Artificial-Intelligence-Enabled 6G

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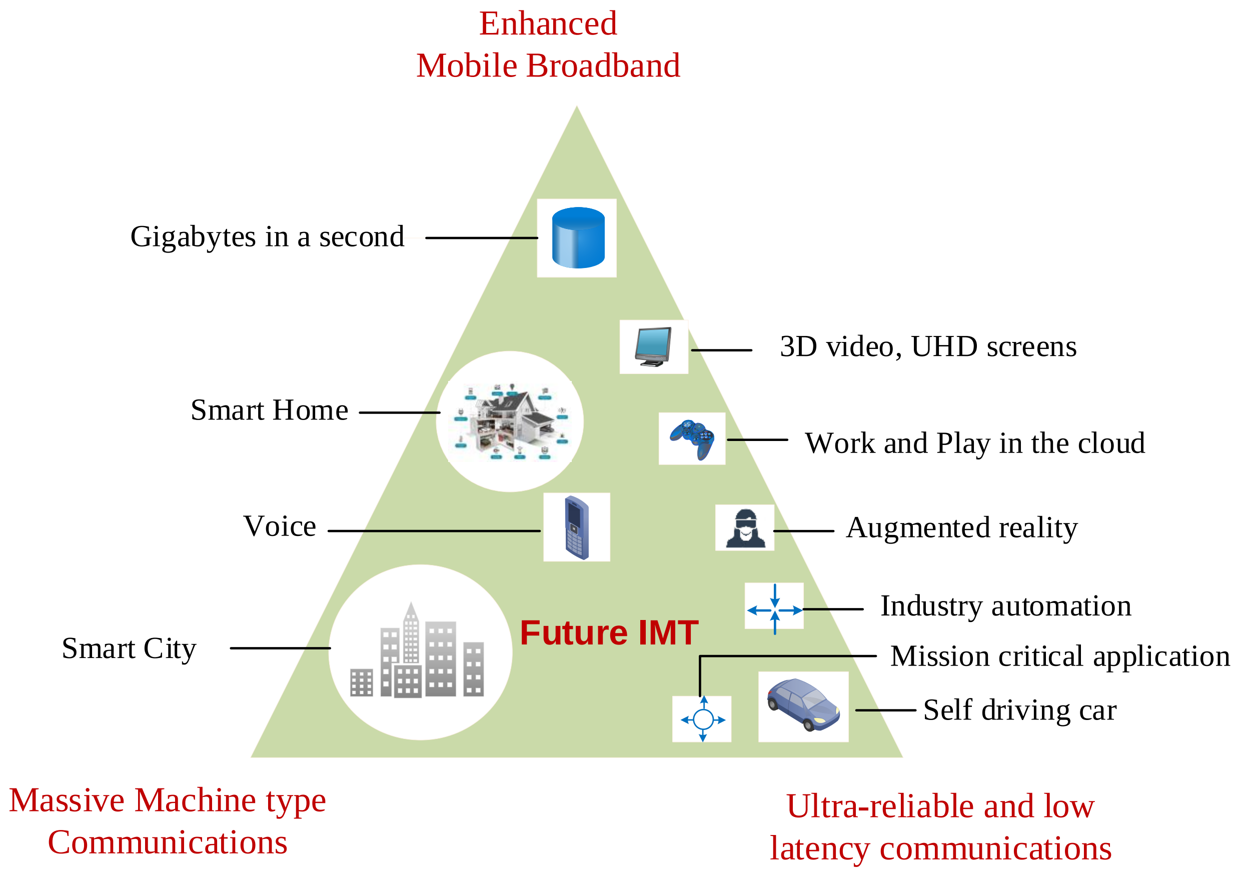
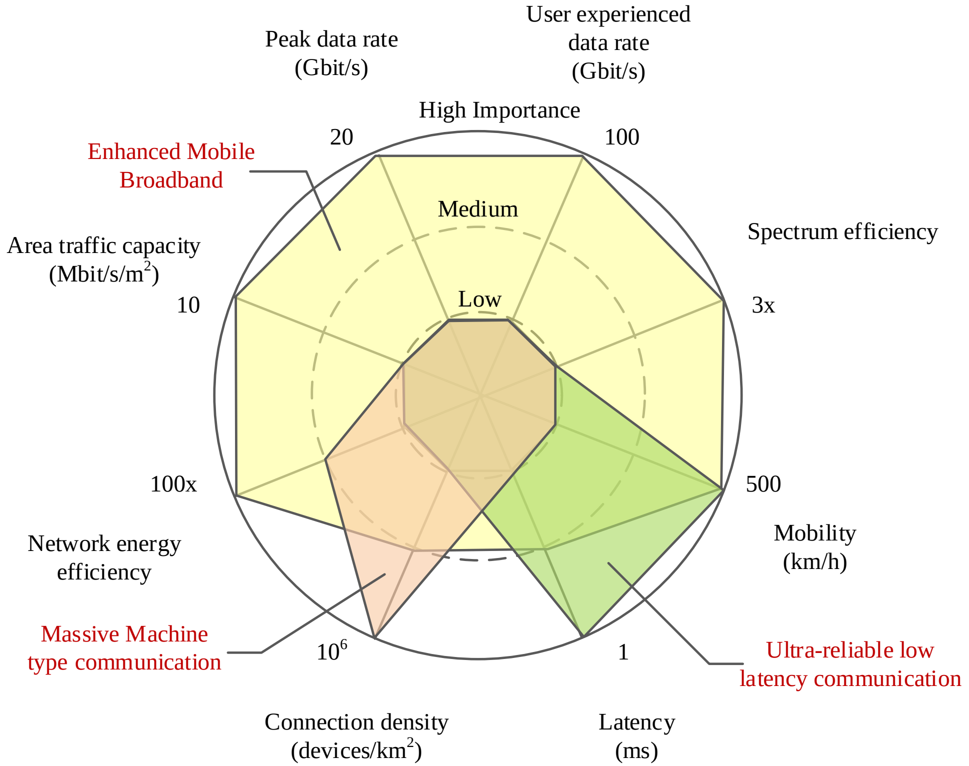
Introduction

- Why 6G?
- 6G use cases
- Key communication technologies
- Emerging computing technologies
- Networking technologies

Introduction- Why 6G? (1)

- 5G use cases





Kazmi, S. A., Khan, L. U., Tran, N. H., & Hong, C. S. (2019). Network Slicing for 5G and Beyond Networks. Springer.

Introduction- Why 6G? (2)

- Novel Internet of Everything (IoE) applications.
  - Brain-computer interfaces
  - Extended reality
  - Haptics
  - Autonomous connected vehicles
  - Flying vehicles, etc.

- These IoE applications violates the notion of 5G. Therefore, we need to design new generation of wireless systems namely, 6G wireless systems.

High data rates, unmanned mobility, long-distance communication, ultra-high reliability.

Mostly requires long packets to maximize throughput with ultra-high reliability. However, 5G notion is to use short packets with ultra-high reliability and data rates (i.e., URLLC).

Devices density more than $10^6/km^2$ seems difficult to be fulfilled by 5G.

6G

[1] https://www.digi.com/blog/post/what-is-connected-vehicle-technology-and-use-cases
[2] https://www.its.dot.gov/cv_basics/cv_basics_what.htm

Introduction – 6G Novel Uses Cases (1)

1. Mobile Broadband Reliable Low Latency Communication
2. Massive URLLC
3. Human Centric Services
4. Multi-purpose Convergence of Communications, Computing, Control, Localization, and Sensing (3CLS) and Energy Services

[1] Saad, W., Bennis, M., & Chen, M. (2019). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE network, 34(3), 134-142.
[2] Khan, L. U., Yaqoob, I., Imran, M., Han, Z., & Hong, C. S. (2020). 6G wireless systems: A vision, architectural elements, and future directions. IEEE Access, 8, 147029-147044.

1. Mobile Broadband Reliable Low Latency Communication

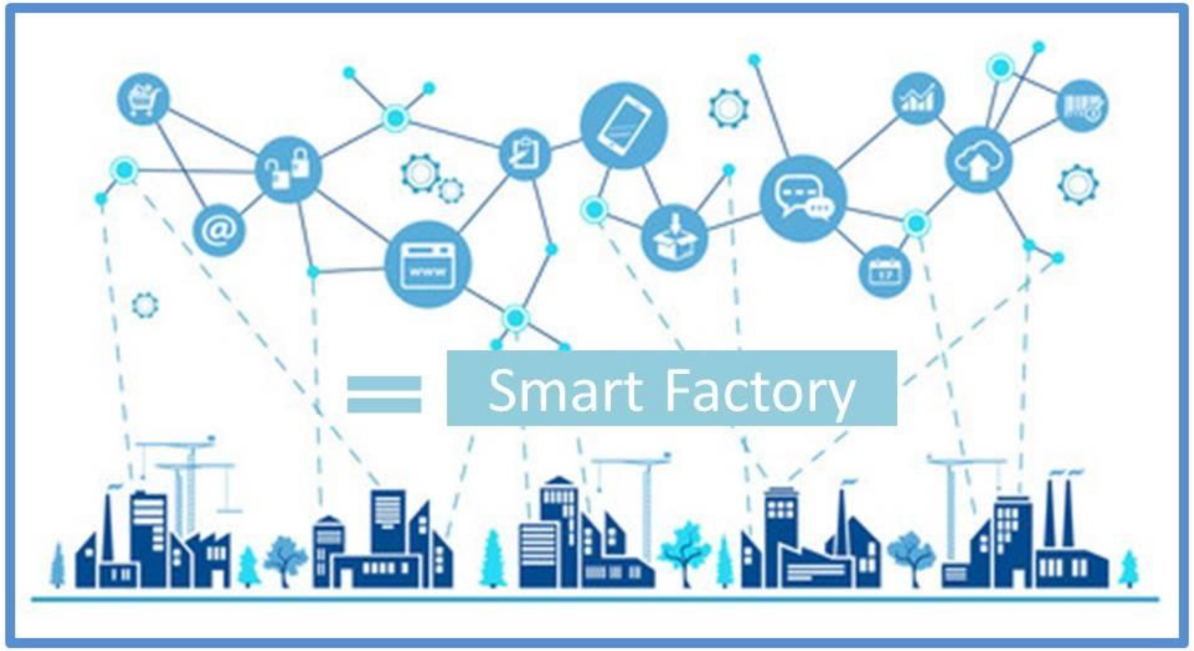
Applications
Extended reality, wireless brain-computer interfaces, etc.

Requirements
High reliability,
Low latency,
High-data rates.

5G

URLLC -> high reliability and low latency.
eMBB -> high data rates.

2. Massive URLLC



Requirements
Ultra-reliability
Low latency
Massive number (i.e., $> 10^6/km^2$)

5G seems difficult to handle massive number of devices (i.e., $> 10^6/km^2$)

[1] https://findnex.com/sensors-network-smart-factory/
[2] Khan, L. U., Yaqoob, I., Imran, M., Han, Z., & Hong, C. S. (2020). 6G wireless systems: A vision, architectural elements, and future directions. IEEE Access, 8, 147029-147044.

3. Human Centric Services (HCS)

Human computer interaction

Requirements

- Wireless brain computer interaction (BCI) is a prime example of HCS in which system performance is determined by the physiological measurements defined through the human behaviors. For such services, a whole new set of quality of physical experience (QoPE) metrics must be defined and offered as function of raw QoS and QoE metrics.
- Using wireless BCI technologies, instead of smartphones, people will interact with their environment and other people using discrete devices, some worn, some implanted, and some embedded in the world around them.

5G does not provide solutions to meet QoPE.

[1] https://mozajka.co/human-computer-interaction/
[2] Khan, L. U., Yaqoob, I., Imran, M., Han, Z., & Hong, C. S. (2020). 6G wireless systems: A vision, architectural elements, and future directions. IEEE Access, 8, 147029-147044.

4. Multi-purpose 3CLS and Energy Services

Autonomous and Connected Robots

Requirements
Joint uplink-downlink designs must meet target performance for the control (e.g., stability), computing (e.g., computing latency), localization (e.g., localization precision), as well as sensing and mapping functions (e.g., accuracy of a mapped radio environment).

5G seems difficult to enable these applications.

* 3CLS : Convergence of Communications, Computing, Control, Localization, and Sensing

[1] https://royalsociety.org/science-events-and-lectures/2015/11/robotics-and-autonomous-systems/
[2] Khan, L. U., Yaqoob, I., Imran, M., Han, Z., & Hong, C. S. (2020). 6G wireless systems: A vision, architectural elements, and future directions. IEEE Access, 8, 147029-147044.
[3] Saad, W., Bennis, M., & Chen, M. (2019). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE network, 34(3), 134-142.

Introduction – 6G Use Cases (6)

Service	Performance Indicators	Example Applications
MBRLLC	• Stringent rate-reliability-latency requirements. • Energy efficiency. • Rate-reliability-latency in mobile environments.	• XR/AR/VR. • Autonomous vehicular systems. • Autonomous drones. • Legacy eMBB and URLLC.
mURLLC	• Ultra high reliability. • Massive connectivity. • Massive reliability. • Scalable URLLC.	• Classical Internet of Things. • User tracking. • Blockchain and DLT. • Massive sensing. • Autonomous robotics.
HCS	• QoPE capturing raw wireless metrics as well as human and physical factors.	• BCI. • Haptics. • Empathic communication. • Affective communication.
MPS	• Control stability. • Computing latency. • Localization accuracy. • Sensing and mapping accuracy. • Latency and reliability for communications. • Energy.	• CRAS. • Telemedicine. • Environmental mapping and imaging. • Some special cases of XR services.

MBRLLC: Mobile Broadband RLLC
HCS : Human Centric Services
MPS : Multipurpose 3CLS(communication /computing/control, localization and sensing) and Energy Services
DLT : Distributed Ledger Technology
BCI : Brain Computer Interaction
XR: Extended Reality
CRAS : Connected Robot and Autonomous System

[1] Saad, W., Bennis, M., & Chen, M. (2019). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE network, 34(3), 134-142.

Introduction – 5G and 6G Comparison

	5G	Beyond 5G	6G
Application Types	• eMBB. • URLLC. • mMTC.	• Reliable eMBB. • URLLC. • mMTC. • Hybrid (URLLC + eMBB).	New applications (see Section II-C): • MBRLLC. • mURLLC. • HCS. • MPS.
Device Types	• Smartphones. • Sensors. • Drones.	• Smartphones. • Sensors. • Drones. • XR equipment.	• Sensors and DLT devices. • CRAS. • XR and BCI equipment. • Smart implants.
Spectral and Energy Efficiency Gains[3] with Respect to Today's Networks	10x in bps/Hz/m^2/Joules	100x in bps/Hz/m^2/Joules	1000x in bps/Hz/m^3/Joules (volumetric)
Rate Requirements	1 Gbps	100 Gbps	1 Tbps
End-to-End Delay Requirements	5 ms	1 ms	< 1 ms
Radio-Only Delay Requirements	100 ns	100 ns	10 ns
Processing Delay	100 ns	50 ns	10 ns
End-to-End Reliability Requirements	99.999%	99.9999%	99.99999%
Frequency Bands	• Sub-6 GHz. • MmWave for fixed access.	• Sub-6 GHz. • MmWave for fixed access at 26 GHz and 28GHz.	• Sub-6 GHz. • MmWave for mobile access. • Exploration of THz bands (above 300 GHz). • Non-RF (e.g., optical, VLC, etc.).
Architecture	• Dense sub-6 GHz small base stations with umbrella macro base stations. • MmWave small cells of about 100 m (for fixed access).	• Denser sub-6 GHz small cells with umbrella macro base stations. • < 100 m tiny and dense mmWave cells.	• Cell-free smart surfaces at high frequency supported by mmWave tiny cells for mobile and fixed access. • Temporary hotspots served by drone-carried base stations or tethered balloons. • Trials of tiny THz cells.

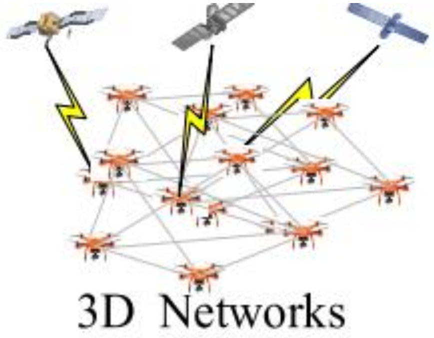
3)Here, spectral and energy efficiency gains are captured by the concept of area spectral and energy efficiency

[1] Saad, W., Bennis, M., & Chen, M. (2019). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE network, 34(3), 134-142.

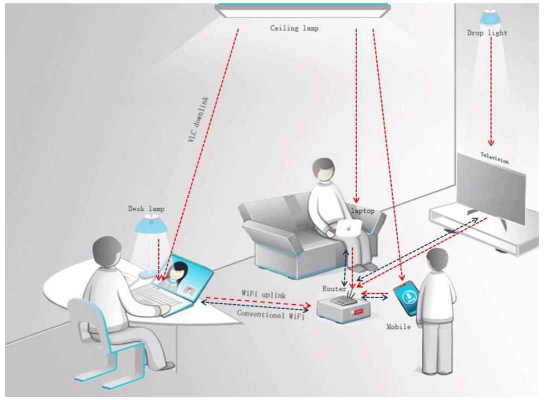
Introduction – Key Communication Technologies

Terahertz Communication

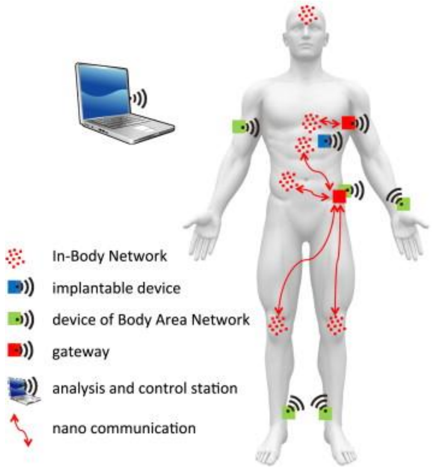
Quantum Communication



3D Communication



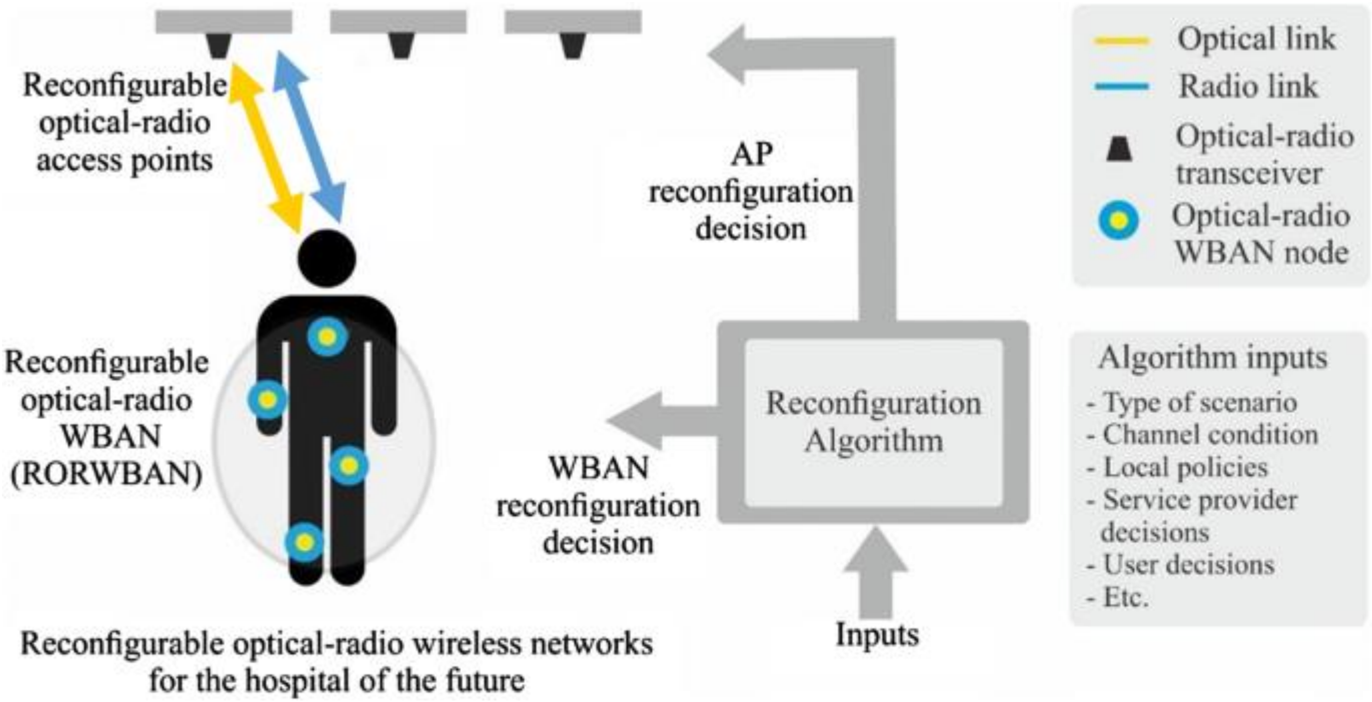
Visible Light Communication



Nano Communication

[1] https://phys.org/news/2017-02-terahertz-wireless-spaceborne-satellite-links.html
[2] https://singularityhub.com/2018/12/26/quantum-communication-just-took-a-great-leap-forward/
[3] https://web.njit.edu/~abdallah/VLC/
[4] https://www.sciencedirect.com/science/article/pii/S1878778915000071

Introduction – Networking Technologies(1)

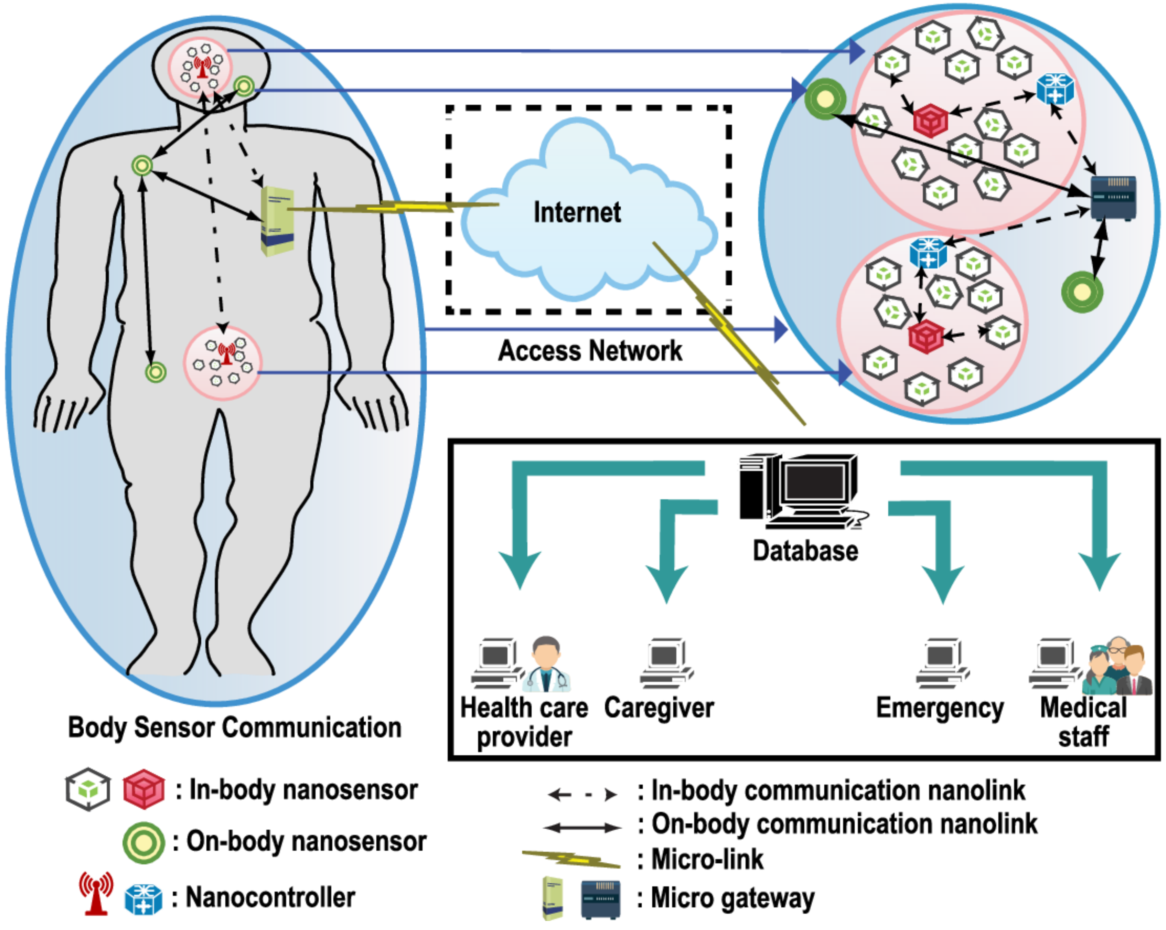


Optical Networking

- Hospital of Future will consist of numerous communication devices and hybrid optical-radio access points to transmit data using radio waves and visible light.
- Light-based communications exploit the idea of visible light communications (VLC), where solid-state luminaries, white light-emitting diodes (LEDs) provide both room illumination as well as optical wireless communications (OWC).

[1] https://link.springer.com/article/10.1007/s10776-019-00468-1

Introduction – Networking Technologies(2)



Bio-Nano Networking

- Advancements made in micro/nano technologies for interfacing, controlling, and manipulating biology show the potential of exploiting the functionalities of biological organisms for designing and engineering communication systems and networks.
- For example, the human nervous system, which consists of several billion neurons located in the brain, the spinal cord, and within nerves throughout the body, truly forms an electrochemical computation and communication network at the nanoscale.

[1] https://www.semanticscholar.org/paper/Cooperative-In-Vivo-Nano-Network-Communication-at-Abbasi-Nasir/ca071f6a78ec44e9a4f1cffc5de5ca3ed122c582
[2] https://ioe.eng.cam.ac.uk/Research/Research-Areas
[3] https://network-data-cabling.co.uk/blog/pon-the-unlikely-revolution-of-simplicity/
F. Afsana, M. Asif-Ur-Rahman, M. R. Ahmed, M. Mahmud and M. S. Kaiser, "An Energy Conserving Routing Scheme for Wireless Body Sensor Nanonetwork Communication," in IEEE Access, vol. 6, pp. 9186-9200, 2018, doi: 10.1109/ACCESS.2018.2789437.

Artificial Intelligence for 6G

- Why AI?
- Challenges in advancing AI-based 6G
- Overview of AI in meeting 6G Requirements
- Algorithm steps for ML-enabled 6G
- AI-Enabled 6G Architecture

Artificial Intelligence for 6G -Why?

- Wide Variety of 6G services with diverse requirements.
- 6G smart devices with more than 2000 configurable parameters are expected.
- Intelligent wireless communication will be one of the foundations of 6G.

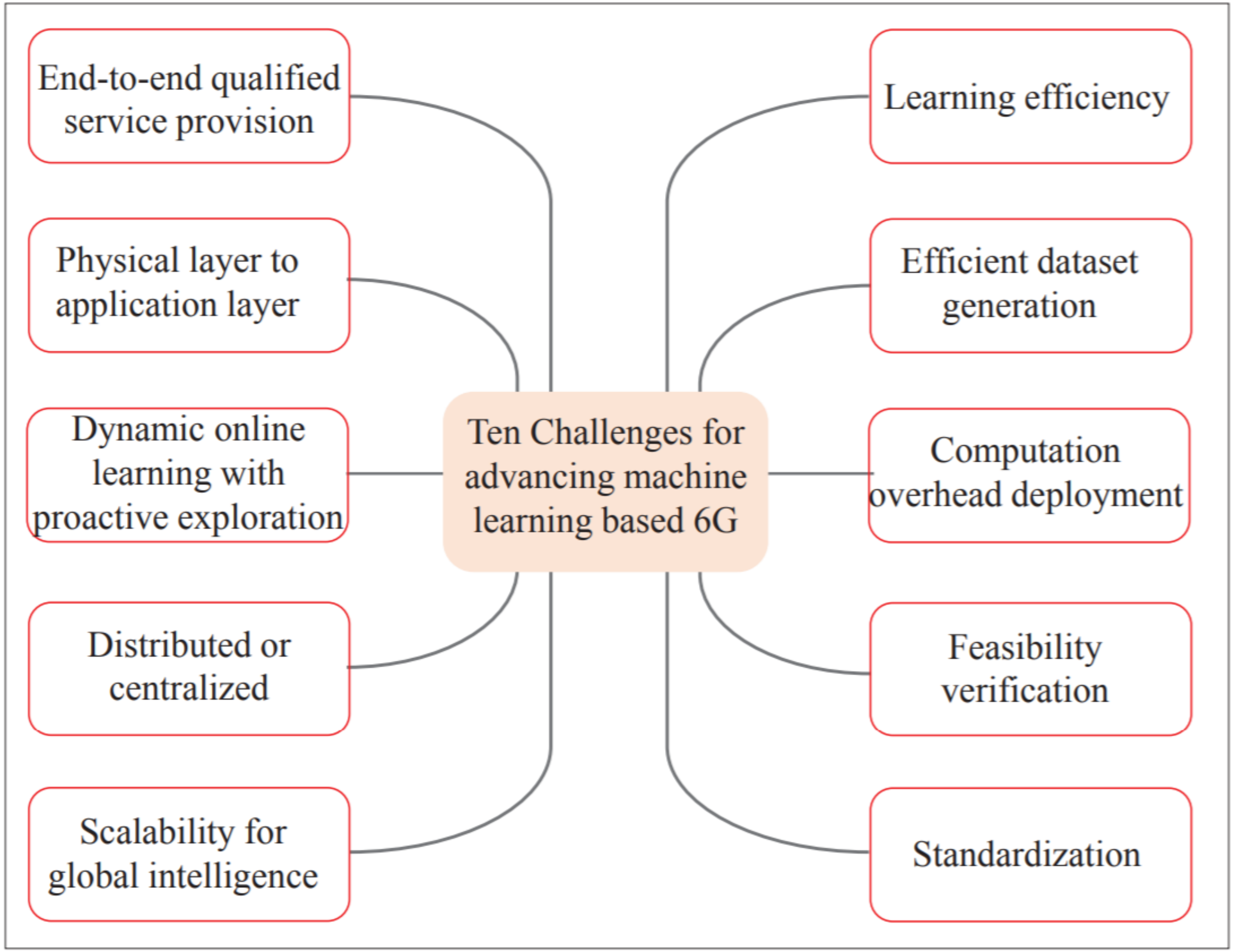
- Conventional schemes based on mathematical optimization theory, game theory, and graph theory will suffer from high complexity for 6G.
- Some of the 6G network optimization problems might not be effectively formulated to be solved by the optimization theory.

[1] https://www.6gchannel.com/items/6g-white-paper-machine-learning/

AI Based Networking Topics what we have dealt

- Machine Learning based Edge Computing
- Federated Learning and Democratized Learning
- AI based Network Resource Management
- AI based D2D Communication Networks
- Vehicular Edge Networking Using Machine Learning
- UAV-Assisted Wireless Networks Using Machine Learning
- Meta-Learning based Networking Architecture

Artificial Intelligence for 6G – Challenges in advancing AI-based 6G (1)



[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- End-to-End Qualified Service Provision

  - Future 6G services will require the end-to-end guarantees, which means the considered metric should be measured from the transceiver to the receiver instead of only the core network part in 5G system.

  - More KPIs should be taken into account instead of only the traditional metrics such as link bandwidth, latency, and security. Future services will also be measured from the perspectives of situational awareness, learning ability, storage cost, and computation capacity.

  - Heterogeneity existing in communication technologies and infrastructure hardware as well as the complex requirements on multiple metrics will accelerate the application of machine learning in networking.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Physical Layer to Application Layer

  - The complete communication process from the bottom to the top is constructed with the conceptual Open Systems Interconnection (OSI) model, which transfers the electronic signals from the physical world to the readable information in cyber-systems.

  - To enable the intelligence in the information transmission process, machine learning is widely employed in OSI layers from the physical to the application layer recently.

  - In the physical layer, machine learning is widely used for improving the signal transmission through intelligent configuration such as AI-aided data coding, channel estimation, signal detection and beamforming. In the physical world, the complex environment with high dimensions and dynamics causes the communication and networking process hard to be expressed analytically with a precise mathematical model.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Distributed or Centralized

  - Centralized Machine Learning can enable 6G with training at a centralized location such as edge-based centralized machine learning or cloud-based centralized machine learning.

  - Although centralized machine learning can perform effectively, however, it has the downside of user-privacy leakage due to migration of end devices data to the server for training.

  - To cope with the privacy leakage downside of centralized machine learning, distributed learning was recently applied to various scenarios.

  - One of the disadvantages of distributed machine learning based networking is that incomplete local information may lead to inaccurate estimation, especially in highly dynamic environments.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Dynamic Online Learning with Proactive Exploration

  - Offline training of agents used in wireless communications might not show promising results due to the fact that collected training might not be sufficient. For instance, autonomous driving cars produce 4000 Gigaoctet data every day.

  - Online learning is the potential AI approach to enable proactivity in networking functions to adaptively make decisions and adjust to the changing environment. One challenge of the online learning algorithm is the online data collection overhead.

  - In some other research, offline and online learning are jointly used to balance the training efficiency and overhead.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Learning efficiency: Architecture design and Optimization

  - Learning efficiency consists of many aspects, to name a few, the parameter adjustment, the choice of activation functions, the initialization functions, and learning rate.

  - To optimize the learning efficiency is not easy since an increasing number of choices exist at each step. Also, the efficiency of each choice can only be found through trial and error, since the detailed work theory of machine learning is still unknown.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Efficient and Noiseless Dataset Generation

  - The dataset of conventional offline training is mainly labeled by humans, and the dataset of online training is calculated with feedbacks from continuous/discrete actions.

  - However, both the human-labeled training dataset and feedbacks of online training face significant challenges in wireless networks.

  - The former requires lots of human resources for terascale networking data, and the latter causes supernumerary signaling overhead.

  - How to efficiently collect training data to optimize both training and networking efficiency emerges as a new challenge of future networks.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Scalability for Global Intelligence

  - Given the extreme heterogeneity of access techniques, service requirements, hardware architectures, and network structures in future 6G systems, the most efficient intelligent strategy should be customized based on definite scenarios to optimize the accuracy of machine learning models.

  - However, frequent network dynamics caused by the node mobility and frequent reconstruction of the virtual subnetworks may lead to accuracy deterioration.

  - Scalable machine learning models must be proposed, which can be copied to different networks or scenarios for realizing the global intelligence.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

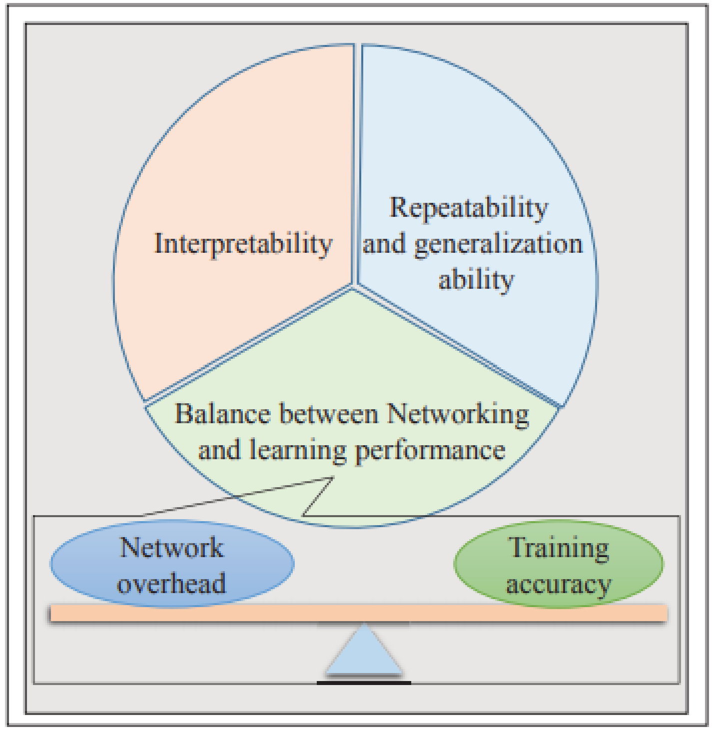
- Computation Overhead Reduction

  - We must propose efficient design based on software-hardware co-design for efficient deployment of machine learning-based solutions.

  - Generally increasing the complexity of the machine learning model improves its performance. However, there are computation resource limitations in the wireless systems. Therefore, we must make a trade-off between accuracy and complexity of machine learning algorithms.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Feasibility Verification
  - Interpretability: When the machine learning based algorithms work, how can the person understand the workflow and learn the principle behind the black box?
  - Repeatability and generalization ability: How can we use design a generalized machine learning algorithm for various scenarios?
  - Networking or learning performance: Different from the typical application with machine learning mainly depending on training accuracy and computing complexity, the network performance should be the first evaluation index for machine learning based communication/networking functions.



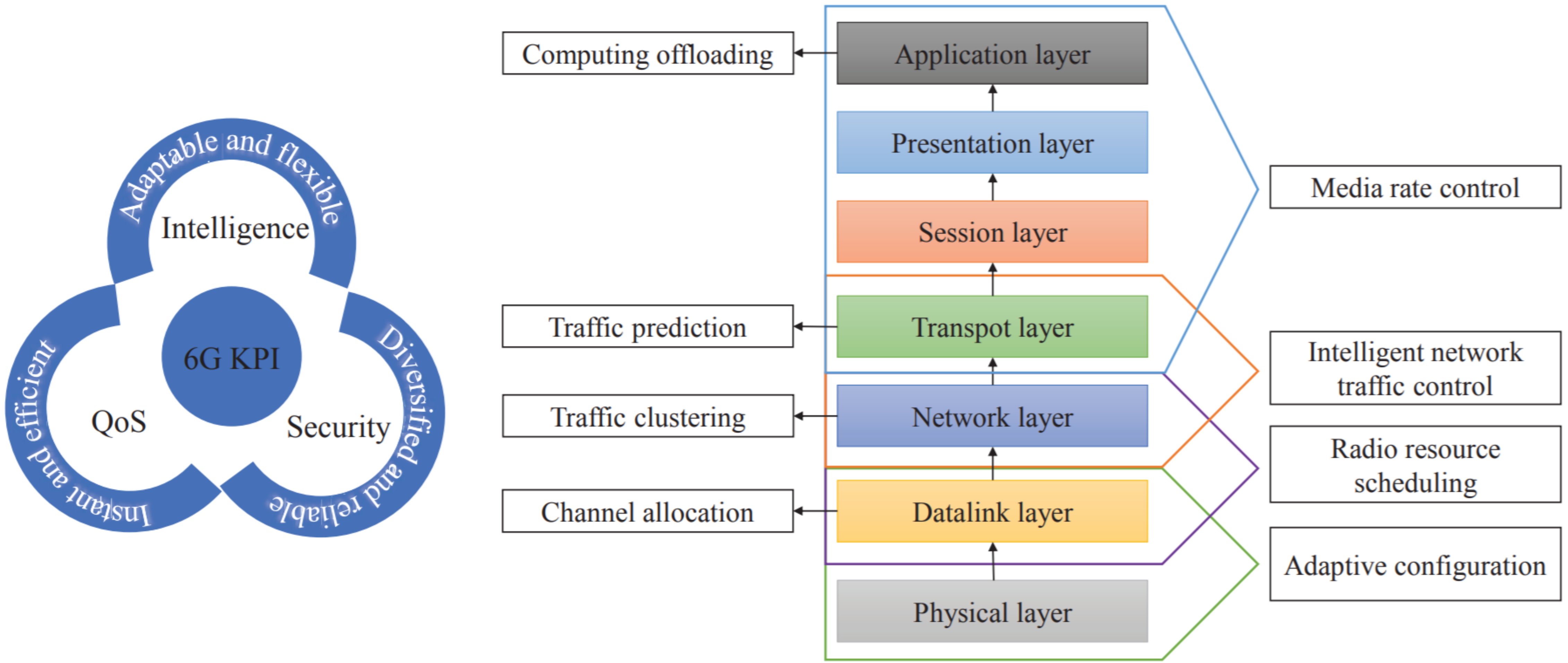
[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

- Standardization of AI-Enabled 6G

  - The standardization of AI embedded communications is still unexplored, while current research still mainly focuses on the final improvement of throughput, latency, or packet loss rate.

  - From the viewpoint of constructing the intelligent 6G system and to accelerate the practical application of AI techniques, researchers from academia and industry should cooperate more to constitute the related standard.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

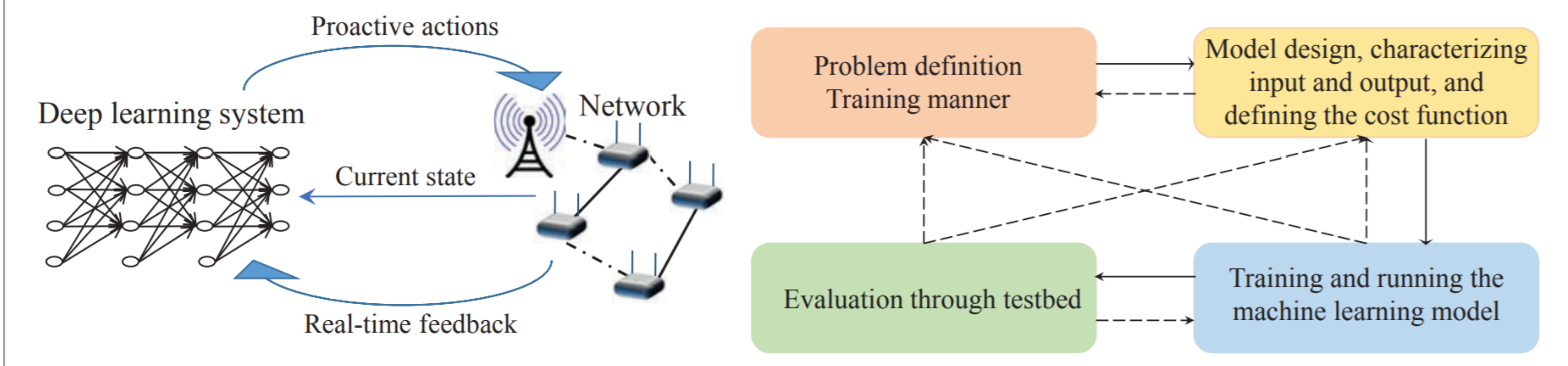


(a) The emerging 6G service requirements.

(b) The machine learning based applications from physical layer to application layer.

[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

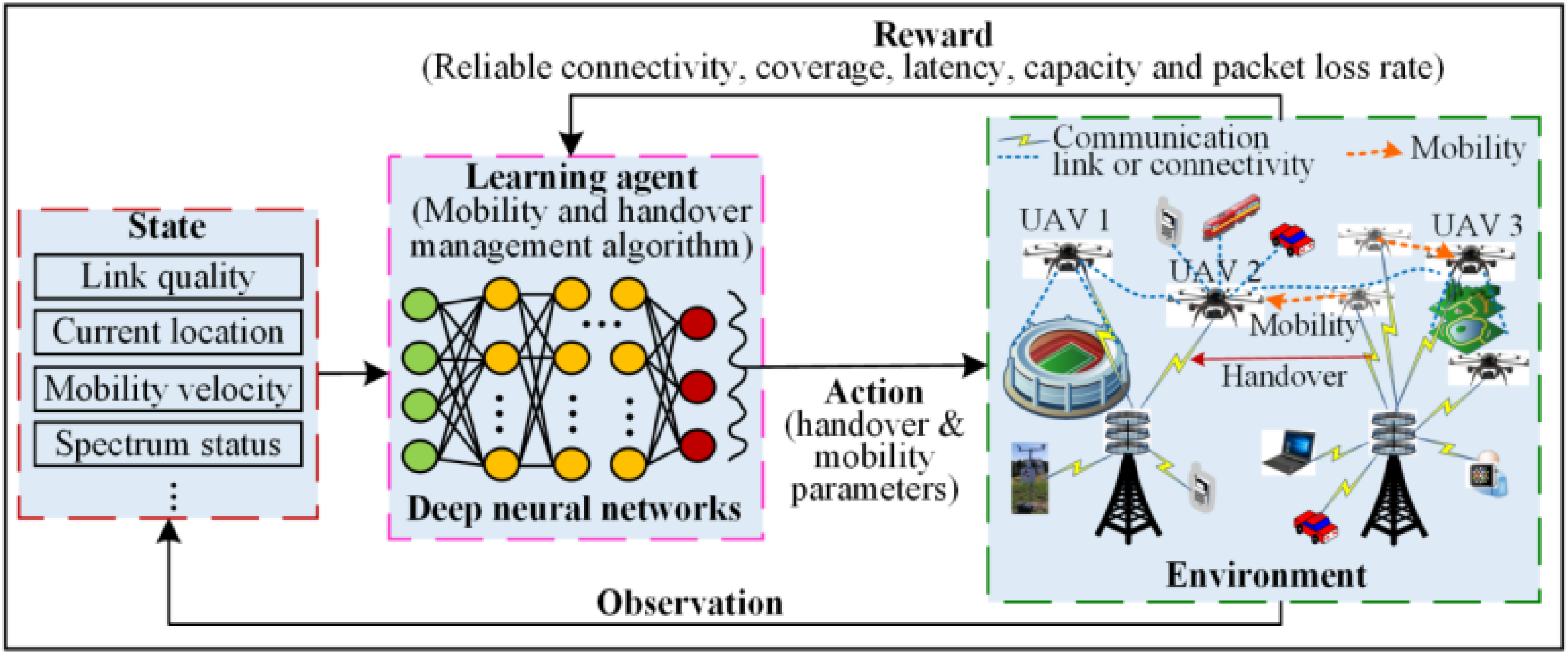
Artificial Intelligence for 6G – Algorithm steps for ML-enabled 6G



(a) The online learning with proactive exploration. (b) The considered four steps for developing intelligent algorithms.

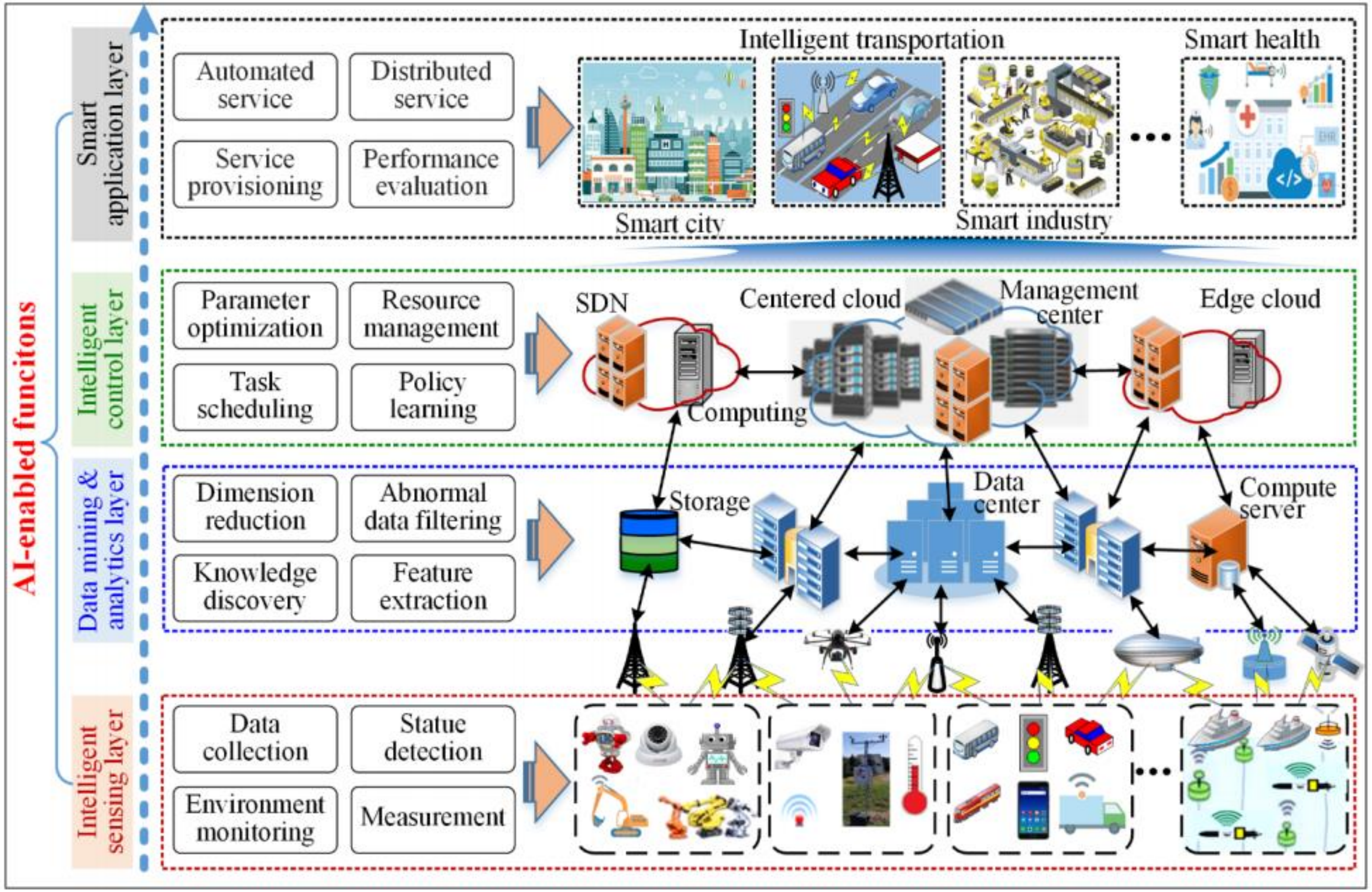
[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

Artificial Intelligence for 6G – DRL for 6G



[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

Artificial Intelligence for 6G – AI-Enabled 6G Architecture (1)



[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

- Intelligent Sensing Layer

  - 6G networks tend to intelligently sense and detect the data from physical environments via enormous devices (e.g., cameras, sensors, vehicles, drones and smartphones) or crowds of human beings.

  - AI-enabled sensing and detecting are capable of intelligently collecting the large amounts of dynamic, diverse and scalable data by directly interfacing the physical environment, mainly including radiofrequency utilization identification, environment monitoring, spectrum sensing, intrusion detection, interference detection, and so on.

[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

- Data Mining and Analytics Layer

  - This layer is a core task that aims to process and analyze the massive amounts of raw data generated from the huge number of devices in 6G networks, and achieve semantic derivation and knowledge discovery.

  - The massive collected data from physical environments may be heterogeneous, nonlinear, and high dimensional, so data mining and analytics can be applied in 6G networks to address the challenges of processing the massive amount of data, as well as to analyze the collected data towards knowledge discovery.

  - On the one hand, it is costly to transmit or store the massive raw data in dense networks. Hence, it is necessary to reduce data dimension of the raw data, filter abnormal data, and finally achieve a more reasonable dataset. AI-based data mining, such as PCA and ISOMAP are two common AI algorithms which can help 6G networks to transform higher-dimensional data into a lower dimensional subspace, which dramatically decreases the computing time, storage space and model complexity.

PCA :Principal Component Analysis
ISOMAP : Isometric Mapping

[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020), Artificial intelligence-enabled intelligent 6g networks, IEEE Network.

- Intelligent Control Layer
  - Intelligent control layer mainly consists of learning, optimization, and decision-making, where this layer utilizes the appropriate knowledge from lower layers to enable massive agents (e.g., devices and BSs) to smartly learn, optimize and choose the most suitable actions (e.g., power control, spectrum access, routing management, and network association), with dual functions to support diverse services for social networks.
  - Intelligence is the important characteristic of 6G networks, where the combination of AI and 6G networks can learn to achieve self-configuration, self-optimization, self-organization and self-healing, finally increasing the feasibility level. For instance, post-massive multiple-input multiple-output (PMMIMO) will be employed in 6G networks to support hundreds or thousands of transmit/receive antennas with mmWave or THz transmissions.

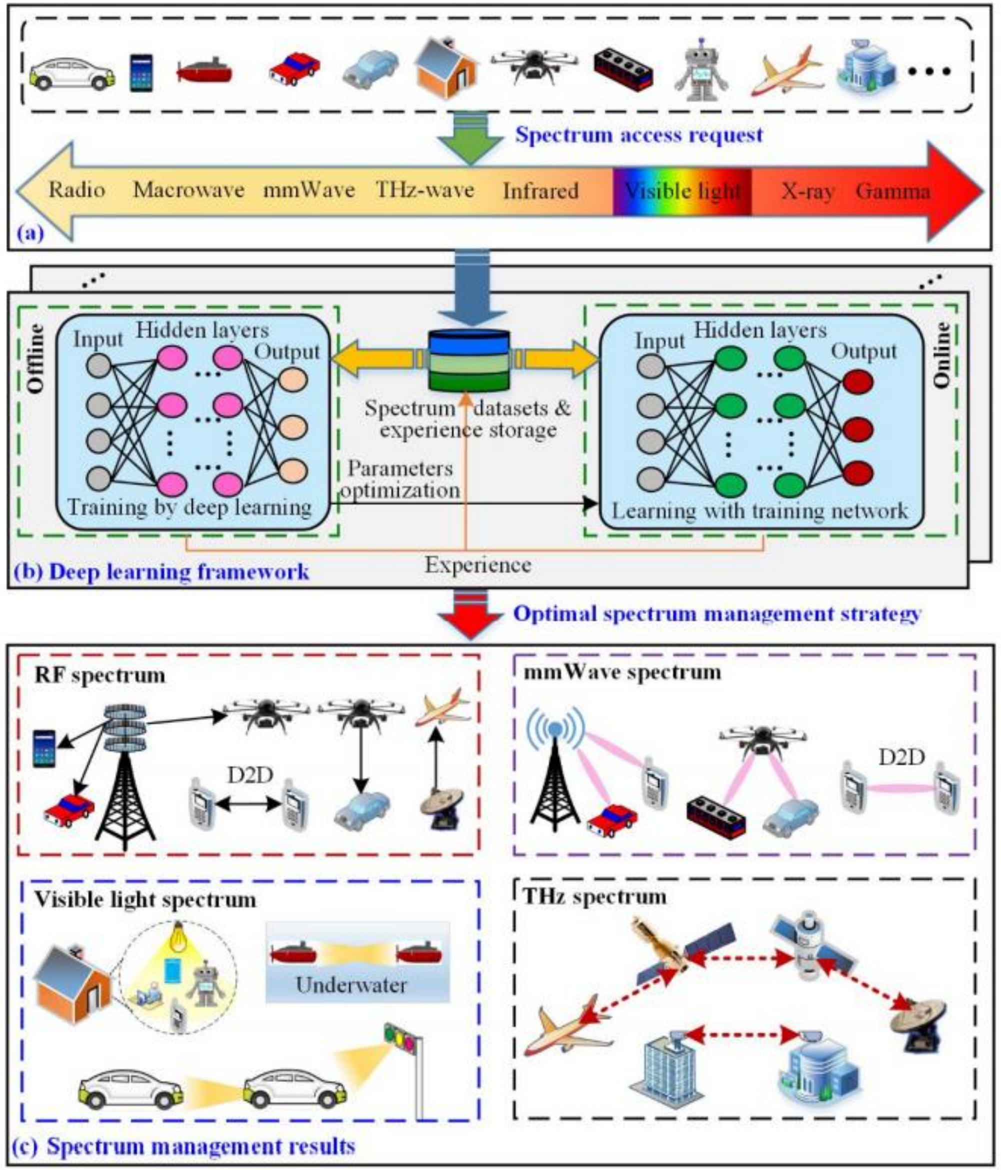
[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

- Smart Application Layer

  - The main responsibilities of this layer are delivering application specific services to the human beings according to their colorful requirements, as well as evaluating the provisioned services before feed backing the evaluation results to the intelligence process.

  - Intelligent programming and management can be achieved by the impetus of AI to support more various high-level smart applications, such as automated services, smart city, smart industry, smart transportation, smart grid and smart health, and handle global management relevant to all smart type applications.

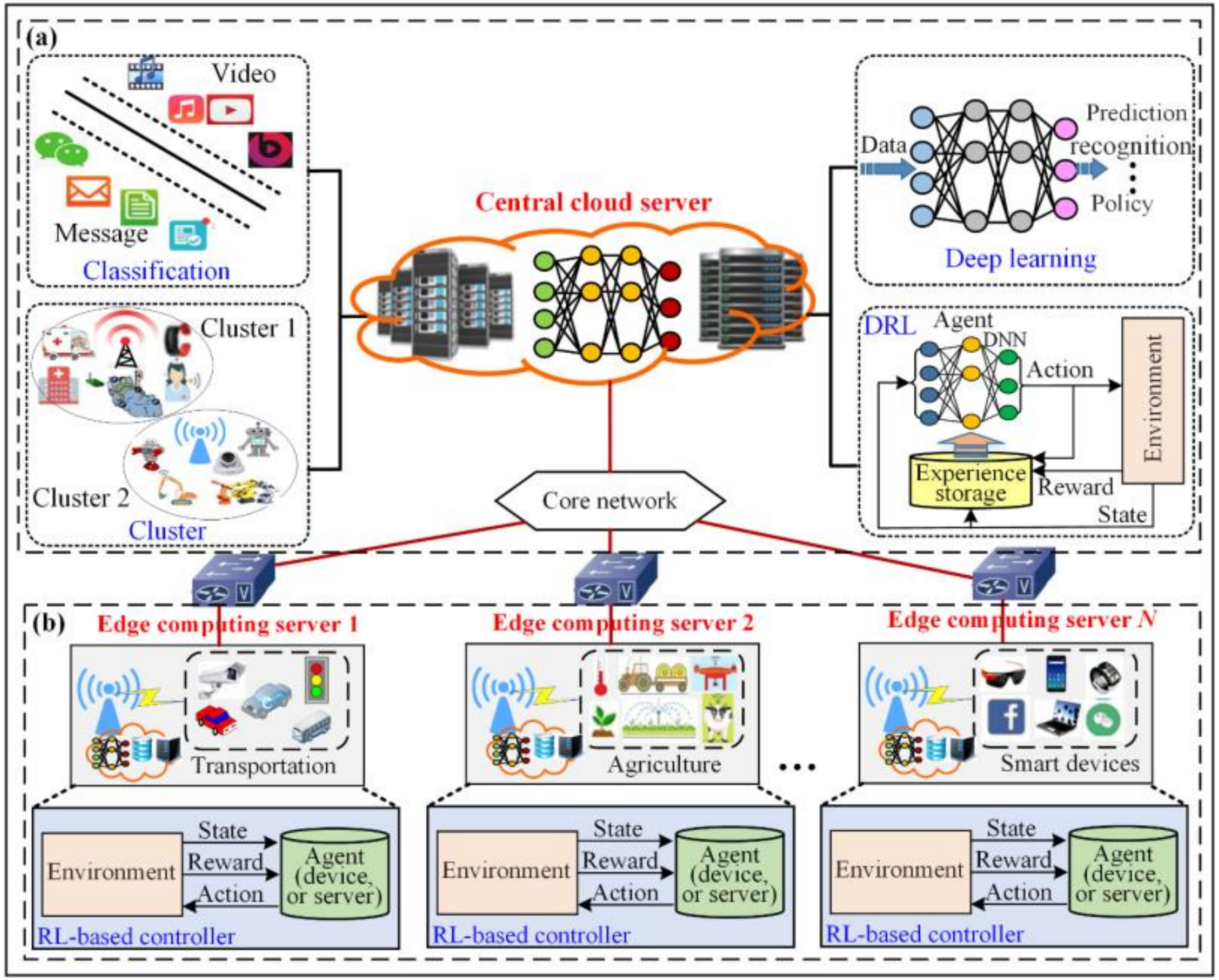
[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.



[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

- 6G networks utilize different spectrum bands (e.g., low radio frequency, mmWave, THz, and visible light spectrum) to support high data rates.
- When a massive number of devices are involved in 6G networks to require spectrum assignment, AI-enabled spectrum management is capable of intelligently supporting massive connectivity and diverse services.
- The AI-enabled learning framework constrains three layer manners, namely input layer, hidden or training layer and output layer.
- It then trains the hidden layers by comprehensively analyzing the characteristics of current or previous spectrum utilization information and discovers meaningful spectrum usage characteristics.
- Finally, the most suitable spectrum management strategies are provided in the output layer in real-time to support massive connectivities for devices.

[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.



[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

Artificial Intelligence for 6G – AI Empowered MEC Framework for 6G (2)

- Mobile edge computing (MEC) will be an important enabling technology for the emerging 6G networks, where MEC can provide computing, management and analytics facilities inside RAN or SDN in close proximity to various devices.

- In edge computing servers, due to the limited capability, lightweight AI algorithms can be utilized to provide smart applications for edge scenarios (e.g., transportation and agriculture).

- RL-Based Solution
  - RL-based edge computing resource management is a model-free scheme which does not need historical knowledge and it can be used to learn the environment dynamics and make suitable control decisions in real-time.

  - In the RL framework, at each step, after obtaining the state (e.g., device mobility, requirement dynamics, and resource condition) by interacting with environments, the possible resource management solutions (e.g., energy management, resource allocation, and task scheduling) are contained into the set of possible actions.

  - Each RL agent (e.g., device or service center) selects the best action from a set of possible actions or chooses one action randomly to maximize its reward, where the reward can be determined by data rate, latency, reliability, and so on.

[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

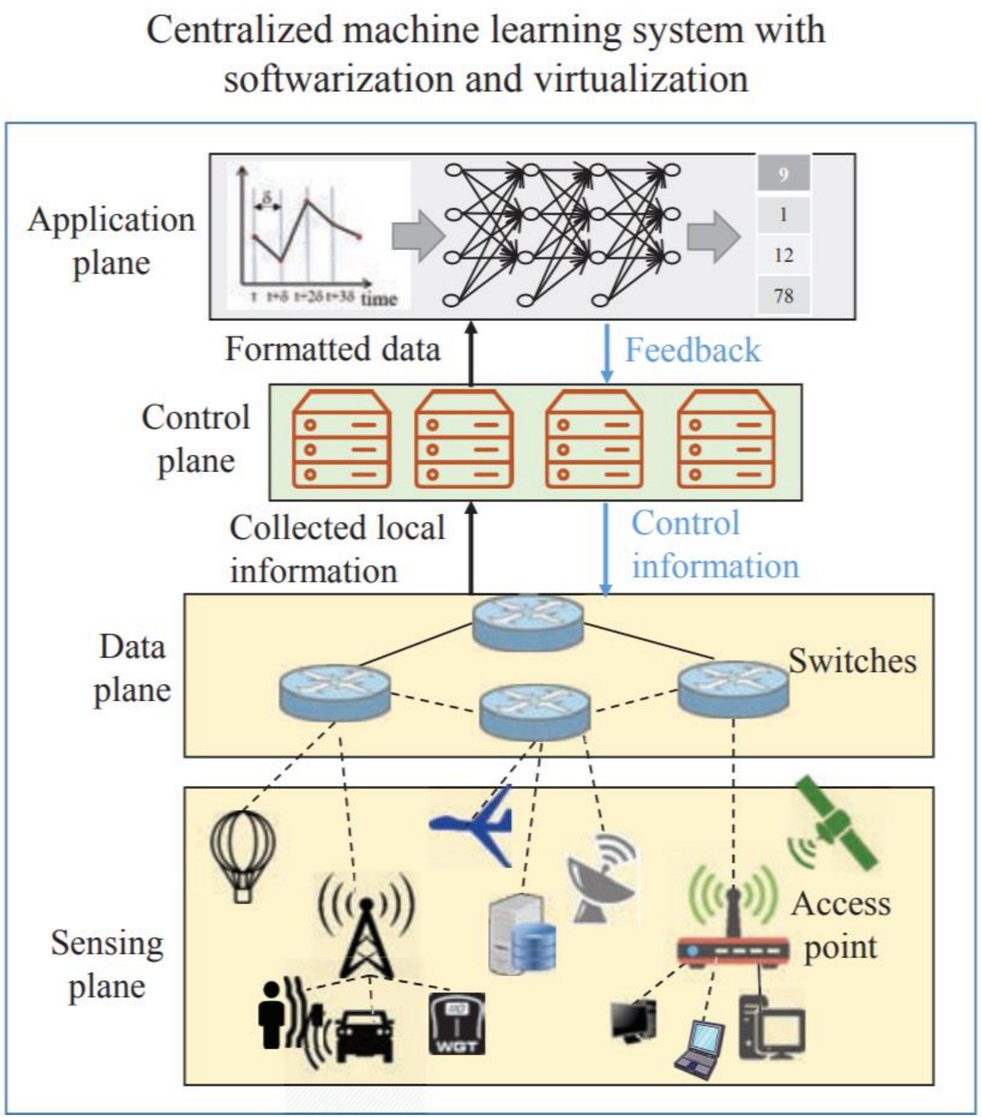
- Centralized Machine Learning-Based Solution
  - In the central cloud server, since it has powerful computation capability, complex centralized large-scale AI algorithms can be employed to provide various learning functions.
  - For instance, as service applications in MEC networks are diverse and dynamic, AI-based classification can be used to efficiently customize traffic flow decision for various service features.
  - In addition, MEC server association can be obtained by AI-based cluster instead of individual decision, which will be more effective to reduce a number of participants greatly.

[1] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial intelligence-enabled intelligent 6g networks. IEEE Network.

Machine Learning for 6G: Classification

- Centralized ML
- Distributed ML

Machine Learning for 6G – Centralized ML for 6G (1)



[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

Machine Learning for 6G – Centralized ML for 6G (2)

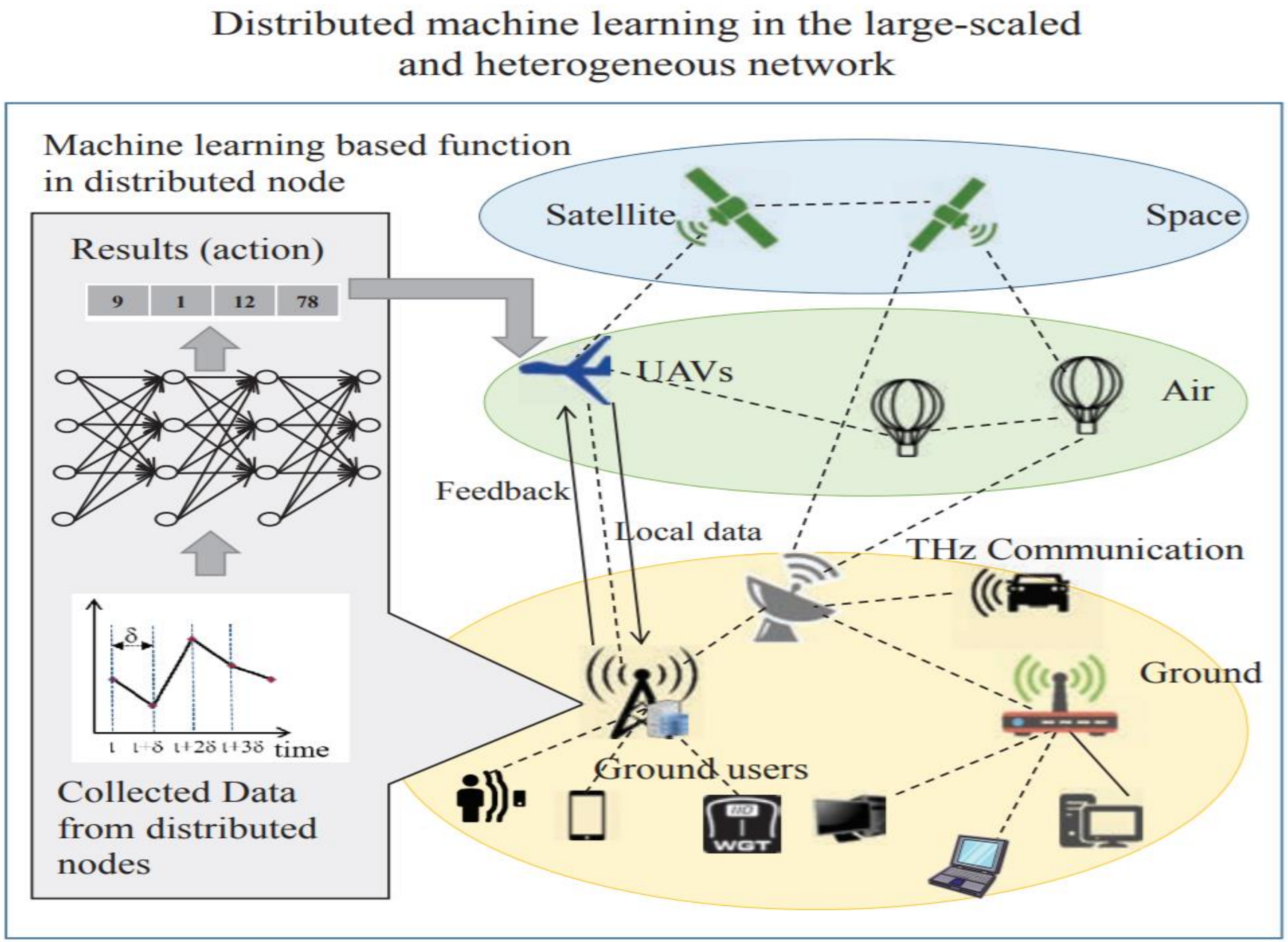
- Centralized ML is based on training of a ML learning model at a centralized location.
- Training at one location can effectively model the network functions, however, it suffers from end users privacy leakage.
- Another Drawback of centralized ML is the high training time for large data sets.
- To avoid the issue of high training time, distributed machine learning was introduced.

Machine Learning for 6G – Distributed ML for 6G (1)

- Distributed ML is based on training at distributed locations.
- Two main types:
  - Model parallel approach
  - Data parallel approach

- Model parallel approach is based on computing different parts of a machine learning model at different servers with each server having exactly same data.
- Data parallel approach is based on division of data among the set of servers where exactly same model is trained and then all models are ensemble to yield a final model.
- In all cases, machine learning models can not be divided into parts. Therefore, data parallel approach is more preferable for use.

Machine Learning for 6G – Distributed ML for 6G (2)



[1] Kato, N., Mao, B., Tang, F., Kawamoto, Y., & Liu, J. (2020). Ten Challenges in Advancing Machine Learning Technologies toward 6G. IEEE Wireless Communications.

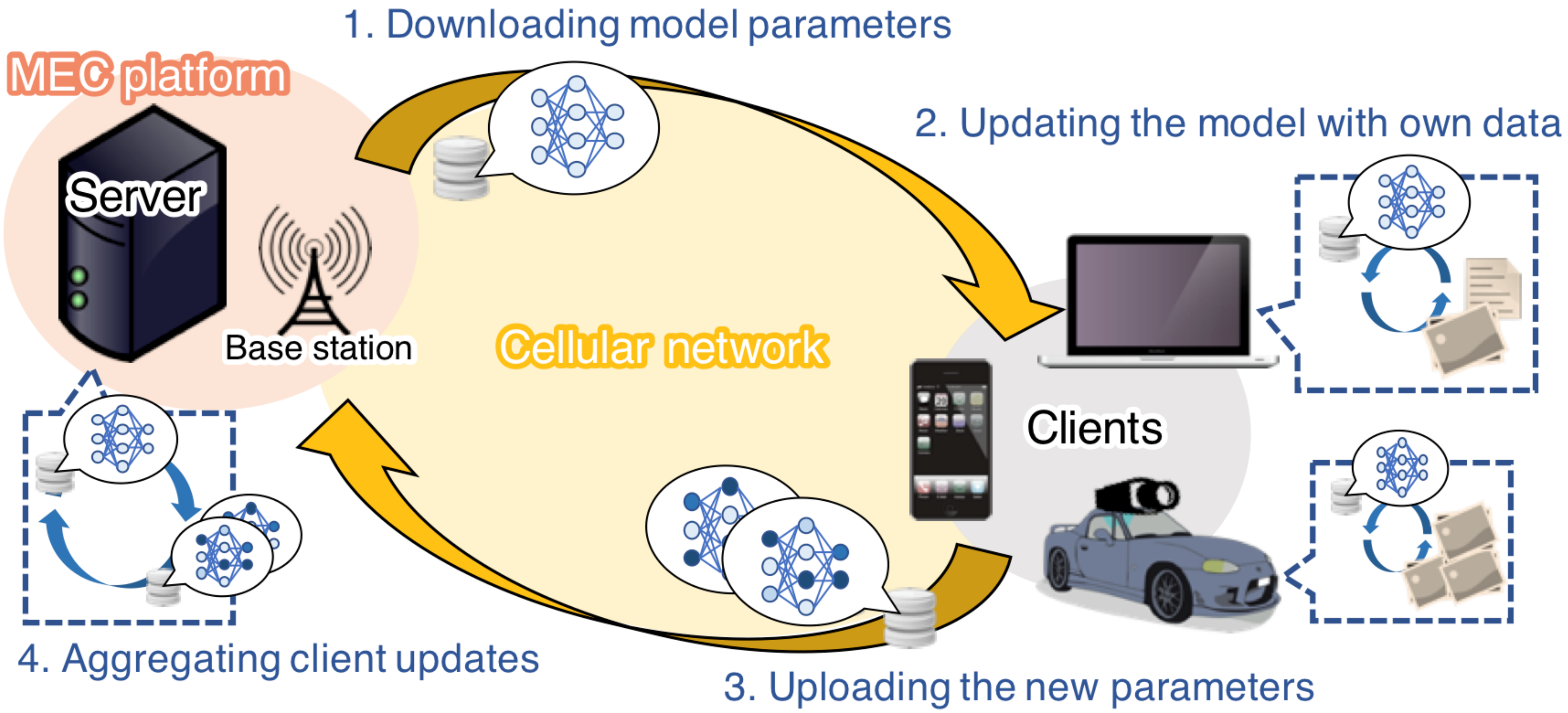
- Typically, distributed ML approaches did not take into account the users privacy leakage issue.

- To preserve the end-users privacy Federated Learning (FL) was introduced.

- FL is based on local models computation at end-devices. The local learning models from all devices are then sent to the centralized server for global aggregation.

- The global model is then sent back to the end-devices to update their local models. This process of FL continues in an iterative manner until convergence.

Machine Learning for 6G – Distributed ML for 6G (4)

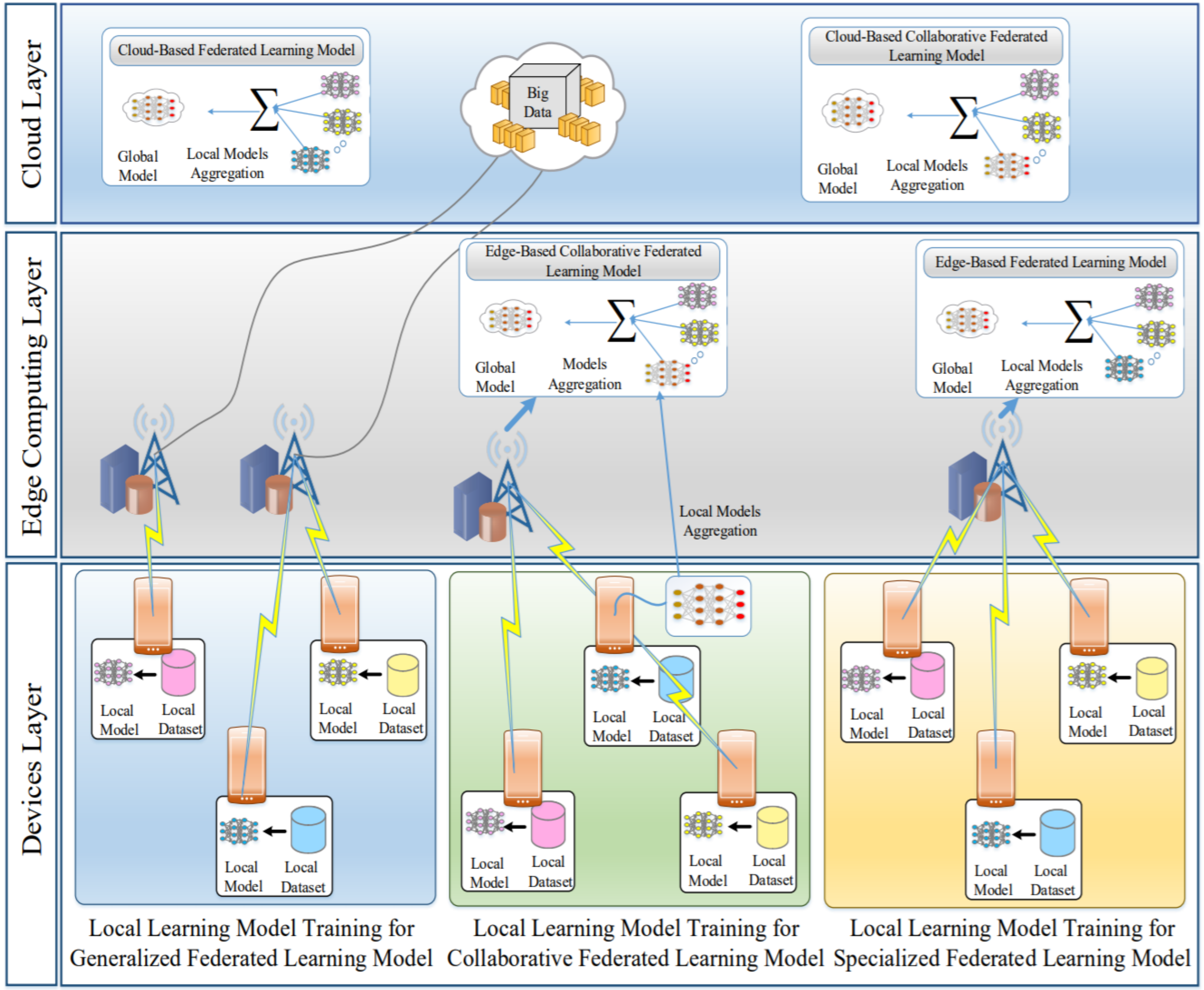


https://yonetaniryo.github.io/2018/04/24/ny-arxiv2018.html

Federated Learning for 6G

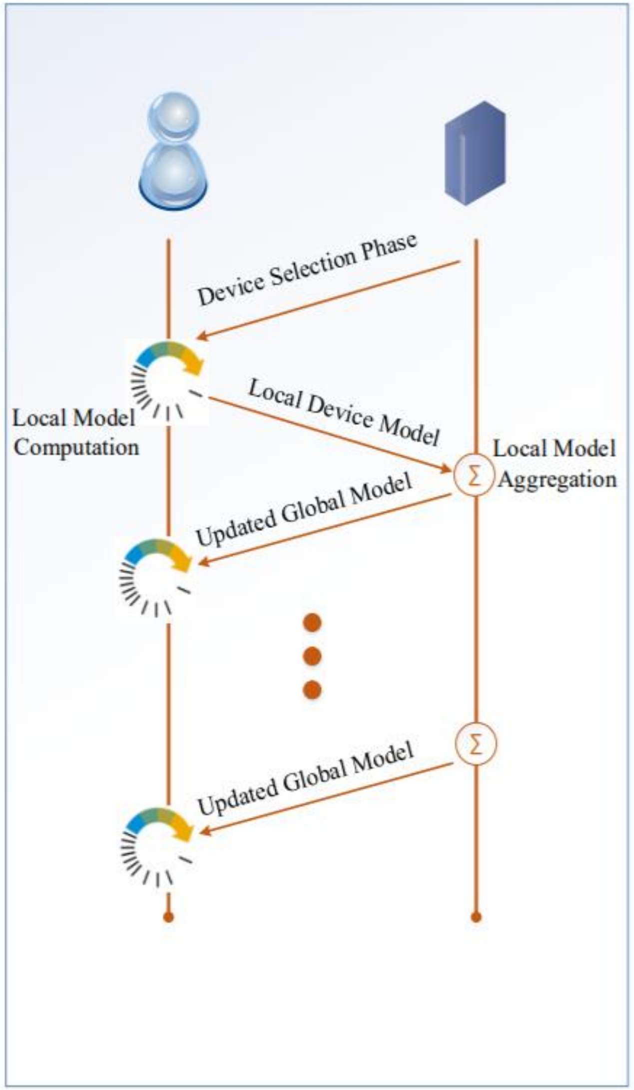
- Overview
- Key Design Aspects
- Collaborative FL
- Security and Privacy Issues in FL
- Use Cases

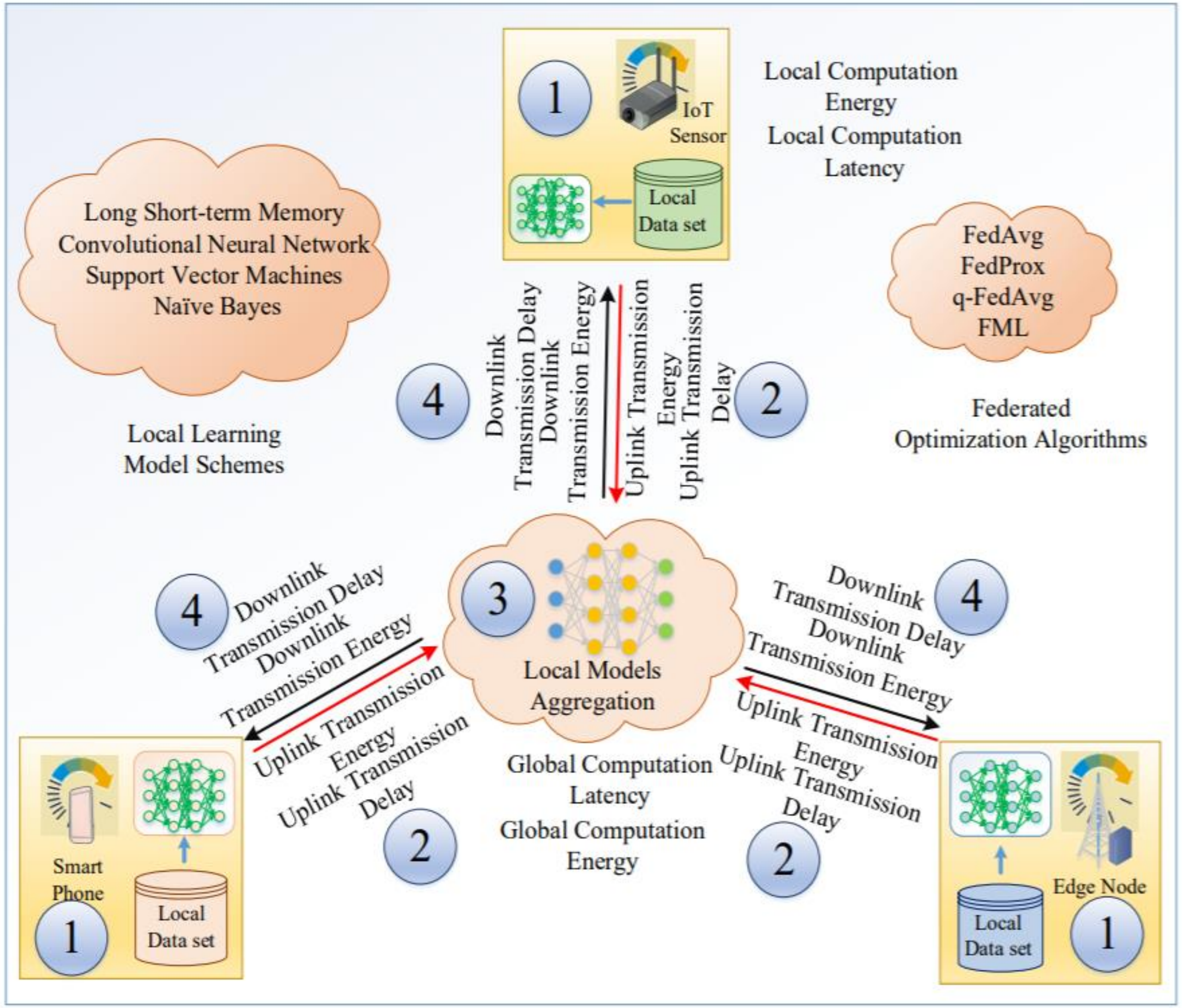
Federated Learning for 6G – Overview



[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.

Federated Learning for 6G – Key Design Aspects(1)





[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.

Federated Learning for 6G – Key Design Aspects (2)

- Design aspect of FL for 6G

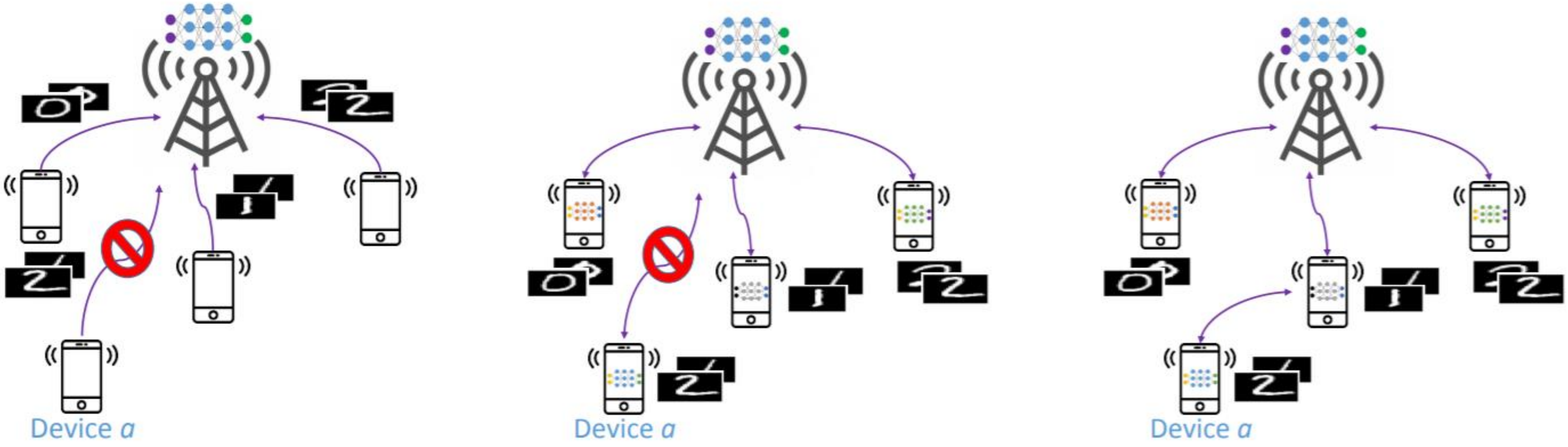
1) Resource Optimization
   a) Communication resource
   b) Computational resource
2) Learning Algorithm Design
   a) Federated optimization schemes (e.g., FedAvg, FedProx, etc)
   b) Local device learning algorithm (e.g., DNN, LSTM etc.)
3) Incentive Mechanism Design
   a) Contract Theory-based design
   b) Stackelberg game-based design

[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.
[2] Tra Huong Thi Le, Nguyen H. Tran, Phuong Luu Vo, Zhu Han, Mehdi Bennis and Choong Seon Hong, "Joint Cache Allocation With Incentive and User Association in Cloud Radio Access Networks Using Hierarchical Game," IEEE Access, Vol.7, pp.20773-20788, February 2019
[3] Shashi Raj Pandey, Nguyen H. Tran, Mehdi Bennis, Yan Kyaw Tun, Aunas Manzoor and Choong Seon Hong, "A Crowdsourcing Framework for On-Device Federated Learning," IEEE Transactions on Wireless Communications, DOI:10.1109/TWC.2020.297198

Federated Learning for 6G – Collaborative FL (1)

- Due to communication resource constraints, some of the nodes might not be able to participate in the learning process [2]. Additionally, 6G will suffer from a massive number of devices.
- To enable the participation of these nodes in a FL process, we can adopt collaborative FL [1].
- In collaborative FL, a device that is unable to connect to an aggregation server due to communication resources constraints, send its local learning model parameters to another device.
- The receiving device aggregates the local learning model of the communication resource deficient device with its local learning model parameters before sending to the aggregation server.

[1] Chen, M., Poor, H. V., Saad, W., & Cui, S. (2020). Wireless Communications for Collaborative Federated Learning in the Internet of Things. arXiv preprint arXiv:2006.02499.
[2] Khan, L. U., Pandey, S. R., Tran, N. H., Saad, W., Han, Z., Nguyen, M. N., & Hong, C. S. (2020). Federated learning for edge networks: Resource optimization and incentive mechanism. IEEE Communications Magazine, 58(10), 88-93.



(a) Architecture of CL (b) Architecture of OFL (c) Architecture of CFL

Fig. 1. Architectures of centralized learning, original FL, and collaborative FL.

[1] Chen, M., Poor, H. V., Saad, W., & Cui, S. (2020). Wireless Communications for Collaborative Federated Learning in the Internet of Things. arXiv preprint arXiv:2006.02499.

Federated Learning for 6G – Collaborative FL (3)

SUMMARY OF THE ADVANTAGES, DRAWBACKS, AND USAGE CONDITIONS OF ML OVER WIRELESS NETWORKS.

	Advantages	Drawbacks	Usage Conditions
CL	• Ability to find a globally optimal ML model. • Ample computational resources and energy available for ML training. • Imperfect wireless transmission has a minor impact on ML model training. • Better performance for ML models with non-convex functions compared to FL.	• Private data must be shared with a centralized controller such as a BS or cloud. • Significant overhead for data collection. • Difficult to implement for resource and energy-limited edge devices such as IoT devices. • Large delays due to long-range transmission to a remote cloud or BS.	• Each device must be willing to share its private data. • All devices can transmit data to the BS.
OFL	• Privacy-preserving framework. • Devices can learn a common ML task in a distributed manner. • Ability to train ML models at device level.	• Imperfect wireless transmission affects the ML model training process. • Number of users (and their data) that can perform FL is limited. • All devices must have a direct and reliable wireless connection to the BS.	• All devices must be able to transmit FL model parameters to a controller or aggregator (e.g., a BS). • All devices must be able to receive the FL model parameters from the BS. • Devices can locally train ML models (at the edge).
CFL	• Privacy-preserving framework. • Ability to include more training data samples for training compared to OFL. • Amenability for implementation in large-scale systems (e.g., IoT) because CFL can accommodate more devices in the FL process compared to OFL.	• Imperfect wireless transmission affects the ML model training process. • Lower convergence speed compared to OFL. • The ML model of each device at convergence may be different since each device connects to a subset of devices.	• A reliable communication link can be formed between any two devices that need to use CFL. • Each device can locally train its ML model and aggregate the local FL models received from its associated devices.

[1] Chen, M., Poor, H. V., Saad, W., & Cui, S. (2020). Wireless Communications for Collaborative Federated Learning in the Internet of Things. arXiv preprint arXiv:2006.02499.

Federated Learning for 6G – Collaborative FL (4)

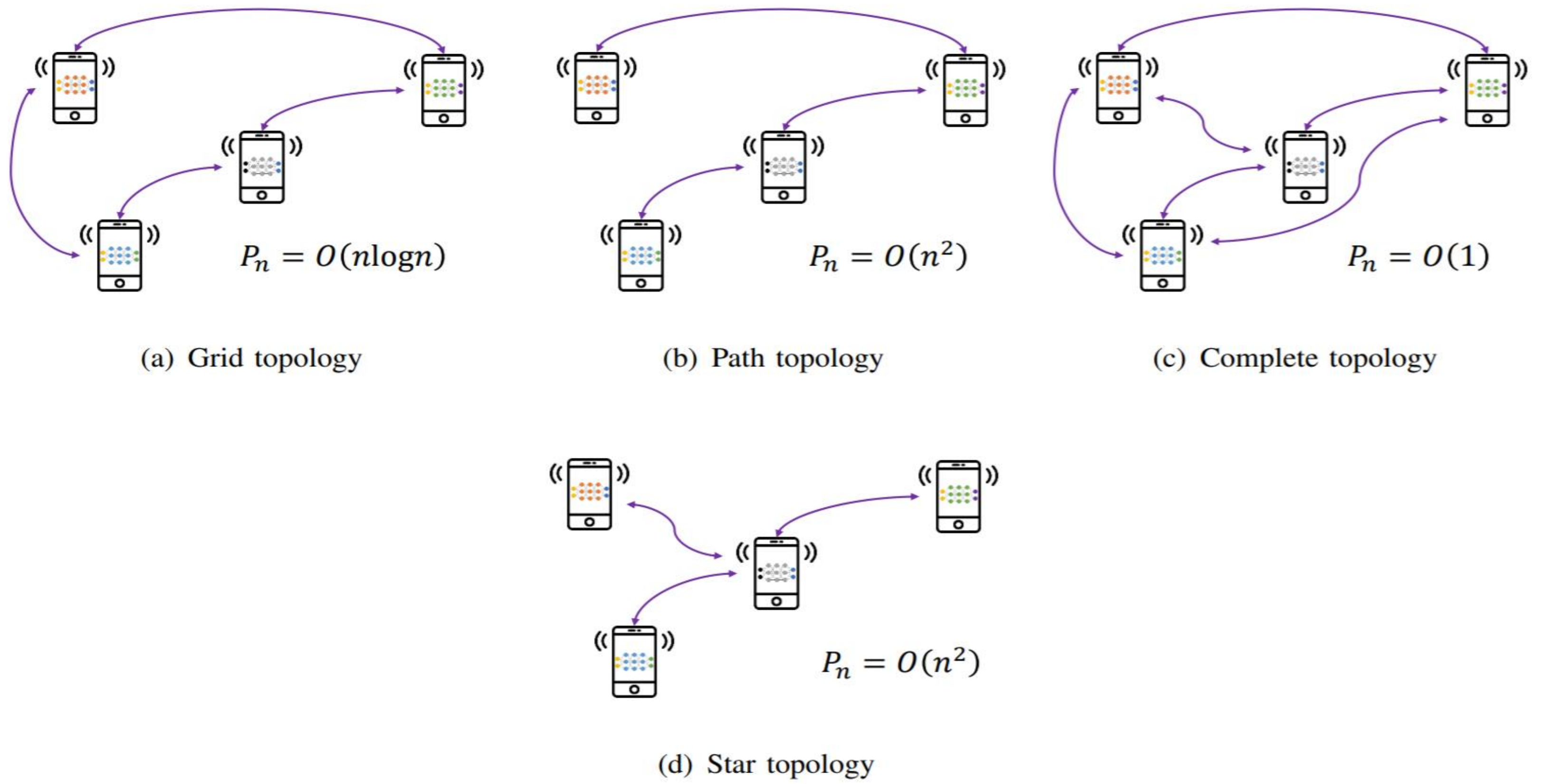
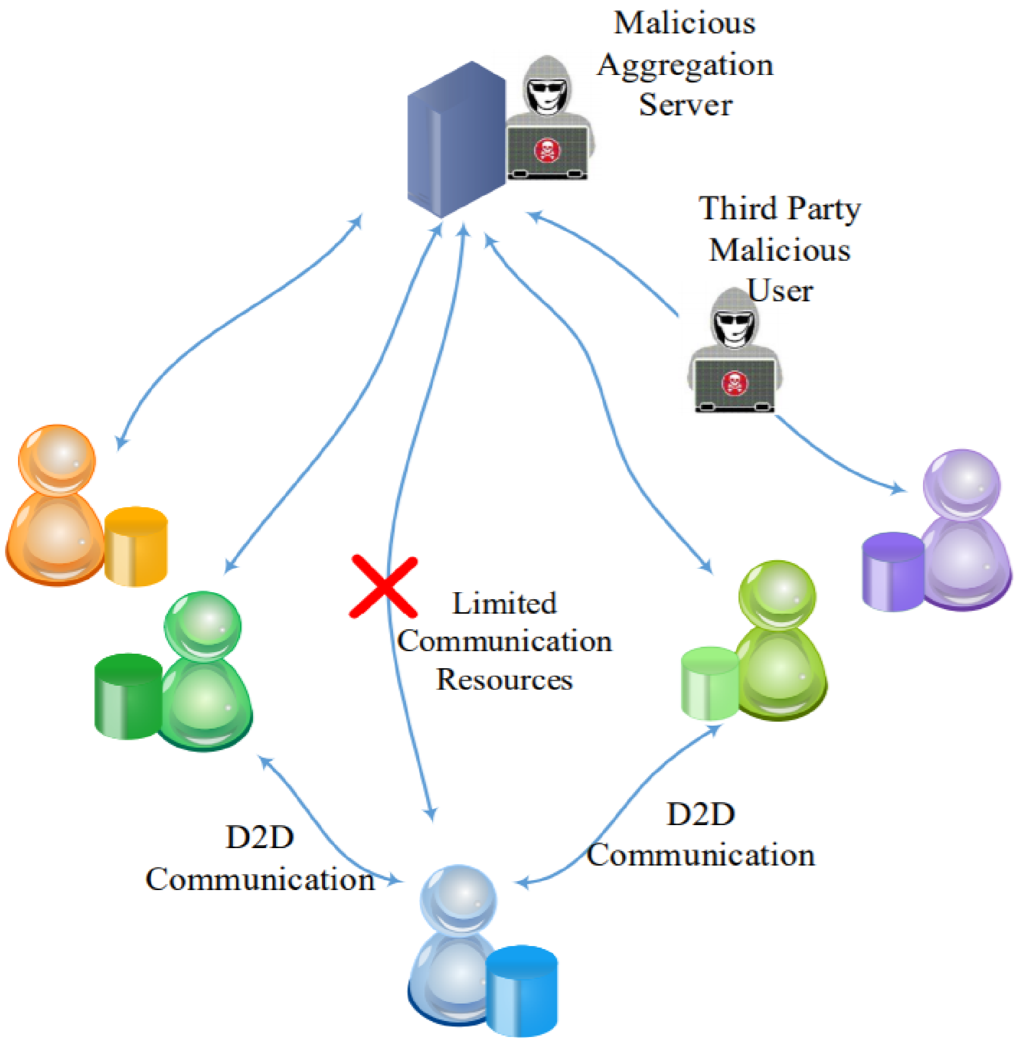


Fig. 3. Number of iterations needed to converge for different CFL algorithms with different topologies. In this figure, $O\left(\frac{\max\left(\left(\boldsymbol{g}^0-\boldsymbol{w}^*\right)^4, L^4 P_n^2\right)}{\varepsilon^2}\right)$ is the upper bound of the number of iterations that a CFL algorithm needs to converge, where n is the number of devices that perform the FL algorithm, ε is the target accuracy which implies the difference between the optimal FL model and the FL model at convergence, L is the upper bound of the gradient of the loss function, $\boldsymbol{g}^0 = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{w}_i^0$ with $\boldsymbol{w}_i^0$ being the initial local FL model of device i, and $\boldsymbol{w}^*$ is the optimal local FL model at convergence.

[1] Chen, M., Poor, H. V., Saad, W., & Cui, S. (2020). Wireless Communications for Collaborative Federated Learning in the Internet of Things. arXiv preprint arXiv:2006.02499.

Federated Learning for 6G –FL Security and Privacy Challenges (1)



[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.

- A malicious end device and aggregation server can infer end-devices sensitive information from their local learning model parameters [1].

- Due to sensitive information inferring capabilities of malicious devices and aggregation sever from other end-devices local learning model parameters, FL has itself privacy leakage issues.

- There is a need to preserve the privacy of FL. One way is to use differential privacy preservation scheme that is based on addition of noise to the local learning model parameters before sending them to the aggregation server.

[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.

- One of the promising way to enable privacy-aware FL is through homomorphic encryption.
- In homomorphic encryption, the encrypted local learning model parameters are send to the aggregation server, where aggregation takes place without decrypting the local learning models.
- Finally, the global model parameters are sent back to the end users.

[1] Khan, L. U., Saad, W., Han, Z., Hossain, E., & Hong, C. S. (2020). Federated Learning for Internet of Things: Recent Advances, Taxonomy, and Open Challenges. arXiv preprint arXiv:2009.13012.

6G Challenges

- 6G Network-As-An-Intelligent-Service
- Self-sustaining 6G Networks
- Modeling for Terahertz and Millimeter Wave Communication
- Zero-Energy-Enabled 6G
- Meta-Learning-Enabled 6G

- 6G NETWORK-AS-AN-INTELLIGENT-SERVICE
  - Network-as-a-service offers the use of shared physical resources via network slicing to serve different smart services.
  - Network slicing uses SDN and NFV as key enablers. SDN offers separation of the control plane from the data plane, thus offering efficient network management .
  - NFV allows the cost-efficient implementation of different networking functions on generic hardware using virtual machines.
  - Although network slicing enables efficient resources usage while fulfilling end-user demands, it might not perform well with an increase in network heterogeneity and complexity.
  - Therefore, network-as-a-service must be transformed to network-as-an-intelligent-service. Network intelligentization will enable 6G systems to adjust various parameters adaptively, thus offering enhanced performance.

- SELF-SUSTAINING 6G NETWORKS
  - A self-organizing (i.e., self-operating) network offers optimization, management, configuration, and planning in an efficient, fast manner.
  - Self-organizing network was systematically outlined in 3GPP Release 8.
  - Traditional self-organizing networking scheme might not be feasible for 6G systems due to the presence of a complex, dynamic environment. Therefore, a novel, self-sustaining 6G network architecture must be proposed.
  - Self-sustaining 6G systems must adapt to the highly dynamic environment sustainably.

- MODELING FOR TERAHERTZ AND MILLIMETER WAVE COMMUNICATION

  - We must propose novel models (physical layer and networking layer) for millimeter-wave and terahertz bands because of their substantially different nature compared with existing lower-frequency bands.

  - For fixed nodes, terahertz communication has fewer challenges than mobile nodes. Therefore, we must propose novel schemes for terahertz communication in case of mobile nodes.

  - Based on the new design models, we can propose an optimization framework to enable 6G services according to their key performance indicators.

- ZERO-ENERGY-ENABLED 6G

  - We recommend designing zero-energy 6G systems. A 6G wireless communication system must use renewable energy and radio-frequency-harvesting energy for its operation (i.e., hybrid energy sources).

  - Energy from the grid station must be used when radio frequency harvesting energy level fall below the required energy level for their operation.

  - The zero-energy wireless system must return the equivalent amount of energy to the grid during the time of excess radio frequency harvesting energy to account for the consumed energy from the grid.

- META-LEARNING-ENABLED 6G

  - Machine learning is considered an integral part of 6G. However, training the machine learning model by selecting appropriate learning model parameters requires extensive experimentation.

  - By contrast, meta learning provides machine learning models the capability to learn. However, 6G smart applications enabled by machine learning have a substantially different nature.

  - Therefore, we recommend novel meta learning models to assist the learning of numerous machine learning models by offering them appropriate learning model parameters to enable different 6G smart applications.

  - A two-stage meta learning framework can be used to solve different machine learning problems. The first stage can select the machine learning model, and the second stage will implement the selected machine learning model.

Conclusions

- AI will be considered an integral part of 6G.

- Emerging ML schemes such as federated learning with its variants (e.g., collaborative FL) will serve as a key implementation technique for enabling intelligent wireless communication for 6G.

- Although ML can be widely used in 6G for various functions, there are still open challenges that must be resolved to truly realize the vision of ML-enabled 6G. These challenges are security, privacy, and resource allocation for distributed ML.