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Intelligence-at-the-Edge for Space-Air-Ground Integrated Networks

Digital Twins for Space Manufacturing and Satellites

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Da un secolo, oltre.

Who I am

Associate professor at the University of Florence, Italy.

Research interests: Wireless Communications and Networks, Satellite Communications and Networks, Resource Management, Edge/Distributed Computing, Joint Computing and Communication, Distributed Machine Learning, and Optimization Techniques.

Author of 72 articles, 91 conference papers, 3 book chapters. h-index: 27 (Source: Scopus)

Editorial Board member for IEEE Transactions on Vehicular Technology, IEEE Open Journal of the Communication Society and IET Communications.

Symposium co-chair for IEEE WCNC 2011, IEEE Globecom 2014, IEEE Globecom 2018, and IEEE ICC 2020, and workshop co-chair at IEEE ICC 2015 and IEEE Globecom 2024.

IEEE Senior Member since 2012

My web page: https://cercachi.unifi.it/p-doc2-0-0-A-3f2b3429353030.html

Collaborative intelligence

6G and (Artificial) Intelligence

6G as Cyber-physical continuum: connects the physical world of senses, actions, and experiences with its programmable digital representation.

6G as an Intelligent and synchronized network: delivers limitless connectivity and full synchronization between physical and digital realms.

Massive sensing: vast numbers of sensors continuously update the digital twin in real time.

Real-world actuators: execute commands from intelligent digital agents.

AI as a key enabler: artificial intelligence is essential for developing 6G applications.

AI-native system: 6G will be designed with AI at its core.

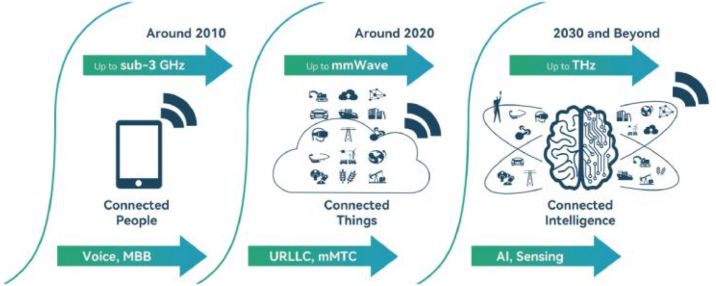
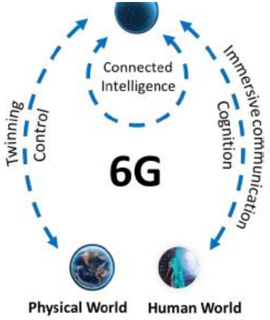
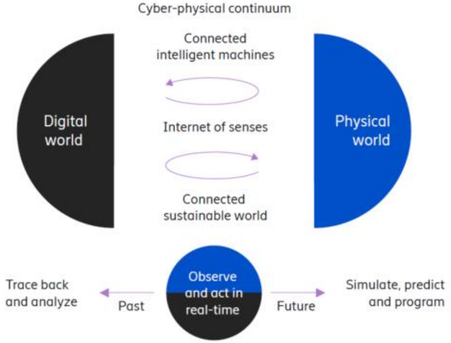


Figure 1 Mega-trends of mobile communications toward 2030 and beyond

Huawei Technology





Source: Hexa-X

Digital Twin & 6G: A Powerful Synergy

What is a Digital Twin?
A virtual, real-time model of a physical object or system, powered by data and simulations.

Why 6G for Digital Twin?
Next-gen connectivity enables real-time updates, AI-driven analytics, and seamless global integration.

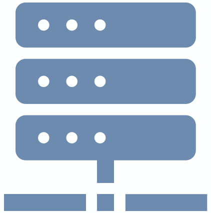
Role of Satellite Networking in 6G

- **Global coverage** for Digital Twin applications in remote, mobile, or underdeveloped regions
- **Seamless integration** of terrestrial and non-terrestrial networks (NTN)
- **High-reliability communication** for mission-critical digital twin systems (e.g., aerospace, maritime, defense)

Key Use Cases

- **Space-based Digital Twins** for satellites, spacecraft, and orbital logistics
- **Remote monitoring** of critical infrastructure (e.g., oil rigs, offshore wind farms)
- **Planet-scale simulations** for climate, agriculture, and disaster response

Enabling Technologies and Challenges for Next generation Intelligent Networks



Network Softwarization

Network Function Virtualization (NFV)

Software-Defined Networking (SDN)

Cloud Computing

Distributed Computing

Edge Computing

Enabling Technologies and Challenges for Next generation Intelligent Networks

Network Function Virtualization (NFV)

No more dedicated hardware: Network functions are no longer installed on proprietary, hardware-based appliances.

Virtualized network functions: NFV decouples network functions from hardware and runs them as software instances in VMs or containers, known as **Virtual Network Functions (VNFs)**.

Standard resource utilization: NFV enables the use of standard resources (compute, storage, networking) on **Commercial Off-the-Shelf (COTS)** hardware.

Software-Defined Networking (SDN)

Flexible and programmable networks: Enables dynamic network configuration to meet critical service and application requirements.

Logical separation of planes: SDN separates the **control plane** from the **data plane**, allowing more efficient network management.

Centralized control: A centralized controller unit handles all control operations, forming a fully programmable wireless network.

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Cloud/Edge Computing

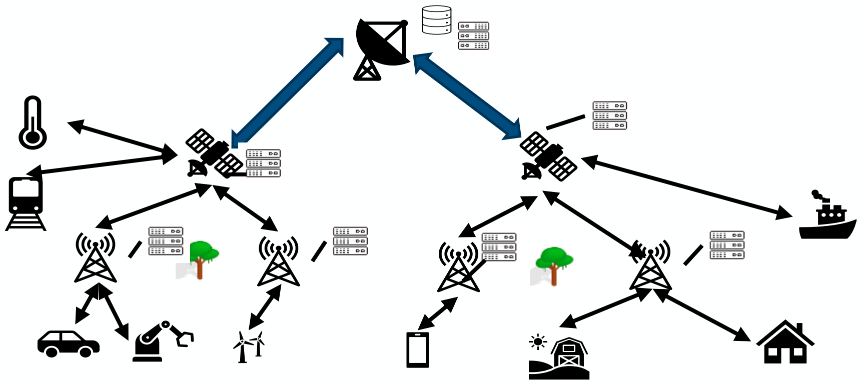
Modern applications require intensive processing.

Long transmission of tasks to the cloud causes delay and invokes extra transmission energy.

Edge Computing can overcome those issues allowing users to offload their tasks to the network edge leading to lower latency and computing agility.

Data offloading in Edge Computing has been widespread investigated where endpoints can offload to edge nodes:

- Heavy-sized tasks
- Heavy-sized processing
- Energy issues
- VNF relocation
- **ML (distributed) processing**



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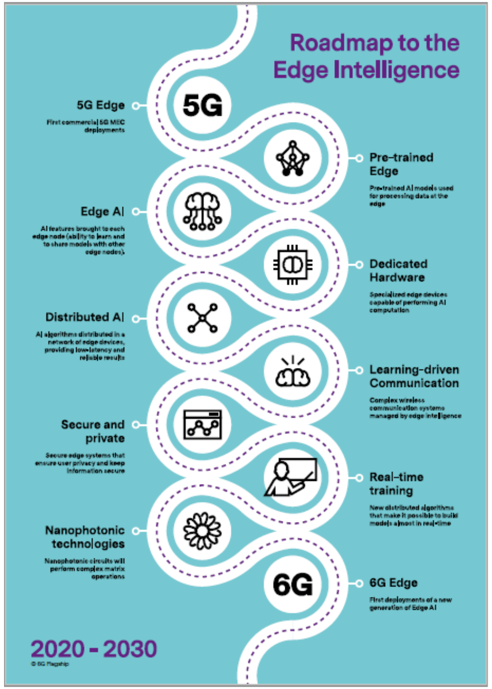
Edge Intelligence



Key enabling factor for future 6G networks

ML models with a small memory footprint, i.e., TinyML

Edge Intelligence
- Edge Computing + Machine Learning + Distributed Networks (i.e., TN/NTN)
- Data analysis and the development of solutions at or near the site where the data is generated and further utilized.
- Ideal for Latency Critical Scenarios

Further Read: https://www.6gflagship.com/6g-white-paper-on-edge-intelligence/

Machine Learning

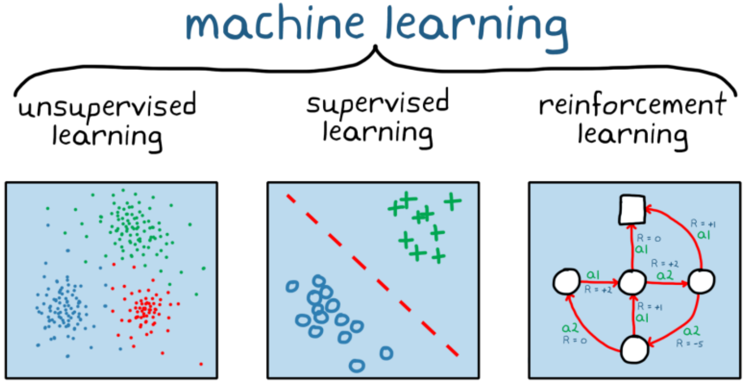
Machine Learning (ML)

- branch of artificial intelligence (AI) and computer science
- focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy (Source -IBM).

In ML an agent acts as an intelligent entity for getting knowledge for the surrounding environment

Supervised ML

- The agent is trained through labelled data
- The training data is processed, building a function that maps new data on expected output values



Source -MathWorks

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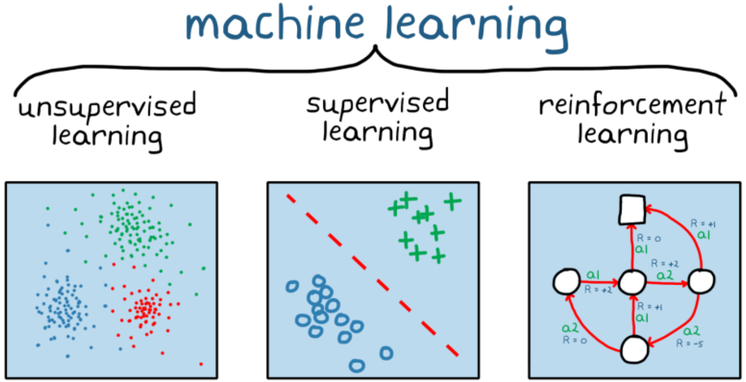
Machine Learning

Unsupervised ML

- The agent is trained through unlabeled data.
- ML tries to find similarities, differences, patterns, and structure in data by itself.
- No prior human intervention is needed.

Reinforcement Learning (RL)

- The agent is trained while processing data
- The agents take actions in an environment for maximizing a given cumulative reward.



Source -MathWorks

Machine Learning Deployment

Deploying ML machine learning is usually based on a centralized approach.

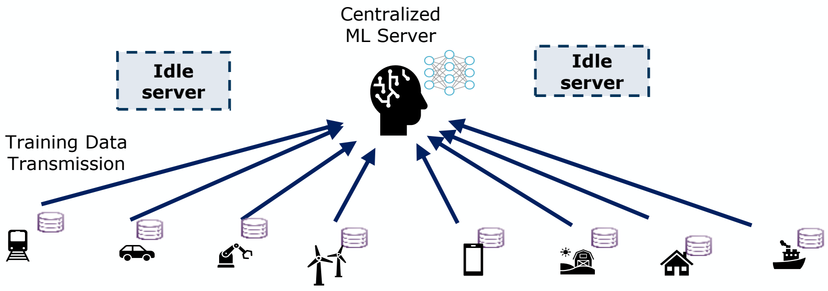
End-user data is sent to a central server (ML-server) for model training.

Data migration: Raw data from distributed users is transmitted to a centralized, resource-rich ML server.

Key limitations:

- High data transmission costs
- Increased training latency
- Serious data security and privacy concerns

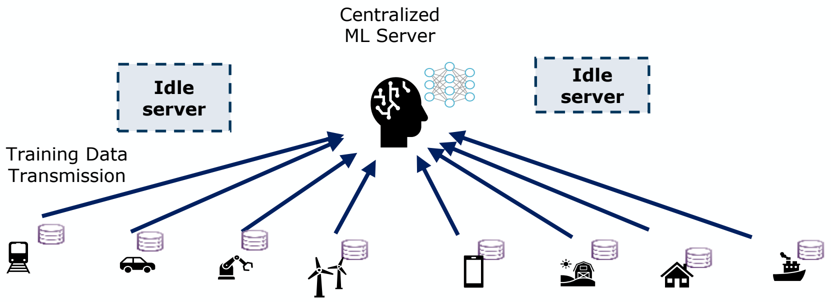
Critical in constrained scenarios: These issues are especially problematic in **satellite communication environments,** where bandwidth is limited and latency is high.



Centralized Learning (CL)

Issues associated with the centralized machine learning

- **Training** a centralized machine learning model for **very large datasets** have long training time.
- **Difficult to provide large computing power** required for training of models for large datasets within a certain amount of time.
- Communication resource occupancy due to **very large dataset transfer**
- **Privacy leakage** due migrating the devices data to the centralized server for training.



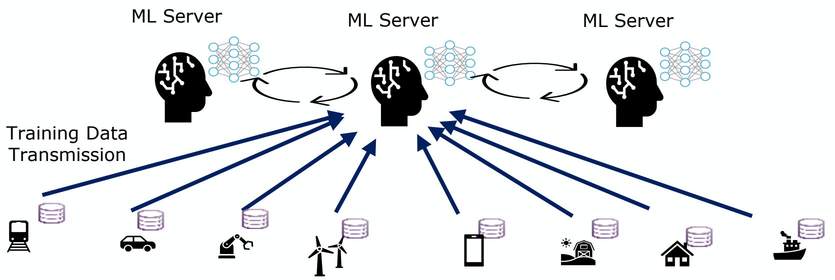
Fundamental Concepts of Distributed Machine Learning

Distributed Machine Learning allows to solve the previous issues

Distributed machine learning performs learning at various geographically distributed servers.

Two main approaches of distributed machine learning:

- **data-parallel approach**
  - data are divided among multiple servers
  - parallel training takes place for the same machine learning model
- **model-parallel approach**
  - various parameters of a typical machine learning model are trained at distributed servers using exactly the same data.
  - The model-parallel can be used only in case of machine learning model can be split



The simplest approach is data-parallel approach

- more practical because of the different data at distributed locations.

Model-parallel approach has been more recently introduced thanks to softwarization

- Models can be split into multiple blocks, each executed at a different location

Distributed Machine Learning

In the literature several models of collaborative learning have been introduced

Federated Learning: Training models across decentralized devices.

- Collaborative Federated Learning: Training models across decentralized devices through P2P connections.
- Federated Distillation: Training models across decentralized devices through output exchange.

Group alternate direction method of multipliers: Distributed learning without a central entity

Multi-Agent Reinforcement Learning: MARL allows to take into account multiple agents, acting as RL nodes, where their decision take into consideration the other agent decision

Split Learning (SL): SL divides complex ML models for distributed training, reducing resource requirements and enhancing privacy however it is a bit slow.

Transfer Learning (TL): TL leverages knowledge from previous tasks to improve training efficiency, making it a valuable complement to FL.

Federated Split Transfer Learning (FSTL): is introduced as a novel DL methodology to train ML models effectively for NTN-based, resource-constrained ITS scenarios.

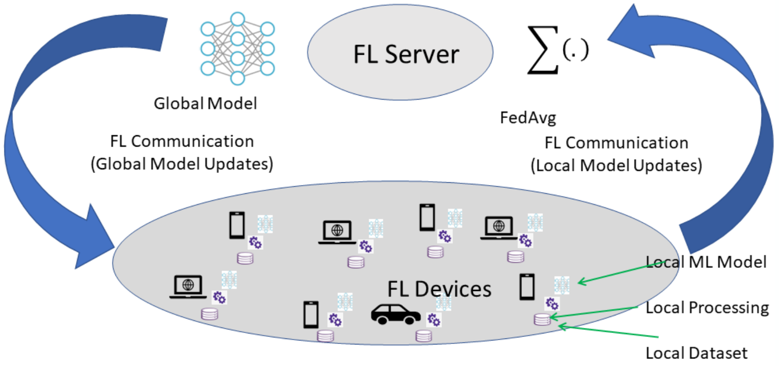
Federated Learning

Federated learning is a machine learning setting where multiple entities (clients) collaborate in solving a machine learning problem, under the coordination of a central server or service provider.

Each client's raw data is stored locally and not exchanged or transferred; instead, focused updates intended for immediate aggregation are used to achieve the learning objective.

In Federated learning clients and server do not exchange data while only the Machine Learning parameters

Reduced privacy and security concerns



Federated Learning

Popular Distributed Deep Learning Technique

- Widely adopted in wireless networks for privacy-preserving model training.

Training Flow Overview

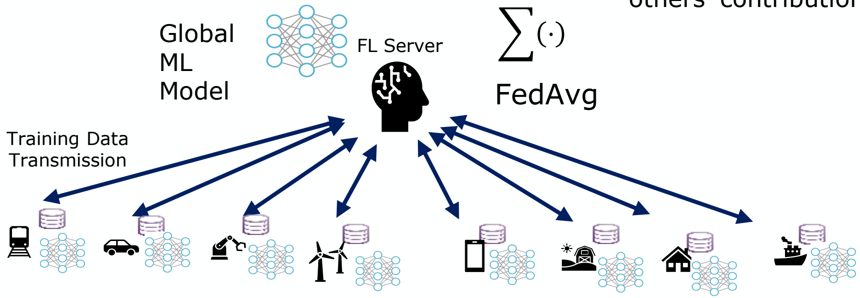
- Devices perform **local training** using their own data.
- Only **model updates** (not raw data) are sent to a central server.

Privacy-Preserving by Design

- No need to share raw data.
- Keeps sensitive user data local while benefiting from collective intelligence.

Three Main Steps in Federated Learning

1. **Local Model Training**
   - Each device trains on its own local dataset.
   - Sends updated parameters (not data) to the central server.
2. **Global Model Aggregation**
   - The central server aggregates updates from all devices.
   - Builds a **global model** based on collective learning.
3. **Model Redistribution**
   - The global model is sent back to all devices.
   - Each device improves by learning from the others' contributions.



Collaborative Federated Learning (CFL)

Challenges in Traditional FL

- Devices may face **energy limitations** or **high latency**, making direct communication with a central server difficult.

CFL: A Decentralized FL Paradigm

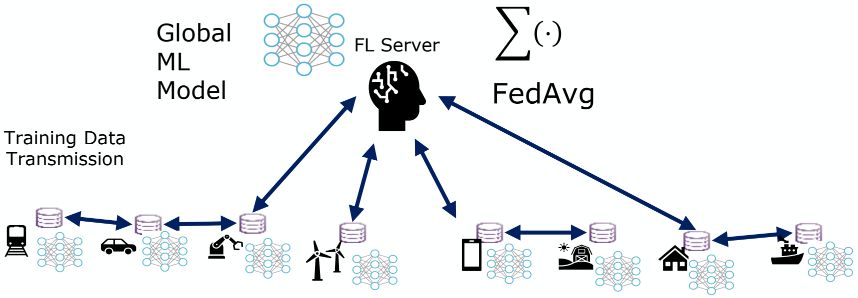
- Enables devices to **participate in FL without direct central server access.**
- Devices communicate and share models with **adjacent or nearby devices.**

Key Features of CFL

- Each device connects to **its nearest neighbors**.
- **Model training is iterative**, similar to traditional FL.
- Devices send **local FL models** to nearby devices and/or the central node.

Global Model Coordination

- A central node (if accessible) aggregates and updates a **global FL model**.
- The global model is then shared with relevant devices.



Decentralized Learning Behavior

- Devices update their local models based on:
  - Parameters received from **neighboring devices**, or
  - Updates from the **central node/base station (BS).**
- Each device must:
  - **Aggregate incoming FL models**, and
  - **Continue training** its own model locally.

Split Learning (SL)

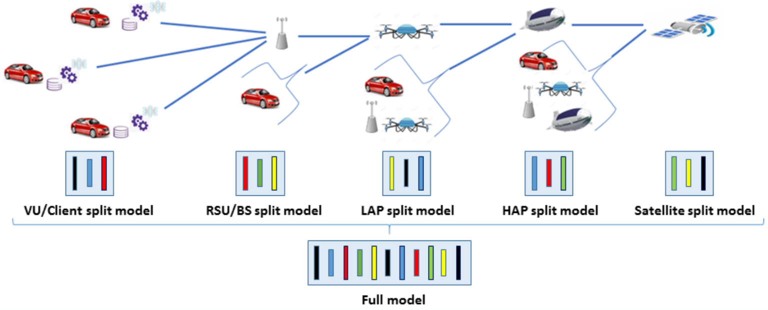
SL allows **resource-limited wireless devices** to train complex models such as Deep Neural Networks (DNN).

During the DNN training process, **the model can be split vertically or horizontally**, allowing multiple nodes to train a portion of the model with limited data samples and training latency.

SL combined with different forms of DL can be useful in dynamic settings for producing reliable complex learning models.

SL does not exchange raw data

- data privacy is maintained.



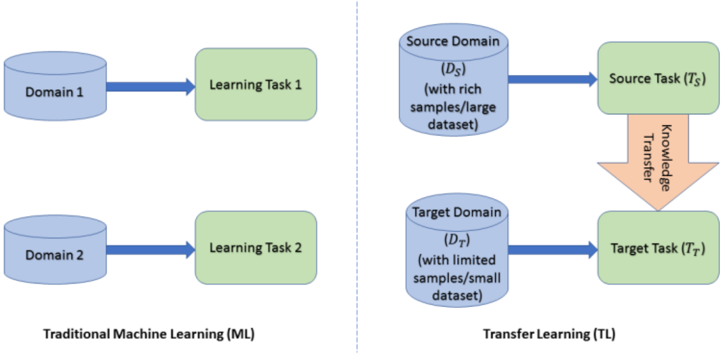
Transfer Learning (TL)

TL enables learning agents to apply knowledge from past experiences to new tasks.

Benefits in Dynamic Settings: Faster convergence, reduced need for labeled data, and improved robustness.

Knowledge Transfer Mechanisms:

- Transferring learned data features and scope.
- Sharing trained model structures and parameters.



Benefits of Collaborative Machine Learning

Challenge: Traditional centralized ML in 5G/6G requires transmitting vast device data to the core, raising privacy concerns and network strain.

Opportunity: Advancements enable on-device processing for local ML model creation. However, isolated local models can have limited accuracy.

Solution: Distributed learning techniques leverage both device-level computing and centralized processing at the network edge (edge computing).

Benefit: Edge computing enables privacy-preserving, efficient ML that utilizes the rich data generated by 5G/6G devices for intelligent network optimization.

Collaborative Intelligence at the Edge for Satellites

Satellite Networking

Satellites can be roughly classified depending on two main parameters:

- the satellite altitude
- the satellite orbital shape (i.e., eccentricity and inclination).

Based on the previous parameters (i.e., altitude, eccentricity, and inclination), it is possible to identify three major categories

- High-Earth orbit satellites, reaching about 36,000 km of altitude
  - Satellite have a geosynchronous orbit (GSO).
  - If a GSO satellite circles Earth above the equator (zero inclination), it is referred to as a GEO satellite
  - GEO satellites allow continuous connections
- Low-Earth orbit (LEO) satellites with an altitude between 160 and 1000 km
  - LEO satellites fly at a much faster pace because of their proximity to Earth (e.g., 7.8 km/s vs 3 km/s);
  - Provide intermittent connections at predictable time intervals.
  - When deployed in constellations, at least 60 LEO satellites are needed to ensure continuous coverage.
- Medium-Earth orbit (MEO) with a wide range of orbits anywhere between LEO and GEO

Why GEO – Pros and Cons

Continuous Network connectivity due to the fixed relative position

Suitable to provide coverage to a specific ground area

Stable channel conditions due to no or very small relative speed

Used for Earth Observation and Surveillance applications

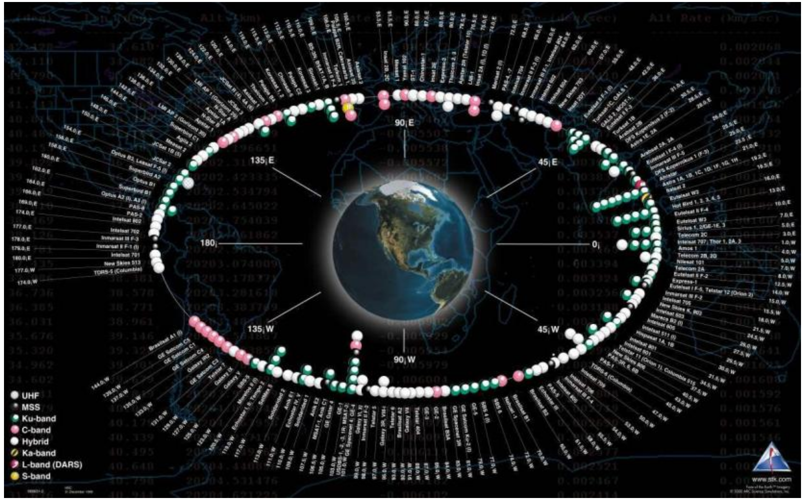
Strong processing capacities

Long latency (around 600 milliseconds RTT)

Do not allow to cover polar regions

Massive access to be considered

Reduced construction cost w.r.t LEO constellations



Why LEO – Pros and Cons

Theoretically smaller latency (around 40 milliseconds RTT)

Lower single unit cost, but requires big constellations for a full coverage

Compatibility with terrestrial devices

Very high density of nodes

Intermittent connection (single/sparse constellation)

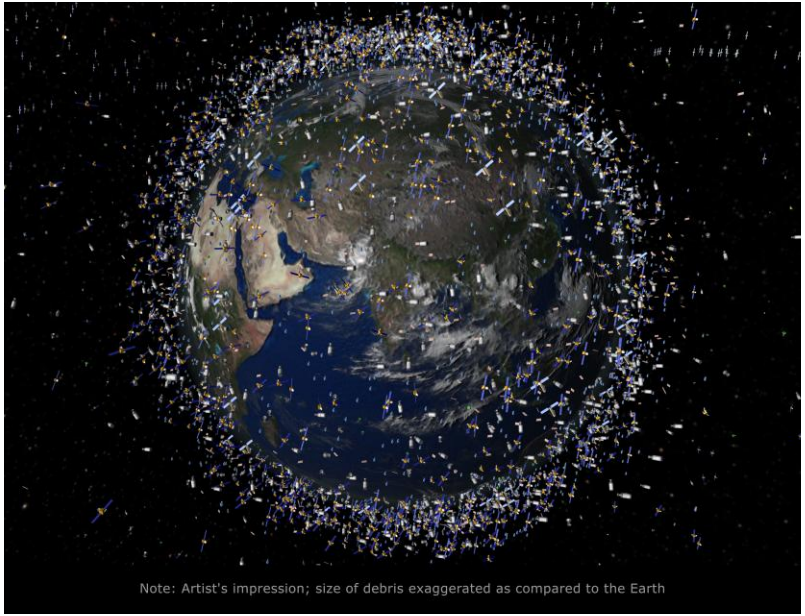
ISL latency in case of megaconstellations

Highly varying channel, despite a predictable orbital trajectory.

Reduced processing capacity

Despite reduced processing capacity, considered as a whole can give a very high processing capacity

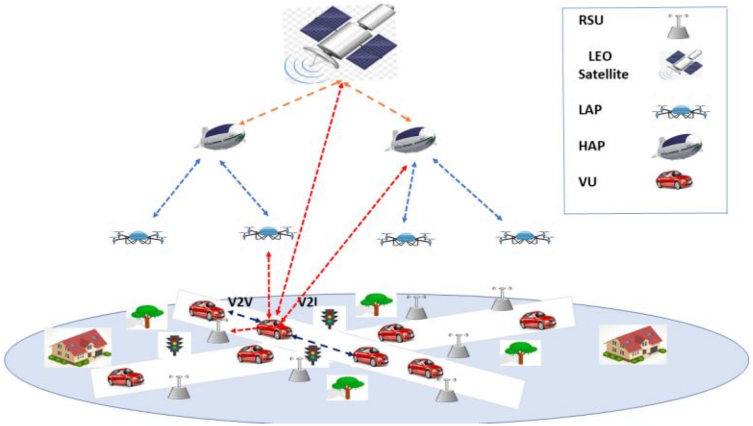
- Requires more complex coordination and orchestration



Integrated TN/NTN

TN/NTN architecture is based on the cooperation of three layers:

- Non terrestrial network: Space network
  - Global coverage
- Non terrestrial network: Aerial network
  - Wide coverage (on-demand/temporary)
- Terrestrial network
  - Capillary network



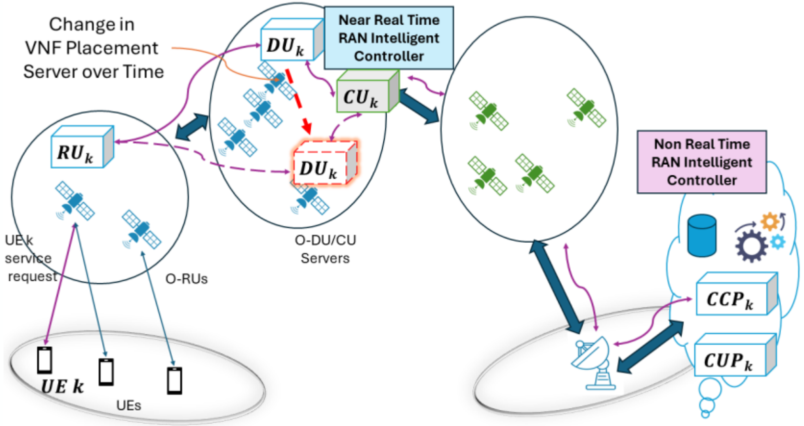
Integrated TN/NTN: A Networking Perspective

5G/6G TN are sought to be extended by integrating the NTN segment in the network architecture

Depending on the integration type several use cases are considered:

- NTN device as a User
- NTN device as a relay for backhauling
- NTN as a relay for end users
- NTN as a BS node

In all these cases NTN nodes rely on the presence of computing facilities and on softwarization for implementing advanced networking solutions



Integrated TN/NTN: A Distributed Environment

An environment characterized by several nodes scattered throughout a 3D scenario open two main perspective.

AI for Networking

- Advanced applications are characterized by an increased complexity
- A distributed environment requires advanced optimization tools
- AI is a perfect tool for optimizing and solving complex problems

Networking for AI

- AI is a fundamental element for Next Generation 6G systems
- Network design should rely on the presence of AI to be deployed throughout the system
- Distributed Networks perfectly fit with AI requirements, especially Distributed AI deployment

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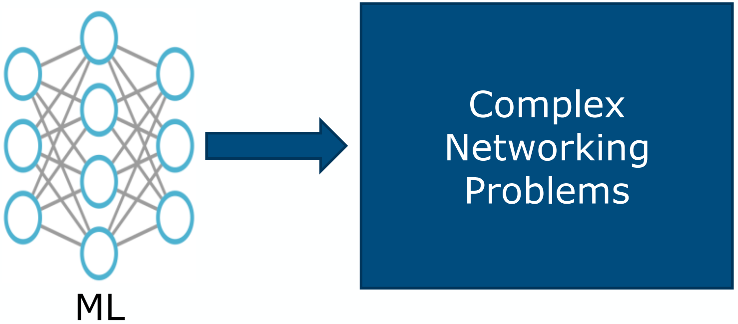
Edge Intelligence – AI for Networking

Q) How to Use ML for Solving Complex Networking Problems

Various communication and network problems such as resource allocation, user scheduling, spectrum management, etc., can be hard to solve.

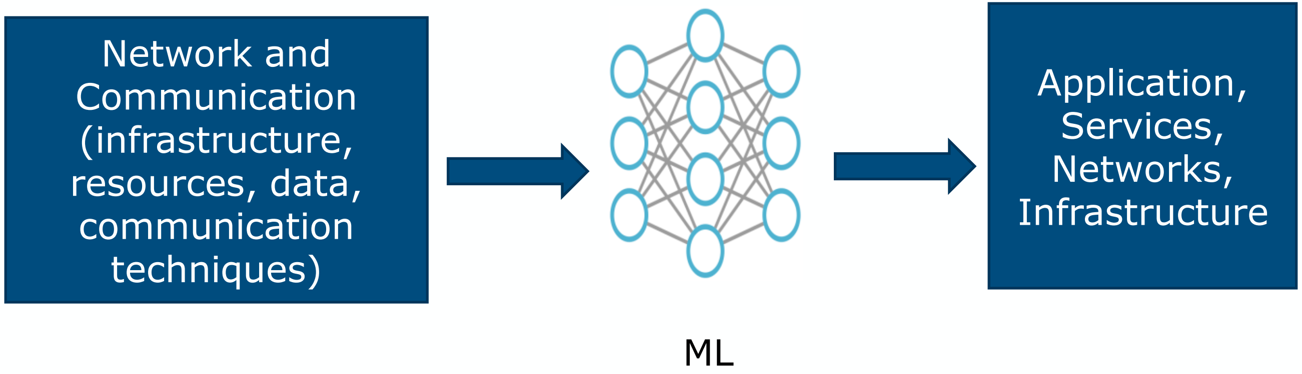
Traditional optimization techniques can be inefficient

With the availability of a large amount of data, processing power, and advanced storage techniques, ML methods are widely used over wireless scenarios

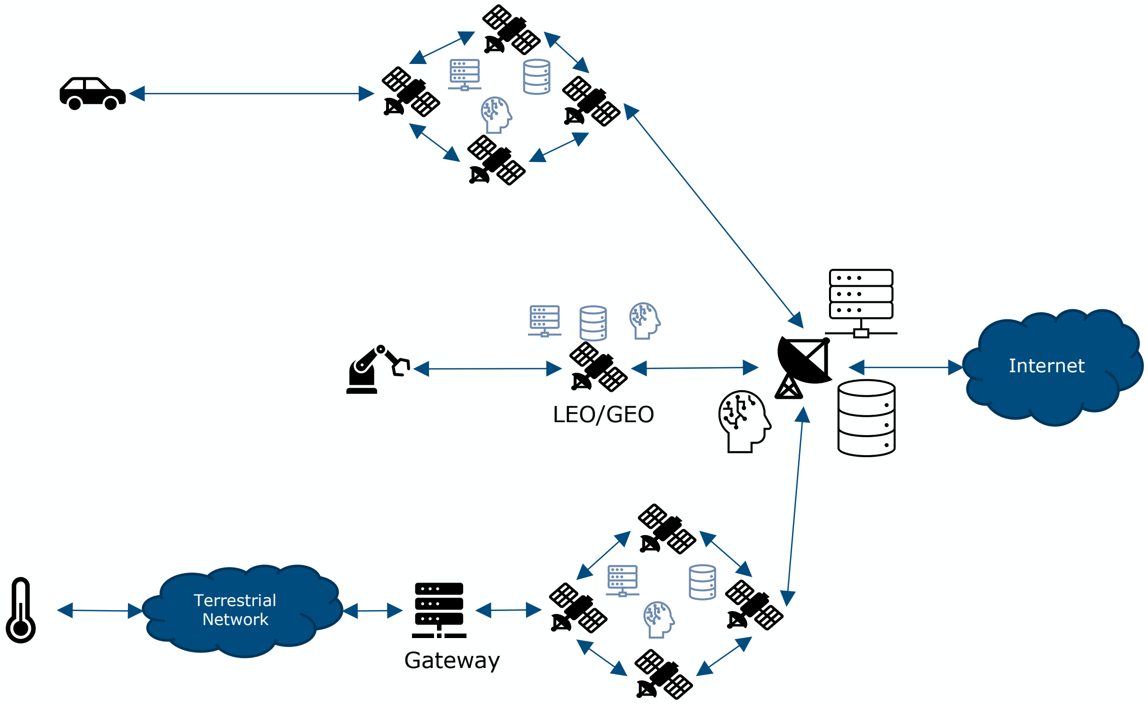


Edge Intelligence – Networking for AI

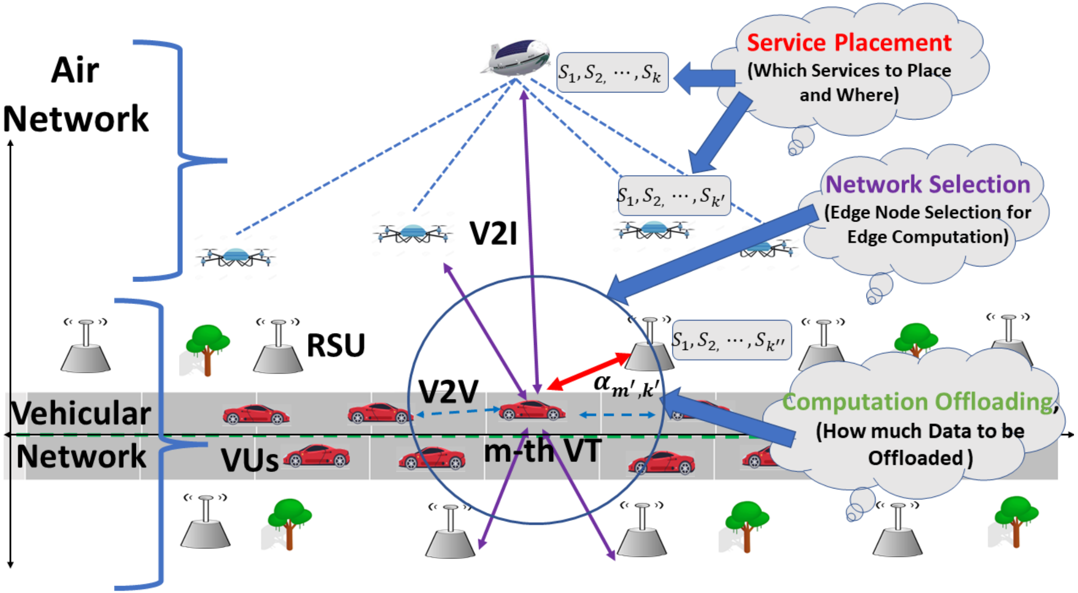
Q) How to use wireless communication to improve the ML model?



Enabling Technologies and Challenges for Intelligent NTN Networks



Integrated TN/NTN: An application driven perspective for vehicular networks



S. S. Shinde and D. Tarchi, "Multi-Time-Scale Markov Decision Process for Joint Service Placement, Network Selection, and Computation Offloading in Aerial IoV Scenarios," in IEEE Transactions on Network Science and Engineering, vol. 11, no. 6, pp. 5364-5379, Nov.-Dec. 2024

Multi-layered Edge Computing

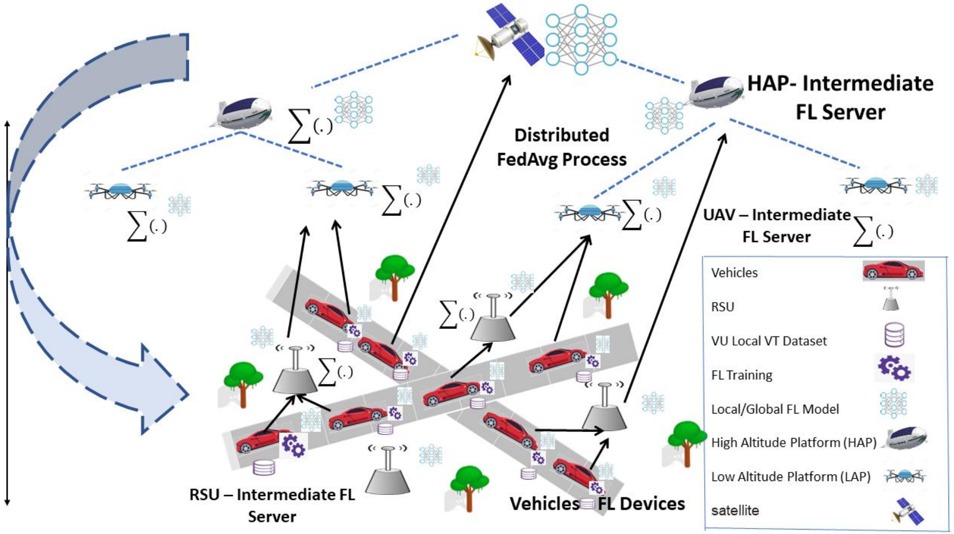
EC Platform	Advantages	Disadvantages
VEC	Reduced Transmission Distance with Line of Sight (LOS) Communication	Limited Resources, Coverage Range, Frequent Handovers
TN-EC (i.e., BS)	Higher Computation and Communication Resources, Better Coverage Range	High Transmission Delay with Degraded Channel Quality (Non-LOS Communication)
Cloud	Unlimited Resources and No Coverage Issues	Huge Transmission Delay, Backhaul Network Congestion, Security Issued Due to Long Distance Communication Channels
LAP-EC	Reduced Transmission Distances with LOS communication, Reduced Deployment and Maintenance Time and Costs	Limited Resources, Low Flight Time
HAP-EC	Moderate Transmission Distances with LOS communication, Can Have High Resources, Solar Energy Source	High Deployment and Maintenance Time and Costs Compare with LAP, Communication can be Affected by Rain Fading
Satellite-EC	High Computation and Communication Resources	Large Transmission Distances (not suitable for latency critical VN), Large Deployment and Maintenance Cost

S. S. Shinde and D. Tarchi, "Towards a Novel Air–Ground Intelligent Platform for Vehicular Networks: Technologies, Scenarios, and Challenges," Smart Cities, vol. 4, no. 4, pp. 1469–1495, Dec. 2021, doi: 10.3390/smartcities4040078.

Limited processing resources and coverage are the main bottlenecks for optimizing the performance of a distributed system.

The coverage limitations along with mobility can add extra cost in terms of handover latencies.

Satellite based Machine Learning

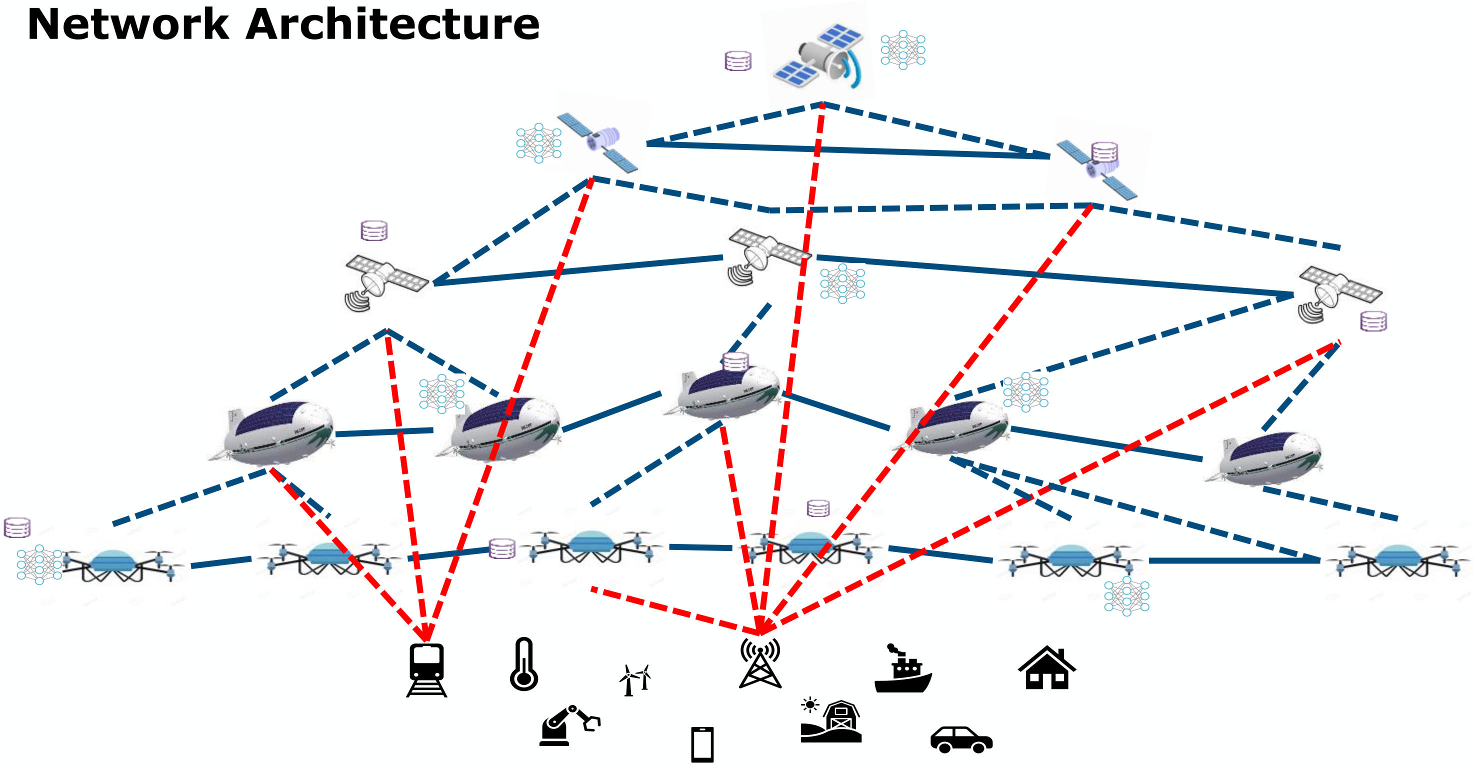


Muscinelli, E.; Shinde, S.S.; Tarchi, D. Overview of Distributed Machine Learning Techniques for 6G Networks. Algorithms 2022, 15, 210

ML Algorithms are modeled on large amounts of data and allowing network efficiency:

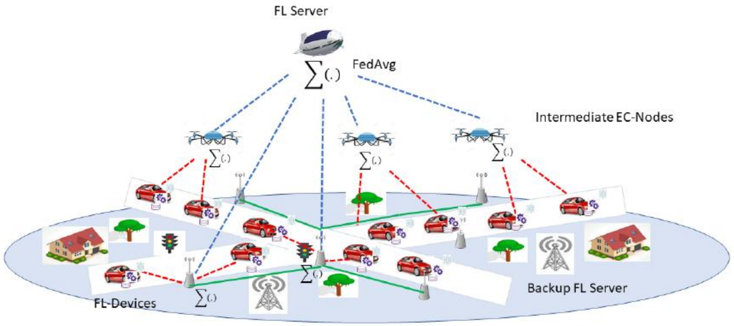
- Development of local ML algorithms.
- Development of ML algorithms by exploiting the computation offloading.
- Use of ML algorithms based on anchor points.

Multiple Edge Computing Platforms Enabled Space-Air-Ground Network Architecture

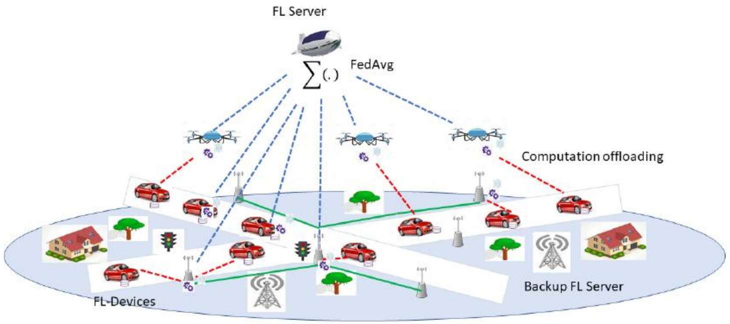


Federated Learning Platform for Vehicular Application

Hierarchical FL Platform over Multi-EC VN Architecture

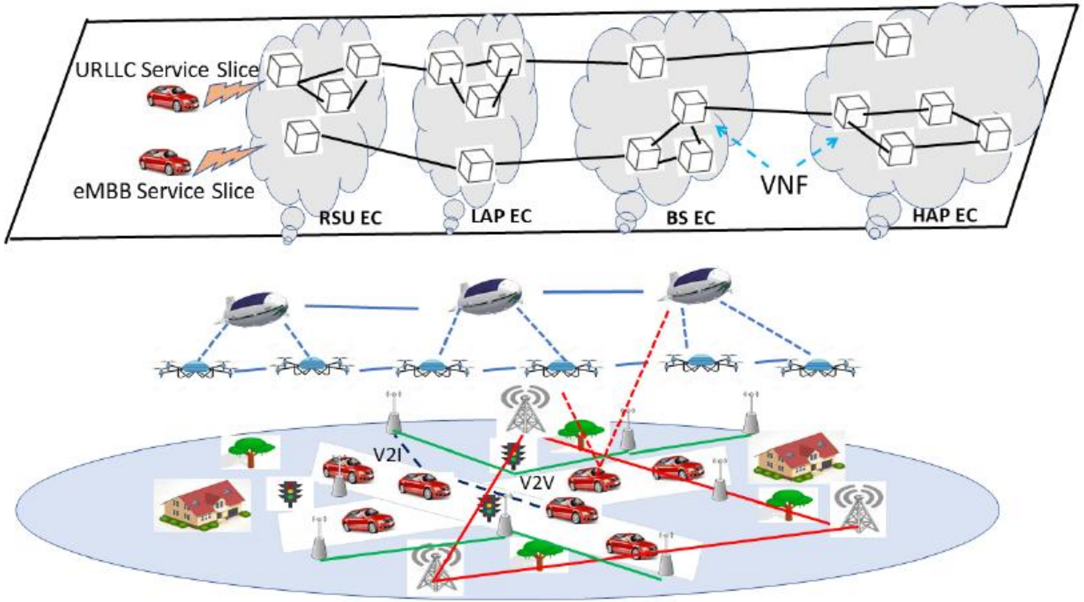


Computation Offloading based FL Platform over Multi-EC VN Architecture



S. S. Shinde and D. Tarchi, "Towards a Novel Air–Ground Intelligent Platform for Vehicular Networks: Technologies, Scenarios, and Challenges," Smart Cities, vol. 4, no. 4, pp. 1469–1495, Dec. 2021, doi: 10.3390/smartcities4040078.

ML-based Network Function Placement for Multi-service Environments



S.S. Shinde, D. Marabissi, D. Tarchi, "A network operator-biased approach for multi-service network function placement in a 5G network slicing architecture," Computer Networks, Vol. 201, 2021, 108598

Network Sliced Distributed Learning: E2E Functional Decomposition

Data Acquisition Function (DAF): The process that allows the composition of the learning dataset.

Data Preprocessing Function (DPrF): the learning data can be in different formats, e.g., texts, images, videos, etc. These data need to be pre-processed in a typical form.

Distributed Learning Function (DLF): Select the learning strategy for the successful implementation of DL..

Data Post Processing function (DPsF): Data post-processing to avoid communication overhead, limit data security risks, and add the appropriate weighting coefficients to the learning process results before its transmission to the outside world.

Data Collection Function (DCF): parameter servers to collect learning updates from the devices and create a global update that can be used for the next round of communication.

Global Model Update Function (GMUF): updates of the learning model based on learning data.

Distributed Model Inference Function (DMIF): Model inference to be considered for the successful implementation of AI applications based on DL.

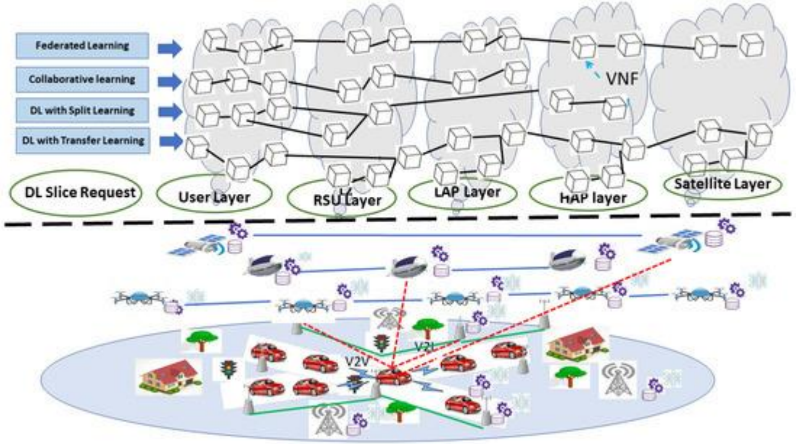
Distributed learning as a service over Network Slices

Different DL algorithms can implement different services with different requirements

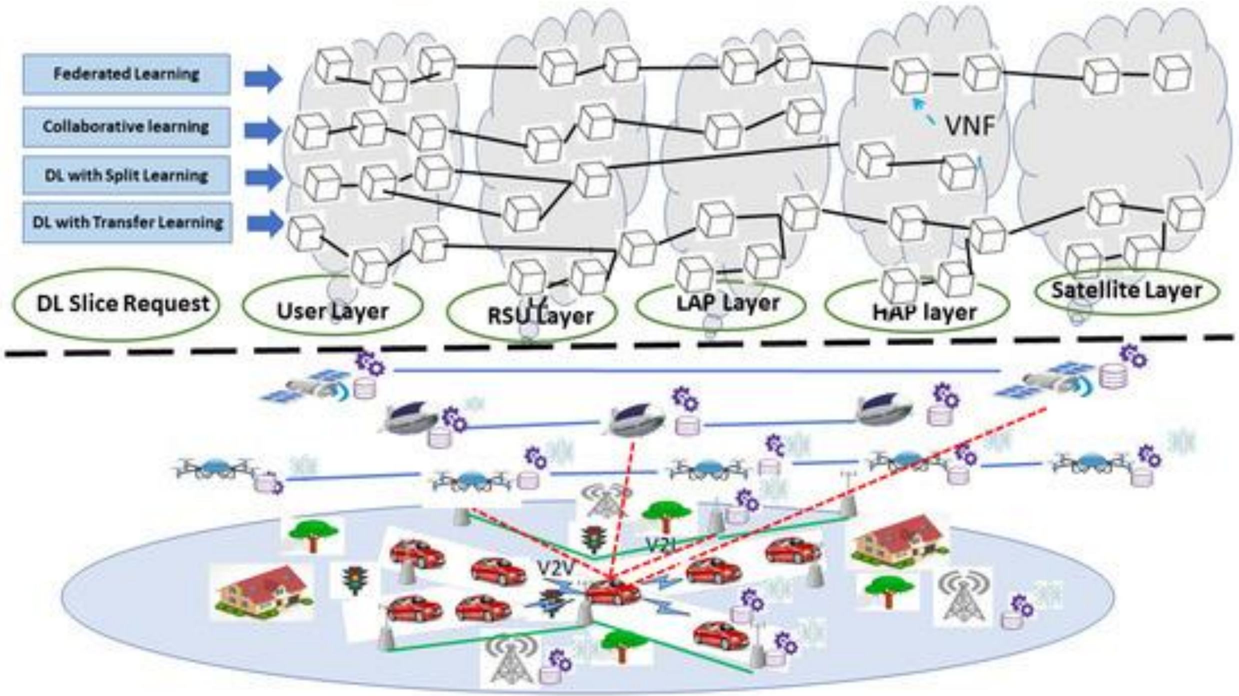
Utilize resources for intelligent 6G network with DL methods

Each network device hosts virtual functions for different DL executions

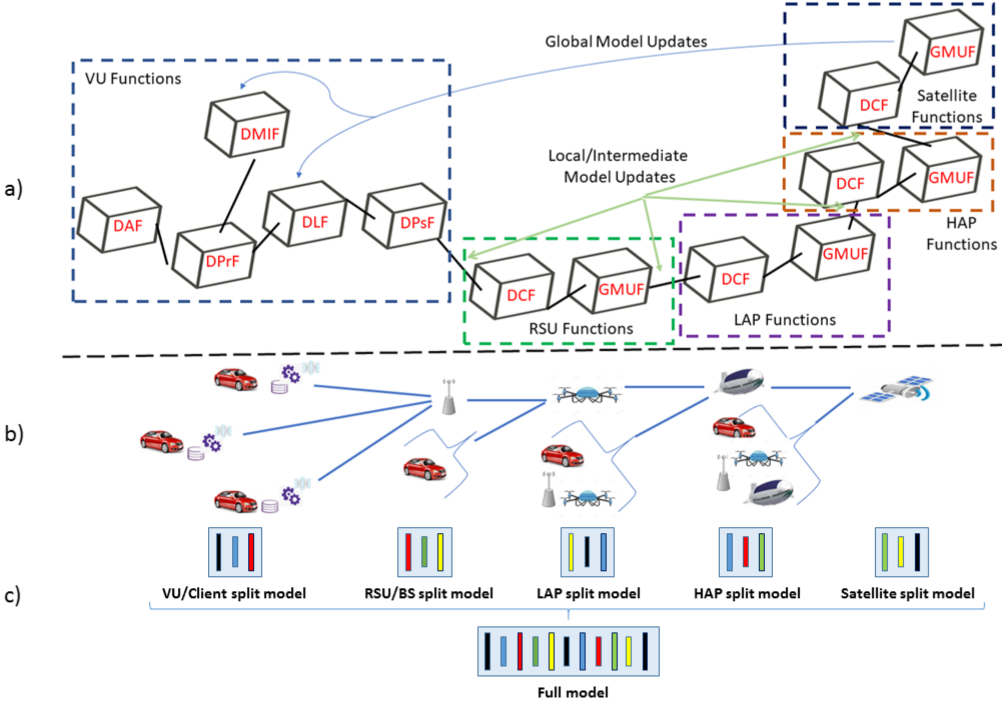
Slice-based approach used with each slice linking various functions



Distributed learning as a service over Network Slices



Multi-Layer Distributed Split Learning for Satellite IoT



Satellite-Air-Ground distributed intelligence for Intelligent Transportation Systems

Satellite-Air-Ground distributed intelligence for Intelligent Transportation Systems

An Intelligent Transportation System (ITS) adopting Internet of Vehicles (IoVs), Edge Computing, and Machine Learning (ML)

Thanks to V2X communication technologies vehicular terminals (VTs) can share their local environment parameters and become aware of their surroundings.

A distributed FL platform able to distribute the FL process on a 3D aerial-ground while reducing the overall communication cost for providing vehicular services is considered.

A constrained optimization problem for reducing the overall FL process cost through a proper network selection between various nodes.

The FL network selection problem is modeled as a sequential decision-making process through a Markov Decision Process (MDP) with time-dependent state transition probabilities.

S. S. Shinde and D. Tarchi, "Joint Air-Ground Distributed Federated Learning for Intelligent Transportation Systems," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 9, pp. 9996-10011, Sept. 2023

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Distributed Federated Learning Over Multi-layer Edge Networks

Internet of Vehicles (IoV) scenario for Intelligent Transportation Systems

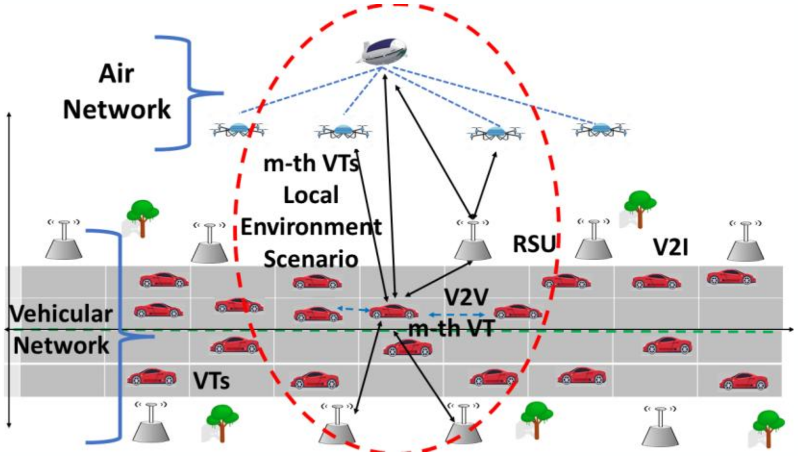
Vehicular Terminals can request heterogenous intelligent services from the nearby edge computing facilities

Edge computing facilities are deployed on a multi-layered joint air-ground network composed of HAPs, UAVs, RSUs

Such scenario may require to solve on site several challenges:

- Service selection
- Computation offloading
- Network selection

Federated learning is a viable solution for this type of problems



Motivation

Main Challenges of FL

High Training Cost: Significant resource demands (compute, data, time).

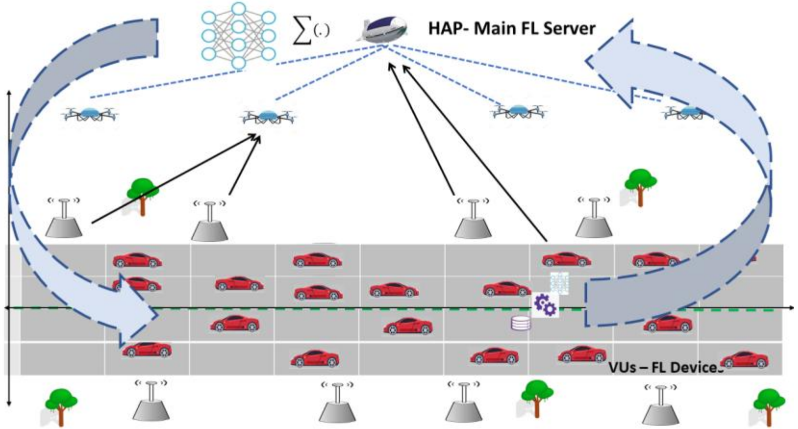
Limited Flexibility: Difficulty adapting models or training.

Slow Convergence: Requires many training iterations.

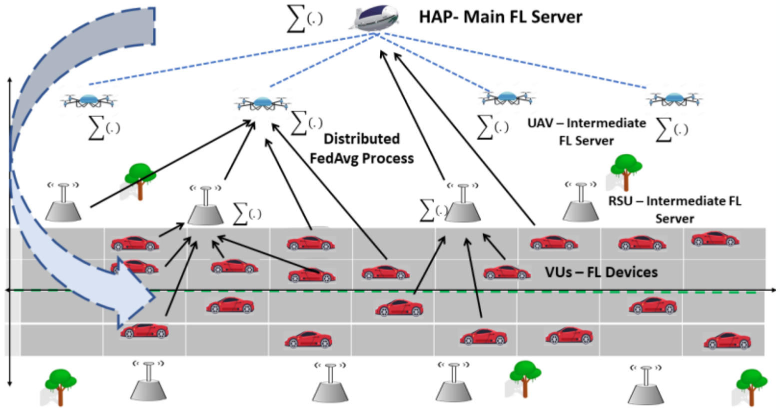
Data Imbalance: Non-uniform data distribution can bias learning.

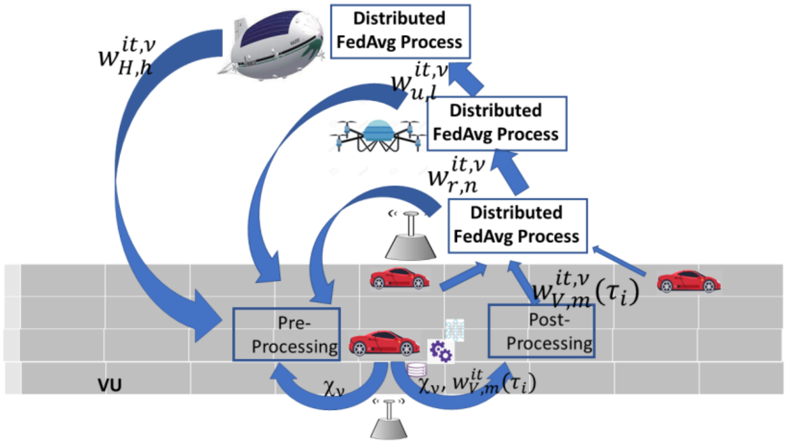
Vehicular Mobility: Dynamic environments and connectivity issues.

Traditional FL Process



Intelligence at the Edge Distributed Federated Learning for Multilayer Air Networks





Joint Air-Ground Distributed Federated Learning for Intelligent Transportation Systems - System Model

FL Local training Model

$$T_{v_m}^{\mathrm{FL,c}} = \frac{\sum_{d=1}^{\mathcal{K}_{v_m}} \psi_d}{c_{v,m} f_{v,m}}, \quad E_{v_m}^{\mathrm{FL,c}} = P_{v,m}^{\mathrm{c}} \cdot T_{v_m}^{\mathrm{FL,c}}.$$

FL Data Pre-/Post-processing

$$T_i^{\mathrm{FL,hp}} = T_i^{\mathrm{FL,pre}} + T_i^{\mathrm{FL,post}}, \quad E_i^{\mathrm{FL,hp}} = P_i^{\mathrm{c}} \cdot T_i^{\mathrm{FL,hp}}.$$

FL FedAvg Process

$$T_i^{\mathrm{FL,FA}} = \frac{N_i \cdot \psi_{FA}}{c_i \cdot f_i}, \quad E_i^{\mathrm{FL,FA}} = P_i^{\mathrm{c}} \cdot T_i^{\mathrm{FL,FA}}$$

FL Data Communication Model

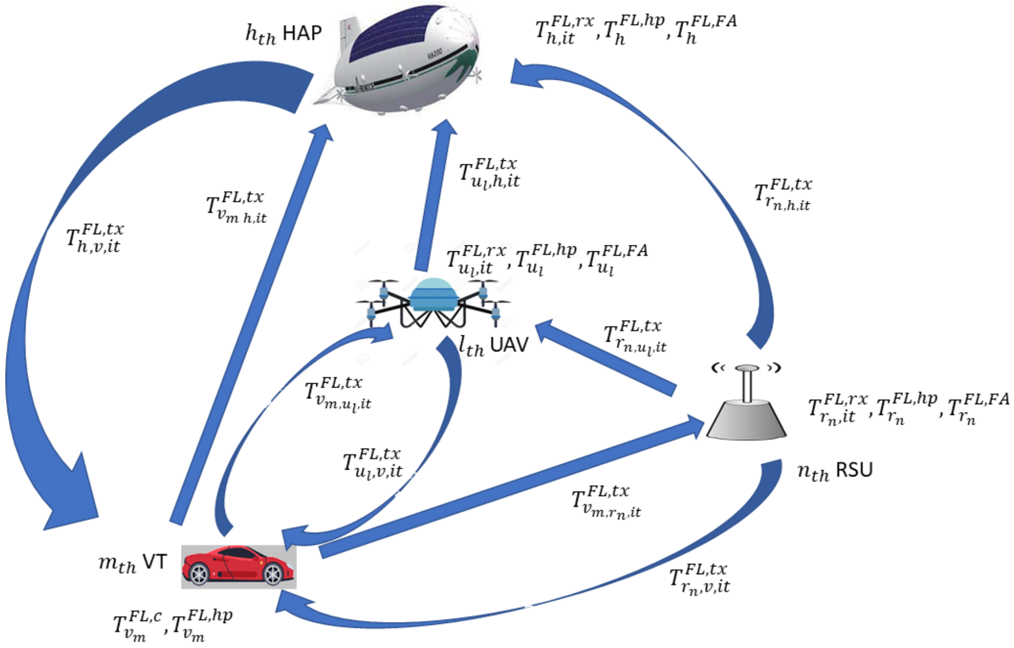
$$T_{ij,it}^{\mathrm{FL,rx}} = \frac{|w_j^{it}|}{r_{i,j}^{it}(B_i^j, d_{i,j})}, \quad E_{ij,it}^{\mathrm{FL,rx}} = P_i^{\mathrm{rx}} \cdot T_{ij,it}^{\mathrm{FL,rx}}, \qquad T_{j,it}^{\mathrm{FL,rx}} = \max_i \{T_{i,it}^{\mathrm{FL,tx}}\}, \quad E_{j,it}^{\mathrm{FL,rx}} = \sum_i P_j^{\mathrm{rx}} \cdot T_{ji,it}^{\mathrm{FL,rx}},$$

FL Cost

$$T^{\mathrm{FL}}(d(v_m, r_n, u_l, \tau_i)) = \rho T_{it}^{\mathrm{FL}}(d(v_m, r_n, u_l, \tau_i))$$
$$E^{\mathrm{FL}}(d(v_m, r_n, u_l, \tau_i)) = \rho E_{it}^{\mathrm{FL}}(d(v_m, r_n, u_l, \tau_i))$$

Distributed Federated Learning Multilayer Air Networks

The different latency components considered during the modeling of the FL latency over different nodes



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Problem Formulation and Proposed Solutions

The goal is that of performing a communication-efficient FL process over a joint air-ground network.

A proper network selection strategy over different platforms is considered

The aim is to maximize the FL process performance

$$\mathcal{A}^* = argmin_{\mathcal{A}} \left\{ \frac{1}{M_\nu^{FL}} \sum_{m=1}^{M_\nu^{FL}} \left(\eta_1 T^{FL}\big(d(v_m, r_n, u_l, \tau_i)\big) + \eta_2 E^{FL}\big(d(v_m, r_n, u_l, \tau_i)\big) + w_1 \mathcal{P}_\nu^{FL} \left(\rho\big(d(v_m, r_n, u_l, \tau_i)\big)\right)\right)\right\}$$

That is the combined set of network selection decisions of all nodes involved during the FL process, where η_1 and η_2 are weighting coefficients for balancing latency and energy consumption, and w_1 is a weighting coefficient for the penalty function for measuring the impact of the number of FL iterations performed

Model based Reinforcement Learning Solution

Proposed MDP model with time dependent state-transition probabilities

Value Iteration Approach for Finding Optimal Policy

Joint Air-Ground Distributed Federated Learning for Intelligent Transportation Systems: Decision Process Approach

Local Environment-based Multi-dimensional MDP Model (S, A, R, P, γ)

State Space: All the possible combinations of paths between the originating node and the potential processing node allowing to have a sufficient number of FL iterations

Action Space: Selection of the next node on which the FL process should be performed

Reward Function: weighted sum of latency, energy and penalty functions cost required to complete a single FL iteration

MDP Environment Dynamics: model the behavior of the MDP environment in terms of state transition probabilities based upon the agents' current state and the actions performed

Proposed MDP model with time dependent state-transition probabilities

Value Iteration Approach for Finding Optimal Policy

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Joint Air-Ground Distributed Federated Learning for Intelligent Transportation Systems: FL Network Selection Strategy

Algorithm 1 MDP Value Iteration

Input: $\epsilon, \gamma, S_\kappa, A_\kappa, Pr, \bar{K}, \Delta$
Output: $\{\pi^*_\kappa\}$

for $\kappa \in \bar{K}$ **do**
  Initialize $it = 0$, $V^0(s_\kappa(\tau_i)) = \infty, \forall s_\kappa(\tau_i)$
  for $s_\kappa(\tau_i) \in S_\kappa$ **do**
    for $a_\kappa(\tau_i) \in A_\kappa$ **do**

$$V^{it+1}(s_\kappa(\tau_i), a_\kappa(\tau_i)) \leftarrow R(s_\kappa(\tau_i), a_\kappa(\tau_i)) + \gamma \sum_{s_\kappa(\tau_i+\delta)\in s_\kappa} Pr(s_\kappa(\tau_i+\delta) \mid s_\kappa(\tau_i), a_\kappa(\tau_i)) v^{it}(s_\kappa(\tau_i+\delta)) \quad (21)$$

    end for

$$V^{it+1}(s_\kappa(\tau_i)) = \min_{a_\kappa(\tau_i)} V^{it+1}(s_\kappa(\tau_i), a_\kappa(\tau_i)) \quad (22)$$

$$\pi^*_\kappa(s_\kappa(\tau_i)) = \operatorname*{argmin}_{a_\kappa(\tau_i)} V^{it+1}(s_\kappa(\tau_i), a_\kappa(\tau_i)) \quad (23)$$

  end for
  if any $|v^{it+1}(s_\kappa(\tau_i)) - v^{it}(s_\kappa(\tau_i))| > \epsilon$ **then**
    $it = it + 1$
  else
    $\pi^*_\kappa = \{\pi^*_\kappa(s_\kappa(\tau_i))\}$
  end if
end for
return $\{\pi^*_\kappa\}$

Variants and Benchmark Methods

We model the **system as a single user**; hence, some assumption should be done for the other users:

- **Minimum distance-based assignment approach**
  - Each node is assigned to the upper layer node with the minimum possible distance
- **Random assignment approach**
  - Each node is assigned to any of the higher layer nodes with a probabilistic rule.

Benchmarks

- Conventional **Centralized FL** Process (C-FL)
  - Each VT transmits its model updates to the centralized HAP server
- **Minimum Distance Based FL** Process (MD-FL)
  - The FL process assumes that each node communicates with the nearest nodes from the upper layer
- **Random Assignment Based FL** Process (RA-FL)
  - The nodes involved in the FL process (i.e., VTs, RSUs, UAVs, and HAP) follow the random assignment strategy
- FedCPF Inspired RSU-Based
  - VTs perform the local training process and transmit the model parameters to the nearest RSU node

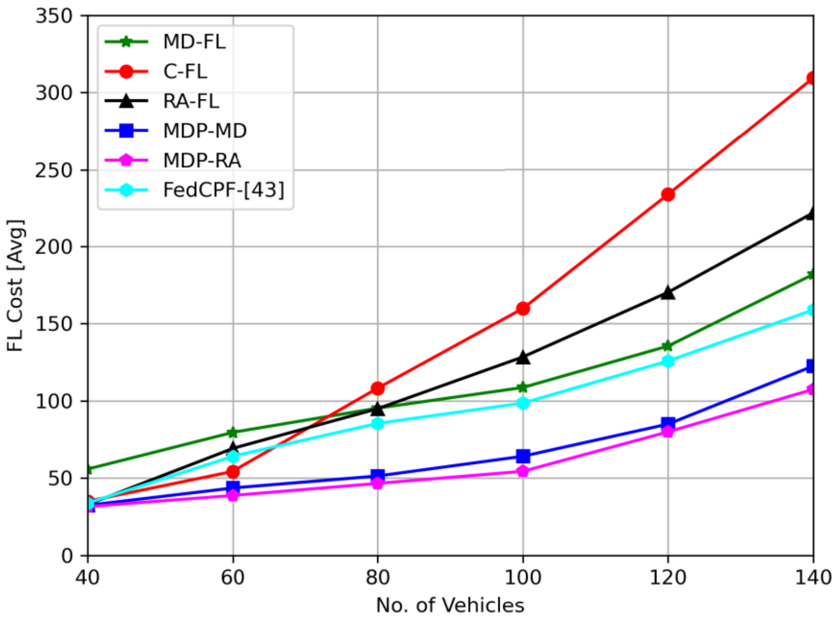
Performance Evaluation

- 1 HAP, 20 UAVs and 40 RSUs
- variable number of VTs between 200 and 700
- VT moves at a variable speed with μ=10 m/s and σ=1
- The maximum number of nodes covering any VT is given by R_{max} = 3, U_{max} = 2 and H_{max} = 1.
- Maximum number of nodes served by each RSU is 8, by each UAV is 16, and by the HAP is 32

TABLE I
SIMULATION PARAMETERS

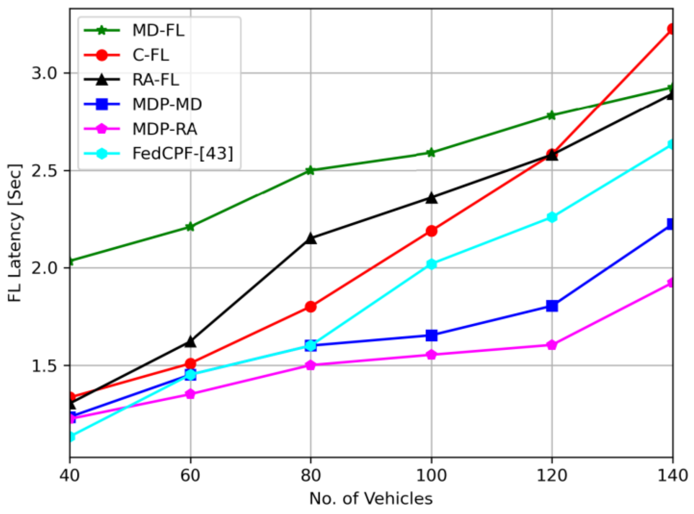
HAP Coverage (R_h)	1.2 km
UAV Coverage ($R_{u,l}$)	100 m
RSU Coverage (($R_{r,n}$))	50 m
VT Computation Cap. ($c_{v,m} \cdot f_{v,m}$)	10 GFLOPS
RSU Computation Cap. ($c_{r,n} \cdot f_{r,n}$)	20 GFLOPS
UAV Computation Cap. ($c_{u,l} \cdot f_{u,l}$)	20 GFLOPS
HAP Computation Cap. ($c_h \cdot f_h$)	40 GFLOPS
HAP Altitude ($\bar{h}_h$)	10 km
UAV Altitude ($\bar{h}_{u,l}$)	1 km
HAP Bandwidth ($B_h^{h\rightarrow(v,r,l)}$)	250 MHz
UAV Bandwidth ($B_{u,l}^{l\rightarrow(v,r)}$)	75 MHz
RSU Bandwidth ($B_{r,n}^{r\rightarrow v}$)	25 MHz
VT Speed Range ($\vec{v}_{\min}, \vec{v}_{\max}$).	(8 m/s m/s, 14 m/s)
HAP Power (Pt_h, Pr_h)	(1.1, 0.9) W
UAV Power ($Pt^l_{c,u}, Pr^l_{c,u}$)	(1.2, 1) W
RSU Power ($Pt^n_{c,r}, Pr^n_{c,r}$)	(1.3, 1.2) W
VT Power ($P^m_{c,v}, Pt^m_{c,v}, Pr^m_{c,v}$)	(1.1, 1.5, 1.3) W
Noise Power (N_T)	−110 dbm [44]
FLOPs Required ($\psi_{pre}, \psi_{post}, \psi_{FA}$)	$10^4, 10^4, 10^5$ FLOPs
Weighting Coefficients (η_1, η_2, w_1)	(0.5, 0.5, 1)

Federared Learning Process Cost

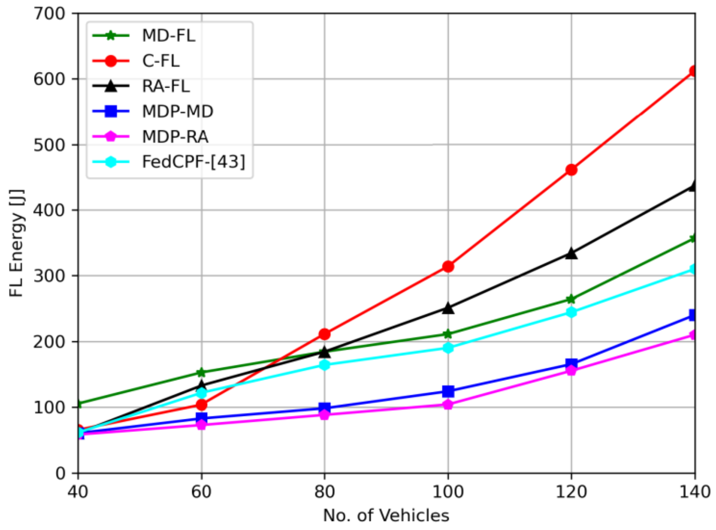


Federated Learning Latency and Energy Cnsumption

FL latency with variable number of active vehicles

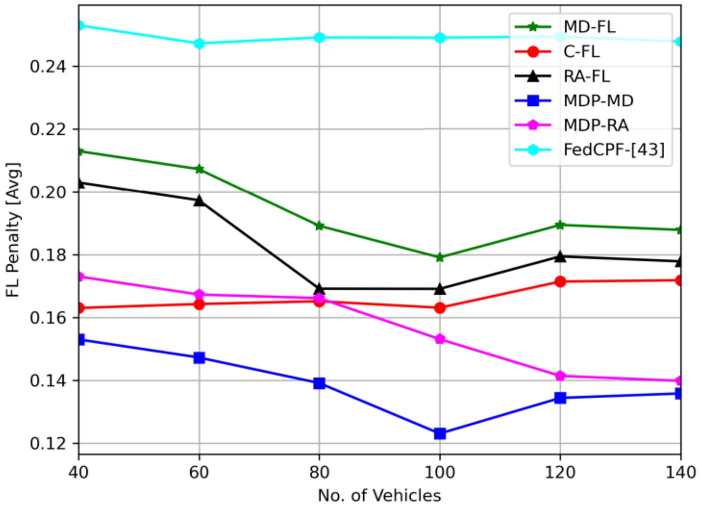


Energy consumption for the FL process with variable number of active vehicles.

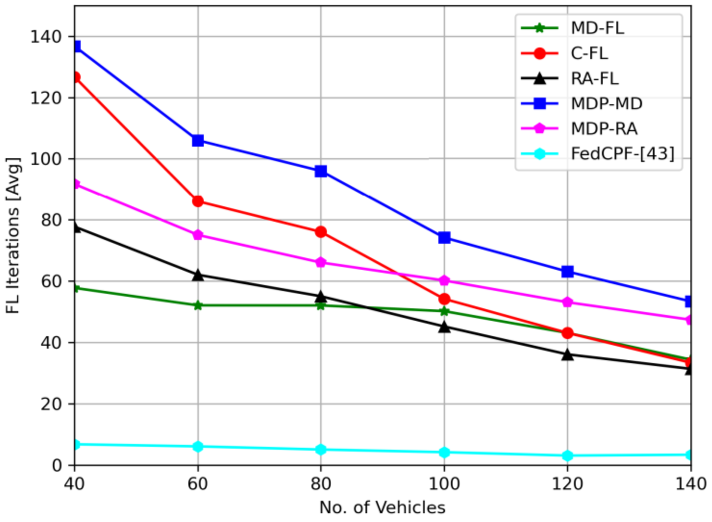


Federated Learning penalty and Iterations

FL Penalty value with variable number of active vehicles.



Average number of FL iterations with variable number of active vehicles



Conclusion

Machine Learning, NTN, and Edge Computing are expected to play an important role in the upcoming 6G world.

Edge-based AI Applications can fulfill the goal of a connected intelligence for vehicular applications

Distributed Learning at the edge can enable the AI@Edge or Edge Intelligence

Satellite Communications can be used to optimize the learning methods with improved performances in wide areas and/or remote areas

6G Networks are expected to support native AI features

Publications (AI for Networks)

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Naseh, David; Shinde, Swapnil Sadashiv; Tarchi, Daniele, Network Sliced Distributed Learning-as-a-Service for Internet of Vehicles Applications in 6G Non-Terrestrial Network Scenarios, «JOURNAL OF SENSOR AND ACTUATOR NETWORKS», 2024, 13

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joint communication and EDGE COmputing Load Balancing for satellite networks (EDGECOLB)

Ongoing project funded by ESA

Partners: DLR (Contractor), University of Florence and Thales Alenia Space Italy (Sub-contractor)

Main Objective:

- Develop load balancing techniques for onboard critical computational tasks as a trade-off between large in-situ computational resources versus distributed processing among less powerful (satellite) nodes and the consequent communication overhead

Sub-goals to be fulfilled:

- Feasibility analysis of the implementation of edge computing and load-balancing schemes in space able to meet the payload constraints of current and future satellite systems.
- Implement AI-based solution in order to achieve deep optimization
- Draw a technology roadmap towards the actual productization of the explored concepts and developed solutions

ITA NTN Project: expected results and envisaged impacts

Design a **3D multi-layered communication architecture** for integrated T/NT networks

Evaluate the **link budget** (Focus on free-space, optical, and radiofrequency communication links)

Design of **advanced transmission techniques**

Conceive innovative methodologies for the **orchestration of communication and computational resources**

Evaluate the **performance** of conceived approach (Proof of Concepts)

Contribute to the ongoing **definition of the 6G**

Define **digital, secure and sustainable** techniques

Reduce the **Digital Divide** (connectivity as a fundamental right)

Improve knowledge through **dissemination**

ITA NTN
Integrated Terrestrial and Non-Terrestrial Networks
PI: Prof. Luigi Alfredo Grieco
Poliytechnic of Bari

5G-STARDUST

Full name: Satellite and Terrestrial Access for Distributed, Ubiquitous and Smart Telecommunications

Stream: A-01-02 Ubiquitous Radio Access

Project Coordinator: Tomaso De Cola, DLR

Technical Manager: Mathieu Arnaud, Thales Alenia Space (F)

Partners: DLR, AW2S, CNIT, CTTC, Fraunhofer Instituite, Hispasat, Martel Innovate, Orange, SRS, Thales Alenia Space

Project Ambition: Design, develop and demonstrate a deeper integration of TN and NTN

- Deliver a fully integrated 5G-NTN autonomous system with novel self-adapting end-to-end connectivity models for enabling ubiquitous radio access.

Among other parts AI on space is considered

https://www.5g-stardust.eu/

Intelligence-at-the-Edge for Space-Air-Ground Integrated Networks

Digital Twins for Space Manufacturing and Satellites

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