# AI for Next-Generation Wireless Networks: Communication and Computation Resource Management, and Channel Estimation

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PhD in Telecommunications from King's College London (KCL), the UK

September 6, 2024

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# Brief Introduction


- I am now a Research Fellow at the Computer Networks and Communication Lab (CNCL), the College of Computing and Data Science (CCDS), Nanyang Technological University (NTU), Singapore.

- I earned my PhD degree in Telecommunications from the Centre for Telecommunications Research (CTR) at King's College London (KCL), supervised by *Professor A. Hamid Aghvami*, Life Fellow of IEEE, Fellow of IET and Fellow of the Royal Academy of Engineering (RAEng), and *Professor Osvaldo Simone*, Fellow of IEEE and IET.

## Research Expertise and Interests

Sixth-Generation (6G) Wireless Systems, Internet of Things (IoT), Terahertz (THz) Communications, Machine Learning (ML)-Aided Channel Estimation, NonTerrestrial Communications (e.g., UAV-Aided Networks), Space-Air-Ground Integrated Network (SAGIN), (Scalable/Multi-Agent) Deep Reinforcement Learning (DRL), (Quantum) Machine Learning, Low Latency Communications, Communication and Computing Resource Management, and Secure & Covert Communications.

I have authored over 20 papers in these areas in top-tier journals and prestigious conferences including IEEE TWC, IEEE TCOM, IEEE WCL, IEEE GLOBECOM, and IEEE ICC. I am also an active reviewer for these journals, conferences and beyond. I have authored 9 CN patents in the fields of wireless communications and signal processing. I served as a session chair for IEEE ICC 2022 - Selected Areas in Communications: Machine Learning for Communications Track - Networks.

# Participated Research Grants

I have participated in multiple research projects funded by the National Research Foundation (NRF) Singapore, the Infocomm Media Development Authority (IMDA) Singapore, and the Engineering and Physical Sciences Research Council (EPSRC) from the UK.

- *NRF Singapore*, Competitive Research Programme, NRF-CRP23-2019-0005, *On-chip Terahertz Topological Photonics for 6G Communication (TERACOMM)*
- *NRF Singapore & IMDA*, Future Communications Research & Development Programme, FCP-NTU-RG-2022-014, *Hybrid TeraHertz/Free Space Optics (THz/FSO) for 6G Communication Networks*, 2022-10 to 2025-03, SGD 910,000
- *EPSRC*, Programme Grants, EP/T021063/1, *COG-MHEAR: Towards cognitively-inspired 5G-IoT enabled, multi-modal Hearing Aids*, 2021-03 to 2026-02, GBP 3,259,000
- *EPSRC*, Research Grant, EP/X04047X/1, *Platform Driving The Ultimate Connectivity*, 2023-05 to 2024-03, GBP 2,030,860

# Research Expertise (During My PhD at KCL)

## Unmanned Aerail Vehicle (UAV)-Aided Networks

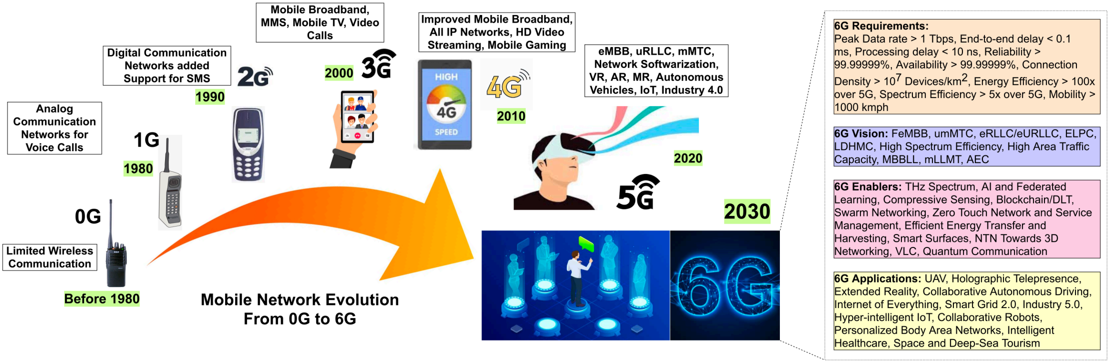
- **Performance Analysis**
  - Derive closed-form performance metrics
  - MATLAB
  - 1 IEEE TWC; 1 IEEE PIMRC
- **Trajectory Optimization**
  - Tailor quantum-aided DRL algorithms
  - Python (TensorFlow, PyTorch, Cirq, Qiskit, PennyLane)
  - 1 IEEE TWC; 1 IEEE WCL; 2 IEEE ICC
- **Radio Resource Management**
  - Design DRL-aided solutions
  - Python (TensorFlow, PyTorch)
  - 1 IEEE TCom; 1 IEEE GLOBECOM

# Research Expertise (During My Research Fellow at NTU)

## Hybrid Terahertz/Free Space Optics (THz/FSO) for 6G Networks

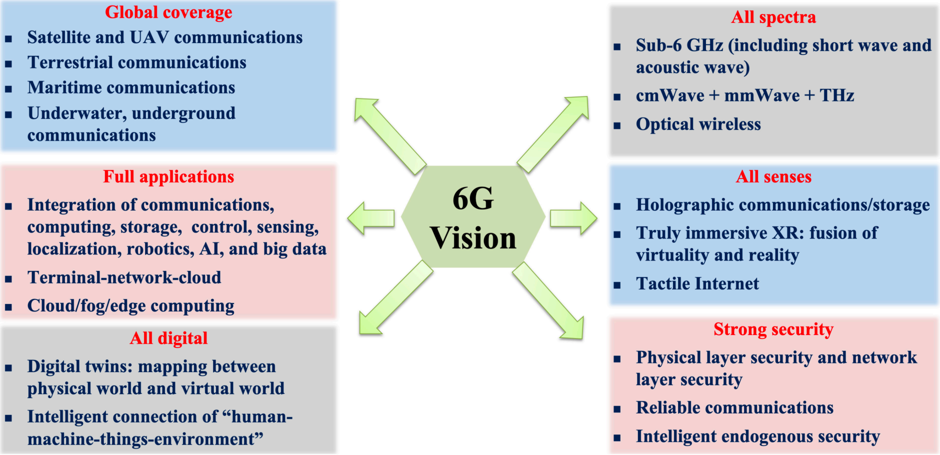
- **Multi-Access Edge Computing (MEC) over THz Band**
  - Design scalable many-agent DRL solutions
  - Python (TensorFlow, PyTorch)
  - Submitted to IEEE TCom; 1 IEEE GLOBECOM
- **THz UM-MIMO Channel Estimation**
  - Tailor CS-based and/or model-driven ML algorithms
  - Python (Tensor-Flow, PyTorch) MATLAB
  - Major Revision for IEEE TWC

# The Advancement of Wireless Communications



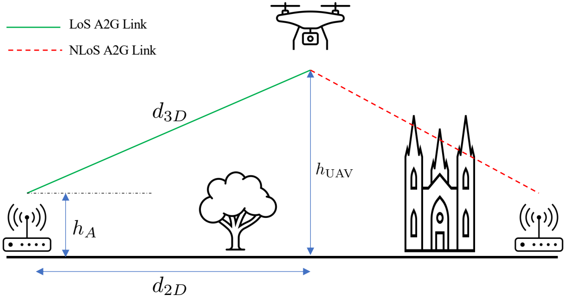

C. De Alwis, A. Kalla, Q.-V. Pham, P. Kumar, K. Dev, W.-J. Hwang, and M. Liyanage, "Survey on 6G frontiers: Trends, applications, require- ments, technologies and future research," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 836–886, 2021.

# The Next-Gen (6G) Wireless Systems



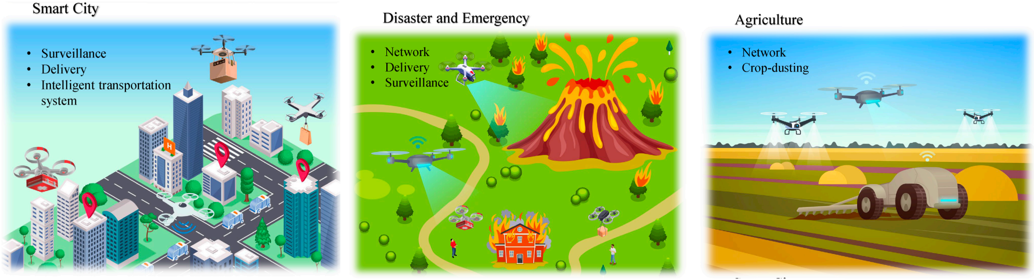

C.-X. Wang, X. You, X. Gao, X. Zhu, Z. Li, C. Zhang, H. Wang, Y. Huang, Y. Chen, H. Haas et al., "On the road to 6G: Visions, requirements, key technologies, and testbeds," *IEEE Communications Surveys & Tutorials*, vol. 25, no. 2, pp. 905–974, 2023.

# Why UAV-Aided Network?



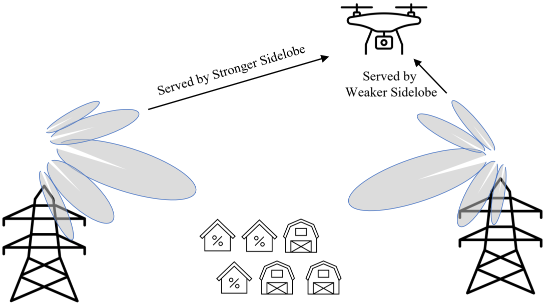

- Enhanced coverage and connectivity
- More likely to establish line-of-sight (LoS) air-to-ground (A2G) wireless links due to high altitude
- Configurable mobility and on-demand deployment
- Support for IoT & smart applications

# Some Examples of UAV-Assisted IoT Application Scenarios



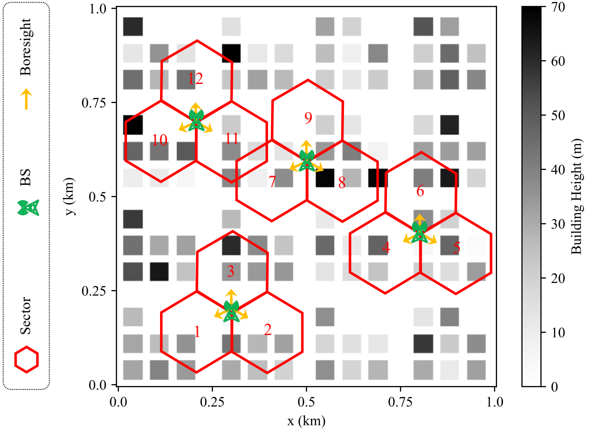

SN. Cheng, S. Wu, X. Wang, Z. Yin, C. Li, W. Chen, and F. Chen, "AI for UAV-assisted IoT applications: A comprehensive review," *IEEE Internet Things J.*, vol. 10, no. 16, pp. 14 438–14 461, 2023.

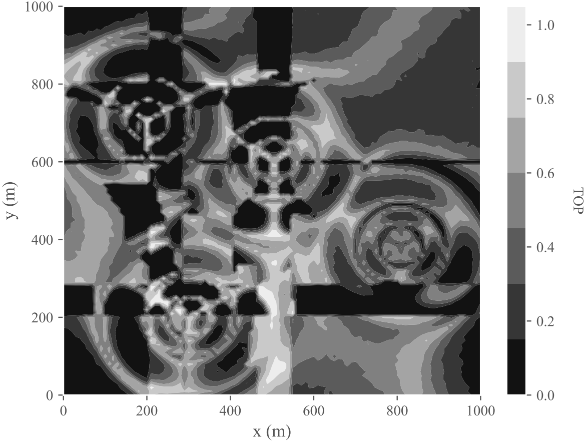
# Cellular-Connected UAVs



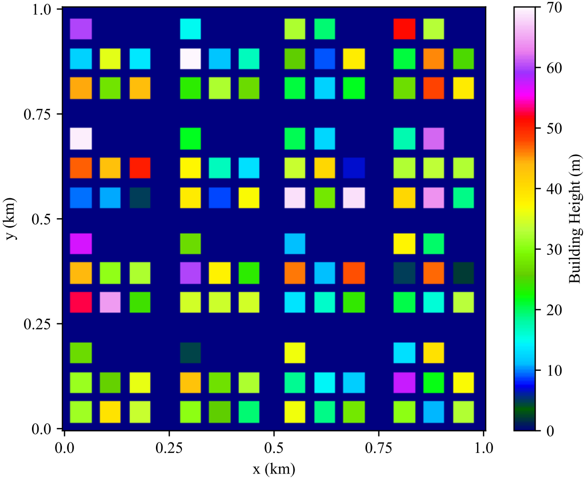

- Beyond visual and radio LoS (BVR-LoS) communications
- Reuse cellular networks thus cost-effective
- Compensate GPS coverage for better UAV navigation
- Main lobes of terrestrial base stations (BSs) are downtilted towards ground
- UAVs can be served by side lobes

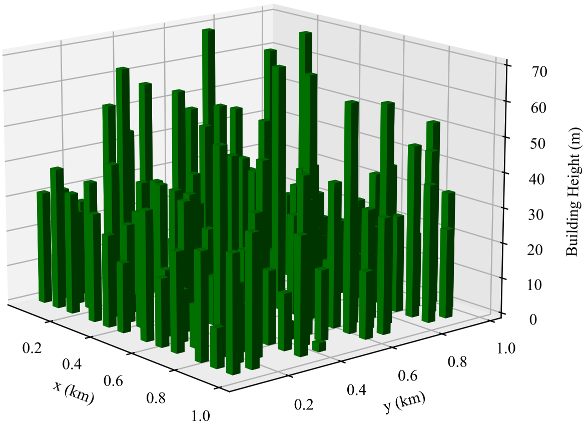
# The Cellular-Connected UAV Environment



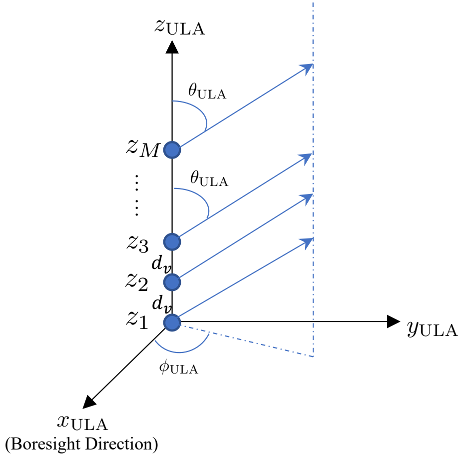
# A Closer Look at the Considered Building Distribution



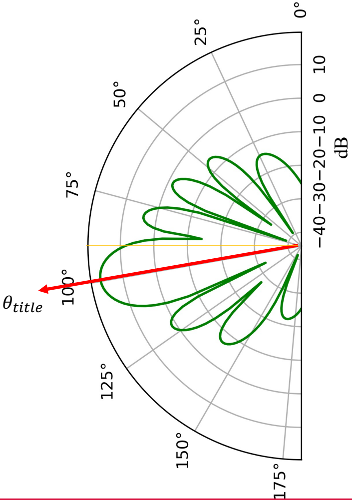



# Demonstration of ULA's coordinate system and vertical radiation pattern

## Uniform Liner Array (ULA)




## The main lobe of the ULA's radiation pattern is down-titled



# Machine Learning from Artificial Intelligence

**Artificial Intelligence** *involves any method that enables machines perform intelligently*

**Machine Learning** *empowers machines to solve problems via learning from, usually, dataset*

**Supervised Learning**

**Semi-Supervised Learning**

**Unsupervised Learning**

**Deep Learning**

*uses multiple layers to progressively extract higher-level features from the raw input*

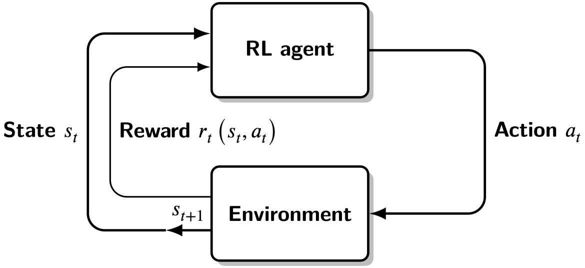
**Deep Reinforcement Learning**

*incorporates deep learning into the framework of reinforcement learning, representing the policy or other learnt functions as a neural network*

**Reinforcement Learning**

*learns from reward signals while interacting with the environment, to make optimal decisions for observations*

# The Interaction between Reinforcement Learning Agent and Environment

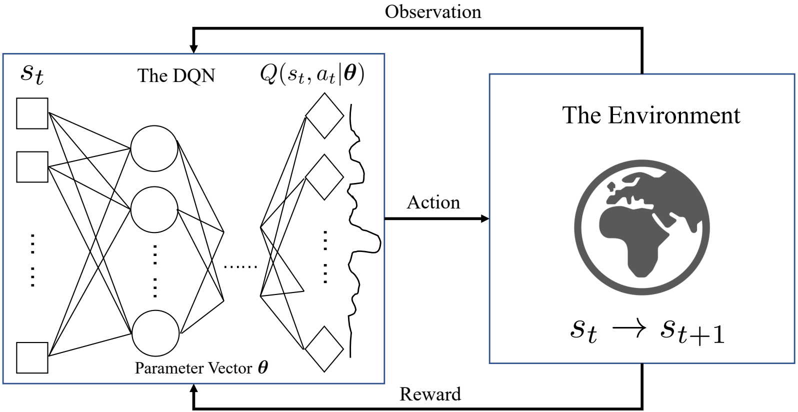



Reinforcement learning works by allowing an agent to learn optimal behavior through trial and error, receiving feedback in the form of rewards from its environment to improve its actions over time.

$$Q_u\left(s, a|\boldsymbol{\pi}\right) = \mathbb{E}\left[\sum_{t=0}^{+\infty} \gamma^t r_{u,t+1} | s_0 = s, a_0 = \mathbf{a}, \boldsymbol{\pi}\right]$$

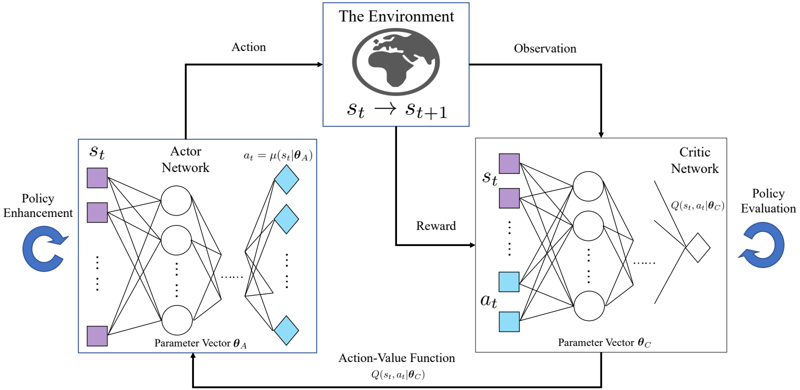
- **State ($s_t$):** Agent's current state
- **Action ($a_t$):** Agent's selected action
- **Reward ($r_t$):** The feedback from the environment based on the action taken
- **Next State ($s_{t+1}$):** The next state the agent would be in

# The Interaction between Deep Q Network and Environment



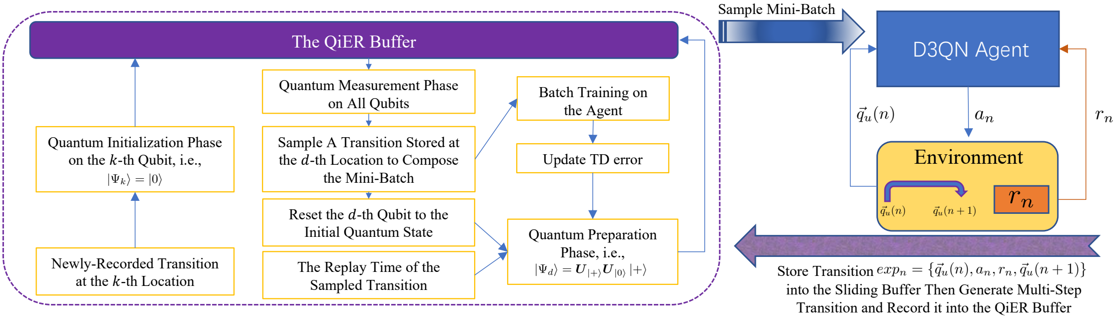

We need deep reinforcement learning because it leverages deep neural networks (DNNs) to handle complex, high-dimensional environments, enabling better scalability and generalization than traditional reinforcement learning.

# The Interaction between Actor-Critic Agent and Environment



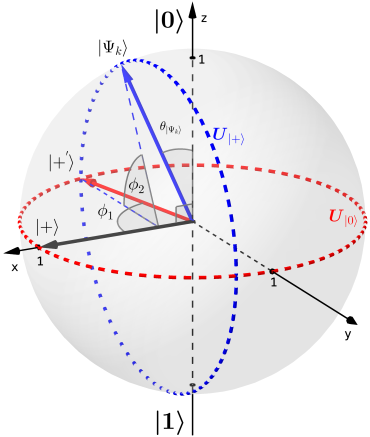

We need actor-critic deep reinforcement learning because it efficiently handles continuous action spaces by simultaneously learning a policy for action selection and a value function for evaluating actions, improving stability and performance.

# The Proposed DRL-QiER Algorithm



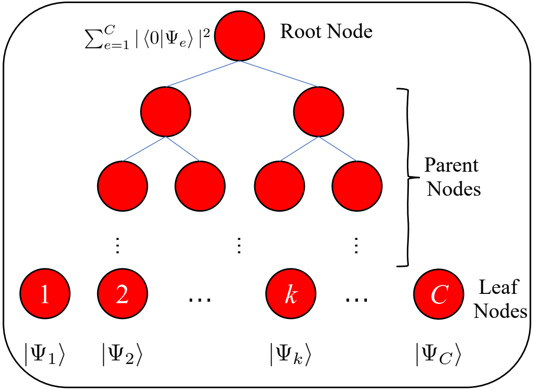

QiER is short for quantum-inspired experience replay, which invokes quantum computing to aid in DRL learning frameworks.

# How QiER Works?



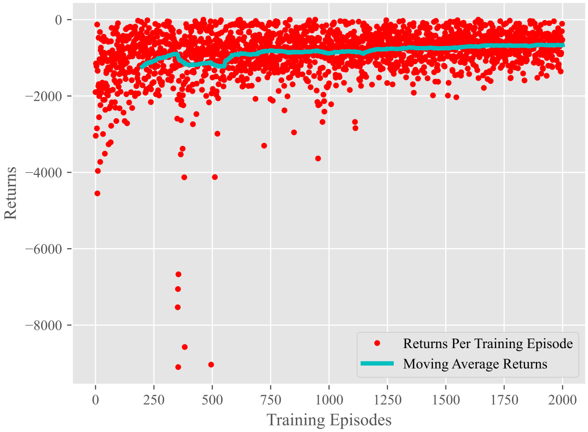

- Quantum superposition: $|\Psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$
- Probability amplitude: $\alpha = \langle 0|\Psi\rangle$, $\beta = \langle 1|\Psi\rangle$
- $|\alpha|^2 + |\beta|^2 = 1$
- After measurement, $|\Psi\rangle$ will collapse onto one of its eigenstates $|0\rangle$ and $|1\rangle$ with probabilities $|\alpha|^2$ and $|\beta|^2$, respectively.
- The idea is to use Grover iteration from quantum computing to manipulate the collapse distribution

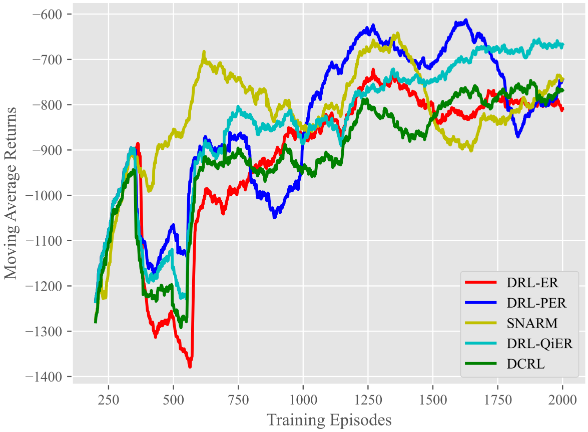
# How to Reduce Implementation Complexity?




- The complexity should not depend on $C$ which could be unbearably large in practice
- Either the root node or the parent node contains at most two child nodes as their offspring while their values equal to the sum of their child nodes
- Enabling $\mathcal{O}[\log(C)]$ updating and sampling

# Training Return History and Performance Comparison



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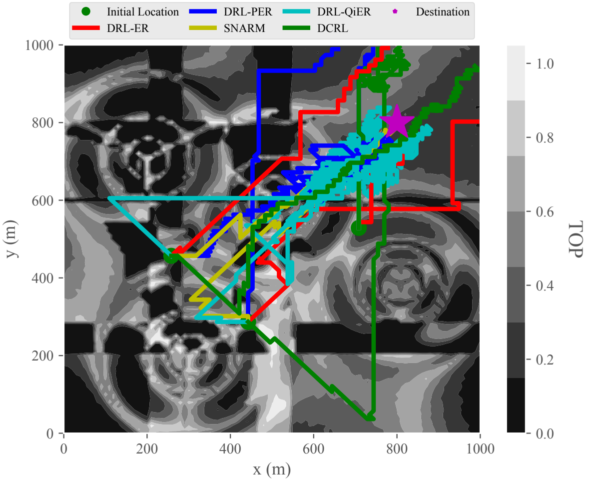


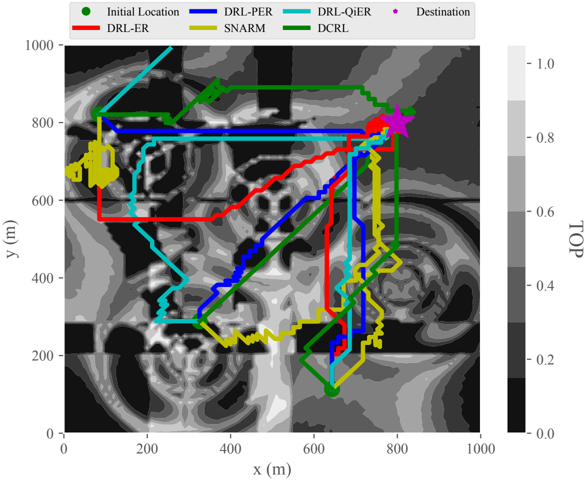

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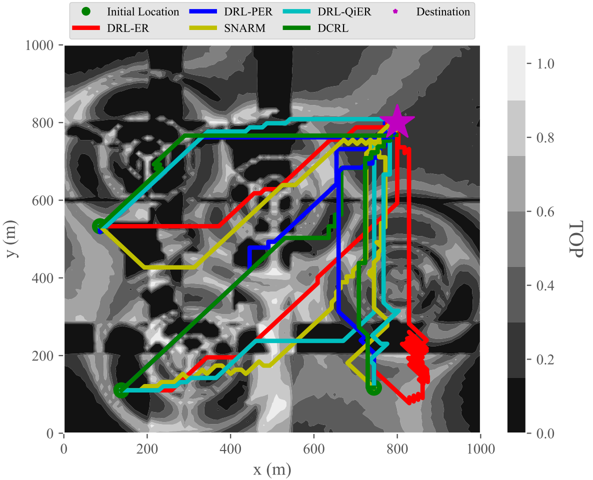


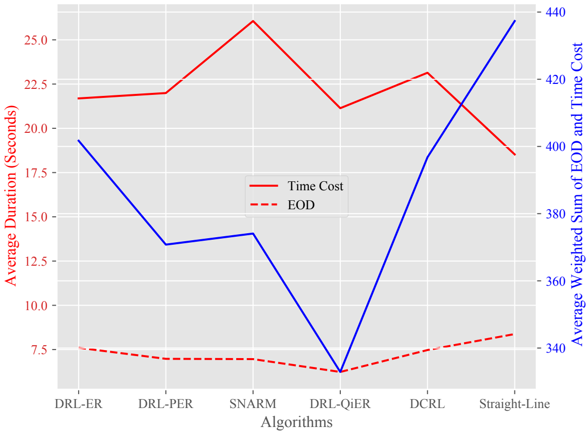

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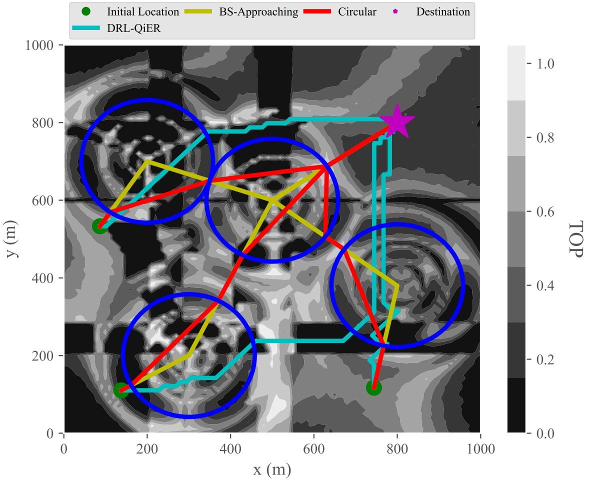


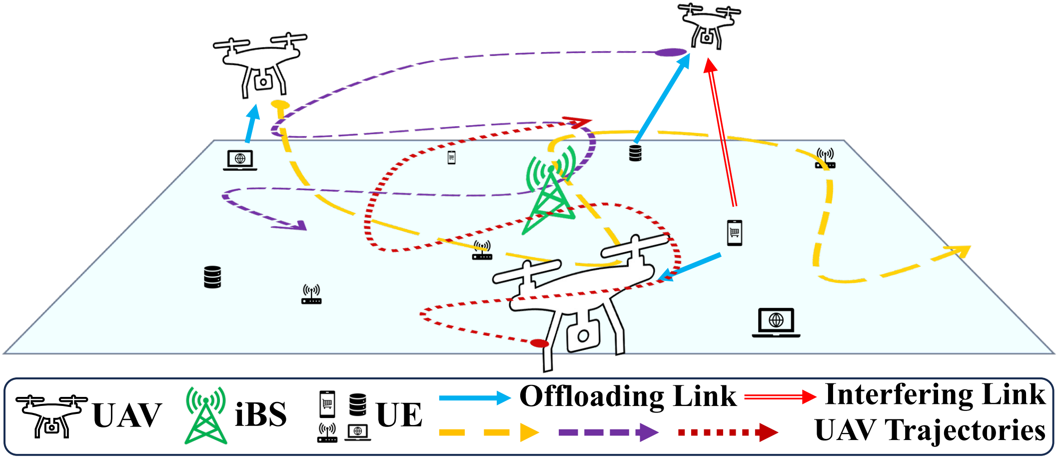

| | Circular | BS-Approaching | DRL-QiER |
|---|---|---|---|
| Time Cost | 28.440 s | 31.916 s | 31.234 s |
| EOD | 10.469 s | 12.128 s | 8.136 s |
| Weighted Sum of Time Cost and EOD | 551.890 | 638.316 | 438.034 |

# Mang-Agent Deep Reinforcement Learning (MADRL)-Aided Communication and Computing Resource Coordination for Multi-Access Edge Computing (MEC) Systems

This work focuses on developing MADRL-driven strategies to optimize key performance metrics, such as energy efficiency, in MEC systems. Multiple unmanned aerial vehicles (UAVs) are deployed to provide energy-limited computation-scare terrestrial IoT user equipments (UEs) with accessible task offloading services.

The optimization process jointly considers communication and computation resources, including UAVs' trajectories, UEs' local central processing unit (CPU) clock speeds, UAV-UE associations, time slot slicing, and UEs' offloading powers, after mapping the original problem into a stochastic (Markov) game.

# System Model Diagram of Multi-UAV Computation Offloading for IoT UEs



## Key Considerations

To achieve energy-efficient implementation of multi-UAV-assisted MEC frameworks in IoT, the following core challenges need to be tackled beforehand.

- How to manipulate UAVs' flights to design proper trajectories for establishing high-quality ground-to-air (G2A) transmission links, thus facilitating task offloading for multiple user equipments (UEs)?
- What is the proper way to jointly manage communication and computation resources such as transmit power, UAV-UE associations, CPU clock speeds and time slicing factors, to optimize key system metrics for multi-UAV multi-UE (MUME) drone-assisted MEC systems, e.g., energy efficiency?
- How to tailor an agile multi-agent learning solution that can efficiently handle and intelligently adapt to the stern non-stationarity inherently existing in MUME drone-aided MEC systems?

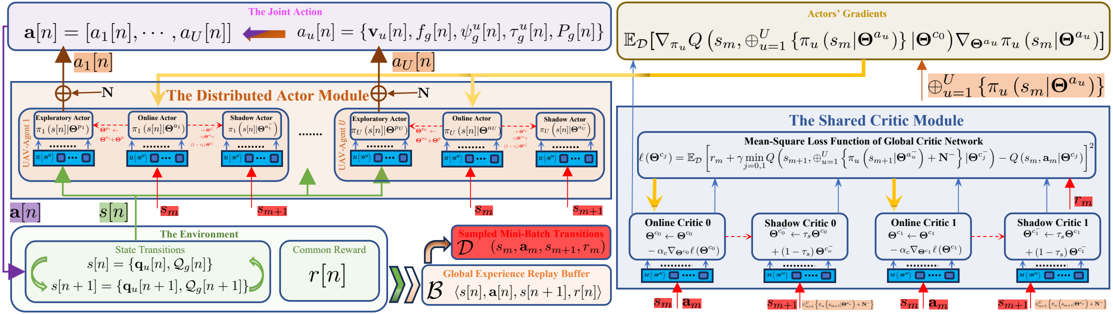
# Main Difficulties in Solving the Formulated Joint Computation and Computing Resource Management Problem

- **High-dimensional spaces:** both continuous state and action representatives lead to a severe curse of dimensionality
- **Exploration vs. Exploitation:** balancing exploration of new strategies against exploitation of learnt policies is difficult in continuous domains, as the space of possible actions and states are infinitely vast
- **Non-stationarity:** the environment is highly dynamic and thus non-stationary, as state transitions and global reward function are affected by the joint action, while the behavior of multiple agents are time-varing as per their local learning progresses
- **Scalability:** as the number of agents increases, e.g., systems with thousands of wireless devices, the complexity and action spaces increase exponentially
- **Sample inefficiency:** larger number of experiences, i.e., samples, is demanded by the multi-agent learning system to ascertain effective policies or equilibria for distributed agents

# Why Multi-Agent Reinforcement Learning?

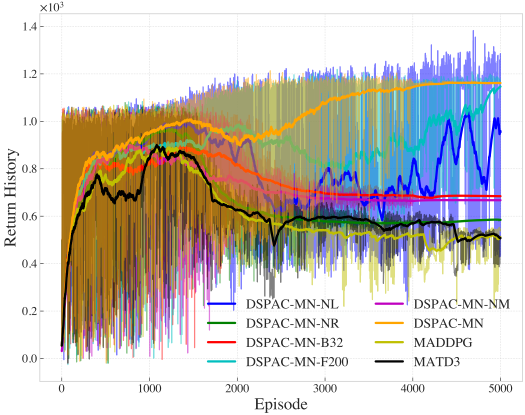
- MADRL enables implementing distributed wireless protocols at the edge
- MADRL agents can share experiences so that less-trained agents can learn from their better-skilled partners
- MADRL can accommodate heterogeneous agents with various learning goals and device capabilities.

# Workflow of the Proposed DSPAC-MN Algorithm



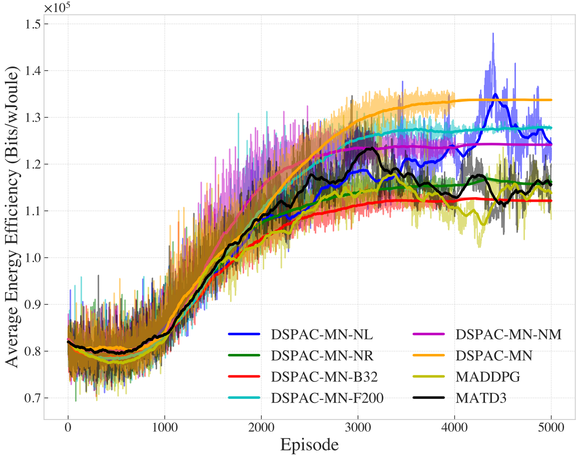

- *Distributed Agents*: explore in parallel
- *Shared Critic*: cooperative learning
- *Modularized Inputs*: balanced dimension
- *Perturbed Actors*: enhanced exploration

# Return History of the Online Training Process




- *MADDPG*: an extension of DDPG to handle multi-agent scenarios
- *MATD3*: an extension of TD3 to reduce overestimation bias of MADDPG
- *DSPAC-MN-NM*: DSPAC-MN without modular networks
- *DSPAC-MN-NR*: Regularization-less DSPAC-MN
- *DSPAC-MN-NL*: DSPAC-MN without learning rate scheduling
- *DSPAC-MN-B32*: DSPAC-MN with batch size of 32
- *DSPAC-MN-F200*: DSPAC-MN with policy renewal frequency of 200

# Performance Comparison on Expected Energy Efficiency

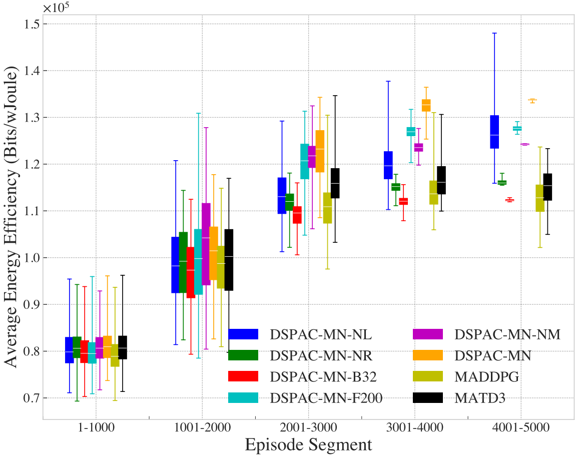


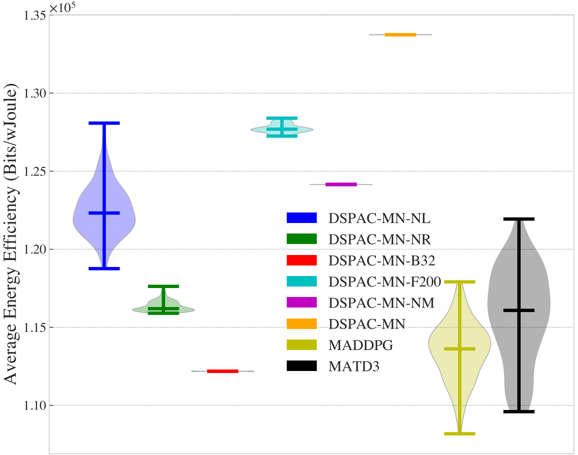

$$\max_{\{\mathbf{v}_u[n], f_g[n], \psi_g^u[n], \tau_g^u[n], P_g[n]\}} \frac{1}{N} \sum_{n=1}^{N} \frac{d[n]}{E[n]}$$

$$d[n] = \sum_{g \in \mathcal{G}} d_g[n].$$

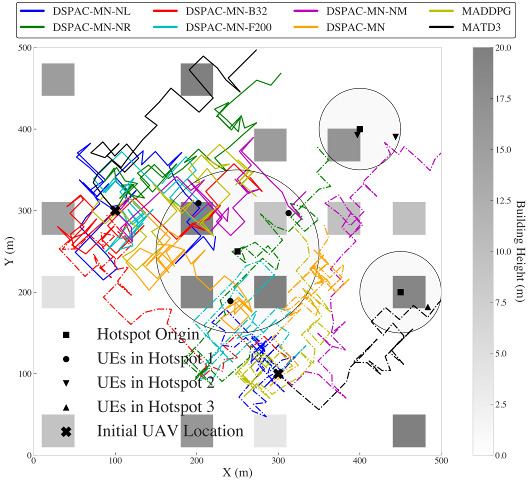
$$E[n] = \sum_{g \in \mathcal{G}} E_g^l[n] + \sum_{u \in \mathcal{U}} \left( E_u[n] + \kappa E_u^p[n] \right),$$

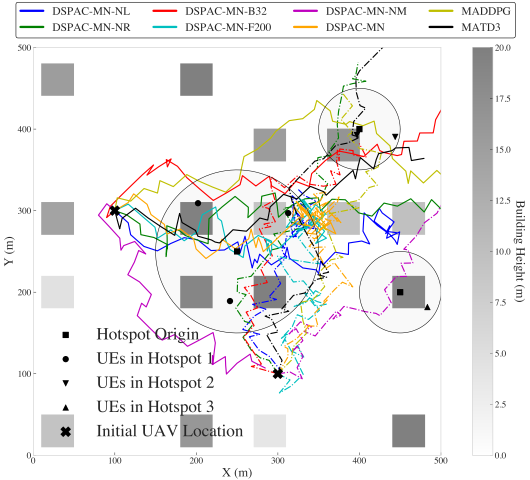
# Box and Violin Plots of Performance Comparison on Expected Energy Efficiency



# Visualization of and Comparison on Devised Trajectories over Various Algorithms



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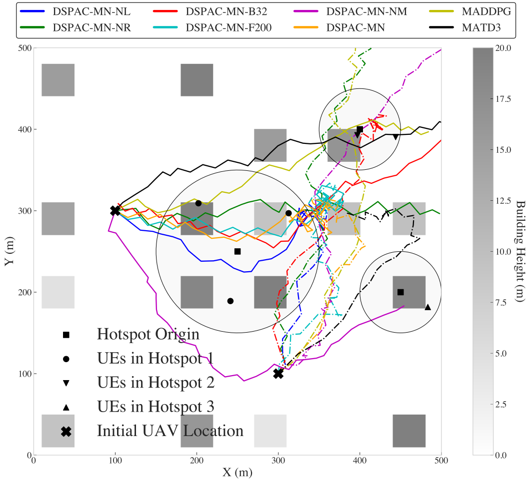
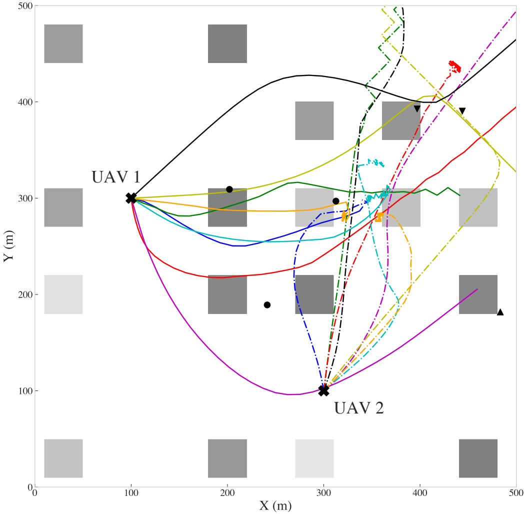
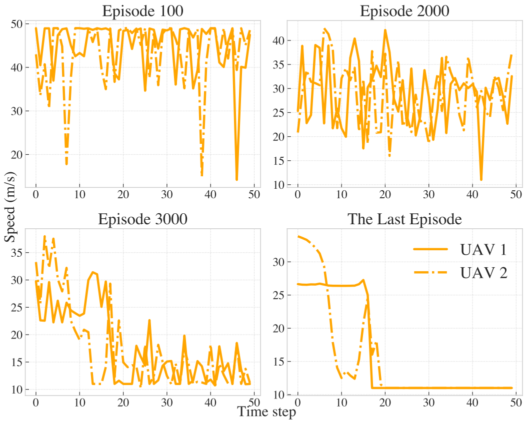


# Safe Flight Probability and Designed Propulsion Speed

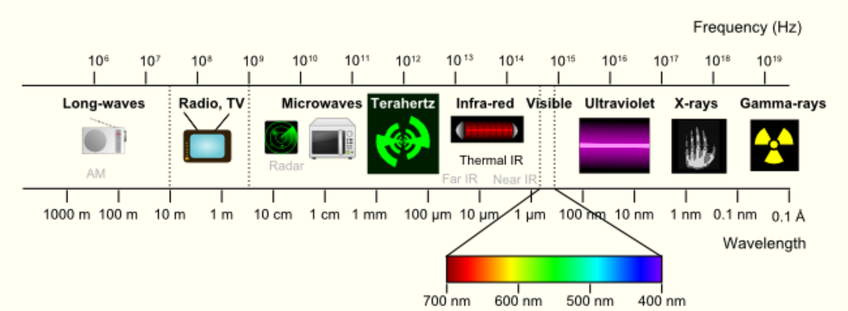



## *Comparison on Safe Flight Probability*

| *Algorithms* | MADDPG | MATD3 | DSPAC-MN-NM | DSPAC-MN-NR |
|---|---|---|---|---|
| *The last 1000 episodes* | 0.5729 | 0.59992 | 0.73998 | 0.62 |
| *The last 200 episodes* | 0.5853 | 0.6015 | 0.74 | 0.62 |
| *The last 10 episodes* | 0.62 | 0.598 | 0.74 | 0.62 |

| *Algorithms* | DSPAC-MN-NL | DSPAC-MN-B32 | DSPAC-MN-F200 | **DSPAC-MN** |
|---|---|---|---|---|
| *The last 1000 episodes* | 0.73734 | 0.77556 | 0.90374 | **1.0** |
| *The last 200 episodes* | 0.8205 | 0.78 | 0.9905 | **1.0** |
| *The last 10 episodes* | 0.848 | 0.78 | **1.0** | **1.0** |

# Why Terahertz (THz)?




Terahertz (THz) transmissions, operating in the 0.1-10 THz frequency range, offer the potential for ultra-high data rates, reaching up to several Terabits per second (Tbps) with ultra-broad spectrum blocks. This capability is considered a key building block of the forthcoming 6G communications in supporting applications such as immersive virtual reality (VR), edge intelligence, and holographic communications.

# Why Ultra-Massive Multiple-Input Multiple-Output (UM-MIMO) for THz?

However, the appealing multi-Gigahertz bandwidth comes with severe propagation attenuation due to substantial atmospheric and spreading losses from molecular absorption and high carrier frequency, respectively. An emerging solution to broadening THz transmission coverage is ultra-massive multiple-input multi-output (UM-MIMO) technology, which offers high-level array gain to compensate THz propagation losses by forming pencil-thin directional radiation beams.

# An Example of the Large-Scale Path Loss Model on the THz Band

Speed of Light

Distance

$$\mathrm{PL}\left[d, f\right] = \left|\left(\frac{c}{4\pi d f}\right) \exp\left[-\frac{1}{2}\,\kappa\left(f, \mu\right) d\right] \exp\left[-j2\pi f \frac{d}{c}\right]\right|^2$$

Carrier Frequency

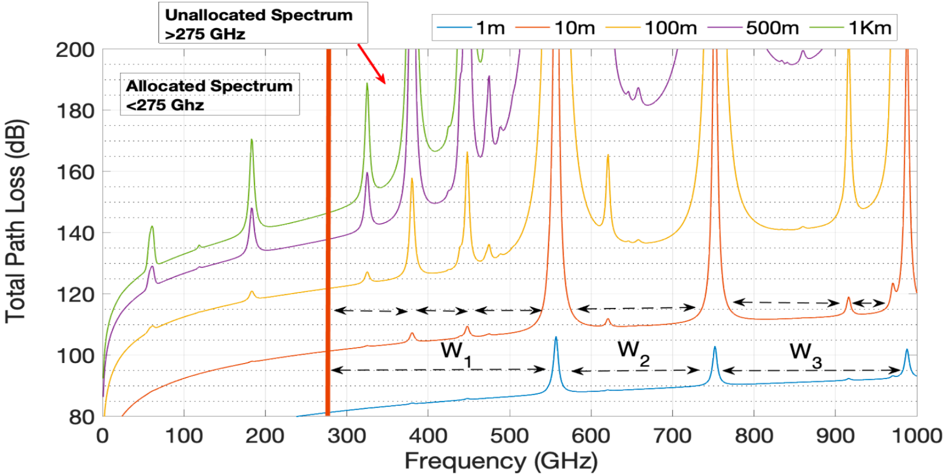
time-of-arrial

Molecular Absorption Coefficient

the volume of the mixing ratio of water vapor

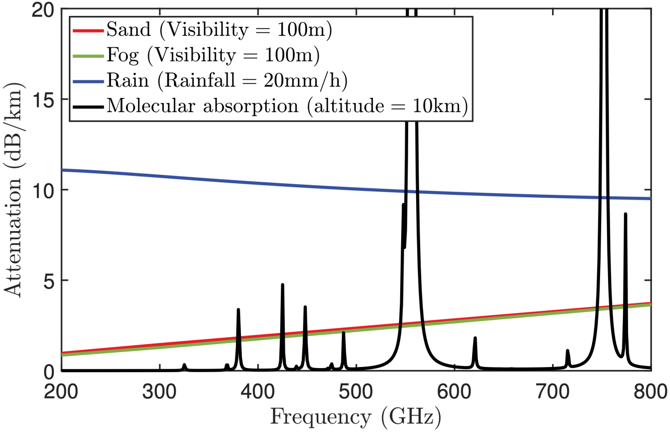
*Distance-Dependent and Frequency-Selective!*

# Distance-Dependent and Frequency-Selective THz Path Loss




Singh, Rohit, and Douglas Sicker. "Thz communications-a boon and/or bane for security, privacy, and national security." TPRC48: The 48th Research Conference on Communication, Information and Internet Policy. 2020.

# Attenuation versus Frequency for the Different Weather Conditions

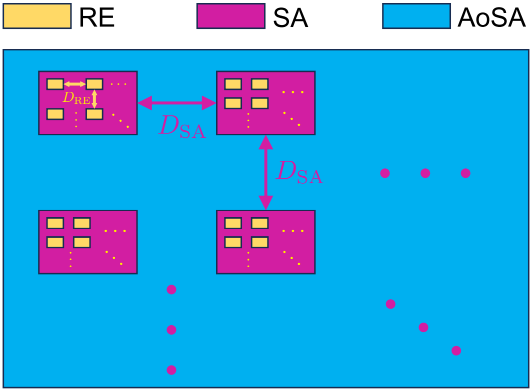



Han, Chong, et al. "Molecular absorption effect: A double-edged sword of terahertz communications." IEEE Wireless Communications (2022).

# Machine Learning (ML)-Enabled Channel Estimation for Terahertz (THz) Ultra-Massive Multi-Input-Multi-Output (UM-MIMO) Communications

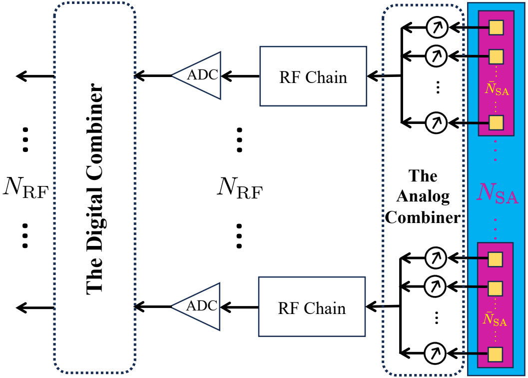
To facilitate efficient THz communications, UM-MIMO systems that provide substantial beamforming gains are essential. However, tailored channel estimation solutions are necessary to fully leverage UM-MIMO for THz transmissions. This involves practical modeling of the near-field propagation characteristics, molecular absorption, and scatter reflection effects. To address challenges such as angular-domain energy spread and the beam split effect, a dictionary learning framework that creates an adaptive sparsifying matrix from the THz channel dataset is proposed. Furthermore, a model-driven deep learning approach is introduced, which unrolls iterative algorithms into a finite-length, layer-wise deep neural network designed to learn the sparse representation of the THz channel from the THz channel dataset and received pilot signals.

# Array-of-Subarray (AoSA)-Based UM-MIMO Architecture



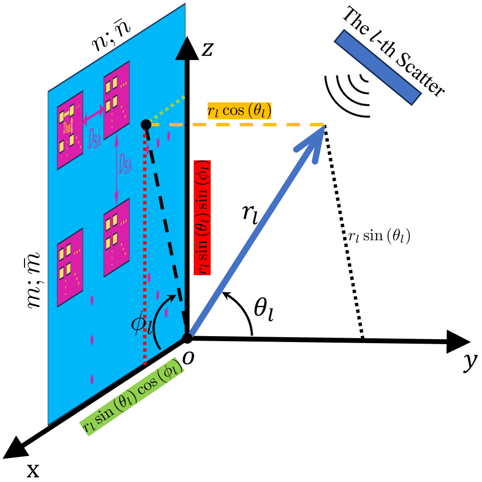

- Each subarray (SA) comprises $\bar{N}_{\mathrm{SA}} = \bar{N} \times \bar{M}$ radiating elements (REs), antennas
- The amount of SAs is denoted by $N_{\mathrm{SA}} = N \times M$
- The AoSA consists of $A = \bar{N}_{\mathrm{SA}} N_{\mathrm{SA}}$ antennas/REs in total
- RE displacement $D_{\mathrm{RE}} = \lambda_c/2$ in each SA
- SA displacement $D_{\mathrm{SA}} = wD_{\mathrm{RE}}$, where $w \gg 1$

# Partially-Connected Hybrid Combining Scheme




- An energy-efficient hybrid combining strategy are implemented at the AoSA, where REs in each SA share the same RF chain via dedicated analog combiner, in a partially-connected manner, i.e., the amount of RF chains $N_{\rm RF} = N_{\rm SA} \ll A$.
- Following each RF chain, an analog-to-digital converter (ADC) is adopted to sample and quantize the analog waveform, transforming it into digitalized data for baseband signal processing.
- The fully-connected hybrid combining architecture: $N_{\rm RF} \times A$ RF links, while the partially-connected strategy: $A$ links.

# AoSA-Based UM-MIMO with Partially-Connected Hybrid Combining



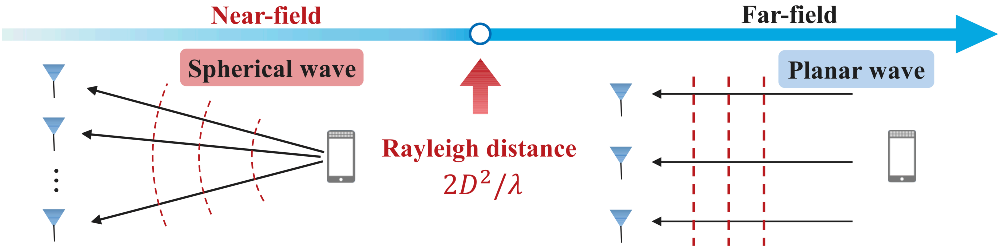

- $\phi_l \in [-\pi, \pi]$ is the azimuth angle-of-arrival (AoA) and $\theta_l \in [-0.5\pi, 0.5\pi]$ is the elevation AoA of the propagation path from the $l$-th scatter to the AoSA's origin

- The location of the $l$-th scatter is

$$\mathbf{l}_l = r_l [\sin(\theta_l)\cos(\phi_l), \cos(\theta_l), \sin(\theta_l)\sin(\phi_l)],$$

where $r_l$, $\phi_l$ and $\theta_l$ are measured w.r.t. the AoSA origin, i.e., the $(1, 1)$-th SA's origin.

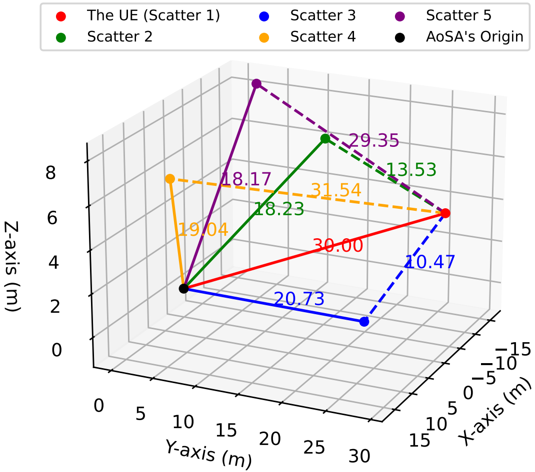
# Near- and Far-field Radiation Regions




The renowned Fraunhofer (Rayleigh) distance is commonly adopted to distinguish near-field and thus far-field regions, which is given by $D_{\mathrm{F}} = 2D_{\mathrm{A}}^2/\lambda_c$ and is increased with the aperture of the antenna array and the operating frequency, where $D_{\mathrm{A}}$ denotes the AoSA's array aperture, i.e., the diagonal length of the AoSA. If the receiver is located inside the Fraunhofer distance from the radiating unit, the near-field radiation characteristics should be considered and the wavefront has to be modelled as spherical.

Cui, Mingyao, and Linglong Dai. "Channel estimation for extremely large-scale MIMO: Far-field or near-field?." IEEE TCom 70.4 (2022): 2663-2677.

# Hybrid Near- and Far-Field THz Transmission




- In the multi-path propagation from the UE to the AoSA, there might be some scatters in the far-field, while some in the near-field.
- Therefore, the hybrid-field THz radiation is considered, where the overall THz channel consists of portions of near- and far-field paths.

## Why Dictionary Learning?

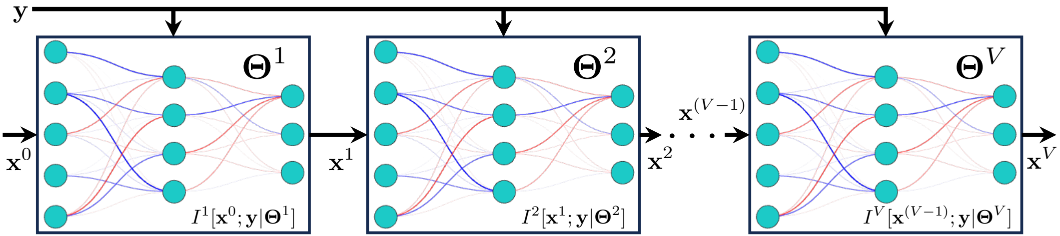
If far-field radiation is sorely considered, the discrete Fourier transform (DFT)-based dictionary can be invoked to generate the sparse angular-domain representation for the original THz channel. In the case of pure near-field radiation, the dictionary has to be formulated from the joint distance and angle space, i.e., polar-domain sparsifying matrix. If the DFT-based dictionary matrix is directly used for the near-field radiation, fatal energy spread phenomenon in the angular domain will occur. However, neither angular- nor polar-domain dictionary can properly sparsify the considered hybrid-field THz channel model, as the appropriate dictionary design is subject to the proportion of near- and far-field components. Thus, existing field-specific compressive sensing (CS) solutions suffer from significant channel recovery performance degradation.

# The Proposed Channel Estimation Schemes

To address this challenge, we propose a batch-delayed online DL (BD-ODL) solution, which aims to construct the *adaptive* sparsifying matrix tailored for the hybrid-field THz channel model.

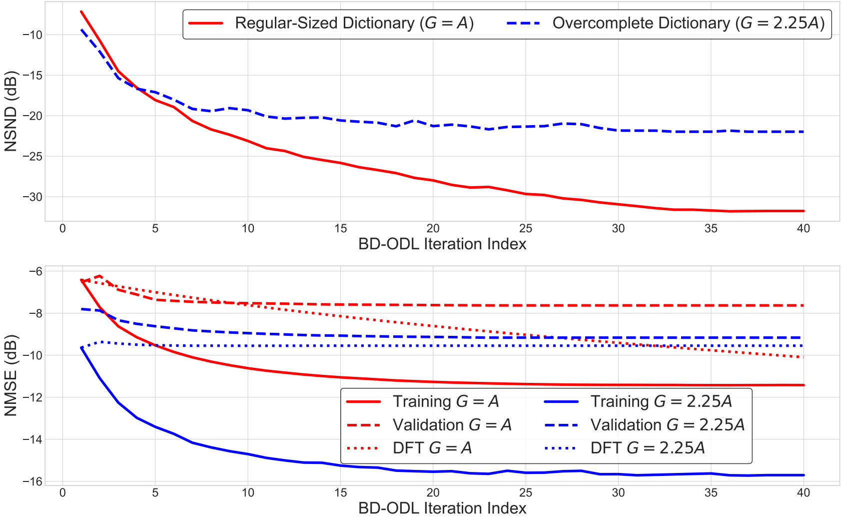
Then, we develop a Bayesian learning (BL)-based channel estimation (CE) algorithm to conduct accurate CE with reduced pilot overhead. We also invoke a model-driven deep learning frameworks called deep unfolding to perform THz channel estimation. In contrast to data-driven deep learning counterparts that are computation-hungry, complexity-intensive and with black-box characteristics, model-driven DL methods blend domain knowledge with data and DNNs to achieve more efficient function approximations and inferences, which offers better convergence, robustness and interpretability

# How Deep Unfolding Works?

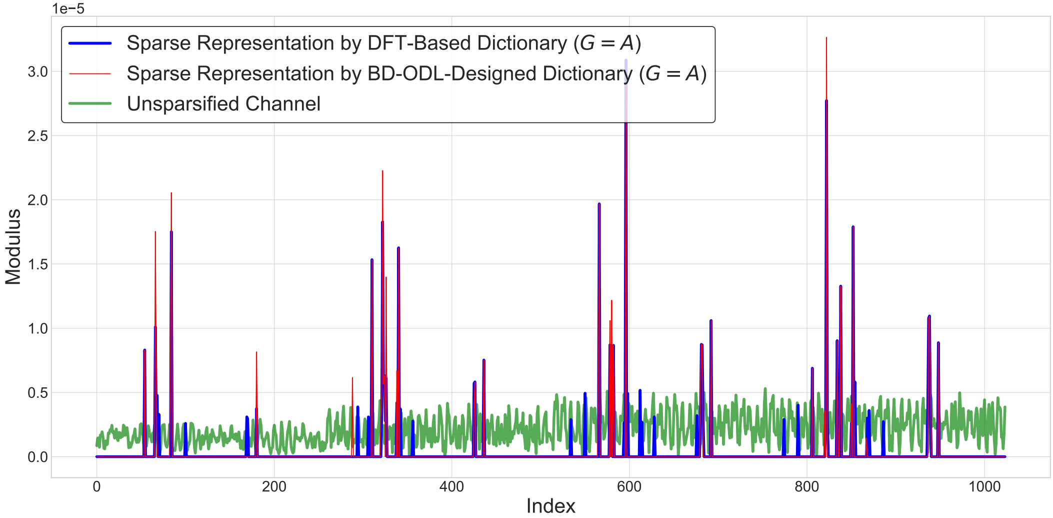



The training process aims to minimize the loss function, i.e., $\min_{\boldsymbol{\Theta}} \Delta\left[\boldsymbol{x}^V, \boldsymbol{x}^*\right]$, in which $\Delta[\cdot,\cdot]$ is the loss function, $\boldsymbol{\Theta} = \{\boldsymbol{\Theta}^1, \boldsymbol{\Theta}^2, \cdots, \boldsymbol{\Theta}^V\}$ denotes the set of each layer's trainable parameters, $V$ measures the number of layers, $\boldsymbol{x}^*$ represents the ground-truth channel vector, $\boldsymbol{x}^V = (I^V \triangleleft \cdots I^2 \triangleleft I^1)[\boldsymbol{x}^0; \boldsymbol{y}|\boldsymbol{\Theta}^V, \cdots, \boldsymbol{\Theta}^2, \boldsymbol{\Theta}^1]$ captures the final output of the deep unfolding network after $V$-layer inference, and the symbol $\triangleleft$ indicates the feed-forward process.

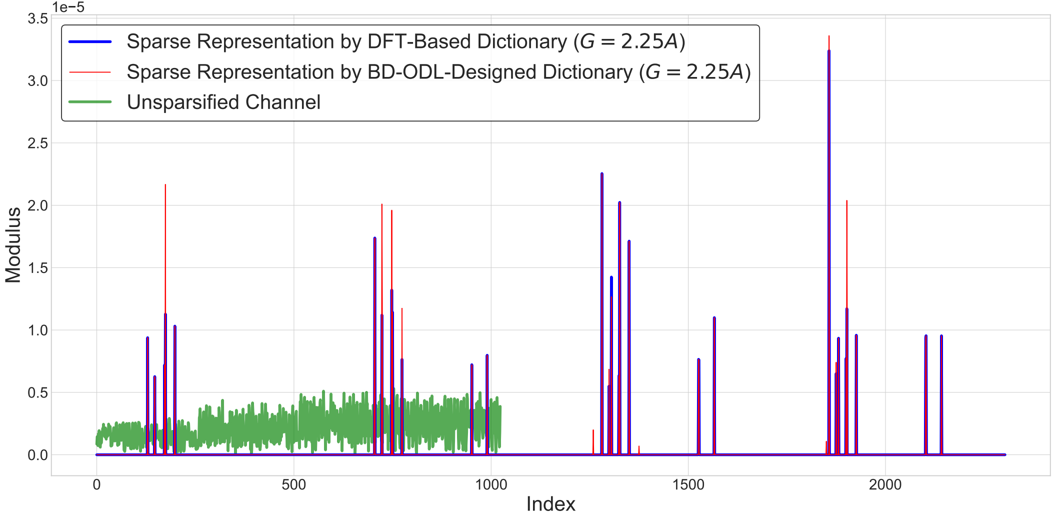
# Training History of BD-ODL



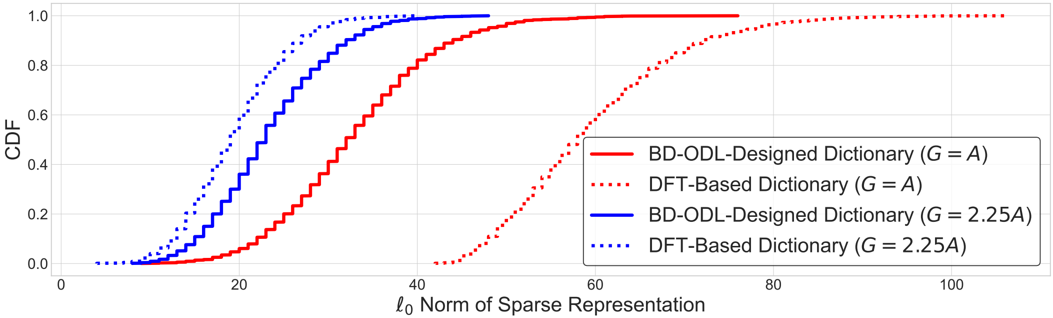
# Element Modulus Curves versus Vector Index (Square Dictionary)



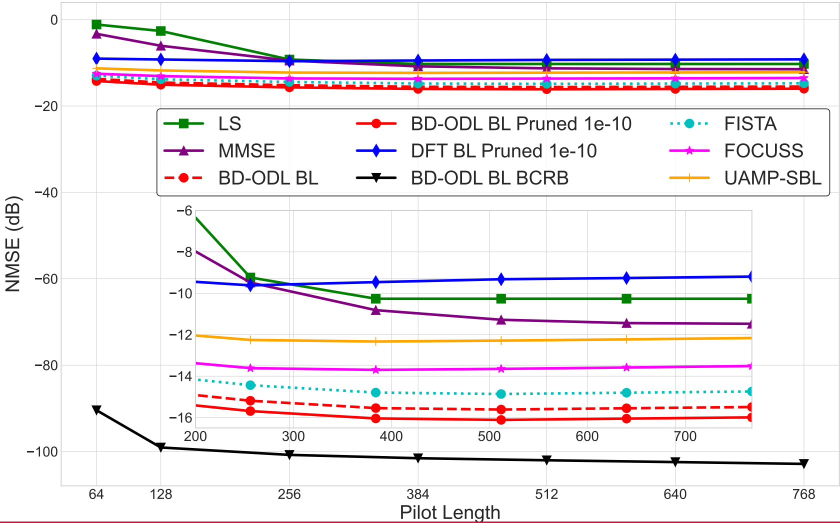
# Element Modulus Curves versus Vector Index (Overcomplete Dictionary)



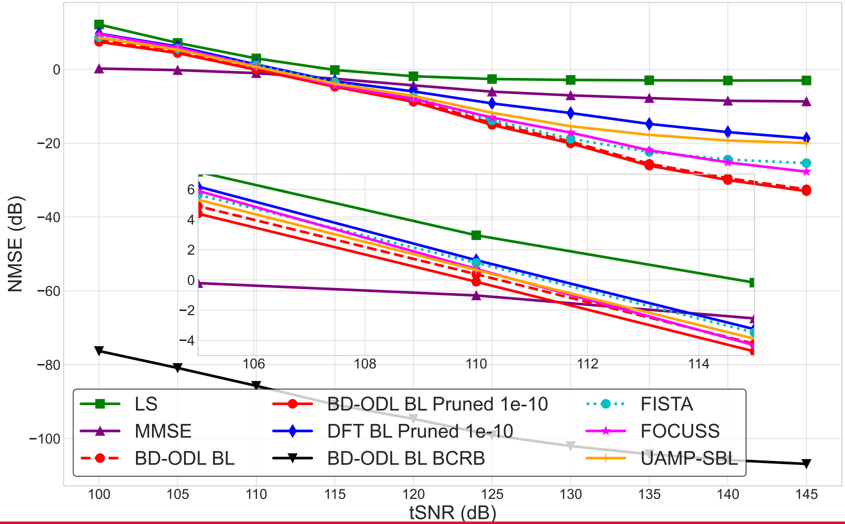
# Cumulative Distribution Function (CDF) of the $\ell_0$ Norms of the Sparse Representations



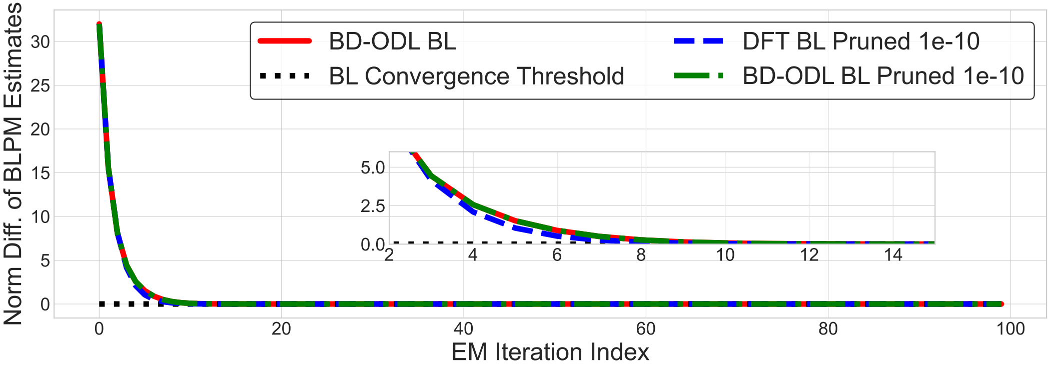
# NMSE versus Pilot Length



# NMSE versus tSNR

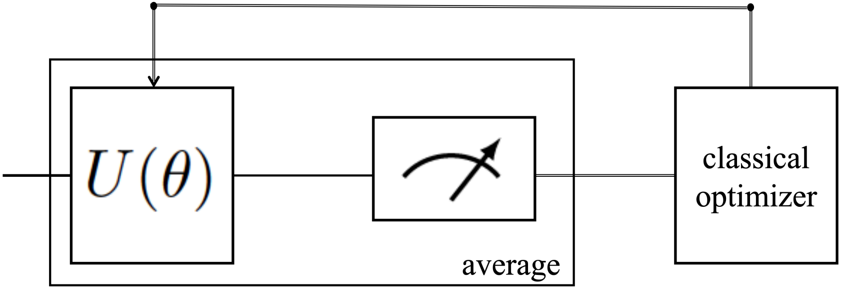


# Parameter Estimates' Norm Difference versus BL Iteration Index



# What is Quantum Machine Learning (QML)?

*QML refers to a small-scale quantum circuit with a classical optimizer, in the noisy intermediate-scale quantum (NISQ) era.*




A high-level description of the quantum machine learning design methodology. A parametric quantum circuit (PQC) implementing a unitary matrix $U(\theta)$ is optimized via its vector of parameters, $\theta$, based on measurements of the output of the PQC.

# Why Quantum Machine Learning for Next-Gen Wireless Networks?

Recent advancements in quantum computing devices, e.g., quantum supremacy reported by IBM and Google, and the latest Nobel prize in Physics for ground-breaking experiments with quantum entangled particles, further reveal the promise and importance of quantum computing for leading the next industrial revolution. QML is one of the most active research areas that combines the advantages of quantum computing and machine learning. By taking advantage of quantum effects such as entanglement and superposition, QML can process data more efficiently and thus achieve faster convergence rate and increased accuracy in prediction which often leads to improved end performance. Besides, recent works on QML showed that quantum computing is beneficial for improving efficiency and enhancing generalization for ML systems, e.g., comparable or better learning performance with much lighter parameter updating of quantum DRL algorithm has been reported, compared to the conventional deep neural network (DNN)-based DRL.

## The End

# Thanks for your attentions

This is the end of today's demonstration

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