

# **Beyond 5G White Paper 6G Radio Technology Project “AI/ML and Digital Twin Technologies” [Version 1.0, Overview]**

**XG Mobile Promotion Forum  
AI and Digital Twin Working Group  
September 30, 2025**

# AI and Digital Twin WG

- Organization
  - Chair: Tomoaki Otsuki (Keio Univ.)
  - Vice Chair: Takahiro Yamazaki (NTT), Tetsuya Yamamoto (Panasonic Holdings)
  - WG members: 37 members
- Activities
  - Researching technology and standardization trends, and creating white papers
  - Disseminating information both domestically and internally (e.g., by organizing workshops), and exchanging opinions with overseas organizations
  - Establishing a shared database for AI training
  - Sharing a platform for leveraging AI and digital twins
- Examples of outputs
  - Beyond 5G white paper
  - Shared database for AI training
  - Collaborative projects in conjunction with international conferences

# Outline of White Paper

- Preface
- I. Trends of AI/ML and Digital Twin towards 6G
  - I-1. Standardization in 3GPP and O-RAN for AI/ML
    - A summary of the standardization trends related to AI/ML within the 3rd Generation Partnership Project (3GPP) and the Open Radio Access Network (O-RAN) Alliance
  - I-2. Introduction of AI and Digital Twin Technologies for 6G
    - A brief summary of technological trends in the following technology fields, which are primarily associated with the content of Chapter II
      - AI for Signal Processing / Air-interface
      - AI for RAN
      - AI for Radio Propagation / Digital Twin
      - Network Architecture for AI/ML Usage in RAN
- II. Recent Activities of AI/ML and Digital Twin in Japan
  - An introduction to Japan's advanced research and development initiatives and achievements related to the utilization of AI/ML and digital twin for 6G

# Preface

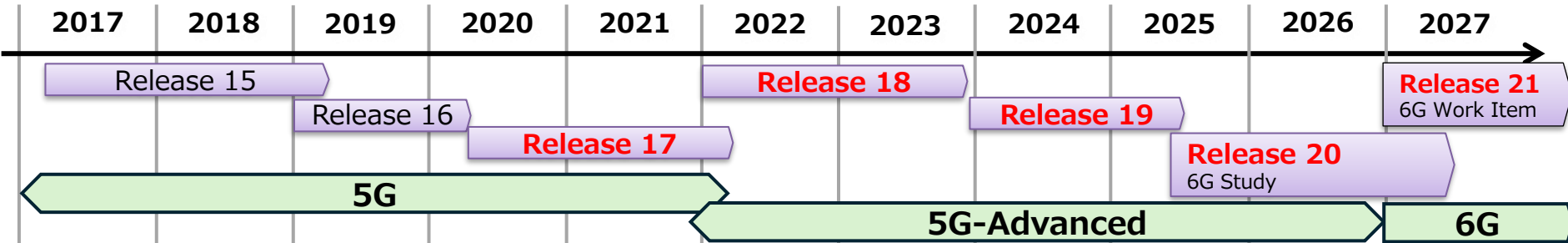
- Communication networks are evolving rapidly in the Beyond 5G(B5G)/6G era, and AI/ML technologies will play a significant role in this evolution.
- In the 6G era, digital twin (DT) technology is considered to be very important, in which the real world is reproduced in cyberspace, and data collected from the real world is used to simulate/emulate beyond the constraints of the real world using AI, etc., to gain new knowledge, and to feedback to the real world.
- AI/ML and DT technologies are expected to be used in various fields to enhance B5G/6G capabilities.
- The existing Beyond 5G White Paper Supplementary Volume "AI/ML Technologies" presents AI/ML technologies in network operation and management, optimization of radio access resource management, AI/ML technologies for user/application-centric communication.
- This white paper targets expands the content on the utilization of AI/ML technologies in the field of wireless technology in addition to that of mentioned above, and also focuses on the utilization of DT technologies. This white paper summarizes the latest trends, R&D activities, standardization and status of global technology studies.
- This white paper aims to provide a comprehensive overview of the potential, challenges and future direction of AI/ML and DT technologies, and to provide useful information for future discussions on business creation and solving social issues through collaboration between industry, academia and government.
- This white paper was prepared with the generous support of many people who participated in the AI and Digital Twin WG of 6G Radio Technology Project, XGMF.

# I. Trends of AI/ML and Digital Twin towards 6G

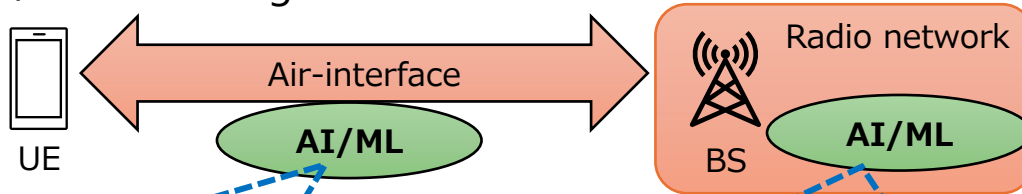
- Outline
  - I-1. Standardization in 3GPP and O-RAN for AI/ML
    - I-1.1. Standardization in 3GPP
      - I-1.1.1. Framework of AI/ML to Air-interface
      - I-1.1.2. CSI Feedback Enhancement
      - I-1.1.3. Beam Management
      - I-1.1.4. Positioning
      - I-1.1.5. Mobility
    - I-1.2. Standardization in O-RAN
      - I-1.2.1. AI/ML Framework
      - I-1.2.2. Massive MIMO Beamforming Optimization
      - I-1.2.3. RAN Slice SLA Assurance
      - I-1.2.4. Energy Saving
  - I-2. Introduction of AI and Digital Twin technologies for 6G
    - I-2.1. AI for Signal Processing / Air-interface
    - I-2.2. AI for RAN
    - I-2.3. AI for Radio Propagation / Digital Twin
    - I-2.4. Network Architecture for AI/ML Usage in RAN

# I-1.1 Standardization in 3GPP (1/2)

- 3GPP Standardization timeline



- Application of AI/ML technologies to RAN



## Application of AI/ML to air-interface

### Use of AI/ML for communication between UE and BS

- Study in Rel.18, and partially standardized in Rel.19
- Further specification in Rel. 20 is under discussion

## Application of AI/ML within RAN

### Apply AI/ML to various BS processing

- Study in Rel.17, and partially standardized in Rel.18
- Further study and specification in Rel.19
- Further study and specification in Rel.20 is under discussion

# I-1.1 Standardization in 3GPP (2/2)

- Use cases (Specified in Rel.19 or to be specified in Rel.20 (under discussion))

## **Application of AI/ML to air-interface**

- Channel state information (CSI) feedback enhancement
  - Time-domain CSI prediction
  - Spatial-frequency (+time) domain CSI compression
- Beam management
  - Spatial domain beam estimation
  - Time domain beam prediction
- Positioning
  - Direction location information estimation
  - Intermediate statistical information (e.g., timing and LOS/NLOS conditions) estimation for positioning estimation
- Mobility (e.g., cell selection)
  - Measurement reduction for mobility
  - Handover event prediction

## **Application of AI/ML within RAN**

- Network energy saving
- Load balancing
- Mobility optimization
- Network slicing
- Optimization of coverage and capacity
- QoE optimization



**This white paper provides details on the application of AI/ML technologies mainly to air-interface.**

# I-1.2 Standardization in O-RAN

- One of the key innovations driven by O-RAN is the concept of RAN intelligent controller (RIC).
  - RIC: Role in automatic optimization of parameter design and operation
- Integration of AI/ML in O-RAN with RIC for intelligent RAN
  - Improvement of communication performance, optimization of resource allocation, and improvement of user experience quality, etc.
  - Multiple scenarios considering the arrangement on combination of training, model management and inference, etc.
- Use cases
  - Massive MIMO beamforming optimization
    - Application of AI/ML technologies to advanced network management techniques such as beam shaping, beam-based load balancing, optimized beam mobility, and adaptive cell coverage areas
  - RAN slice SLA assurance
    - Application of AI/ML technologies to the network control function by RIC to efficiency control network slides and guarantee requirements such as quality and low latency, etc.
  - Energy saving
    - Application of AI/ML technologies to cell and RF channel ON/OFF and sleep control

**This white paper provides details on the AI/ML framework (e.g., deployment scenarios) and each use case in O-RAN.**



# I-2. Introduction of AI and Digital Twin Technologies for 6G (1/4)

- I-2.1: AI for Signal Processing / Air Interface
  - Challenges in Beyond 5G
    - The increasing complexity of wireless communication systems makes it difficult to control a large number of interdependent parameters using conventional methods
  - Expectations for AI/ML technologies
    - Optimization of wireless signal processing and air-interfaces by solving complex non-linear problems and analyzing huge amount of data
    - Serving as the key technology to achieve dynamic and highly efficient optimization, resulting in becoming a central component of Beyond 5G systems
  - Application areas of AI/ML technologies
    - Physical-layer signal processing (channel coding, channel estimation, beamforming, transmit power control, etc.)
      - Replacing conventional wireless signal processing with AI/ML models such as neural networks is expected to reduce the computational complexity and improve accuracy
    - AI-native air-interface
      - Representing an evolution from traditional, fixed air interface protocols, toward new communication methods that dynamically adapt to the constraints and variability of the wireless environment
    - Application to high-frequency areas such as millimeter-wave and terahertz bands
      - Non-linear compensation techniques using AI/ML for complex nonlinear distortions in power amplifiers that difficult to deal with using conventional polynomial models
      - Technologies that compensate for multiple RF impairments (power amplifiers, IQ imbalance, etc.) by utilizing AI/ML
    - Performance indicators considering both communication and AI/ML perspective, integrated system design

## I-2. Introduction of AI and Digital Twin Technologies for 6G (2/4)

- I-2.2: AI for RAN
  - Expectations for AI/ML technologies
    - AI/ML technologies are expected to be used for operations, administration and maintenance (OAM) and dynamic control of RAN.
    - AI/ML technologies are expected to reduce operation costs of RAN, to improve quality of communication of RAN. Following 5G system, it will also become important for Beyond 5G and 6G systems.
  - Application areas of AI/ML technologies
    - OAM of RAN
      - Instead of a manual parameter configuration, an automatic parameter configuration by AI/ML technologies is proposed for reducing human operation resources and human errors.
    - Dynamic control of RAN
      - Dynamic traffic offloading, resource allocation and power control by AI/ML technologies are proposed to improve quality of communication and power efficiency.
    - Application-aware RAN control
      - With O-RAN RIC standardized in O-RAN, application-based resource allocation will be enabled.
    - System failure detection
      - With AI/ML, the threshold for failure detection can be dynamically configured, and it makes the probability of failure detection higher.

## I-2. Introduction of AI and Digital Twin Technologies for 6G (3/4)

- I-2.3: AI for Radio Propagation / Digital Twin
  - Expectations for AI/ML technologies
    - AI/ML technologies are expected to evolve radio propagation and radio simulation in digital virtual environments such as digital twin.
    - AI/ML is a promising approach to make close radio propagation model to the real one. It should accelerate the development of digital twin and cyber physical system.
  - Application areas of AI/ML technologies
    - Radio propagation
      - AI/ML technologies can be applied for channel parameter estimation, channel modelling, channel prediction and LOS / NLOS identification.
      - AI/ML technologies can make ML models with multimodal values such as measured received signal strength indicator (RSSI), geographical information, camera images, states of UEs and etc.
      - Using this ML model, it is expected to support more flexible radio propagation situations and scenarios for Beyond 5G and 6G.
    - Radio simulation in digital twin
      - Many AI/ML approaches have been investigated to implement more realistic and cost-effective radio simulation.
      - AI/ML technologies can reduce computational cost while maintaining simulation accuracies.

## I-2. Introduction of AI and Digital Twin Technologies for 6G (4/4)

- I-2.4: Network Architecture for AI/ML Usage in RAN
  - Challenges in Beyond 5G
    - Conventionally, AI/ML application functions are placed in core network or cloud infrastructure. However, it increases the latency due to AI/ML processing is carried out in a location farther away than the cellular area provided by the RAN.
  - Application areas of AI/ML technologies
    - Placing AI/ML application functions to RAN side, such as MEC or computing infrastructure for vRAN, is proposed.
    - Additionally, for 6G, a network architecture which distributes AI/ML application functions to core network, RAN, user devices and all of the network functions is proposed.
      - It will enable an adaptive computing resource allocation for AI/ML in end-to-end communications.
      - With this architecture, more AI/ML applications will be effectively utilized in 6G systems.

## II. Recent Activities of AI/ML and Digital Twin in Japan (1/2)

This section introduces leading-edge R&D efforts on AI/ML and Digital Twin for Beyond 5G in Japan.

### AI for signal processing / air-interface

|      | Contributor (Affiliation of first author) | Contents Title                                                                                  |
|------|-------------------------------------------|-------------------------------------------------------------------------------------------------|
| II-1 | Nokia                                     | Scalable AI/ML for Radio Cellular Access                                                        |
| II-2 | Panasonic Holdings                        | Study on Training Collaboration at UE- / NW-side for CSI Compression with Two-sided AI/ML Model |
| II-3 | NTT                                       | Proof-of-concept for AI-native Air Interface toward 6G                                          |
| II-4 | KDDI Research                             | Neural Network-based Digital Pre-distortion for Wideband Power Amplifiers using DeepShift       |
| II-5 | NTT                                       | AI Calibration Network under Hardware Limitations                                               |
| II-6 | Huawei Technologies Japan                 | Performance Requirements and Evaluation Methodology for AI and Communication in 6G              |

### AI/ML for RAN

|       | Contributor (Affiliation of first author) | Contents Title                                                                                   |
|-------|-------------------------------------------|--------------------------------------------------------------------------------------------------|
| II-7  | KDDI Research                             | Study on AP Clustering with Deep Reinforcement Learning for Cell-Free Massive MIMO               |
| II-8  | Sharp                                     | Cross-layer Access Control Techniques using AI                                                   |
| II-9  | NEC                                       | AI-based Application-aware RAN Optimization                                                      |
| II-10 | KDDI Research                             | AI Ops for Autonomous Network                                                                    |
| II-11 | NEC                                       | Logic-oriented Generative AI Technology for Autonomous Networks                                  |
| II-12 | Huawei Technologies Japan                 | In-Network Learning for Distributed RAN AI, ~Distributed LLMs via Latent Structure Distillation~ |

## II. Recent Activities of AI/ML and Digital Twin in Japan (2/2)

This section introduces leading-edge R&D efforts on AI/ML and Digital Twin for Beyond 5G in Japan.

### AI/ML for radio propagation and / digital twin

|       | Contributor (Affiliation of first author) | Contents Title                                                                        |
|-------|-------------------------------------------|---------------------------------------------------------------------------------------|
| II-13 | NTT                                       | Throughput Prediction Technology for 28 GHz Channels using Physical Space Information |
| II-14 | Tokyo Denki University                    | AI/ML-based Radio Propagation Prediction Technology                                   |
| II-15 | KDDI Research                             | AI-Based Radio Propagation Modeling for Wireless Emulator                             |
| II-16 | NTT DOCOMO                                | 6G Simulator Utilizing Future Prediction Control Technology Based on AI/ML            |
| II-17 | NTT DOCOMO                                | Optimization of 6G Radio Access Using Digital Twin                                    |
| II-18 | Osaka University                          | Digital-Twin for and by Beyond 5G                                                     |

### Network architecture for AI/ML usage in RAN

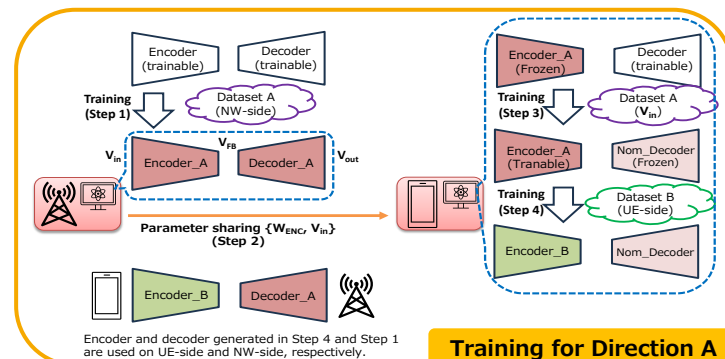
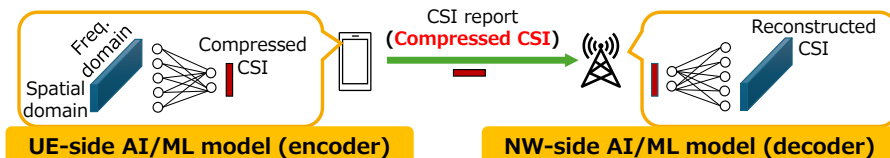
|       | Contributor (Affiliation of first author) | Contents Title                                  |
|-------|-------------------------------------------|-------------------------------------------------|
| II-19 | Huawei Technologies Japan                 | Task-Oriented 6G Native-AI Network Architecture |

- Abstract:

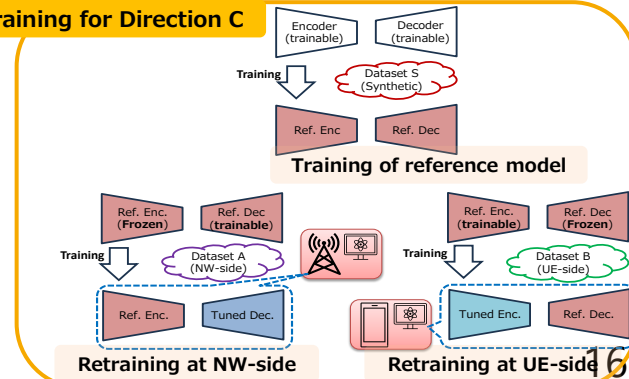
- Wireless networks are expected to move towards self-sustaining networks in 5G-Advanced and in 6G, where Artificial Intelligence (AI) and Machine Learning (ML) play a critical role in maintaining high performance in dynamically changing environment. AI/ML solutions that operate separately at the device or network side, or jointly on both will emerge. Similarly, lifecycle management procedures will be needed to enable interoperable automation in the radio, providing a framework with the necessary tools for deploying and operating ML solutions in radio at scale.

# Study on training collaboration at UE-side / NW-side for CSI compression with two-sided AI/ML Model

- AI/ML-based CSI compression
  - Two-sided model:** Inference is executed on both UE-side and NW-side
  - Issue:** How to coordinate training between UE-side and NW-side?
- Methods to alleviate the issue related to inter-vendor training collaboration
  - Direction A
    - Reference model structure is standardized.
    - NW-side shares UE-side with parameters of the trained encoder model.
    - UE-side develops actual encoder against the nominal AI/ML model (reference model structure + shared parameters).
    - Potential issue:** Performance impact due to NW / UE data distribution mismatch with respect to UE-specific conditions
    - Evaluation:** The impact of the dataset distribution mismatch regarding UE-side antenna configuration between NW-side training (Dataset A) and UE-side training (Dataset B) is small
  - Direction C
    - Reference model (structure + parameters) is standardized.
    - The actual implementation of the AI/ML model on UE-side / NW-side is developed against with a reference model.
    - Potential issue:** Performance impact due to mismatch between the distribution of the dataset used for reference model training, UE-side / NW-side data distribution
    - Evaluation:** Performance improvements can be observed when UE-side or NW-side retrains using datasets that match the inference environment.



## Training for Direction C



In terms of performance improvement, Direction A > Direction C, and then the need for training collaboration between NW-side and the UE-side is suggested.

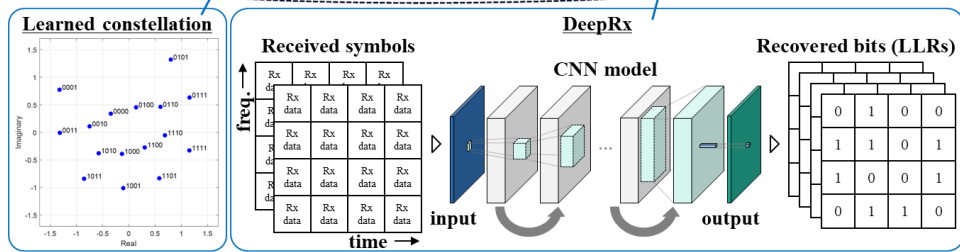
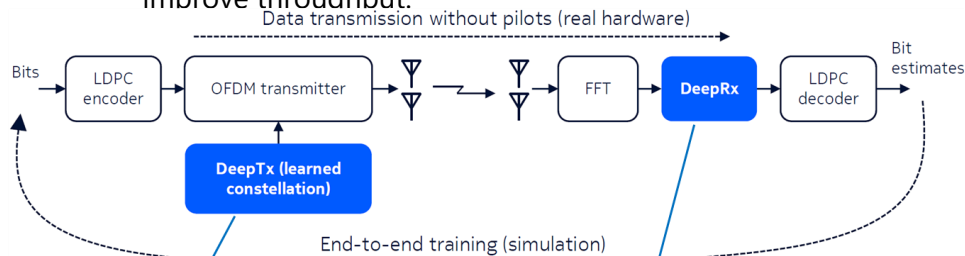


## AI-native air interface (AI-AI)

- AI/ML is used to **optimize the air interface end-to-end** to serve an application with the data it needs in an optimal way.

## Deep Learning- Based Pilotless Transmission

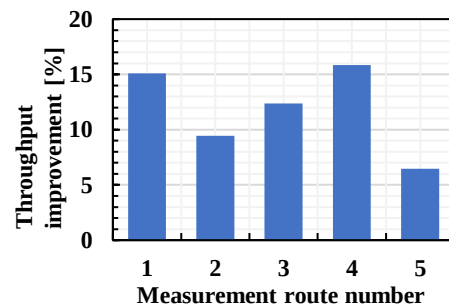
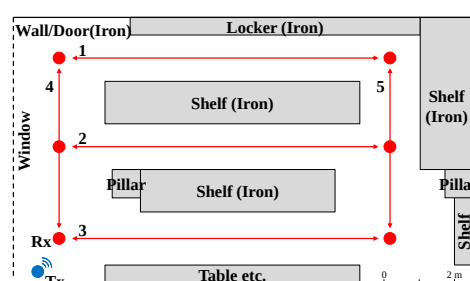
- Transmit constellations** and the receiver that handles **channel estimation, equalization, and demodulation** are jointly learned by data based on channel model.
- It can transmit data using all available resources, **without having to transmit pilot signals**, which is expected to improve throughput.



## Proof-of-concept for AI-AI

- To evaluate the **performance in a real environment**, the **throughput improvement** by the proposed scheme was measured in an indoor environment with obstacles.

## Deep Learning- Based Pilotless Transmission improves throughput on any measurement route



- In addition, experiments using a channel emulator show that the proposed scheme significantly improves throughput in a **high-speed mobile environments**.

### Simulation parameters for training

|               |                  |
|---------------|------------------|
| Channel model | 3GPP TDL-A, B, C |
| Velocity      | 0~200 km/h       |
| Delay spread  | 10~500 ns        |
| SNR           | 0-20 dB          |

### Specifications of the PoC system

|                    |            |
|--------------------|------------|
| Center frequency   | 4.8 GHz    |
| Subcarrier spacing | 30 kHz     |
| Bandwidth          | 9 MHz      |
| MCS index          | 10 (16QAM) |

# Neural Network-based Digital Pre-distortion for Wideband Power Amplifiers using DeepShift

## Challenges

- In wideband communications at millimeter-wave and terahertz bands, nonlinear distortion in power amplifiers (PAs) poses a serious problem.
- While neural network (NN)-based Digital Pre-distortion (DPD) shows excellent performance, it requires numerous floating-point multiplications, resulting in high hardware implementation costs.

## Proposed Method

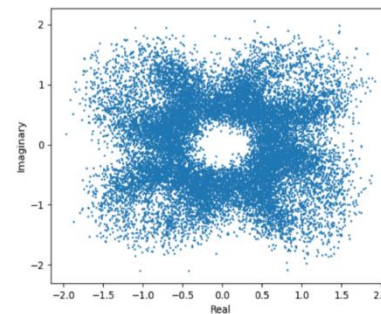
DPD using DeepShift: Replacing multiplication operations in NNs with bitwise-shift and sign operations to reduce hardware implementation costs.

## Evaluation Results using THz PA

Achieved compensation performance equivalent to conventional NNs without any multiplications.

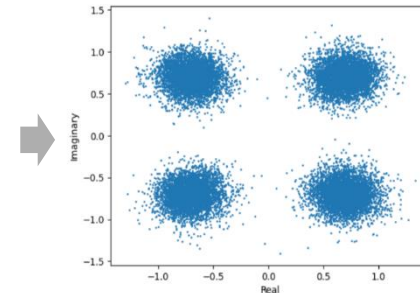
| Model type         | operation counts |                |                     |        |            |
|--------------------|------------------|----------------|---------------------|--------|------------|
|                    | EVM [%]          | Multiplication | Bitwise shift& sign | Add    | Activation |
| Without DPD        | 55.25            |                |                     |        |            |
| RVTDNN             | 29.92            | 20400          | 0                   | 20400  | 200        |
| RVTDNN (DeepShift) | 29.96            | 0              | 20400               | 20400  | 200        |
| DNN                | 20.74            | 100400         | 0                   | 100400 | 600        |
| DNN (DeepShift)    | 20.93            | 0              | 100400              | 100400 | 600        |

EVM:55.25 %

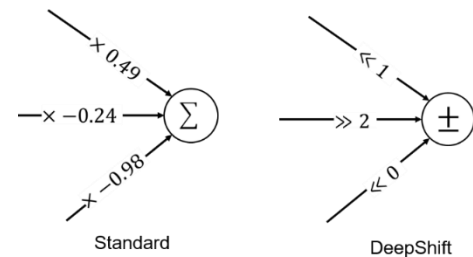


Without DPD

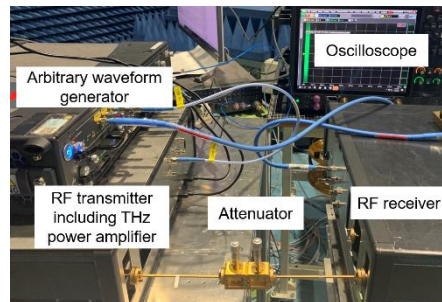
EVM:20.93 %



DNN (DeepShift)



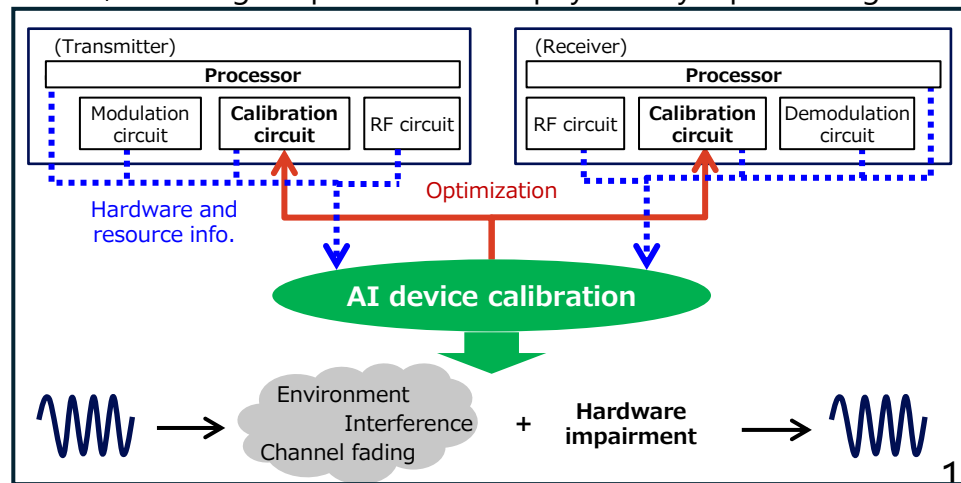
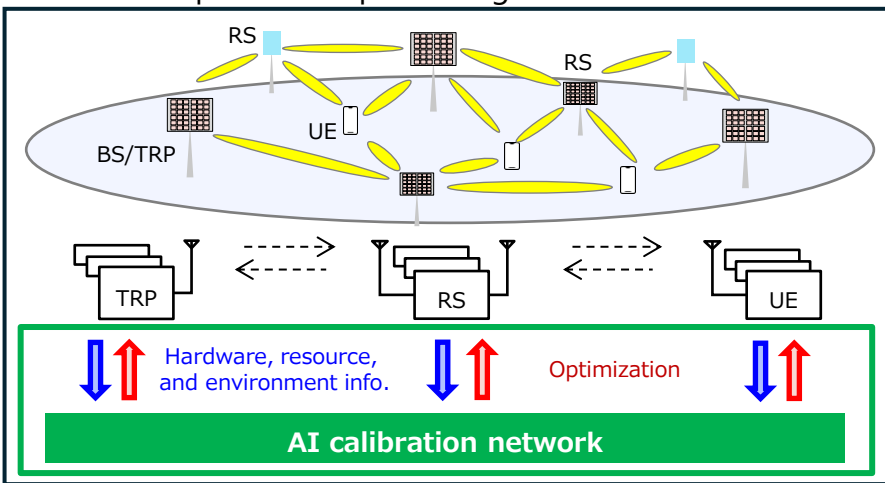
Overview of DeepShift



Experimental setup using THz PA

# AI Calibration Network under Hardware Limitations

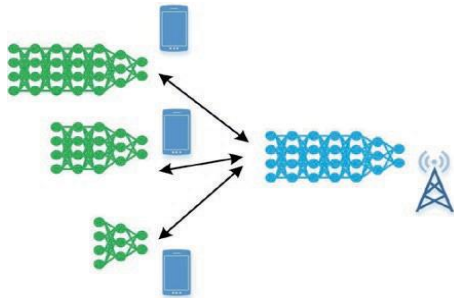
- AI processing needs to be optimized according to hardware resource and limitation (e.g., RF characteristics, processor capability, or power consumption) available for DSP
  - ✓ Calibration performance for hardware impairments
  - ✓ Processor resource allocation for AI processing
- AI device calibration**
  - ✓ In AI device calibration, the performance/cost of AI processing for physical layer processing can be dynamically optimized in accordance with limitation of available hardware/resource and required KPIs (e.g., throughput, cost, or power consumption) from applications
- AI calibration network**
  - ✓ The AI calibration network, which applies the concept of AI device calibration to coordination across the RAN, optimizes AI processing resource allocation across the RAN, including adaptive control of physical layer processing



## Abstract:

- This paper describes the "AI and Communication" scenario and the typical AI services in 6G.
- It also introduces general principles for performance definition, and detailed performance indicators.
- Then, this provides an evaluation methodology for the proposed performance indicators, along with an example.

## Sec 2.2: Typical Services in the "AI and Communication" Scenario

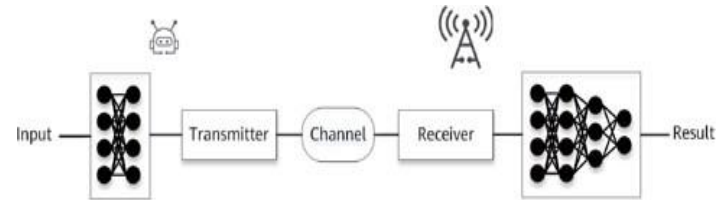


A Model  
Training Service  
Example

## Sec 3.3: Proposed Performance Requirements for AI & 6G Communication

- AI service functionality requirements
- AI service accuracy (or AI service quality)
- AI service latency
- AI service density

## Sec 4.2: Evaluation Example



Distributed AI inference service example

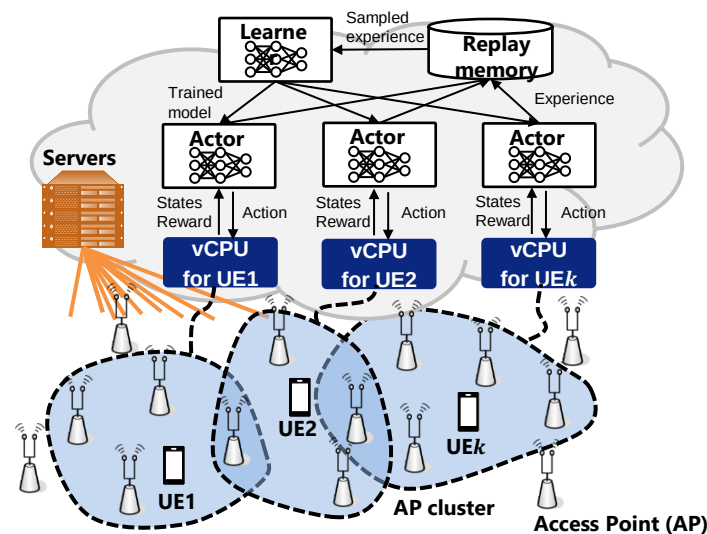
## Sec: 5 Conclusion

- This illustrated the motivations, typical AI services, and performance requirements of the "AI and Communication" usage scenario.

# Study on AP Clustering with Deep Reinforcement Learning for Cell-Free Massive MIMO

- The challenge lies in selecting the optimal AP cluster (antenna selection for distributed MIMO) considering the vast combinations of APs and UEs, as well as the radio conditions and quality requirements.
- By applying reinforcement learning, it is possible to achieve the selection of the minimal necessary AP cluster that satisfies the quality requirements of UEs while minimizing signal processing load.
- Dynamic and real-time control can be enabled by distributing small models for each UE and performing parallel inference.

- Cell-Free Massive MIMO (CF-mMIMO): A technology that eliminates inter-cell interference by performing multi-user MIMO processing on signals from distributed access points (APs) collectively.
- AP Cluster: a combination of access points or antennas that transmit and receive data for each UE.



## •Objective

The demand for large-capacity, latency sensitive applications such as ultra-high-definition video transmission is increasing in wireless communication systems. In high-demand applications such as ultra-high-definition video transmission, there is a problem that increasing the capacity of wireless communication does not necessarily lead directly to the realization of such applications.

## •Approach

We have studied the cross-layer access control techniques, which improves video throughput based on whether the requirements for ultra-high-definition video are satisfied, rather than conventionally called throughput, which is calculated from correctly received bits

Utilizing AI (Reinforcement Learning) to efficiently connect the diverse application requirements with the available frequency resources.

- Utilization of video throughput (Optimization of frequency band selection)

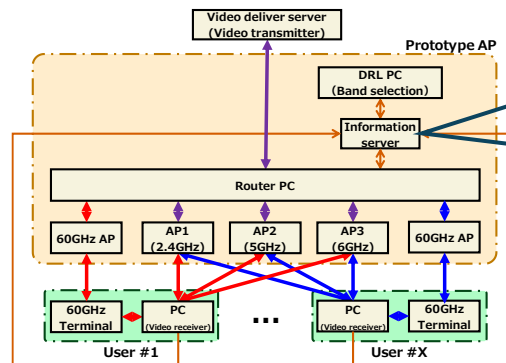
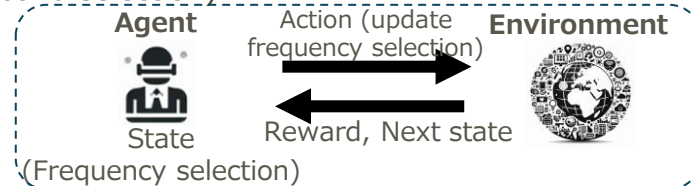


Fig. 2: Experimental system model

Selecting the optimal frequency band through deep reinforcement learning, with the achievable video throughput serving as the reward.

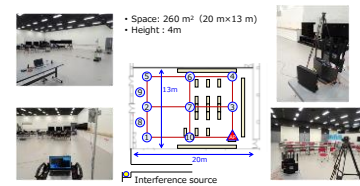


Fig. 3: Test environment

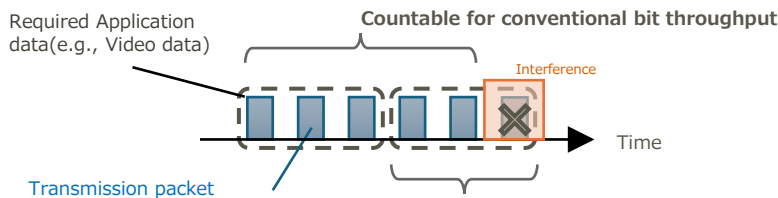


Fig. 1: Relation between the radio and application layer throughput

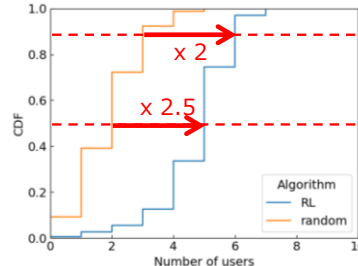


Fig. 4 : Experimental result

The field test conducted using the prototype demonstrated the potential for improving application capacity

- Abstract:
  - It has become increasingly important for industries to promote digital transformation by utilizing 5G/6G, Internet of Things (IoT), and Artificial Intelligence (AI) to realize a highly productive and prosperous society. In addition to conventional policies of improving the average Quality of Service (QoS) at each mobile coverage area, there is an increasing need to strengthen policies that precisely adhere to QoS requirements per User Equipment (UE) and in real-time to enable the stable use of applications at high-performance levels, e.g., work speed or productivity. The Open Radio Access Network (Open RAN), specifically standardized by the O-RAN Alliance (O-RAN), offers significant potential to enable flexible resource management to address diverse QoS requirements. This article introduces an application-aware RAN optimization method that can support such policies based on O-RAN architecture.

- Abstract:
  - This report provides an overview of Autonomous Networks expected to be realized in Beyond 5G. Furthermore, this report describes the details of network operation by AI, which is a necessary element of the Autonomous Network, and especially summarizes the strategy for managing network failures, and provides the overall framework required for future network operation.



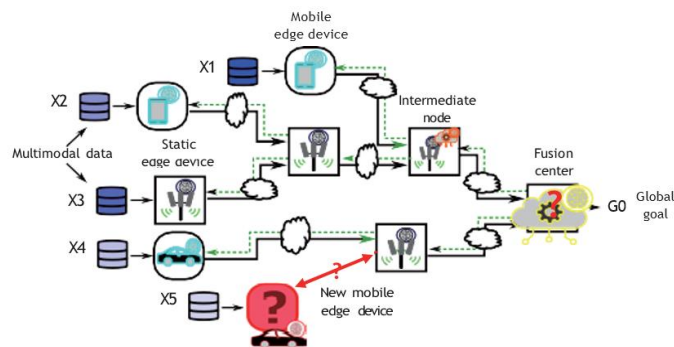
- Abstract:
  - Autonomous network operation technology based on intent has been attracting attention toward advanced automation of network operation. However, the realization of intent translation, which is the key to this technology, faces the challenge of achieving both flexibility and faithfulness. In this paper, we propose a logic-oriented generative AI for intent translation, which is a logical search engine enhanced by AI/ML technology. This paper presents the position of our proposal with respect to related techniques, and then briefly outlines its method.

# In-Network Learning for Distributed RAN AI

## ~Distributed LLMs via Latent Structure Distillation~

### Abstract:

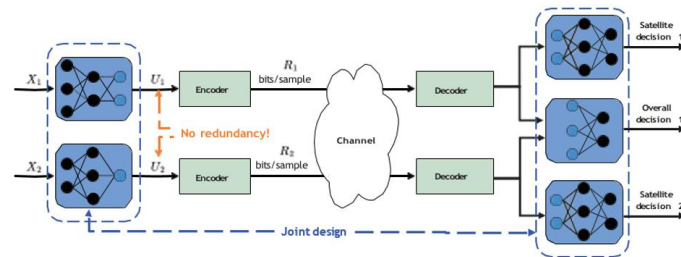
- This proposes a distributed learning on In-Network Learning (INL) for inference over RANs.
- This algorithm is particularly suitable for both multimodal and heterogeneous data settings.
- It also examines Horizontal and Vertical FL and Horizontal and Vertical Split Learning (SL) under the accuracy (Gain) under given bandwidth requirements.



Distributed inference over RAN

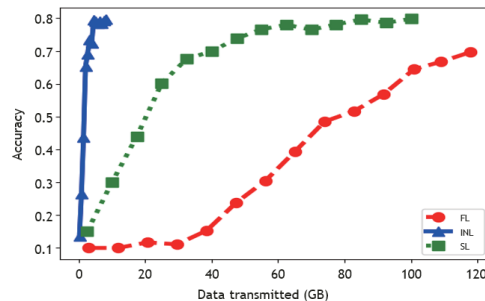
### Sec 2: In-Network Learning Key Features

- Network Feature Fusion & Feature Redundancy Removal
- Feature Extraction Depends on Network Channel Quality & Satellite Decoders



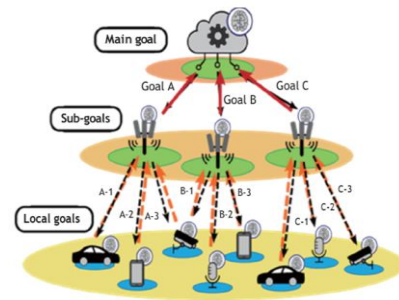
(b) INL

### Sec 3: Performance Gain



Accuracy vs. bandwidth cost for Exp-1

### Sec 4: LLM deployment



Hierarchical goal decomposition

# Throughput Prediction Technology for 28 GHz Channels using Physical Space Information

## ■ Issues with 28GHz channels used in 5G NR

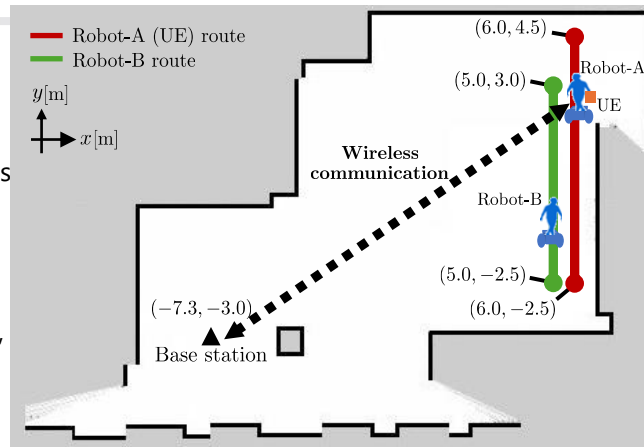
- Since 28GHz channels have strong direct wave radio propagation, link quality is easily degraded by physical obstructions.  
→ Goal: predict and prevent quality degradation caused by obstructions in advance

## ■ Proposed method: Throughput prediction using physical space information

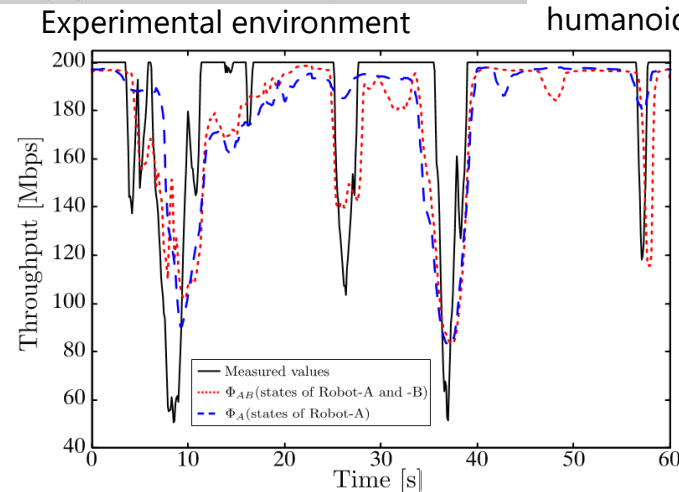
- Target scenario: Indoor scenario, two people moving around in a room, one has a UE which always transmits packets with 5G NR 28GHz. Depending on the relative positions of two people, the UE communications may be blocked.
- Experimental environment: Instead of two people, we made two autonomous mobility humanoid robots (A, B) moving around in the room, and measured physical space information of robots (position, direction, speed) and uplink throughput of UE with 5G NR 28GHz.
- For learning, using DNN(LSTM).  
Input: past one-second physical space information of the robots and uplink throughput of the UE.  
Output: one-second-ahead uplink throughput of the UE

## ■ Evaluation

- Confirmed improved throughput prediction accuracy by using physical space information from two robots instead of just one which has UE.  
→ Not only UE but also physical space information of obstructions is useful for throughput prediction



Autonomous mobility humanoid robot



- Abstract:
  - Recently, advancement of AI/ML has been remarkable, and many applied research studies are attracting attention now. This is also true in the field of radio propagation. This paper introduces its application to radio propagation prediction, which is currently under intensive study.

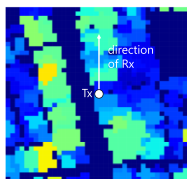
## ■ Wireless Emulator

- Aims to accelerate and reducing the cost of evaluation and verification processes of wireless systems.
- Reproduces the behavior of wireless communication systems using large-scale virtual wireless devices and actual wireless devices connected via physical interfaces.
- Requires models that reproduce site-specific radio propagations in real environments.

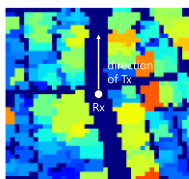
## ■ Site-Specific Path Loss Model Based on ResNet

- We express site-specific environmental information, which was not considered in traditional statistical models.
- We designed an architecture suitable for path loss prediction based on Residual Networks (ResNet), which are widely used in image recognition.
- Evaluation results using actual measurement data in Yokohama show a significant improvement in accuracy compared to the conventional model (UMa).

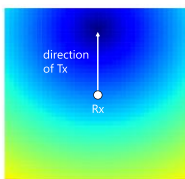
Input features



(a) Relative Height Map around Tx

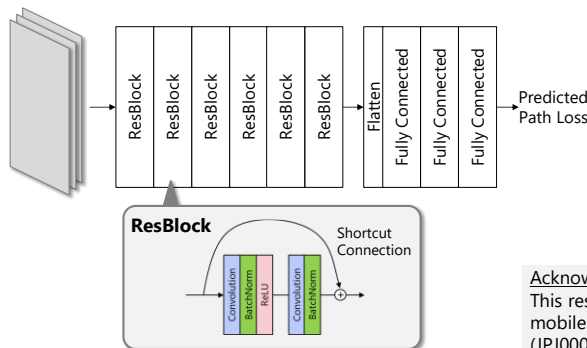


(b) Relative Height Map around Rx



(c) 3D distance map between Tx and Rx

Path Loss Model based on ResNet



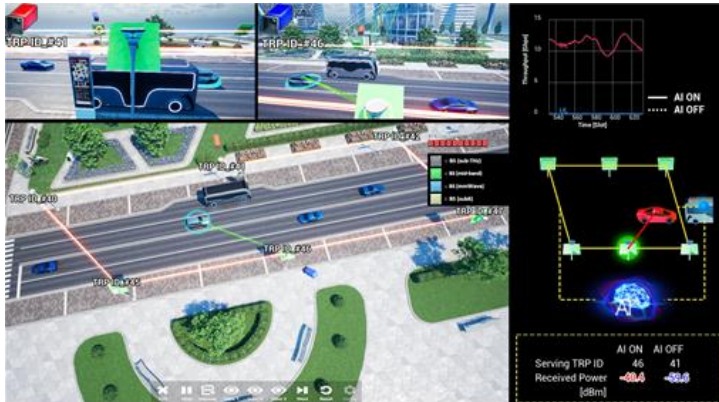
Evaluation Results

| Frequency | RMSE [dB]              |                          |
|-----------|------------------------|--------------------------|
|           | 3GPP Urban Macro (UMa) | <b>ResNet (proposed)</b> |
| 922 MHz   | 8.8                    | <b>3.8</b>               |
| 2462 MHz  | 7.4                    | <b>4.3</b>               |
| 4850 MHz  | 8.2                    | <b>2.7</b>               |
| 28.35 GHz | 17.6                   | <b>3.5</b>               |

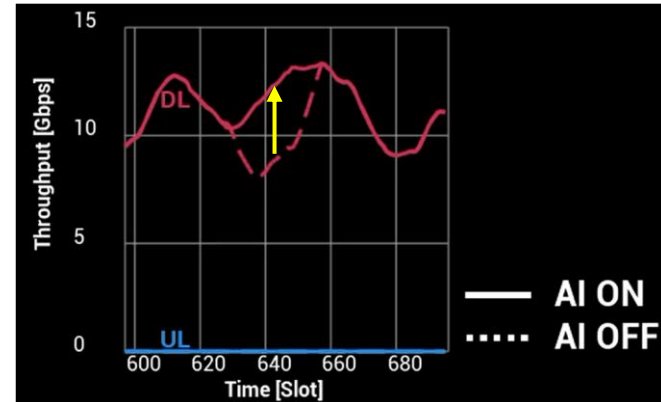
### Acknowledgement

This research has been conducted under the contract "R&D on the deployment of mobile communication systems in the millimeter wave band and other frequencies" (JPJ000254) made with the Ministry of Internal Affairs and Communications of Japan.

- 6G simulator has been developed to evaluate 6G systems
  - ✓ It assesses and visualizes technologies for 6G as a complete system
  - ✓ Sub-THz band, mid-band, and NRNT have been incorporated
  - ✓ Evaluations are conducted in a virtual outdoor urban environment
- AI/ML algorithms have been integrated into the 6G simulator
  - ✓ Future prediction control to avoid the impact of unexpected obstructions
  - ✓ Use cases for AI in wireless communication systems are shown

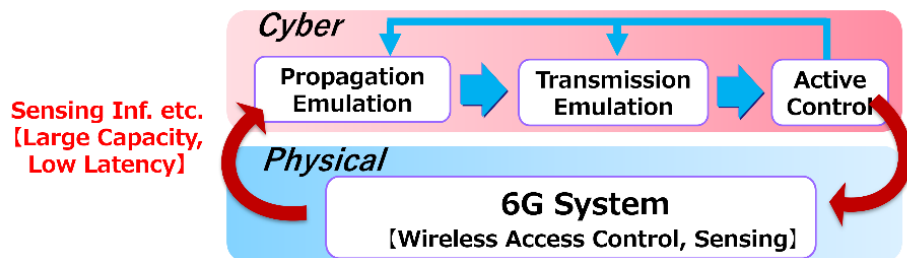


Scenario for Future Prediction using AI/ML



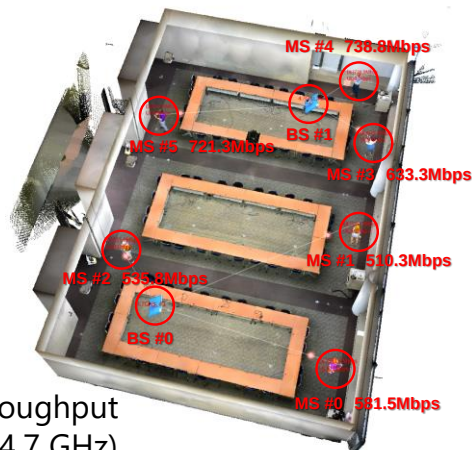
The Improvement of Throughput by AI Prediction

- Advanced Cyber-Physical Systems (CPS)
  - ✓ AI recreates the real world in cyber-space
  - ✓ Future predictions and new insights gained through emulation are fed back in the real world
- Development of 6G simulator aimed at evaluating system performance in real environments
  - ✓ Through ray tracing based on propagation characteristics derived from real environment models using point cloud data
  - ✓ For both Evaluation and Visualization purposes

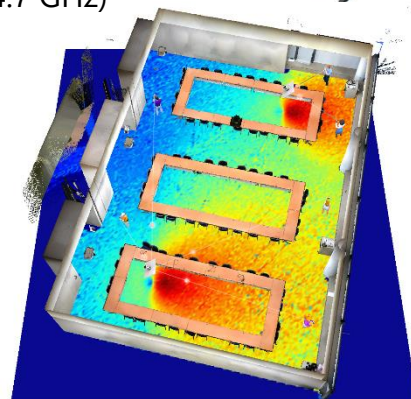


6G system utilizing dynamic control through CPS

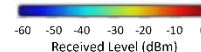
### Ex. of Conference Rooms



Throughput  
(Ex. of 4.7 GHz)

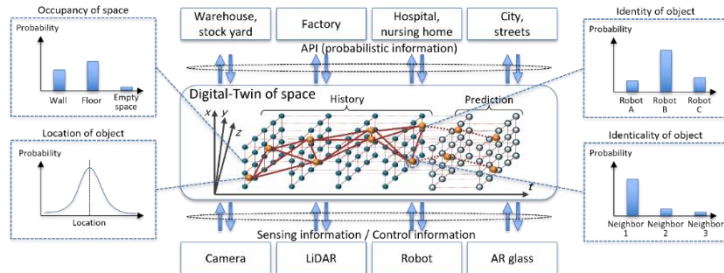


Map of Received Power Level

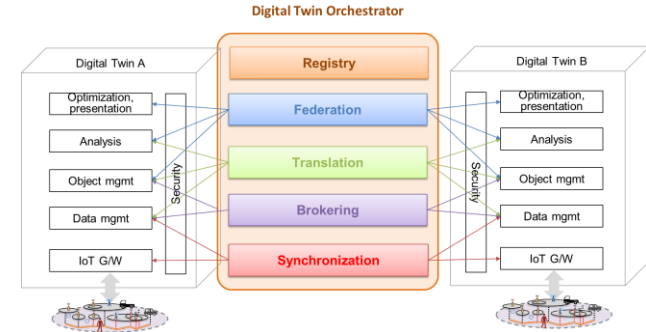




- Integrate **“Real world digital twin” (Digital-Twin by B5G)**, which will be further evolved by B5G, and **“Network digital twin” (Digital-Twin for B5G)**, which will further evolve B5G, to realize a digital twin infrastructure for their co-evolution.

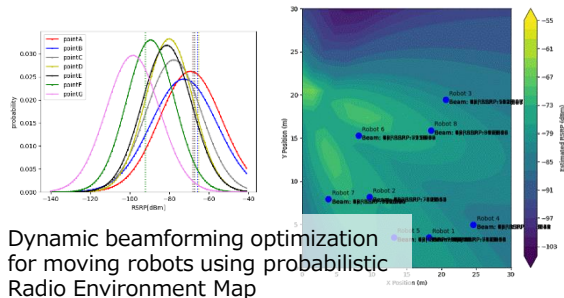


A) Probabilistic framework for integrating diverse real-world data as a digital twin



B) Orchestrate digital twins from diverse domains

Use case (1)  
Digital-Twin for Radio Communication Environment



Use case (2)  
Digital-Twin for Human-Robot Cooperation

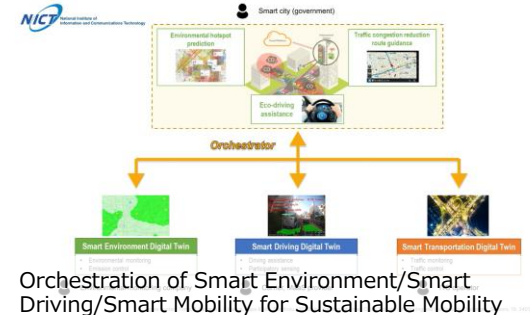
$$J = \frac{1}{\beta} \log \{E[\exp(\beta S)]\}$$

$S$ : Original evaluation function  
 $\beta$ : Risk parameter

Safe coexistence of humans and robots through risk-sensitive probabilistic robot control



Use case (3)  
Digital-Twin for Smart Sustainable Mobility





- Abstract:
  - The vision for 6G networks is to offer pervasive intelligence and internet of intelligence, in which the networks natively support artificial intelligence (AI), empower smart applications and scenarios in various fields, and create a "ubiquitous-intelligence" world. In this vision, the traditional session-oriented architecture cannot achieve flexible per-user customization, ultimate performance, security and reliability required by future AI services. In addition, users' requirements for personalized AI services may become a key feature in the near future. By integrating AI in the network, the network AI has more advantages than cloud/MEC AI, such as better QoS assurance, lower latency, less transmission and computing overhead, and stronger security and privacy. Therefore, this article proposes the task-oriented native-AI network architecture (TONA), to natively support the network AI. By introducing task control and quality of AI services (QoAIS) assurance mechanisms at the control layer of 6G.