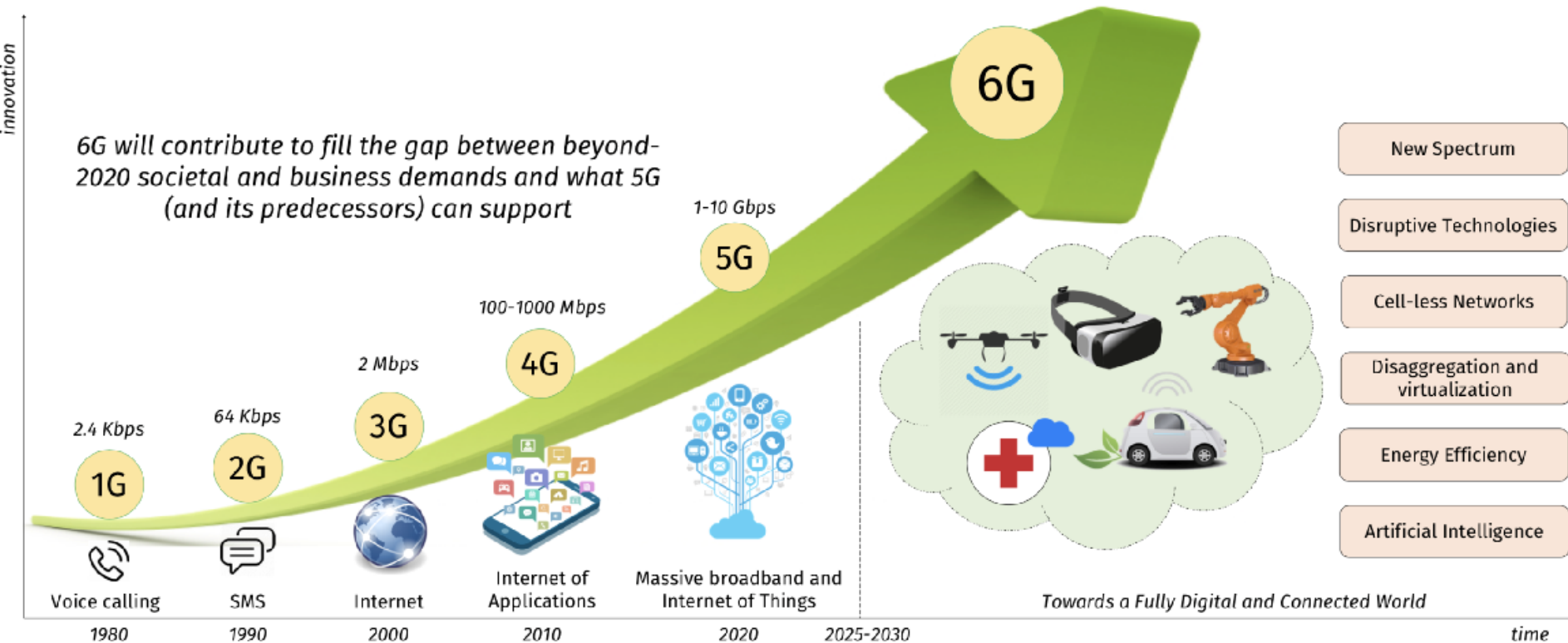


# An Overview of AI for 6G Joint PhD Programs

Prof. Branka Vucetic  
Centre for IoT and Telecommunications

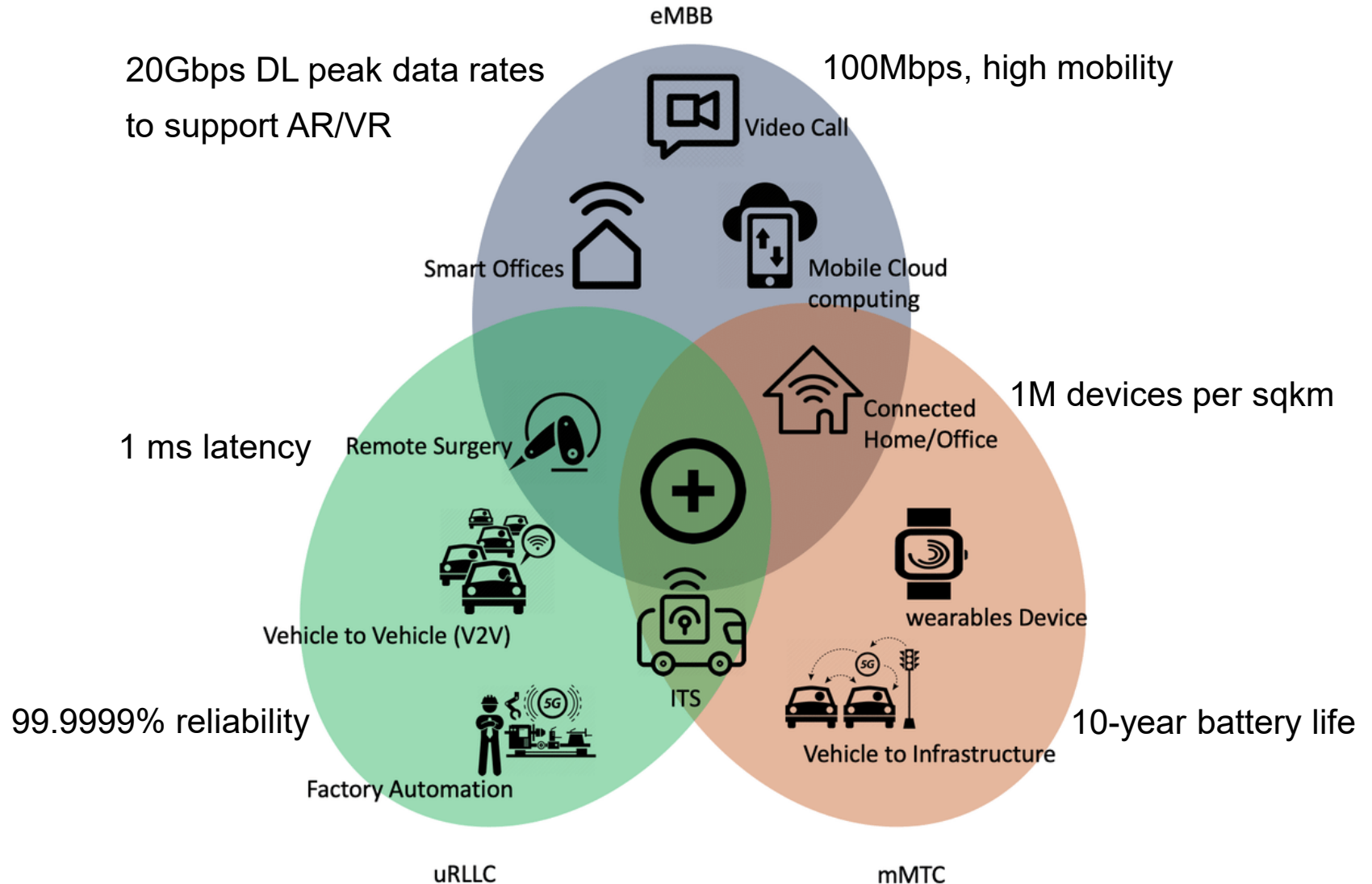


# Evolution of Wireless Cellular Networks



# 5G Vision and KPIs

10,000 x more traffic



# 6G Vision and Possible Use Cases



Holographic  
connectivity

- Ultra-high fidelity VR/AR
- Holographic telepresence
- Multi-sense experience



Bio  
connectivity

- Wearable and implantable bio-sensors
- Healthcare applications
- Brain-machine communications
- Brain-brain communications



Ubiquitous  
connectivity

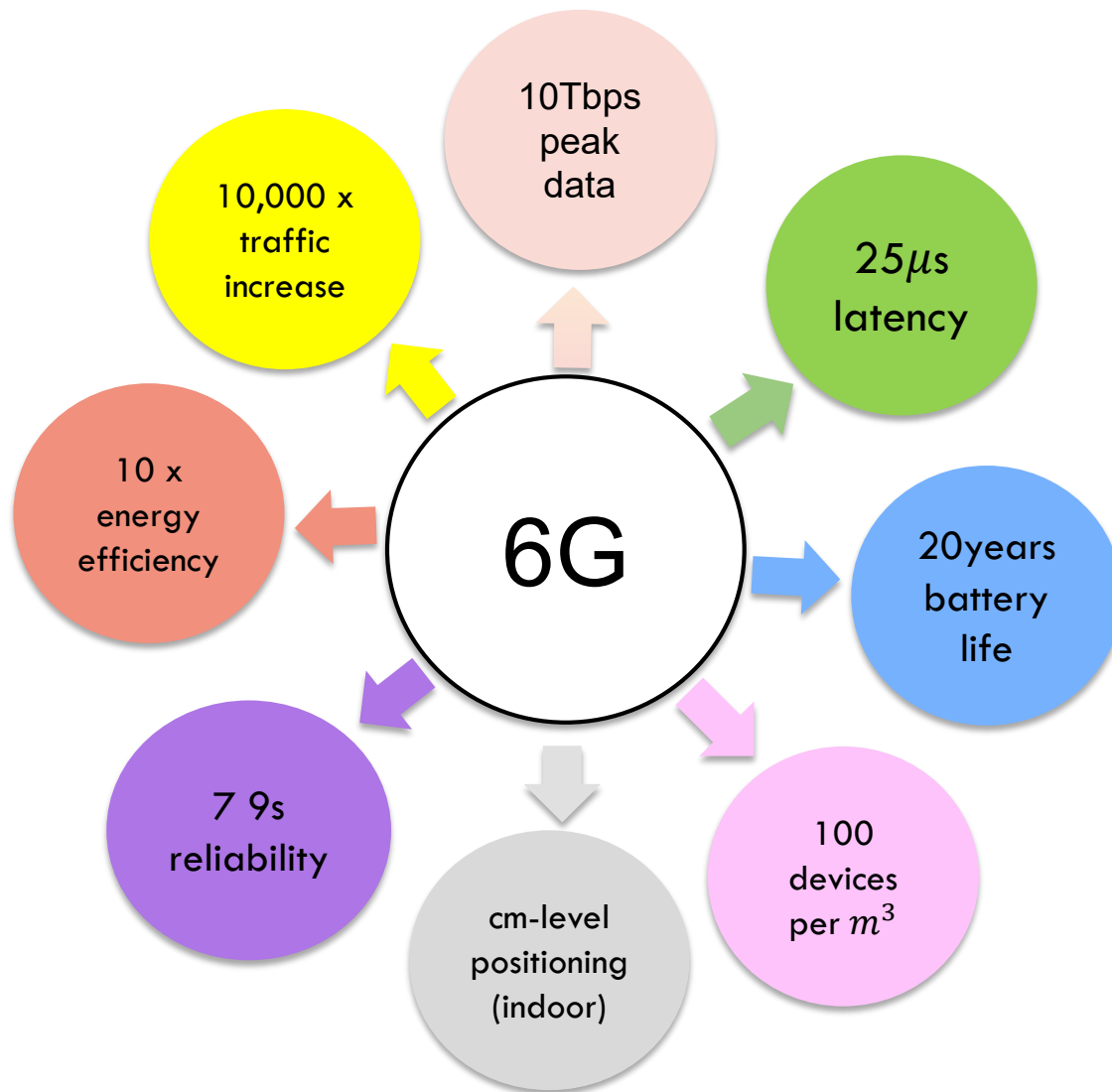
- Space
- Air
- Ground
- Underwater



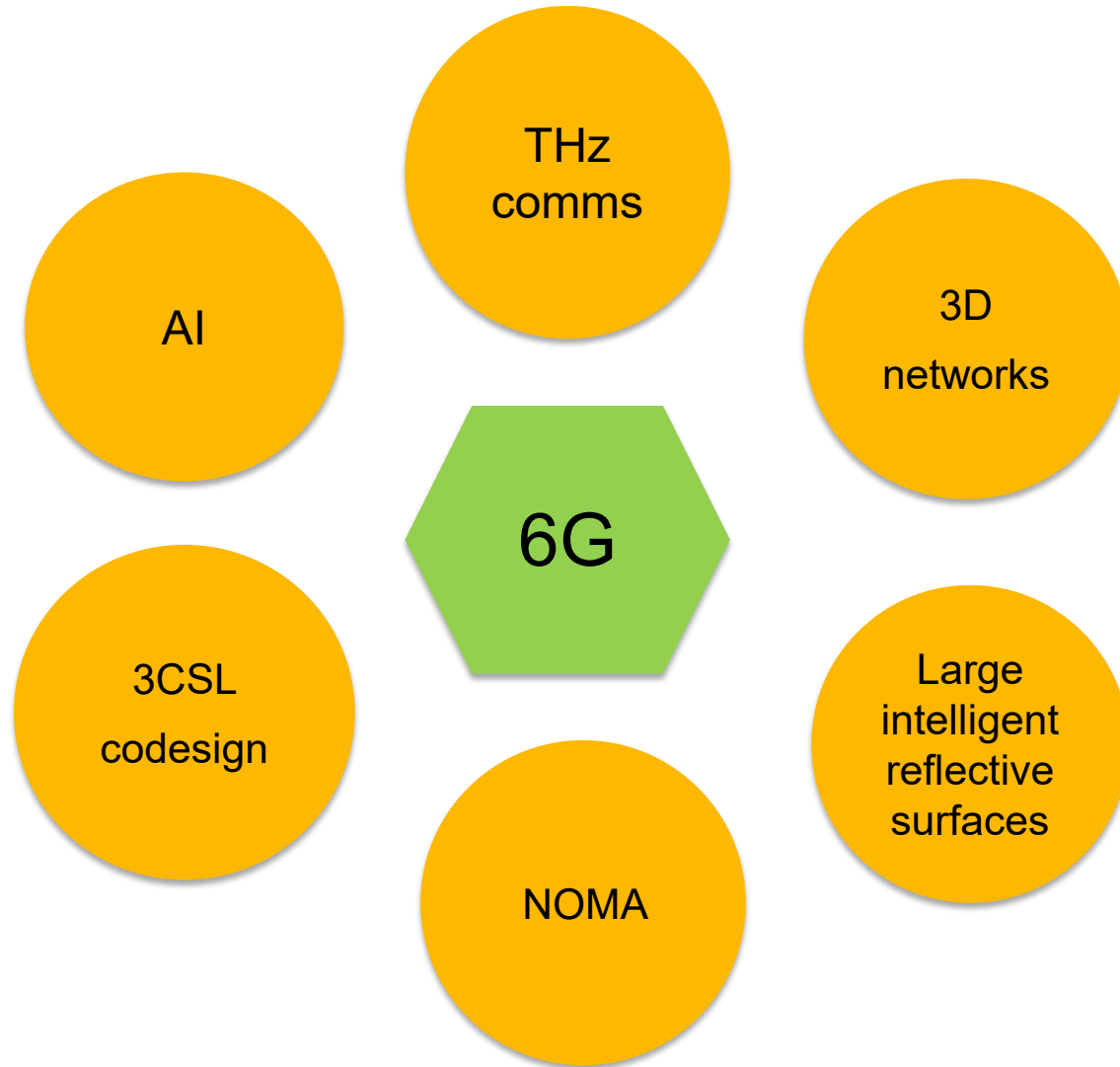
Deep  
connectivity

- Deep sensing and learning for IoT applications
- Human-machine collaboration
- Collaborative robots in factories and healthcare

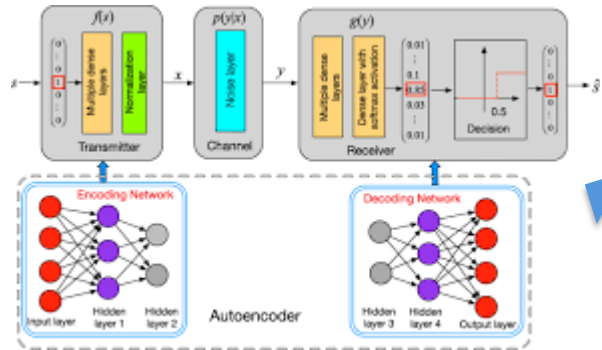
# 6G KPIs



# 6G Technologies



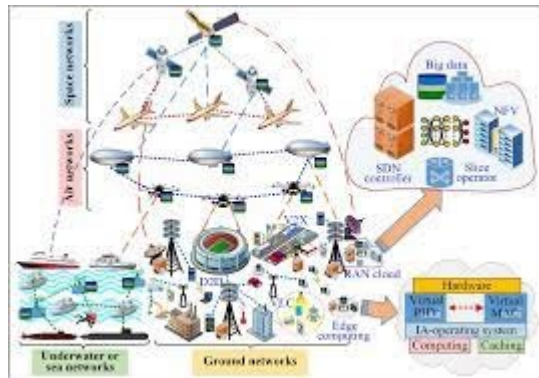
# Use Cases for AI in Wireless Networks



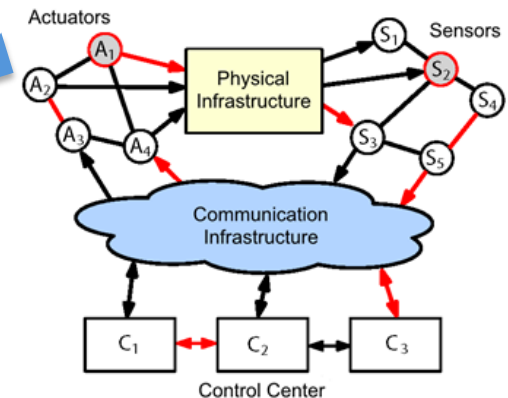
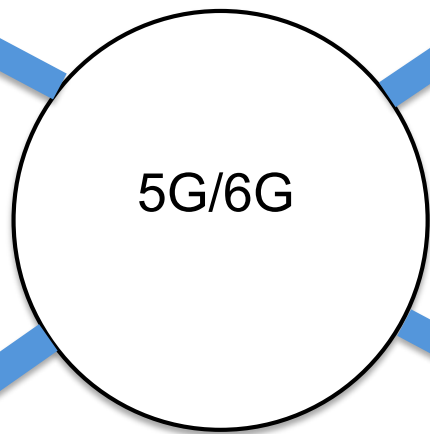
Physical layer design



Propagation and channel modelling



Network resource allocation



Communications and control co-design

# Principles of Machine Learning in Wireless Networks

Data Collection

Data Cleaning

Model Building

Training

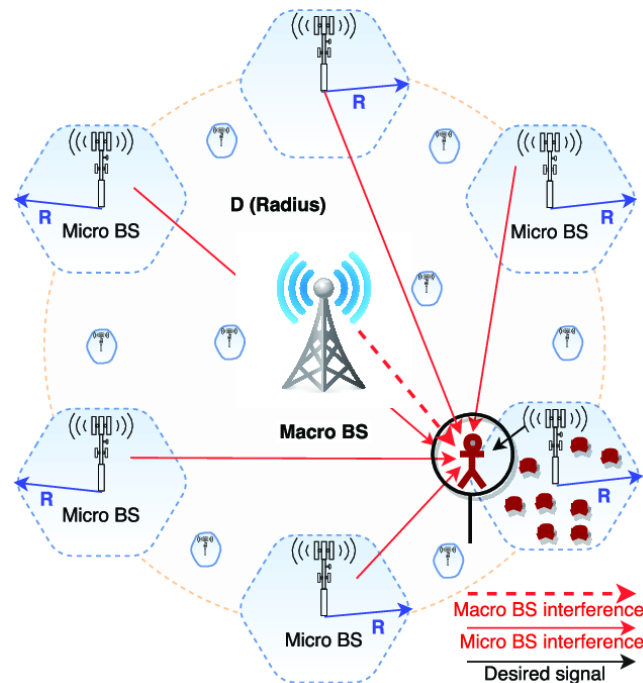
Decision Making

Performance Evaluation



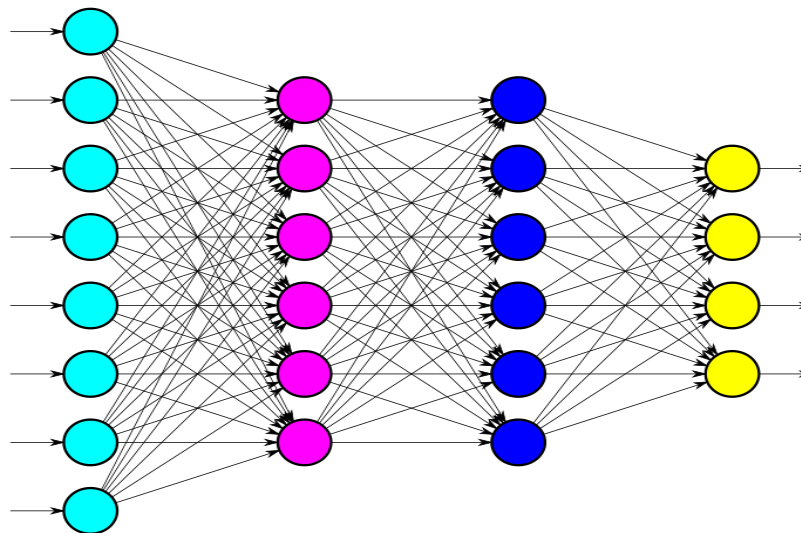
# Signal Strength Prediction in Cellular Networks

- Signal strength information required for deploying communication towers
- Theoretical models are not accurate
- Real measurements give accurate signal strength values
- They are costly and inflexible
- AI-based models are superior for signal strength modelling

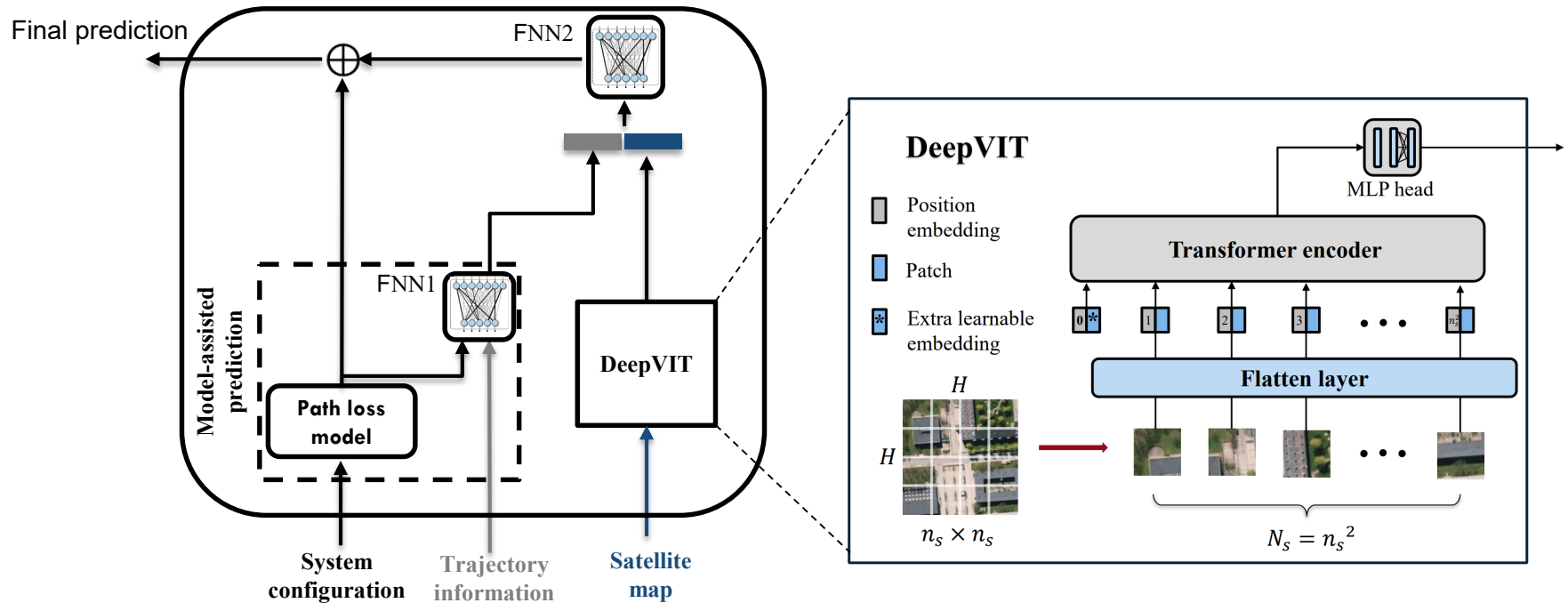


# AI-based Signal Strength Prediction

- AI-based propagation modelling for outdoor environments
- The current empirical models use the information on transmit and **receive antenna heights**, **frequency**, and the **distance** between the transmitter and receiver, and **correction factors** for the environment types
- The AI model uses **high-resolution satellite images** that capture the environment features.



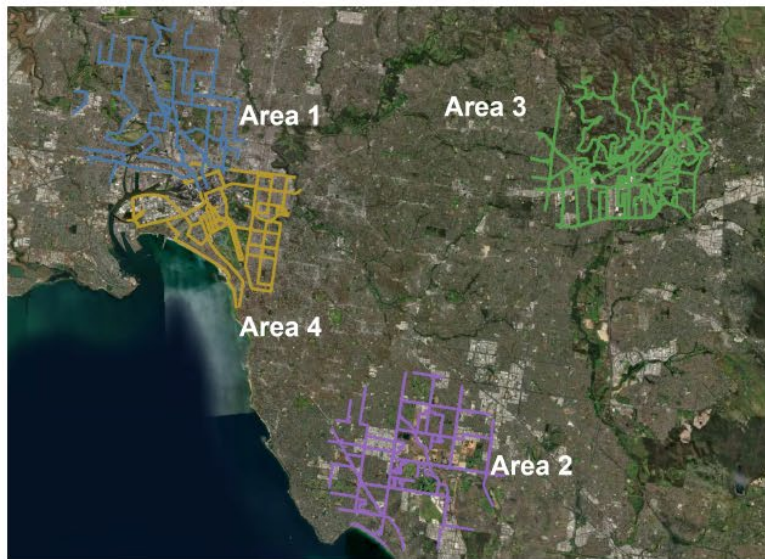
# An AI Model for Propagation Modelling



- System configuration: BS transmitter power, BS height, user height, and the ground distance between user and BS.
- Trajectory information: user location, BS location, and the ground distance.
- Satellite map: nearby satellite map of users

Yu, Z. Hou, Y. Gu, et al., "Systems and methods for received signal strength prediction using a federated learning framework," A.U. Patent 051437, Dec. 2022.

# AI-Based Propagation Modelling - LTE Telstra(2.6GHz)



(a) Sites from areas 1-4 in Victoria, Australia

(b) Sites from areas 5-8 in New South Wales, Australia

The location of different sites

# Prediction Results for LTE Signal Strength

## – Baseline: Path loss model (from 3GPP)

UMa\_A

LOS

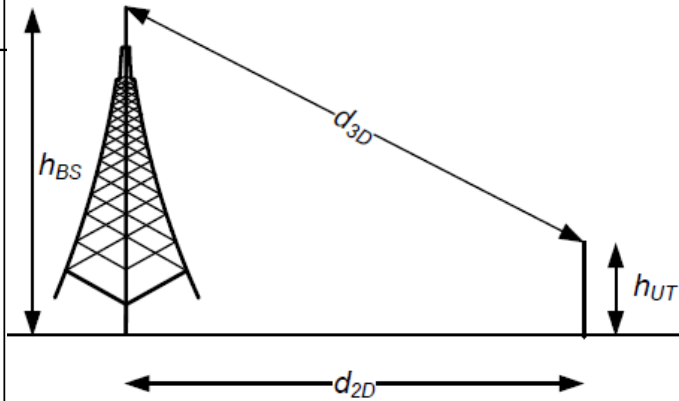
$$0.5\text{GHz} \leq f_c \leq 6\text{GHz} \text{ and } 6\text{GHz} < f_c \leq 100\text{GHz}$$

$$PL_{\text{UMa-LOS}} = \begin{cases} PL_1 & 10\text{m} \leq d_{2D} \leq d'_{BP} \\ PL_2 & d'_{BP} \leq d_{2D} \leq 5\text{km} \end{cases}, \text{ see Note 3}$$

$$PL_1 = 28.0 + 22 \log_{10}(d_{3D}) + 20 \log_{10}(f_c), \quad \sigma_{SF} = 4 \text{ dB}$$

$$PL_2 = 40 \log_{10}(d_{3D}) + 28.0 + 20 \log_{10}(f_c) - 9 \log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2),$$

$$\sigma_{SF} = 4 \text{ dB}$$



$PL$ : Path loss

$h_{BS}$ : Base station height

$f_c$ : Carrier frequency

$\delta_{SF}$ : Shadow fading

$d_{2D}$ : Distance between base station and user in 2 dimension

$h_{UT}$ : User height

$d_{3D}$ : Distance between base station and user in 3 dimension

$d'_{BP}$ : Break point distance

3GPP TR 38.901 version 16.1.0 Release 16, "Study on channel model for frequencies from 0.5 to 100 GHz," Nov. 2020.

# Prediction Results for LTE Signal Strength –Telstra

For each site: first 80% data for training and last 20% data for testing

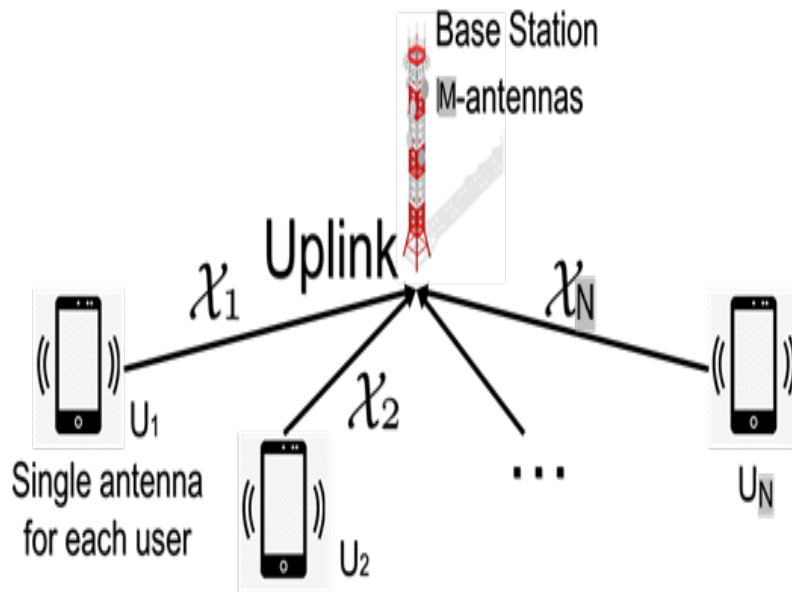
<b>Areas</b>	<b>AI-based model RMSE [dB]</b>	<b>Path loss model RMSE[dB]</b>
Area1	<b>5.63</b>	<b>9.18</b>
Area2	<b>5.85</b>	<b>9.06</b>
Area3	<b>6.24</b>	<b>10.38</b>
Area4	<b>5.32</b>	<b>8.94</b>
Area5	<b>6.21</b>	<b>8.61</b>
Area6	<b>6.26</b>	<b>9.68</b>
Area7	<b>4.81</b>	<b>8.54</b>
Area8	<b>5.98</b>	<b>10.11</b>

H. Yu *et al.*, "Distributed Signal Strength Prediction using Satellite Map empowered by Deep Vision Transformer," *2021 IEEE Globecom Workshops (GC Wkshps)*, 2021, pp. 1-6, doi: 10.1109/GCWkshps52748.2021.9682021.

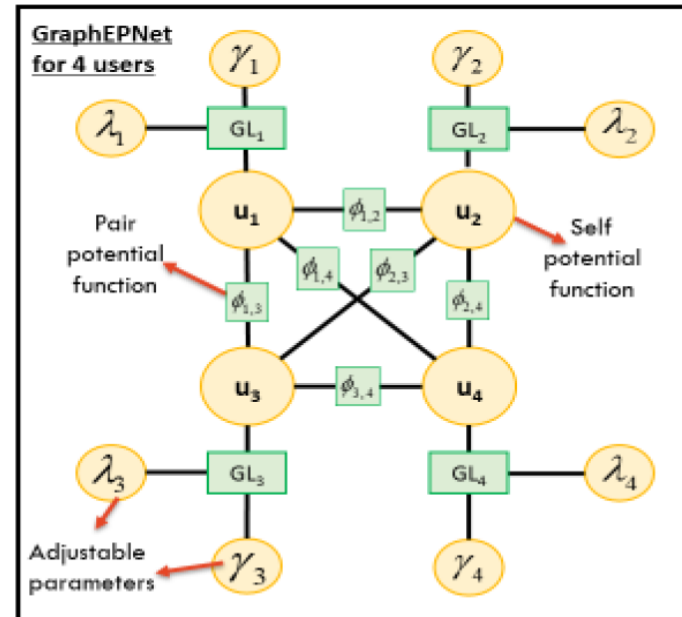
# Prediction Results for LTE Signal Strength –Telstra

- **Training sites: Area1&2&3**
  - **Testing sites: Area4**
  - **Testing RMSE: 5.93dB**
- 
- **Training sites: Area5&6&8**
  - **Testing sites: Area7**
  - **Testing RMSE: 6.33dB**

# AI-based Detector Design in Massive MIMO Systems



System Model

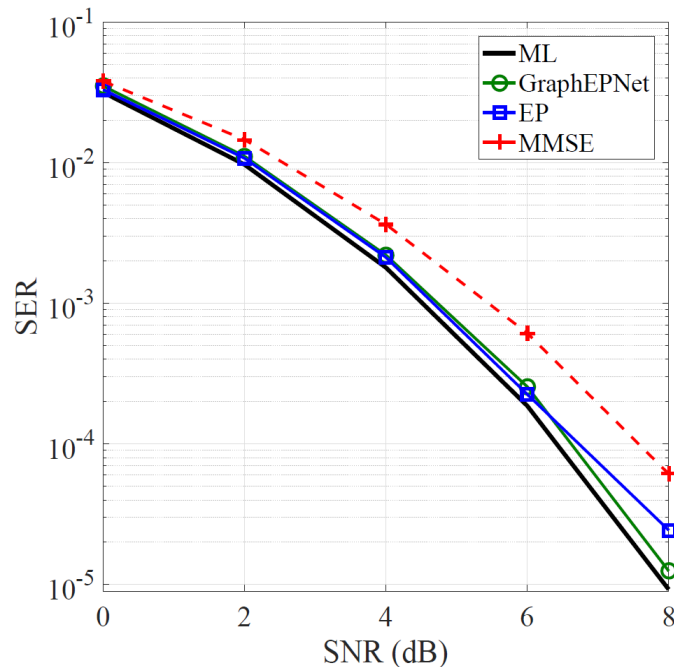


Graph Neural Network-based Detector

A. Kosasih, V. Onasis, V. Miloslavskaya, W. Hardjawana, V. Andrian, and B. Vucetic, Graph neural network aided MU-MIMO detectors, IEEE Journal on Selected Areas in Commun., Vol. 40, No. 9, July 2022, pp. 2540-2555.



# Performance of the AI-based Detector in Massive MIMO Systems



Symbol Error Rate

## System configurations:

- Quadrature Phase Shift Keying (QPSK)
- Number of Rx : 32, Tx : 8
- Total samples : 100000
- Batch size : 64
- Number of training iterations : 500
- Number of layers for each MLP : 3
- Hidden layer neurons in each MLP : 128
- Optimizer : Adam

# Receiver Complexity

Detector	Complexity	Complexity Values
Maximum likelihood	$O(A^N)$	4294967296
Minimum mean square error	$O(M^3)$	430080
Expectation propagation	$O((M^3 + M^2N + MN^2)T)$	124288
GraphEPNet	$O((N^2 + MN + L)T)$	32768 (26% of EP)

N – the number of users, each with a single antenna

M – the number of base station antennas

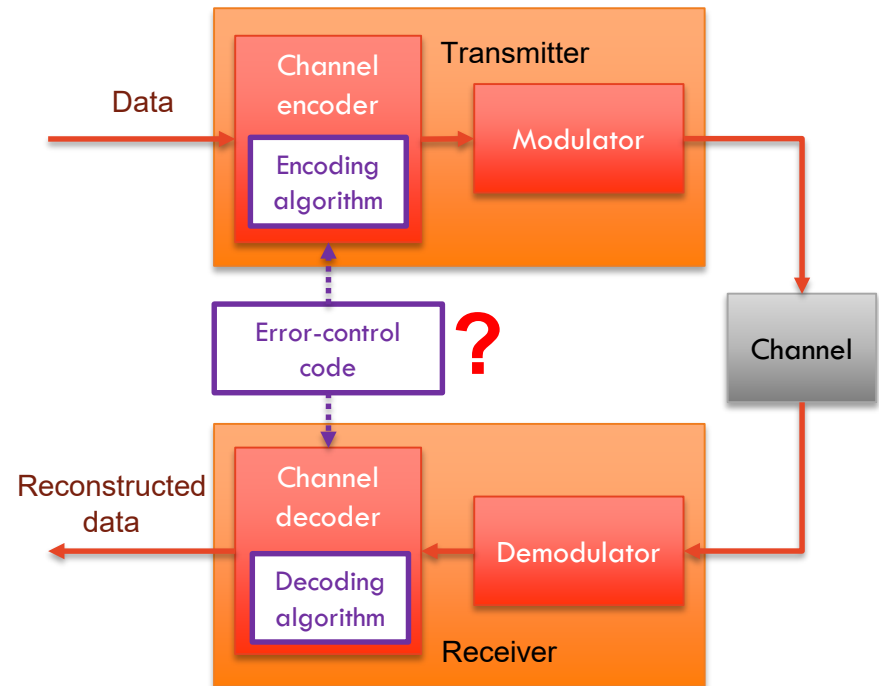
A – the number of points in the constellation set

T – the number of iterations

L – the number of neurons

# AI-based Error-Control Code Design for 6G

- Beyond 5G and 6G networks:
  - Channel codes with high error-correction capability are needed to meet the stringent reliability, latency and throughput requirements of emerging applications
- Start-of-the-art codes:
  - 5G New Radio standard:
    - **Polar codes** with cyclic redundancy check (CRC) were adopted for control channel
    - Low density parity check (LDPC) codes were adopted for data channel
- Can AI improve the complexity-performance tradeoff?



# Reinforcement Learning-based Polar Code Design

## – Flexible construction

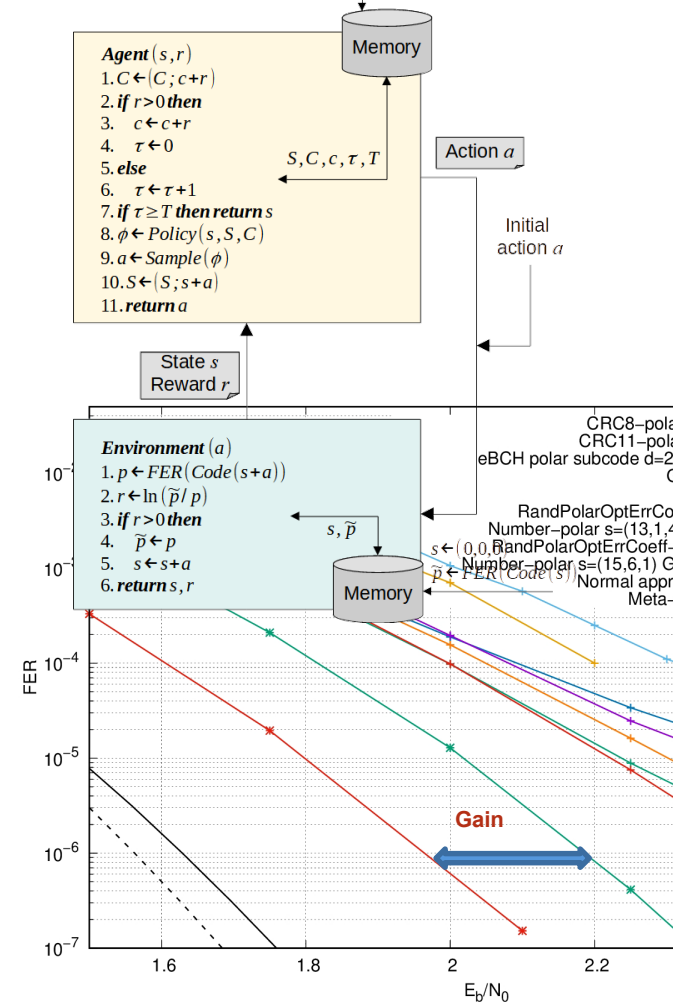
- Code optimization using **reinforcement learning** for the SCL decoder with any list size
- Agent's actions are sampled in accordance with the policy
- The proposed policy benefits from our frame error rate (FER) prediction approach
- Applicable for various code lengths and rates

## – Low description complexity

- Each code is specified by just three integer parameters, while the reliability sequence is fixed

## – High error-correction capability under SCL decoding

- Provide lower FER than the state-of-the-art polar code constructions (5G polar codes with CRC11, randomized polar subcodes, and polar codes optimized using artificial intelligence techniques).
- Codes of lengths 512, 1024, 2048 and 4096 are considered
- (512,256) code is within 0.2 dB from the normal approximation bound
- The proposed codes are potential candidates for beyond 5G and 6G networks



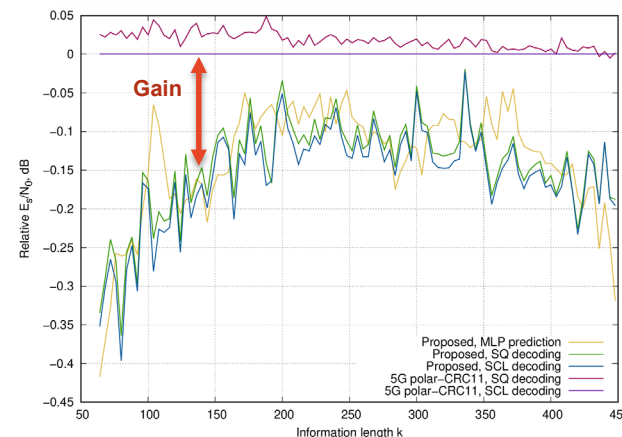
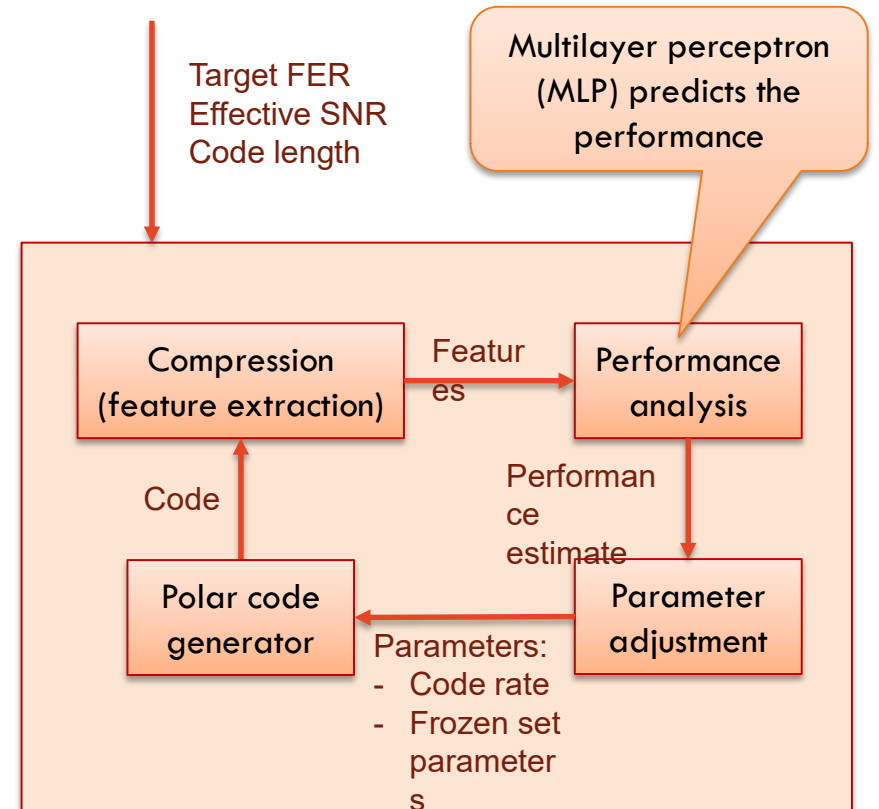
(1024,512) codes under SCL decoding

# AI-based Adaptive Polar Coding for Time-Varying Channels

- Transmitter performs **adaptive coding** based on the actual channel state information
- Precoded polar code is adjusted for given target FER, effective SNR and code length
- The **key elements** are the code feature extractor and FER predictor
  - Six features are extracted
  - The features are fed to the **multilayer perceptron (MLP)**, which returns a performance estimate. The MLP is trained based on simulation results for a few codes. A single MLP is used for various target FERs, decoding list sizes  $L$  and code parameters.
- **Bit-level optimization** of the number of information bits
- The proposed approach is suitable for precoded polar codes with various structures
- Description complexity
  - 5G polar codes: a reliability sequence consisting of 1024 integers
  - Overhead of the proposed approach compared to 5G: 65 weights defining the MLP

V. Miloslavskaya, Y. Li, and B. Vucetic, "AI-Based Adaptive Polar Coding", Submitted to IEEE Transactions on Communications in March 2023.

The University of Sydney



The relative  $E_s/N_0$  for the target FER  $10^{-3}$ , where the 5G polar codes with CRC11 under SCL decoding are used as zero level

Code length  $n=512$   
Message length  $k=128, \dots, 384$   
Decoding with list sizes  $L=8$   
Successive cancellation list (SCL) decoder  
Sequential (SQ) decoder

# AI-based Error-Control Code Design for 6G

Blocklengths 32 and 64: V. Miloslavskaya and B. Vucetic, “Design of short polar codes for SCL decoding,” *IEEE Transactions on Communications*, vol. 68, no. 11, pp. 6657–6668, November 2020.

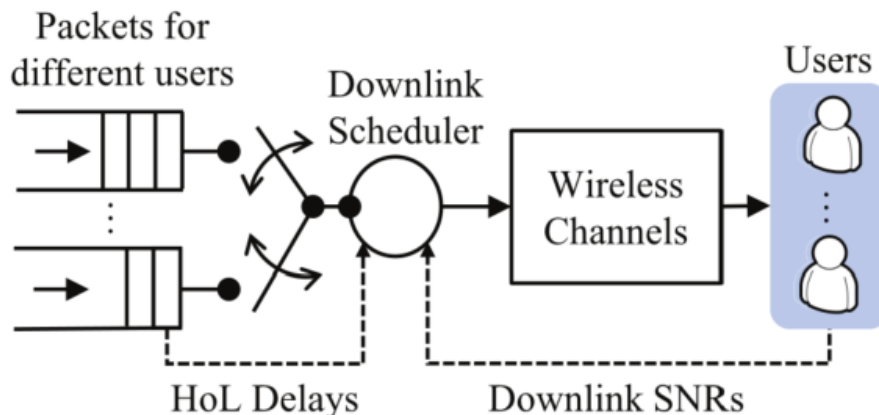
Blocklengths 128 and 256: V. Miloslavskaya, B. Vucetic, Y. Li, G. Park, and O.-S. Park, “Recursive Design of Precoded Polar Codes for SCL Decoding”, *IEEE Transactions on Communications*, vol. 69, no. 12, pp. 7945–7959, 2021.

Blocklengths 512 to 4096: V. Miloslavskaya, Y. Li and B. Vucetic, “Design of Compactly Specified Polar Codes with Dynamic Frozen Bits Based on Reinforcement Learning”, *submitted to IEEE Transactions on Communications*.

Analysis of precoded polar codes: V. Miloslavskaya, B. Vucetic and Y. Li, “Computing the Partial Weight Distribution of Punctured, Shortened, Precoded Polar Codes”, *submitted to IEEE Transactions on Communications*.

# AI-based Scheduler Design

- Scheduling is allocation of communication resources
- Its input is the queue state of the packets in a buffer and channel state information
- The output is the amount of communication resources allocated to each user
- This is a sequential decision-making problem
- Analytical resource allocation is too complex



# Deep Deterministic Policy Gradient-Based Scheduling Design

- The scheduling optimisation problem can be solved by Deep Deterministic Policy Gradient (DDPG) algorithm

$s(t)$  {  
■ HoL Delays  
■ Downlink SNRs

$a(t)$  {  
➔ Users to be scheduled  
➔ Number of resource blocks

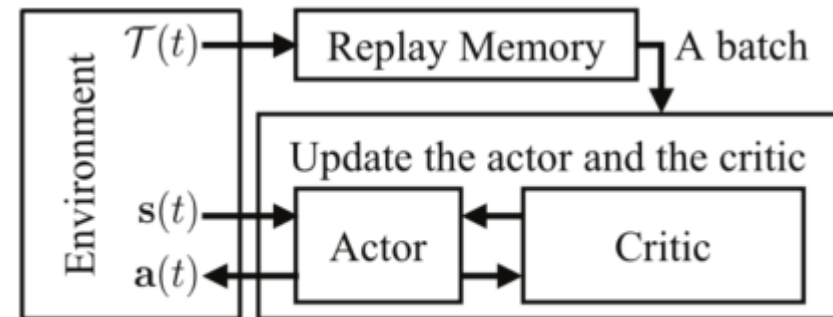


Fig. 2: Illustration of DDPG.



# DDPG Combined with Expert Knowledge

- Straightforward implementation of DDPG converges slowly
- Models, theoretical formulas, and expert knowledge can reduce the convergence time
- By using expert knowledge on the topology of the wireless networks, the potential reward of visiting a state, and the importance of different samples, the scheduling decision is updated according to real-world feedback every few milliseconds, and the inference is executed within each TTI in 5G NR

# AI-based Wireless Scheduler Design

## 5G Time-Sensitive Networks:

- Low Latency
- High Reliability
- Jitter

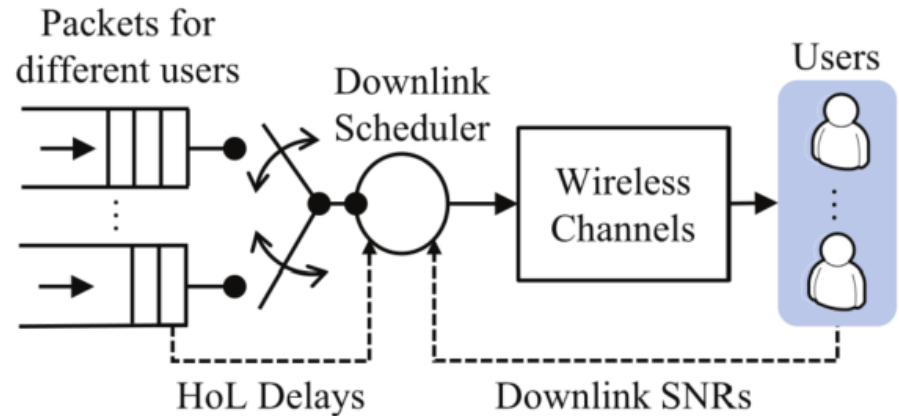
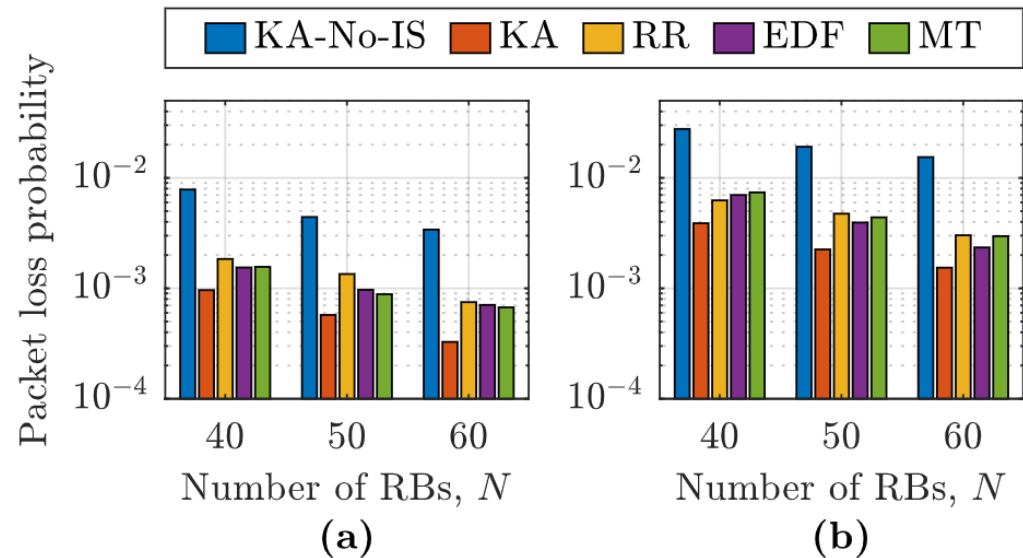


Fig. 1: Illustration of downlink scheduler.

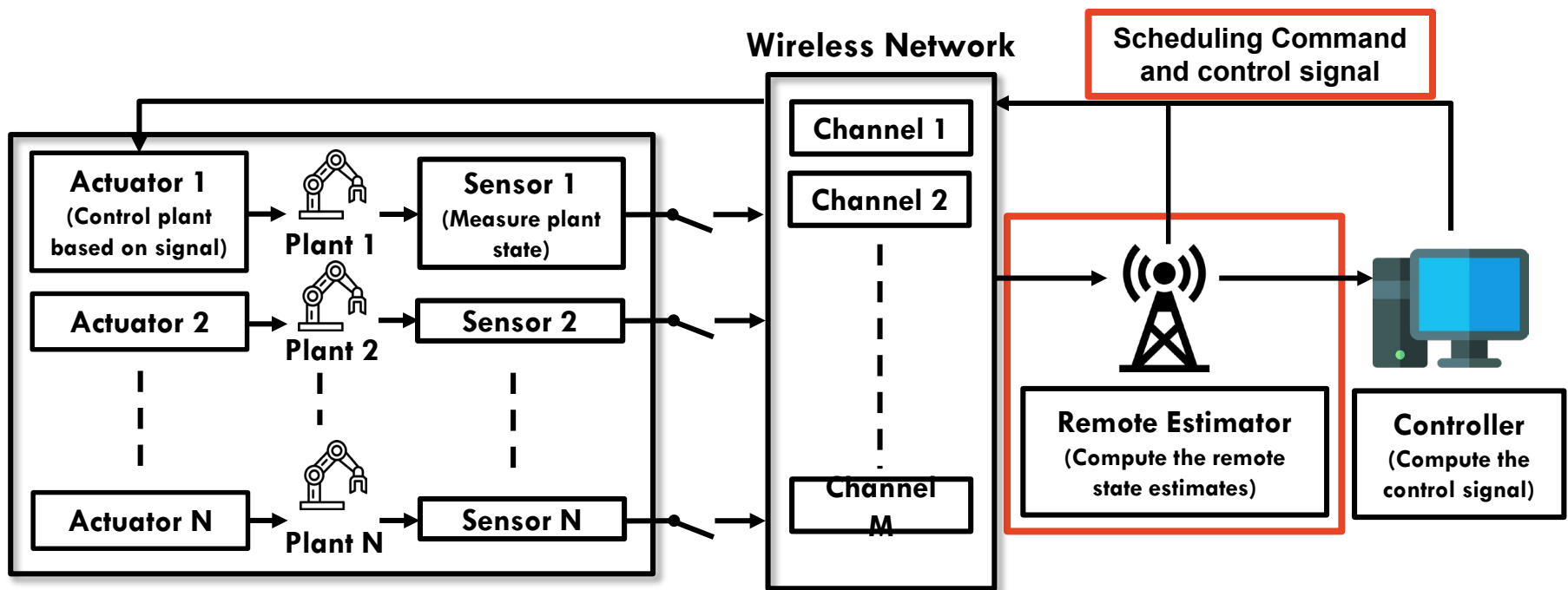
## Solutions:

- Domain knowledge-assisted DRL
- Straightforward implementation
- Traditional scheduler



# AI-based Joint Communication-Control Codesign

- Jointly optimizing the scheduling, remote estimation, and control algorithm is a high-dimensional problem
- The AI based method is powerful in this kind of problem



# AI-based Codesign Framework

- Joint training of AI-based controller, estimator, and transmission scheduler

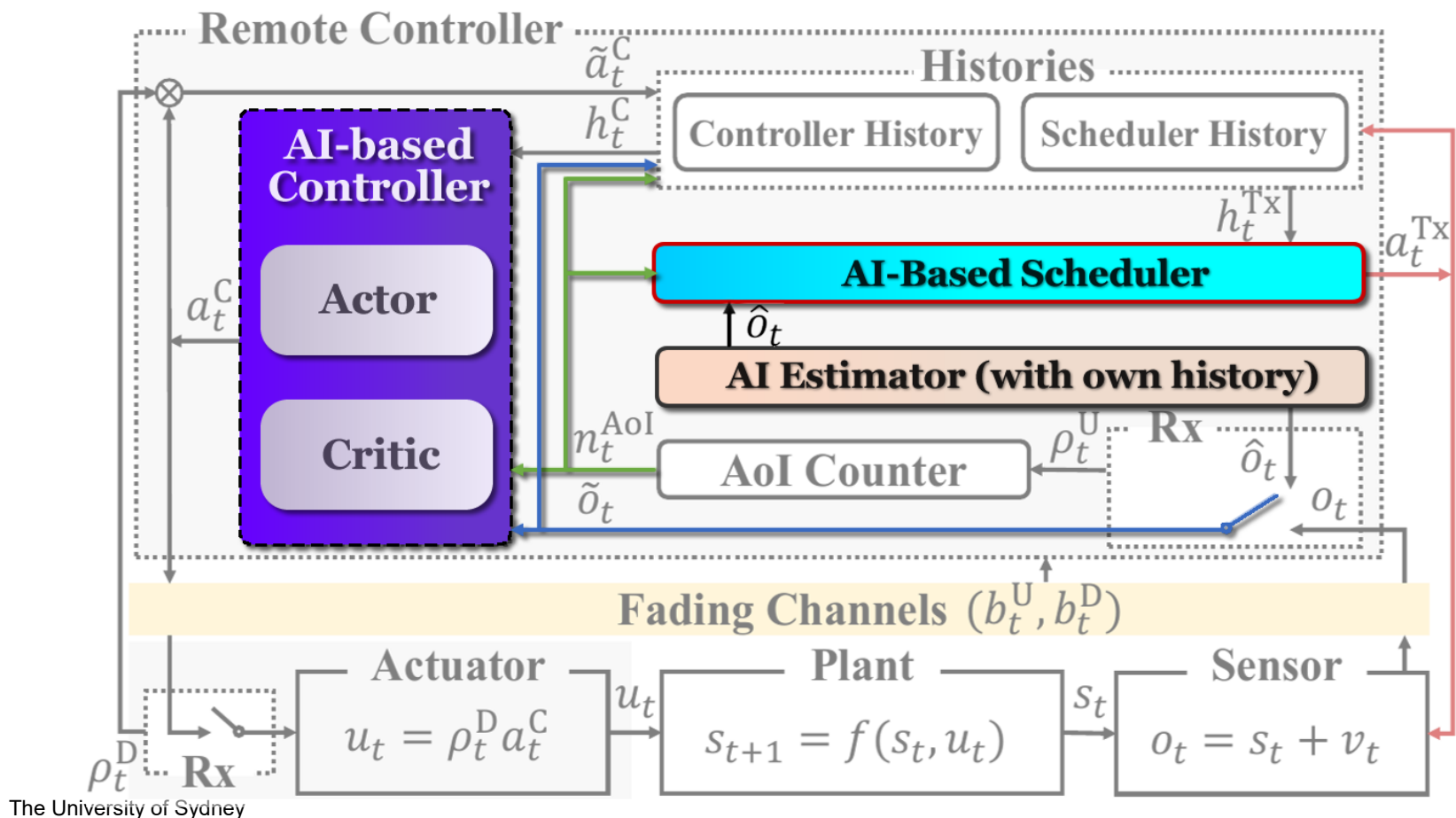


Fig. 2: Joint estimation-control-scheduling design in WNCs

# Performance of Codesign

— Codesign method      — Independent design 2  
— Independent design 1      — Independent design 3

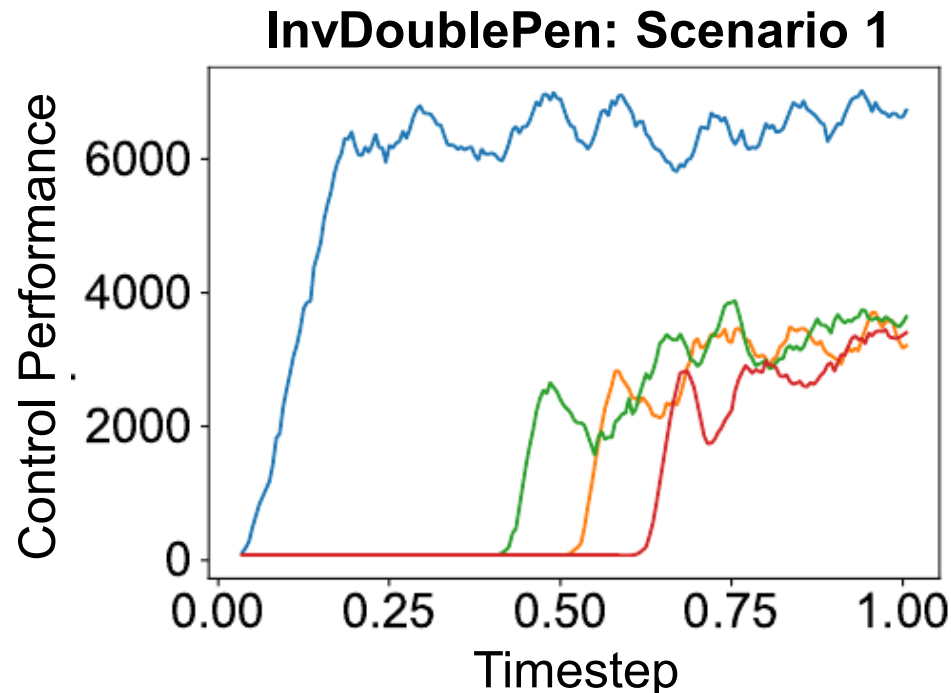


Fig. 4: Comparison of learning curves (low-mobility scenarios)  
– joint and separative estimation-control methods

- Z. Zhao, W. Liu, D. E. Quevedo, Y. Li, and B. Vucetic, “Deep learning for wireless networked systems: a joint estimation-control-scheduling approach,” arXiv preprint, Oct. 2022. [Online]. Available: <https://doi.org/10.48550/arXiv.2210.006>

# Conclusions

- AI is a useful tool for communications system and network design
- It enables more accurate propagation modelling where environment features could be obtained from images
- AI can reduce the complexity of physical layer algorithms and resource allocation protocols
- It can improve the performance of networked control systems by joint design
- 6G will be an intelligent platform with integrated communications, sensing, control, computing, and localization and it will enable distributed AI

# Joint PhD model



THE UNIVERSITY OF  
SYDNEY

# Joint PhD Programs

Definition	Important Elements
<p>A joint PhD is a Doctor of Philosophy program that consists of:</p> <ul style="list-style-type: none"><li>• shared candidature between USYD and one or more institutions;</li><li>• produces a single thesis;</li><li>• jointly awarded by USYD and the partner institution.</li></ul>	<ul style="list-style-type: none"><li>• Enrolment at each institution;</li><li>• Must meet admission requirements at both institutions;</li><li>• Co-supervision by academic(s) from USYD and partner institution(s);</li><li>• 2 separate testamurs that each acknowledge the joint arrangement;</li><li>• Typically, coursework is only required at home institution;</li><li>• Principal Agreement vs Student Agreement</li><li>• Minimum of 30% of the candidature is spent at each institution.</li></ul>



# Joint PhDs: Motivations and Benefits

Institutional Benefits	Student Benefits
<ul style="list-style-type: none"><li>• Institutional prestige</li><li>• Complements existing research collaborations</li><li>• Access to high quality international students</li></ul>	<ul style="list-style-type: none"><li>• Expansion of professional network / opportunities</li><li>• Cross-cultural learning and experiences</li><li>• Access to labs or source materials that may not be available at the home institution</li><li>• No fees at the host institution!</li></ul>

# Partners

## Current partnerships:

Partner Institution	Country	Collaboration Tier
University of Glasgow	Scotland	Multi-faculty
University of Copenhagen	Denmark	Multi-faculty
Sorbonne University	France	Multi-faculty
Aix-Marseille University	France	Multi-faculty
Ca 'Foscari University of Venice	Italy	Faculty-level
Grenoble Alpes University	France	Faculty-level

## Partnerships under negotiation (AUFRADE Program):

Partner Institution	Country	Collaboration Tier
University of Bordeaux	France	Faculty-level
École Centrale de Lyon	France	Faculty-level
University Paris-Est Créteil	France	Faculty-level
Arts et Métiers ParisTech	France	Faculty-level

## Financial Model

Breakdown	Remarks
Tuition fees	Fee-waiver/exchange model (Tuition is paid at the home institution and waived at the host institution)
Living stipends	Students can apply for a broad range of scholarships
Travel & accommodation	May be partially covered by scholarship by home and/or host institution (e.g. \$5,000 SGM Joint PhD Travel Scholarship)

# CloTT Team – Academic and Professional Staff

- 9 academic staff (5 profs, 1 assoc prof and 3 senior lecturers)
- 11 research associates (2 DECRAAs )
- 1 technical officer
- 1 research administrator
- 1 adjunct professor
- 1 adjunct lecturer
- 47 HDR students (38PhD and 9MPhil)
- UG&PG capstone project students 125

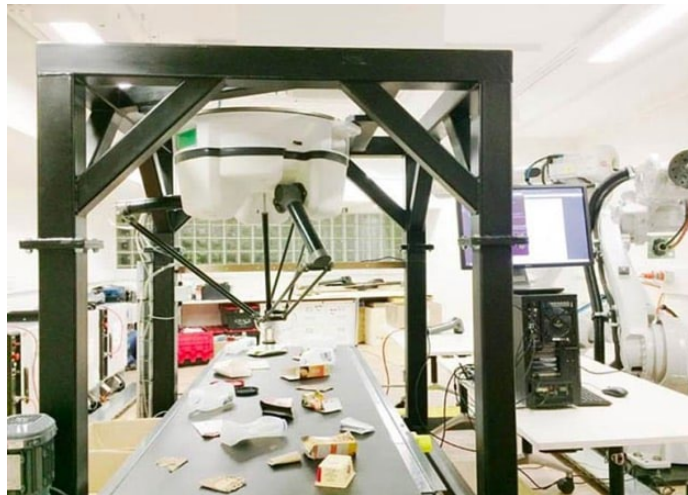
# Research Focus

- 5G and 6G wireless systems and networks
- Advanced satellite communication systems
- Wireless and IoT and security
- IoT applications in smart grids, healthcare, and material recovery facilities
- Long-range WiFi



# CloTT Strengths

- High national and international subject ranking (46<sup>th</sup> in 2018, 21<sup>st</sup> in 2021 and 9<sup>th</sup> in 2022 by ARWU)
- Advanced laboratory equipment (SDN, RF, networked control and industrial robots)
- Critical mass in communications, networking, PHY and IoT security (5 IEEE Fellows)
- Multiple government and industry research grants
- Service in IEEE societies and journals



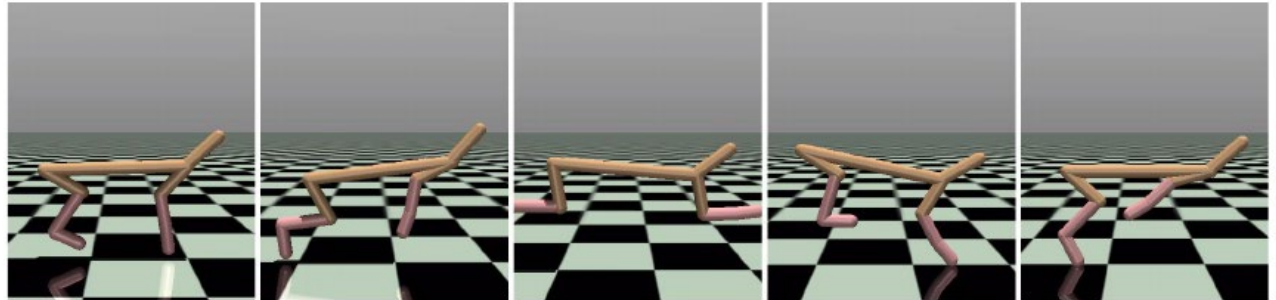
# Proof of Concept Demonstrators

- Recycling robot, IQRenew
- Long-range WiFi for mining, Roobuck
- Low-latency WiFi and AGV for warehouse automation, Damon, ABB
- 4G/5G open source SDR/SDN testbed, collaboration CFEN, and Nokia
- MAC schedulers and rate control in IEEE 802.11ah, Morse Micro
- AI based 5G propagation modelling, Optus
- Heart monitoring and AI-based diagnostics, Westmead Applied Research Centre and St Vincent Hospital
- Brain-machine communications
- Collaborative robot

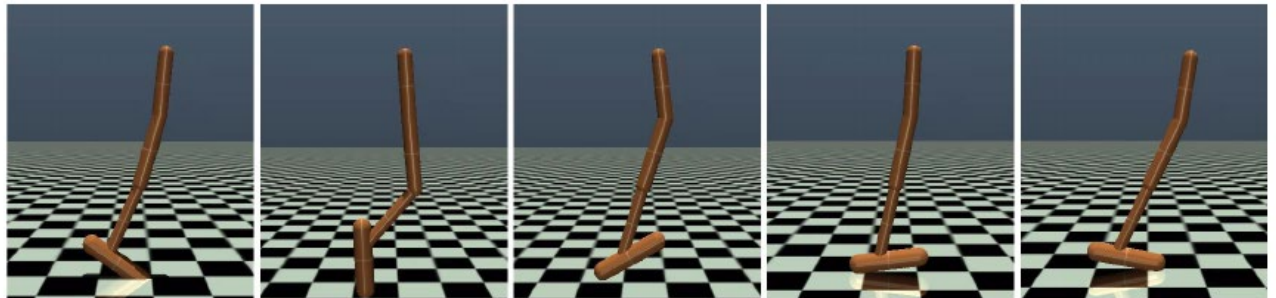
# Performance of Codesign

## – Experient setups

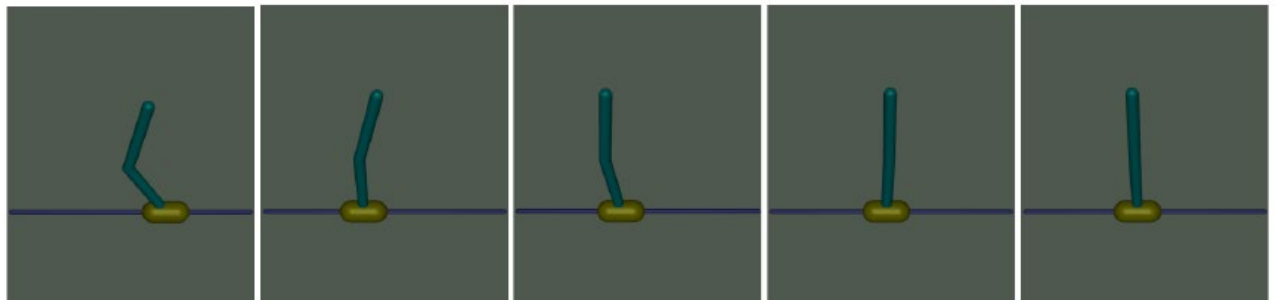
HalfCheetah-v2



Hopper-v2



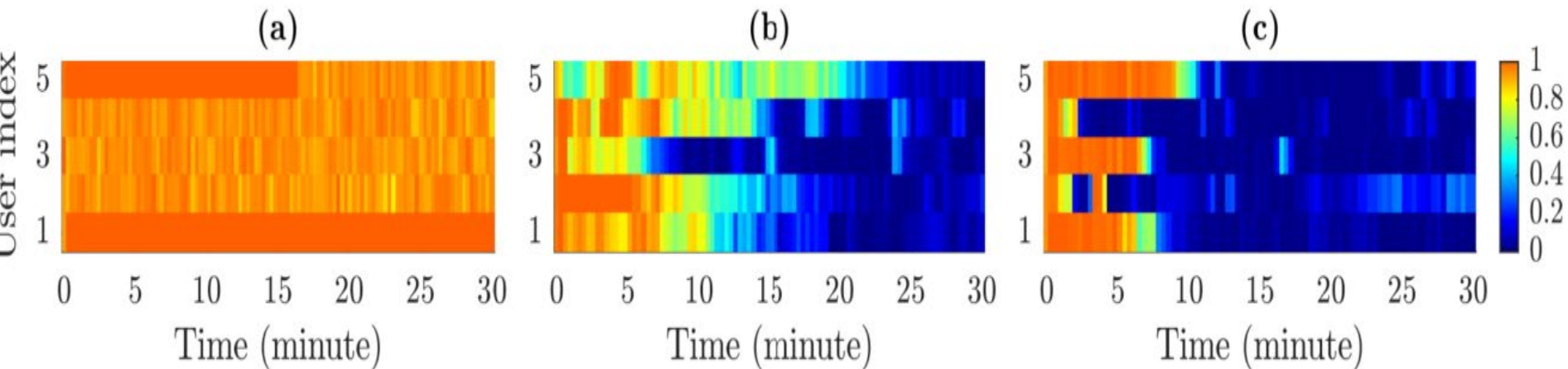
InvertedDouble  
Pendulum-v2





# Packet Loss Probability Results

- (a) Straightforward implementation of DDPG
- (b) DDPG with theoretical formulations in information theory
- (c) DDPG with expert knowledge on scheduler design problem



- The color represents the packet loss probability (orange is high, blue is low)
- The results indicate that theoretical formulations and expert knowledge can help improve the convergence time and final reliability remarkably.