Federated Learning for 6G HetNets' Physical Layer Optimization: Perspectives, Trends, and Challenges Federated Learning for 6G HetNets' Physical Layer Optimization

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Chapter 70

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Perspectives, Trends, and Challenges

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ABSTRACT

This chapter presents a survey that focuses on the implementation of federated learning (FL) techniques in sixth generation (6G) networks' physical layer (PHY) to meet the increasing user requirements. FL in PHY perspectives are discussed, along with the current trends and the present challenges in order to deploy efficient (cost, energy, spectral, computational) FL models for PHY tasks. Moreover, the utilization of FL methods is, also, discussed when channel state information (CSI) is not guaranteed in a 6G scenario. In such conditions, the joint use of cell free (CF) massive multiple-input-multiple-output (mMIMO), reconfigurable intelligent surfaces (RIS), and non-orthogonal multiple access (NOMA) and FL methods is proposed. Finally, an FL-based scheme for relay node (RN) placement in 6G networks is presented as an indicative use case for FL utilization in modern era networks. Results indicate that the proposed FL scheme overperforms state-of-the-art centralized learning schemes concerning the trade-off between machine learning (ML) metrics maximization and training latency.

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1. INTRODUCTION

1.1 The Need for Distributed AI/ML Models in 6G Networks

With the rapid growth of the Internet of Things (IoT), industry 4.0, augmented/virtual reality (AR/VR) applications, massive data volume is generated by end-user devices. In fact, according to Ericsson (Ericsson, 2022), the monthly global internet average per smartphone is expected to exceed 20GB at the end of 2023, while be 2027 all mobile data traffic growth will come from fifth-generation networks (5G), as the fourth-generation network's (4G) traffic will decline. On the same framework, by 2028, 5G's share of mobile data traffic is forecast to grow to 66 percent. Moreover, IoT and connected car applications are expected to be the most growing application type.

5G, which have been recently deployed around the world, support a wide range of trending applications by categorizing them in different usage scenarios. In this way, both enhanced Mobile Broadband (eMBB), massive Machine Type Communications (mMTC), and Ultra-Reliable-Low-Latency Communications (URLLC) are supported. However, despite the numerous benefits of 5G networks, the large amount of generated data and the need for real-time responses by the network itself have raised the discussion in both industry and academia over a new generation of wireless networks, the sixth generation (6G). The main goal of 6G networks, as described in (Letaief *et. al*, 2019), is to provide the relevant technologies that can transform the "connected things" world (as expressed by the 5G-related worldwide wireless web (WWWW) and the service-based architecture (SBA) model) into the "connected intelligence" world by implementing data-aided models for diverse tasks, applications, and Open Systems Interconnection (OSI) levels.

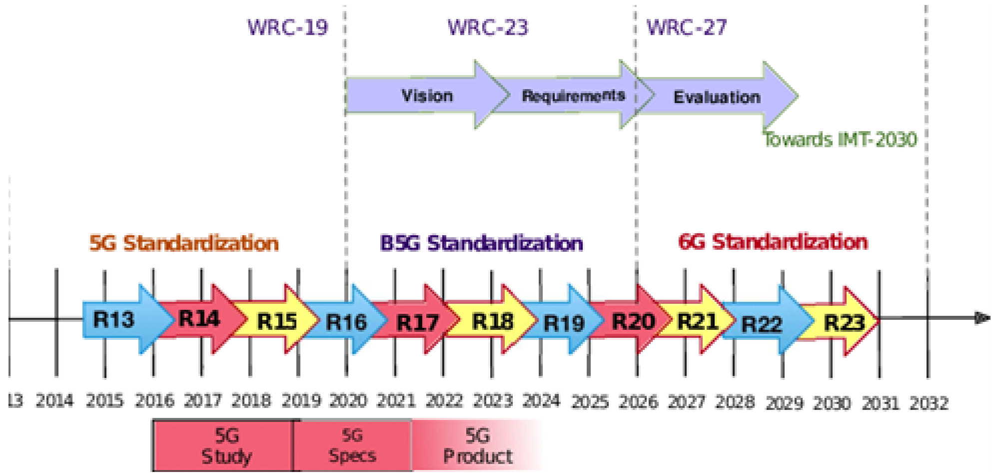
It is already visible that to achieve the aforementioned revolution, user requirements should be even more demanding in 6G networks than the ones existing in 5G. As depicted in both (Letaief *et. al*, 2019) and (Wang *et. al*, 2023), these extended requirements are expected to be the following:

- Increased data rates around 1 Tbps.
- Energy efficiency (EE) as the primary Key Performance Indicator (KPI) to support dense connections and mass connectivity for energy/battery-saving IoT devices and Unmanned ground, air, surface or undersea Vehicles (UxVs).
- Enhanced low latency which is translated in less than 1ms end-to-end latency.
- Upper millimeter wave (mmWave) communication bands and Terahertz bands (e.g., 73GHz-140GHz and 1THz-3THz).
- Increased coverage by minimizing the disconnection probability.
- End-to-end Artificial Intelligence (AI) and Machine Learning (ML) capabilities.

It is significant to point out that 6G standardization is in its early phases currently (see also Fig. 1) and the expected International Mobile Telecommunications-2030 (IMT-2030) standard is to set all the 6G-relevant requirements and use cases. However, the need for new service types beyond the 5G ones (eMBB, uRLLC, mMTC) has been identified. As described in (Letaief *et. al*, 2019) and (Wang *et. al*, 2023) these are:

- **Computation Oriented Communications (COC)**, where distributed and in-network computation enabled by federated learning and edge intelligence, will provide the relevant service provisioning, and define the quality of service (QoS) flows to maximize also computational accuracy.

Figure 1. 5G to 6G standardization progress (Rahman et al., 2021)



- **Contextually Agile eMBB Communications (CAeC)**, which extends 5G eMBB to be more agile and adaptive to the network environment, the physical environment, and the social environment.
- **Event Defined uRLLC (EDuRLLC)**, where 5G uRLLC is extended to support uRLLC in extreme or emergency scenarios where user density, traffic patterns, mobility models and spectrum availability is dynamically changing (opposite to 5G, where uRLLC is performed in static environment conditions).

In the aforementioned evolution, which will be introduced by 6G networks, AI and ML, are recognized as the most significant tools to extract knowledge from available data, support decisions and automate processes. However, the tremendous amount of data (big data) that is produced by the 5G/B5G/6G networks, due to the existence of multiple users in dense environments, which are used in the learning models, such as artificial neural networks (ANNs), support vector machines (SVMs), or training algorithms, such as reinforcement Q-learning models, or deep reinforcement learning (DRL), need powerful computational resources to produce the learning outcome and tune the relevant hyperparameters (Elbir *et. al,* 2021). It is foreseen that the aspect of fast training and response times is vital for the feasibility and efficiency of ML tasks in the context of 6G networks.

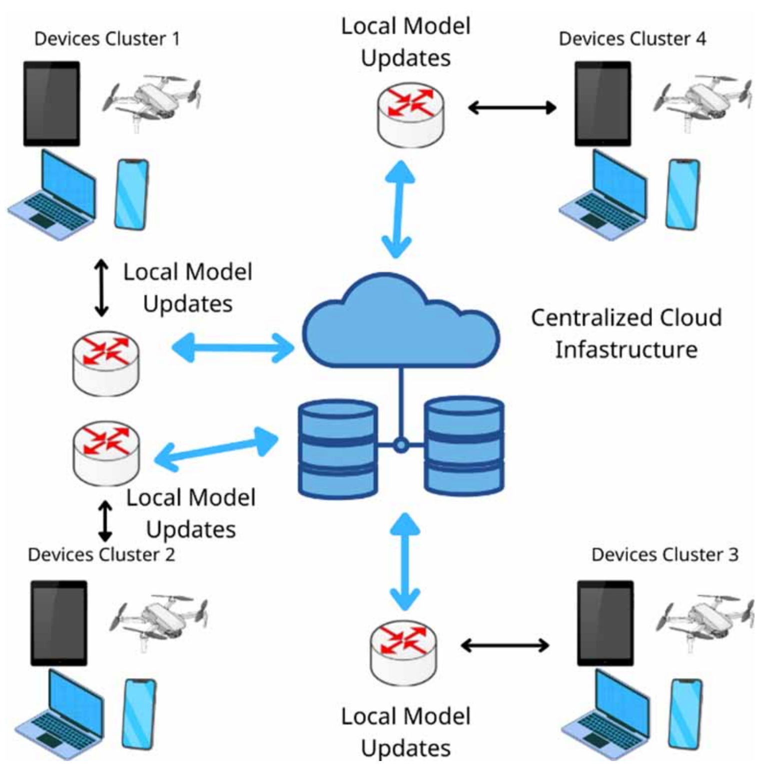
Traditional ML techniques (Supervised, Unsupervised, or even classic distributed learning techniques), which rely on a centralized entity to produce the learning outcome (centralized learning – CL), can phase difficulties in dealing with the limited computational power available on a single machine, memory constraints, scalability and training of complex algorithms on a single machine. For example, most ML models are trained in a central server with lots of processing unit power to produce a global model that will be used by either the network or the end user. However, in the context of 6G networks where numerous interconnected devices, machines and sensors are demanding continuous access to the medium, the computation overload needs to me shared among them, so that the aforementioned challenges can be handled. In this framework, CL approaches may have a significant number of drawbacks when comes to the efficient use of AI/ML techniques, such as not real-time responses, local data dependency, and security threads (e.g., single point of failure). Thereby, decentralized and distributed ML strategies should be taken into account (see also Fig. 3 (a)).

A promising way to tackle these challenges is a specific type of distributed learning technique, introduced in (McMahan, 2017), denoted as Federated Learning (FL), which combines mobile edge computing (MEC) and ML. The key characteristic of FL is that edge devices contribute to a global ML model construction, only by transmitting locally trained models' parameters to a central entity, e.g. a centralized server. This means that the training sets of each enrolled edge device are not distributed to the server, maintaining a secure and robust learning framework (Chen *et. al.*, 2020). FL can also be performed without even sending parameters to the server. In these cases, neighboring devices form a device cluster to exchange parameters for ML models' construction (Yang *et al.*, 2022). As it is visible, a significant advantage of FL schemes has to do with their ability to reduce communication overhead and secure communication, as there are no datasets distributed. For all these reasons, FL has gained increasing interest for compute vision tasks (Elbir *et al.*, 2021).

Recently, FL has been proposed as a promising solution in different physical layer (PHY)-related tasks in 5G and 6G networks. Traffic data are continuously generated by user equipments (UEs), while parameters such as channel state information (CSI) are also present in each UE – Base Station (BS) link. Thus, real-time decision-making can be FL-driven to provide robustness in minimizing the time between data generation and data utilization for these purposes. Thus, FL is useful for convex and non-convex problems in 6G networks', such as interference management, radio resource management (RRM), user profiling and grouping, BS -or even relay node (RN)- selection and others.

Figure 2 (Bartsiokas *et. al.*, 2022) illustrates an FL framework in the context of new era wireless networks as previously described. As stated in (Bartsiokas *et. al.*, 2022):

Figure 2. Federated Learning (Bartsiokas, 2022)



Counter to CL methods, where local data (from UEs in 5G/B5G (Beyond 5G) networks) are uploaded to a centralized server, and also counter to classical distributed approaches, where data is uniformly distributed among the edge devices, FL schemes use local data to train a global model, through multiple training iterations across interconnected edge devices (UEs), in order to achieve the desired global accuracy. Then, local updates, generated by each interconnected device, are aggregated to a cloud or a MEC server (in BSs).

In such scenarios, FL targets ML KPIs (accuracy, F1-score, root-mean-square-error (RMSE)) maximization by the application of multiple communication rounds between the server and the edge devices to train and/or update the model with local datasets.

1.2 Chapter's Scope and Related Works

As the generated data from end-users and the connected devices grow, user demands for uninterrupted access to the medium and ultra-low latency communications, which are translated into network requirements for real-time responses and guaranteed Quality of Service (QoS) and Quality of Experience (QoE) levels, become even more challenging. Moreover, in 6G networks, the use of advanced PHY technologies is mandatory and concerns terahertz communications, massive multiple-input-multiple-output (mMIMO) antennas, non-orthogonal multiple access (NOMA), and cell-free (CF) topologies. These technologies, when applied in a dense environment characterized by high interference levels and complex channel approximations, with increased connection density and near-random user mobility patterns, maximize the computational cost to support strict users' requirements and demands.

This chapter presents a survey that focuses on the utilization of FL techniques in 6G networks' PHY. FL in PHY perspectives are discussed, along with the current trends and the present challenges in order to deploy efficient (cost, energy, spectral, computational) FL models for PHY tasks (such as RRM, BS, or RN selection and placement). Moreover, the utilization of FL methods is, also, discussed when CSI is not guaranteed in a 6G scenario. In such conditions, the joint use of CFmMIMO, NOMA and FL methods is proposed.

The emerging need for FL techniques in PHY, which is presented in the previous sub-section, has, also, motivated other research efforts over the last years. The research efforts under review in this sub-section, have focused on FL deployment for several 6G-related scenarios, applications, and problems. Table 1 summarizes these works, presenting the area(s) of interest and the corresponding contributions.

It is foreseen that, while FL overview has been, also, presented in the other research works, these approaches either consider cross-layer approaches ((Liu *et. al.*, 2022), (Al-Quraan *et. al.*, 2023), (Luo *et. al.*, 2023)) or focus on a different 6G aspect (e.g. security (Sirohi *et. al.*, 2023)) or in another OSI level (e.g. (Yang *et. al.*, 2022)). The proposed chapter focus on discussing the research progress in FL-base methods in the PHY layer -similar to (Elbir *et. al.*, 2021)-, but presents up-to-date research efforts in the field, as well as discusses an exact paradigm to identify the potential gains of FL implementation in 6G networks' PHY.

The key contributions of this chapter are the following:

1. A state-of-the-art review of the most recent FL-based approaches in 6G networks PHY is performed. We are focusing on different RRM sub-problems, such as subcarrier or Physical Resource Block (PRB) allocation, channel estimation, BS or RN selection and others. Moreover, the joint utilization

Table 1. Related Works

Survey	Year	Area(s) of Interest	Significant contributions, conclusions
Liu *et. al.*	2022	Paramilitary considerations about the integration of FL methods in 6G	6G requirements for FL application; need for communication-efficient, secure and effective FL
Al-Quraan *et. al.*	2023	Challenges and future directions FL applications in wireless networks	Cross-layer challenges such as data quality or insufficiency, resources management should be taken into account; Communication latency minimization; encryption mechanisms
Luo *et. al.*	2023	Network layer architecture for FL in 6G networks	Optimization approaches to address the heterogeneity issues in FL; incentive mechanism design; network management; model optimization
Sirohi *et. al.*	2023	Security aspects in FL models construction	Vulnerabilities and threads in FL application concerning space, air, ground, and underwater communications; base models; dataset quality; Blockchain; Encryption
Yang *et. al.*	2022	Overview of FL applications for envisioned sixth generation (6G) wireless networks	Essential Requirements; Potential applications; Open problems and discussions
Elbir *et. al.*	2021	FL for PHY layer design	Symbol detection; channel estimation; beamforming; complexity issues
This chapter	2023	FL for different PHY tasks focusing on RRM; Challenges and research directions	Research efforts presentation; Data issues for FL; enabling technologies; practical paradigm to highlight FL significance

of FL and modern PHY technologies, such as NOMA, CFmMIMO and RIs, is, also, of interest in this review process. The principles of such novel PHY technologies are previously depicted, to introduce the reader to the relevant concepts.

2. Moreover, an indicative comparative simulation scenario is performed to display the potential gains of FL methods implementation in PHY in 6G orientations. More specifically, we develop, train and test several ML models for the effective RN placement in 6G networks' topologies. The ML models are deployed either in a CL or an FL manner. Thus, performance evaluation discusses the FL advantages and disadvantages compared to existing (CL) solutions. In this way, relevant conclusions are made.
3. Thus, the ultimate goal of this chapters is to depict the FL schemes' advantages in 6G wireless systems over the state-of-the-art CL schemes. Moreover, the challenges in designing and deploying such approaches (FL ones) are identified, and, thus, relevant future research trends and directions are given.

2. BACKGROUND

2.1 Distributed Learning Types

As it is depicted –among others- in (Bartsiokas *et. al.*, 2022) ML algorithms' basic classification is performed based on the type of data that they process (labeled or unlabeled) and the corresponding mechanism that is used. To this end, supervised learning considers labeled datasets where the training outcome is a trained model which is used to perform the mapping between the dataset's (test set) features and response variable. Typical supervised learning problems are classification and regression. On the other hand, unsupervised learning considers unlabeled datasets, where the models itself tries to identify relations between different features. Reinforcement learning, utilizes an entity -called agent-, which interacts with the learning environment in order to adjust learning parameters and meet the used KPIs' target values by receiving rewards or penalties after its selected actions. In this process, a learning entity, called agent, is used. Besides the aforementioned types of learning, another learning type is Deep Learning (DL), which is an ML subset, that utilizes multiple layers in neural networks (NNs) significantly larger than the other types, to extract hidden relations between different features. Typically, DL is related to Big Data existence, which makes it vital for wireless networks, where the amount of data generated huge.

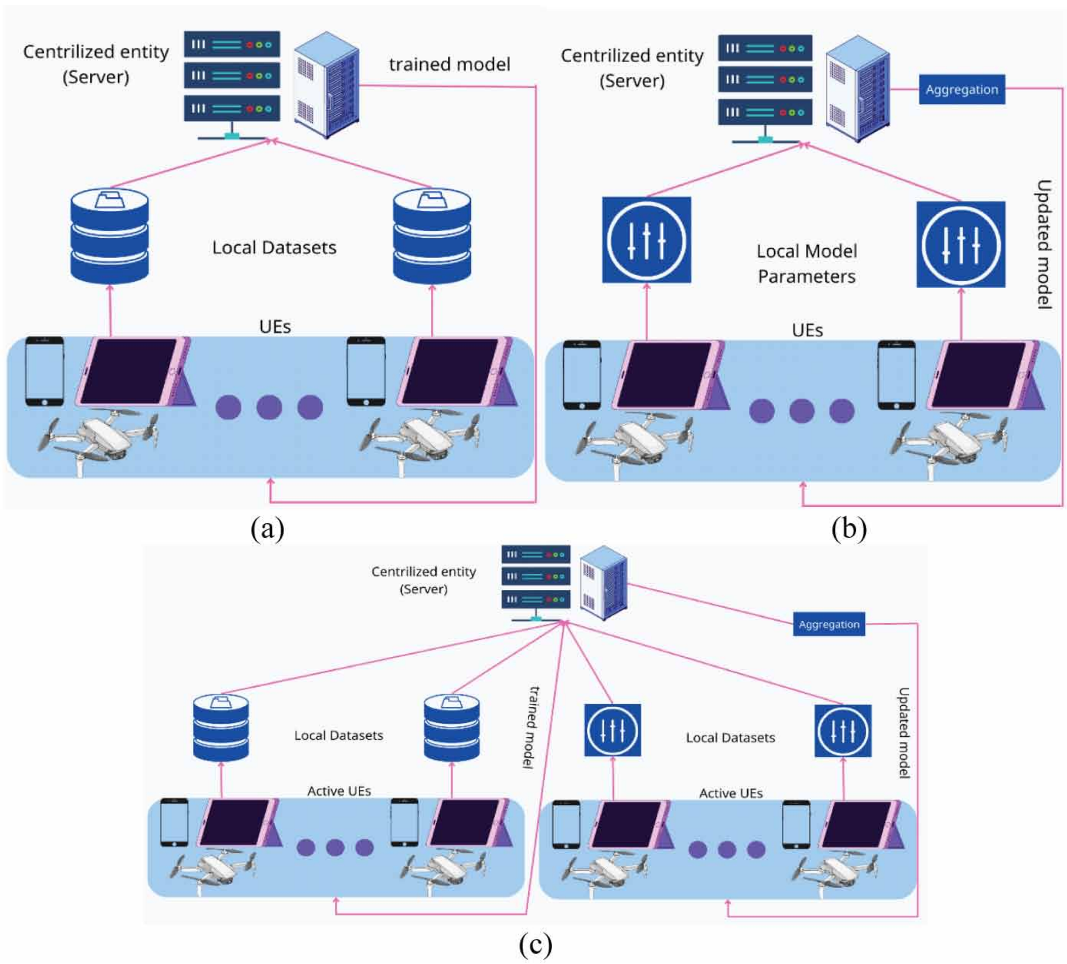
When it comes to the distributed ML techniques, where multiple nodes should cooperate to construct a global ML model, the following tree-type classification exists (as also depicted in Fig. 3):

- In CL, edge devices send their locally gathered data to a centralized entity for training purposes (see Fig. 3a). Thus, the distributed computation is limited to the transmission of the local datasets to the centralized server (Abdulrahman *et. al.*, 2020). The key advantage of CL methods is that a total dataset is formed, which helps towards the maximization of ML KPIs, due to the increased amount of data that are existing (Elbir *et. al.*, 2021). On the other hand, the need for whole datasets transmission to the centralized entity has two basic drawbacks. The first one is related to the increased interference and overhead that is introduced, which, also, affects the total response time, a vital aspect concerning the real-time decision-making nature of 6G communications. The latter is the possible security vulnerabilities and threads that can phase privacy data through transmission.
- In FL, edge devices gather their local data and form a local model, which training is performed at the edges. However, the centralized entity's role is to aggregate the different model's parameters, gathered from the edge devices, and, then, distribute the aggregated parameters or the model updates back to the edge devices (UEs). It is visible that the role of the centralized entity is the flow management of the whole process (Elbir *et. al.*, 2021), (Rodríguez-Barroso *et. al.*, 2023) (Fig. 3b). The key advantage of FL, compared to CL, is that the transmission overhead is minimized, due to the fact that only ML models' parameters or updates are transmitted to the centralized entity. However, this comes along with the drawback that ML KPIs performance may decrease because the amount of data in each of the separate distributed models is significantly less (Rodríguez-Barroso *et. al.*, 2023), (Elbir *et. al.*, 2021).
- In hybrid schemes, CL and FL are combined, to produce a more dynamic framework that can be used in practical scenarios. The need for such schemes originates from the imbalanced computation capabilities of different UEs in wireless networks. In fact, there are computationally powerful UEs, such as computer systems, local networks or even servers, but there are, also, non-powerful UEs, such as cell phones or UxVs. In such scenarios, computationally powerful UEs perform FL tasks (active state), while the others not (inactive state) (Elbir *et. al,* 2021), (Elbir *et. al.*, 2022), as also depicted in Fig. 3c.

2.2 Physical Layer Enabling Technologies in 6G

Building upon the newly developed 5G communication networks, 6G communications focus on the utilization of a number of existing (5G) PHY technologies, but also several new-coming technologies

Figure 3. (a) CL, (b) FL, (c) Hybrid architectures



are proposed in order to enhance the networks' capabilities. The most significant of them, concerning current research in the field, are briefly presented in this paragraph.

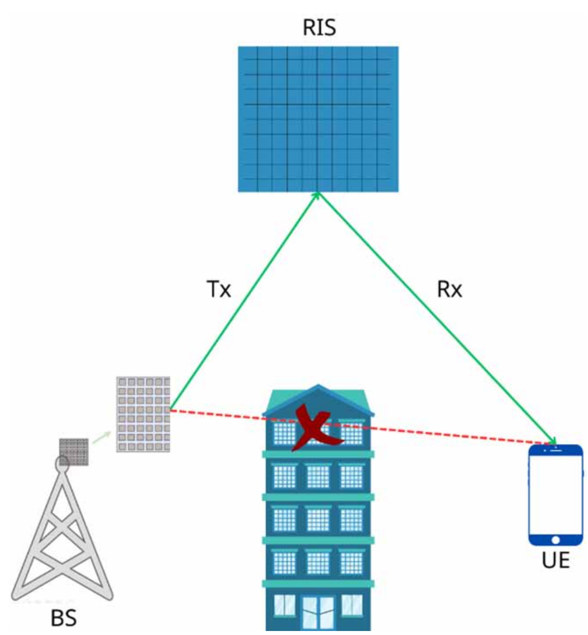
2.2.1 New Spectrum - Terahertz (THz) Communications

In 6G systems, where killer applications will be AR/VR and holographic communications, the need for large data transmission, results in a need for a very high-frequency band to support the increasing service scenarios demands (Hong *et. al.*, 2022). THz and sub-THz bands have been proposed as a potential solution towards this direction. These bands are spread from 0.1 to 10 THz (Han *et. al.*, 2022). However, several challenges have been witnessed in these scenarios. First of all, such a high-band transmission can serve really short-range coverage. Thus, ultra-massive MIMO antenna systems in BSs should be used and BSs should be located near to each other. Limitations can, also, be witnessed concerning hardware availability, transmission power, and increased pathloss (Hong *et. al.*, 2022).

To overcome these difficulties, 3 key technologies have been proposed, gaining increasing interest among the research community in the field. These are:

- **Ultra-massive MIMO:** Antenna arrays can contain over 10,000 very small antenna elements, forming ultra-narrow band beams. In this way, pathloss considerations can be mitigated. Moreover, by the formulation of hundreds of beams the system capacity can be increased and a large number of users can be supported. Furthermore, co-channel interference is also mitigated due to the narrow-band nature of the links (Hong *et. al.*, 2022). However, the necessity of deploying a lot of antennas over short distances may lead to mutual correlations between each other.
- **Cell-free (CF) mMIMO:** A promising technique to mitigate interference between neighboring cells, which are deployed close to each other in 6G orientations, is CF mMIMO. In such case, Access Points (APs) are spread in the coverage area to support UEs that demand service. A central processing unit (CPU) maps UEs to APs. This technique has great influence when CSI changes, even in the order of milliseconds in 6G, which means that certain system parameters become quickly obsolete. In particular, CF mMIMO systems result in negligible effects of small-scale fading by exploiting channel hardening (Vu, 2020). Also, in the case of CF mMIMO, the probability of coverage is higher. In this direction, given that as the number of users increases, the total training time is significantly prolonged. Moreover, APs are equipped with a smaller number of antennas resulting in less demanding power requirements. However, a drawback that has been identified in some research efforts (Wu & Zhang, 2019) is that as network size increases, limitations can exist in the scalability of this approach.
- **Reconfigurable Intelligent Surfaces (RIS):** RIS is proposed as an efficient solution to enhance connectivity in 6G networks, taking into account the hardware and deployment costs. As depicted in Fig. 4, a RIS-assisted wireless link, utilizes an intelligent surface, which is composed of a num-

Figure 4. RIS-assisted wireless 6G communication between BS and UE



ber of 3D reflection units, between the BS and the UE. Thus, intelligent beamforming is achieved by the relevant dynamic adjustment either in the amplitude or the phase of the incoming signal. RISs have a relay role in end-to-end communication, and, as a sequence, they can efficiently be used in blind network spots or to extend the coverage area of the network (Liu, 2021).

2.2.2 Non Orthogonal Multiple Access (NOMA)

In 5G networks, orthogonal frequency multiple access (OFDMA) techniques are utilized, leading to quite good results in terms of the provided QoS levels, but also an increase in the spectral efficiency. The number, however, of the subcarriers used is finite. Thus, the number of users who have access to radio resources, also, remains finite. However, in 6G, there is a need to serve an even larger number of users, with high requirements in terms of delay suppression and transmission rate increase. For this reason, new improved technologies have been developed, such as non-orthogonal multiple access (NOMA), which, unlike conventional orthogonal multiple access technologies, is based on non-orthogonal resource allocation, allowing the same subcarriers to be reused, even within the boundaries of a cell. NOMA allows multiple users to share the same resources (spectrum) at the same time, by performing multiplexing either in the power levels (Power Domain (PD-NOMA)) or in the field of coding (Code Domain (CD-NOMA)). In both cases, the simultaneous transmission of information to multiple users significantly reduces latency, while providing access to the full available spectrum leads to enhanced spectral efficiency.

3. FOCUS OF THE ARTICLE – REVIEW OF RECENT FL APPLICATIONS IN 6GS' PHY

A promising direction to tackle the challenges we highlighted in the previous paragraphs is the deployment of ML algorithms in different PHY sub-problems, in order to formulate a data-driven framework in wireless communications. AI/ML technologies, that are, also, used extensively in the 5G communications era, will be of significant interest in 6G communications. In this direction, the need for new era ML types is witnessed due to the limited computational power in the interconnected devices (UEs). Thus, distributed learning, and more specifically FL, will be an applicable technology for several PHY subproblems.

However, the reported research in the field is still in an early phase, as the standardization process for 6G networks is, also, in an early phase. Although, by 2030, when stable 3GPP release will be published for 6G networks, FL -and, in general, distributed learning- research is expected to be mature enough.

In the following subparagraphs, the related research concerning the use of FL in several PHY problems related to RRM is presented. The classification is performed based on the technologies that are utilized alongside FL in these works. In fact, sub-paragraph A refers in cases where not other studied technology is used. The performance of the used models is also discussed, and conclusions are drawn from them.

3.1 Radio Resource Management

RRM is one of the most vital optimization problems in every wireless networks generation. In fact, user allocation, subcarrier or PRB allocation, power management, BS or RN placement, and selection, are sub-problems of interest in the context of both 5G and the upcoming 6G networks.

Thus, it is visible that the efficiency of the employed RRM strategies is one of the key factors for the overall 6G systems' feasibility. The most significant FL approaches to tackle RRM-related sub-problems are depicted in Table 2.

Table 2. Research work on FL-based RRM in 6G networks

Paper	Year	RRM problem	Key outcomes
Samarakoon *et. al.*	2019	Power and subcarrier allocation in 6G vehicular networks	Power consumption reduction, exchanged data reduction
Parvini *et. al.*	2023	Power and subcarrier allocation in 6G vehicular networks	Use of an FL-DRL algorithm to maximize the data rate in different simulation scenarios
Skocaj *et. al.*	2023	User scheduling for FL tasks	Improved ML metrics (e.g. accuracy), improved EE
Alsulami *et. al.*	2022	Resource allocation in 6G vehicular networks	Improved QoS, EE and SE levels
Fantacci & Picano	2022	Device selection for FL tasks	Improved ML KPIs (accuracy), energy consumption and convergence time
Chen *et. al.*	2020	User allocation, RRM and power management algorithm	Improved FL accuracy compared to several existing approaches
Li *et. al.*	2022	Relay selection for better FL algorithms' training	Reduced energy consumption, ML KPIs similar to state-of-the-art approaches

Samarakoon *et. al.* (2019) consider the problem of joint power and resource allocation for vehicular URLLC communications. The goal is the minimization of the overall system's power consumption subject to high reliability in terms of probabilistic queuing delays. First of all, an extreme-value theory approach is introduced to define the threshold-based reliability measure to detect extreme events to vehicles' queue lengths. A novel FL-based approach is proposed to detect these extreme events, assuming they are independently and identically distributed over different vehicular users. Afterwards, the communication delays detected in the FL scheme over wireless links, are used to define the power management and subcarrier allocation policies for each user. The performance evaluation, indicated that the proposed FL-based model estimates the extreme events presence in vehicle users' queues with the same accuracy as a centralized scheme. Moreover, the data exchange amount is reduced by 79%, while the vehicular users' ques length is reduced by up to 60%. Overall system's average power consumption is, also, reduced compared to a centralized state-of-the-art approach.

On the same framework, Parvini *et. al.* (2023) proposed an FL-based decentralized joint subcarrier allocation and power control scheme in vehicular networks to ensure string stability in a platoon of autonomous vehicle users. The optimization problem of joint subcarrier allocation and power management is studied subject to both string stability and link availability between different vehicular users. Two schemes are proposed for this problem. The first one considers a centralized BS-governed approach where BSs a priori know the large-scale fading parameters of the vehicular links. The second one, considers an FL-based Multi-Agent Reinforcement Learning (MARL) algorithm, where each vehicle incorporated a distributed agent, which tries to define the optimal policy to maximize the expected reward (power consumption minimization). The last step for its agent is to communicate with the CPU in order to compare the local performance to the global one based on the total achievable capacity. Performance evaluation indicated that both approaches outperformed a random allocation scheme concerning the achieved data rate. However, the distributed MARL outperforms the centralized one concerning the same KPI.

Skocaj *et. al.* (2023) consider the problem of user scheduling over resource-constrained 6G channels. The authors are pointing out that the uplink scheduling of different devices where FL processes are performed is a problem of interest. A novel approach is proposed for uplink user scheduling based on EE and importance-awareness. In each devise unsupervised graph representation learning tasks are performed. The key novelty of this approach is that an importance bias is inserted in the scheduling process, which does not require the collection of training feedback from client users, unlike state-of-the-art approaches. Performance evaluation indicated that ML tasks' accuracy can be improved by up to 10%. Moreover, EE can be also improved by approximately 17 times compared to the state-of-the-art approach.

Alsulami *et. al.* (2022) consider QoS as the most significant KPI in 5G/6G communication networks. However, QoS service requirements rely heavily on user mobility and networks density. Considering vehicular communications, even stricter QoS requirements should be met in real-time scenarios. To address the problem of non-convexity of existing optimization techniques, the authors propose a data-aided federated DRL algorithm for resource allocation in 5G/6G vehicle communication networks. Performance evaluation indicated that an FL DRL scheme can optimize the probability to achieve the requested QoS for each vehicular user of the topology. Moreover, EE and spectral efficiency (SE) levels can be also increased compared to CL approaches.

Concerning device-to-device (D2D) communications, Fantacci & Picano (2022) proposed a framework for user device selection to take part in the learning process, as a lot of UEs don't have the computational power to perform FL tasks. Hence, the authors propose a FL framework (based on the matching theory incentive mechanism) to select the devices that will take part in the learning process, aiming to minimize convergence time and to maximize reward (overall users' utility). Moreover, parameters such as energy consumption are, also, taken into consideration. In each device, an echo-state-network is running to forecast channel conditions in a reliable manner. Performance evaluation indicated that the convergence time and energy consumption of the proposed FL framework are far better than conventional approaches. In fact, energy consumption can be improved by ~10 Joules, while global FL delay can be reduced by ~20 ms. Moreover, ML models' accuracy is also improved (~96% compared to ~89%). Thus, such approaches are declared as applicable for potential usage in 6G networks. A similar approach is presented by Chen *et. al.* (2020), concerning both user selection and resource allocation to minimize the FL loss function. The numerical results indicated that identification accuracy can be improved from ~1% to ~4% compared to a random RRM algorithm, a state-of-the-art FL one and an optimization algorithm that minimizes the overall system's error rate.

Li *et. al.* (2022) address the problem of energy consumption in FL-based 6G orientations, as the resource-constrained nature of a variety of edge devices bring up a limitation to efficient learning. In general, the data in wireless networks are characterized as non-identically and independently distributed (non-IID), leading to the need for various global updates rounds until decision-making. As a sequence, the authors propose a generic multi-flow relay learning framework algorithm, FedRelay, where relay-assisted local updates are performed in the training phase of the global model. There, a cooperative communication decentralized relay selection protocol is also proposed. The global optimization is performed subject to energy consumption minimization for both each local update and global model. However, computation frequency is considered, also, to reduce training overhead. Performance evaluation indicated that FL-assisted relay selection led to a 5-time reduction in energy consumption compared to state-of-the-art federated learning approaches. Moreover, global test set accuracy is similar to state-of-the-art ones.

3.2 Non Orthogonal Multiple Access

NOMA is proposed as an efficient alternative to OFDMA, which was in favor of 4G and 5G networks. RRM is one of the most vital optimization problems in every wireless networks generation. The key characteristic of NOMA is that, unlike OFDMA, is based on the non-orthogonality of the resources (e.g. subcarriers, PRBs) to be allocated to users. Thus, the same resources can be reused, even within the boundaries of a cell, allowing a more dynamic RRM scheme, which can improve total capacity, EE, and SE levels. The most significant FL approaches concerning NOMA in 6G networks are depicted in Table 3.

Table 3. Research work on FL-based NOMA in 6G networks

Paper	Year	RRM problem	Key outcomes
Yang *et. al.*	2021	FL in the context of NOMA-aided wireless communications	Techniques, trends, challenges and open research points
Habachi *et. al.*	2022	Subcarrier allocation	Improved total capacity, similar throughput and packet losses levels to state-of-the-art approaches
Al-Abiad *et. al.*	2022	Subcarrier allocation and power control	Reduced energy consumption, more training and transmission time needed

The aspects of FL and MEC orientations for NOMA-aided wireless communication are, firstly introduced by Yang *et. al.* (2022). Authors propose a framework for terrestrial networks, where simultaneous computation offloading enhanced networks' flexibility. In this way, connectivity is highly reliable, while transmission latency and energy consumption are significantly reduced. FL fundamentals are, also, presented along with several implementation techniques to improve or maintain QoS levels. The authors declare that the cooperation between FL and RL is of high interest for RRM-related tasks. Thus, motivations, challenges, and representative results are presented, focusing on key technical challenges and open research issues of the proposed frameworks.

Habachi *et. al.* (2022) investigated the RRM problem in NOMA-based systems, focusing, also, on the device clustering in these networks, based on the required service demands. Two allocation schemes are proposed by the authors. In the first the BS allocates users/devices to clusters based on current CSI and transmit power, to ensure interference mitigation in uplink and downlink. The key characteristic of this approach is the low overall complexity and communication overhead. In the second approach, an FL-based scheme is proposed based on a traffic estimation model, aiming to improve the system's capacity. Thus, BSs, taking into account both traffic prediction and power demands to allocate devices to clusters. Finally, a synchronization method is proposed to synchronize transmissions of the different devices. Performance evaluation indicated that the system's capacity can be increased by ~20 times compared to on OFDMA scheme, while achieved throughput and packet losses are at similar levels.

Concerning, also, RNs, Al-Abiad *at. al.* (2022) proposed an FL-based RRM scheme for RN-assisted 6G IoT communication networks, where energy consumption reduction is of primary interest. Moreover, the minimization of the total training and transmission time is, also, of interest. Thus, a joint relay scheduling, transmit power allocation, and frequency allocation optimization problem is formulated. A near-optimal performance and low computational complexity are achieved using a graph-theory approach. Performance evaluation depicted that the proposed scheme achieves 6, 4, and 2 times lower energy consumption, respectively, compared to the considered fixed, computation adaptation, and power adaptation schemes. As far as total time is concerned, the proposed approach performance is slightly worse than the fixed and computation only adaptation schemes.

3.3 Cell Free mMIMO

As presented in previous paragraphs, CF mMIMO is a recently proposed technology that has gained significant interest due to the scalability that it brings to modern-era orientations. The CF mMIMO architecture is based on the no cell and cell boundaries existence. The main advantages of CF mMIMO, which signify the technology's importance in 6G networks, include huge data throughput, ultra-low latency, ultra-high reliability, high energy efficiency, and ubiquitous and uniform coverage (He *et. al.*, 2021). The fundamental ideas of CF mMIMO are presented in the previous paragraph. The most significant FL approaches concerning CF mMIMO topologies in 6G networks are depicted in Table 4.

Table 4. Research work on FL-aided CF mMIMO in 6G networks

Paper	Year	RRM problem	Key outcomes
Vu *et. al.*	2020	Training time optimization in CF mMIMO environments	Reduced training time
Vu *et. al.*	2021	Training time optimization in CF mMIMO environments for multiple FL processes	Reduced training time
Vu *et. al.*	2021	Struggler effect mitigation in CF mMIMO 6G systems	Reduced transmission times in the FL process compared to the other approaches

Vu *et. al.* (2020) proposed a novel scheme for FL-aided CF mMIMO systems that can support any FL framework. An optimization problem to minimize training accuracy, transmit power, and users' processing frequency is formulated as an indicative example, but the authors declare that the proposed framework can have the same outcomes for every FL model. Performance evaluation highlighted the reduced training times by ~55% compared to state-of-the-art approaches. Moreover, the CF mMIMO approach is depicted as the best-performing one compared to CF time-division multiple access massive MIMO and collocated massive MIMO concerning total models' training time. A similar approach, is also, presented by the same authors in (Vu *et. al.*, 2021) to support multiple FL groups. A CF mMIMO to guarantee the stable operation of multiple FL processes is proposed to allow multiple iterations by different FL processes to be executed together. A novel asynchronous algorithm performs the scheduling of the different flows, while a low-complexity RRM allocates the power and computation resources subject to the minimization of each iteration's execution time. Result evaluation indicated that the per iteration execution time can be reduced by ~60% to ~80%. However, a key problem of both of the aforementioned approaches has to do about the *"struggler"* UE effect. A struggler UE is an edge device that slows down the FL training process and communication between edge devices and centralized entity, due to bad link reasons. The approach in (Vu *et. al.*, 2021) selects only a UE subset to take part in the FL process to minimize the probabilities of the *"struggler effect"* to happen. In this case, performance evaluation indicated that FL transmission times can be significantly reduced compared to the previously presented approaches (~30% to ~60%). Finally, the approaches presented both in (Vu et. al., 2022) and (Sifaou & Li, 2022) propose FL-based CF mMIMO approaches in 6G orientations to reduce the overall execution time and communication overhead in the FL process. Performance evaluation in both approaches confirms the reduced execution time and communication overhead over approaches such as the presented ones in the previous paragraph. However, such effects are more visible when the overall network density levels are low.

3.4 Reconfigurable Intelligent Surfaces

As presented in the previous paragraphs, RIS consists of a novel new era of wireless networks (e.g. 6G) technology, where two-dimensional reflecting surfaces with non-static (reconfigurable) properties intercede in the traditional transmitter-receiver link. These surfaces consist of numerous discrete elements, which are differentiated by amplitude. The enhanced capabilities of this approach concerning the total system's capacity improvements resulted in a growth upon that approach. The most significant FL approaches concerning the cooperation between RIS topologies and FL in 6G networks are depicted in Table 5.

Table 5. Research work on RIS-aided FL frameworks in 6G networks

Paper	Year	RRM problem	Key outcomes
Liu *et. al.*	2021	FL training optimization in over-the-air RIS-aided communication under *"straggler"* effect	Improved models' accuracy even in extremely non-unified UE conditions
Liu *et. al.*	2021	FL training optimization in over-the-air RIS-aided communication under *"straggler"* effect	Improved models' accuracy even in extremely non-unified UE conditions
Mao *et. al.*	2022	RRM optimization for OFDMA/ NOMA-based RIS-aided 6G communications	Improved training latency, NOMA scheme overperforms OFDMA one
Le *et. al.*	2023	RRM optimization for OFDMA/ NOMA-based RIS-aided 6G communications using auction-based techniques	Improved training latency
Zhong *et. al.*	2022	RRM optimization for OFDMA/ NOMA-based RIS-aided 6G	Achieved sum rate improvement

Liu *et.al.* (2021) highlights the advantages of FL approaches, as also, depicted in this chapter, and proposed over-the-air computation as an efficient way to improve communication efficiency and support numerous simultaneous local model uploading. However, in such scenarios, the *"straggler"* effect is present. For this purpose, the authors propose a RIS-aided learning framework for device selection to be used in FL tasks based on model aggregation error and convergence time of the over-the-air FL. Then, a unified communication-learning optimization problem is formulated to optimize device selection and RIS configuration. Performance evaluation indicated that the aforementioned algorithm improves models' accuracy by ~20% compared with the state-of-the-art approaches. These effects are detected even when channel conditions are a lot different across UEs. Similar results are, also, depicted by the same authors in Liu *et.al.* (2021).

Mao *et.al.* (2022) proposed a RIS-aided FL scheme as a countermeasure to the obstacles that are inserted into the FL process by the randomness of channel conditions, focusing on IoT topologies. The goal of this approach is to improve model aggregation/distribution and decrease training times. The total latency minimization problem is formulated, both concerning OFDMA and NOMA multiple access protocols, subject to energy and RIS constraints. Thus, the optimal RRM policies are depicted to efficiently allocate available resources to the UE of the cell under test. Performance evaluation indicated that the RIS-assisted FL scheme can achieve significant latency (~0.5 s) reduction as compared with other benchmark methods. Moreover, the NOMA-based model achieves slightly better training latency than the OFDMA-based one. In the same context, Le *et. al.* (2023) propose a RIS-assisted NOMA scheme to increase the total system's capacity and support UE selection, focusing on total latency minimization. This is achieved by the per training round latency reduction. Then, an auction-based IRS (Winner determination (WD) and payment methods are used) RRM policy is proposed to optimize total latency in the context of multiple-BS model parameters transmission. Performance evaluation indicated that proposed schemes overperform existing ones both concerning training efficiency through device selection and IRS-NOMA RRM optimization. In the field of RIS-aided NOMA 6G networks, *Zhong et. al.* (2022) propose a framework for the sum rate maximization problem using FL and DRL principles. Performance evaluation indicated that a mobile RIS scheme achieves about ~300% sum rate improvement compared to a fixed RIS scheme. Moreover, the NOMA scheme achieves a sum rate gain of ~42% compared to an OFDMA scheme.

4. SOLUTIONS AND RECOMMENDATIONS – FL FOR RN PLACEMENT PARADIGM

4.1 Problem Formulation and Dataset

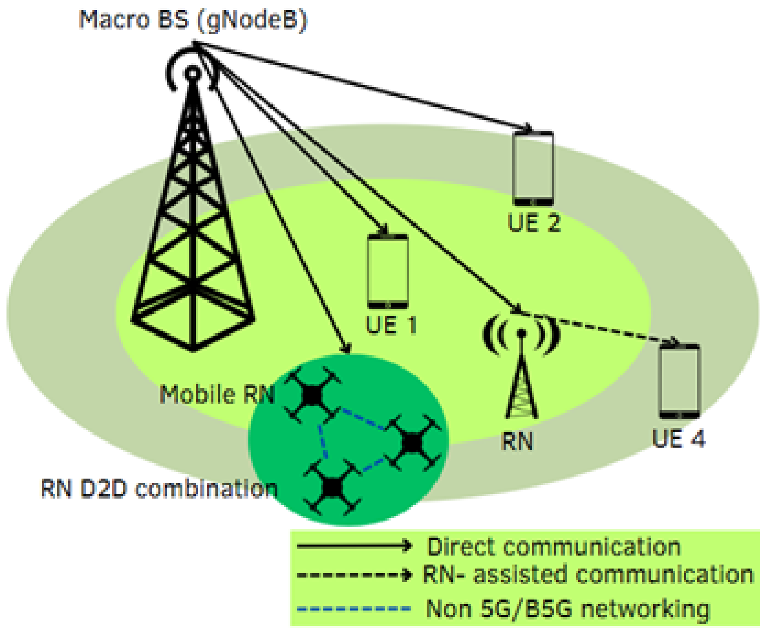
In this section, the performance of a FL-based scheme, used for algorithms' training, for the problem of efficient RN placement in B5G (6G) networks is presented as an indicative use case, which aims to demonstrate the advantages of distributed computation and FL.

The downlink of a cooperative wireless 6G HetNet is considered, where two different levels of base entities exist. Macro-BSs form the main system to provide direct access to UEs requesting service, while RNs form the supporting system, aiming to assist the main system in improving the network's KPIs, such as capacity and coverage area (see also Fig. 5).

The system under test consists of one BS, R RNs and N uniformly distributed users. The goal of this sub-problem is to select the N_{best} positions (set of x-y-z coordinates) for the best-performing RNs –out of N ones- to be deployed in each cell's coverage area. Best-performing RNs are selected subject to the following constraints, as also depicted in (Bartsiokas *et. al.*, 2023):

- $\min\left(PL_n\right), \forall n \in N$, where PL_n is the pathloss between each accepted user by the supporting system and the RN that is assigned to.
- $\min\left(P_{t,r}\right), \forall r \epsilon R$, where $P_{t,r}$ is the total transmitted power by each deployed RN.
- $\max\left(N_{acc}\right), \forall r \epsilon R$, where N_{acc} are the total accepted users, served by the supporting system.

Figure 5. RN-assisted 6G Communications



A MATLAB B5G (6G) link-level simulator, presented in (Psilopanagiotis *et. al.*, 2022), is used to construct the global dataset after adequate Monte-Carlo simulation rounds. The simulator follows the latest 3GPP specifications (basically the latest version of 3GPP TS 138 211 regulation). An overview of the global dataset used is depicted in Table 6 (Bartsiokas *et. al.*, 2023).

Moreover, Table 7 depicts the basic simulation parameters, which configured the aforementioned simulator, in order for the dataset in Table 6 to be constructed.

Table 6. Dataset features

Features	Description
$UE_{x,y,z}$	x-axis, y-axis and z-axis user position
UE_{sec}	User serving sector
$UE\text{-}BS_{angle}$	Angle between BS and UE
PL_{mat}	$Rx1$ matrix with the pathloss between the user device and all the potential RNs
TL_{mat}	$Rx1$ matrix with the total losses between the user device and all the potential RNs
H_{matrix}	$M_r x M_t$ channel coefficient matrix, where M_t is the number of the MIMO transmitting antennas and M_r is the number of the receiving ones
RN_{serve}	ID of the RN that serves the user **(response variable)**

Table 7. Simulator's parameters

Parameter	Value/assumption
Carrier Frequency (GHz)	28
Tiers/Number of cells	1/7
Number of potential RNs	10
Number of users	~150
Total Bandwidth (MHz)	100
Number of antennas per BS/RN/UE	2/2/2
Sectors per BS	3 (120° angular separation)
BS/RN/UE antenna heights (m)	25/12.5/1.5
Indoor UE ratio	80%
Maximum pathloss (dB)	160
BS/RN/UE antenna gains (dB)	18/9/4
Max Tx Power per BS/RN/UE (max $P_{t,r}$)	6.162/1.054/0.024 W
Number of subcarriers per BS	132

4.2 DL Model

For the RN selection task, a Recurrent Neural Network (RNN), long-short memory (LSTM) network is used. The structure of this model is the following (Bartsiokas *et. al.*, 2023):

- Feature input layer with z-score normalization of the input, where the different features are inserted into the DNN (the 6 features that are presented in Table 6).
- An LSTM layer with 52 hidden units.
- A dropout layer with 0.2 probability to randomly set input elements to zero.
- Two sets of LSTM layers followed by a dropout layer. The first LSTM layer has 40 hidden units, while the latter has 15 hidden units.
- A fully connected layer with an output size equal to the number of candidate RNs.
- A soft maximization layer.
- The classification's output layer, which produces as output the predicted best-performing RN for each user. Thus a number from 1 to N (see also Table 7) is the output of the model, which signifies the selected RN for each user.

4.3 CL and FL Model Training

Aiming to demonstrate the advantages of the FL over CL approaches, we consider two different training topologies for the problem of RN placement in B5G (6G) networks. These are the following:

1. **CL-based approach:** In the first approach all the training is performed in the centralized entity. The centralized entity in this occasion is the cell's BS, which receives the data gathered in the

wireless environment by the RNs. Afterwards, the global dataset is formed and the DL model is trained in a centralized manner.

2. **FL-based approach:** In this approach, the data gathered in the wireless environment train local models located in each of the R RNs of the wireless topology (as depicted in Fig. 5). Thus, local models are trained and parameters are transmitted in the centralized entity (BSs) to be optimized according to the implemented federated averaging function.

Except for the two scenarios concerning the learning type, two scenarios are examined, also, based on the existence or not of CSI information. These are (Bartsiokas *et. al.*, 2023):

Scenario A: The channel coefficient matrices are not known both for the link of each UE and the BS, and for the RN-UE link.

Scenario B: There is CSI information available for both links.

4.4 Performance Evaluation

We consider the downlink of a wireless B5G (6G) orientation, where extensive use of RNs takes place. The topology under test considers one BS and 10 RNs, where users are uniformly distributed. We simulate the performance of a large number of total users (50.000 indoor/outdoor moving/static) to construct both the global dataset for the CL case and the local datasets for the FL case. During the training phase of both approaches, an 80%-20% training-test set split is performed, as well as a 10-fold cross-validation procedure to split the dataset into training, validation, and test set. The 10-fold cross-validation splits the training set into ten parts where, in each case, nine of them are used for training and the remaining one for validation. The training phase of all algorithms ran on a personal PC (CPU i7-8700; 3.2 GHz; RAM 8 GB; no GPU usage).

The problem of optimal RN placement is examined as a classification one, by selecting the best-performing RN out of the 10 potential RNs for each user. The performance of the abovementioned approaches is evaluated both concerning ML KPIs (accuracy, precision, recall, F1-score) and based on the total training latency and inference time.

Training latency is of significant importance in wireless networks task, especially when considering FL solutions, as an optimal tradeoff between the number of interconnected devices that are sharing the computational (training) tasks execution and the ML KPIs should be achieved. On the same context, inference times is, also, important in the 6G domain, as the ultra-low-latency applications served be these networks, require the minimization of the time needed for the response generation of the ML/DL models.

Table 8 and Table 9 summarize the performance of the two approaches (CL, DL) in the RN placement based on test set classification accuracy, precision, recall and F1-score for both Scenario A and Scenario B, respectively.

As can be observed from Tables 3 and 4 LSTM's performance is better (both accuracy, precision, recall and F1-score) when CSI is known and is included in the training set's features. Moreover, it can be seen that training times and inference times are similar both for Scenario A and Scenario B.

However, when fast, low-latency responses are considered in B5G (6G) networks, it is vital to examine the trade-off between ML metrics and the training time required. In that perspective, it is visible from the aforementioned tables (Tables 7 and 8) that the FL-based approach worsens slightly all the ML-related networks KPIs (accuracy, precision, recall, F1-score) by ~5% compared to the CL approach.

Table 8. LSTM performance - CL scenario

LSTM	Scenario A	Scenario B
Accuracy	0.9513	0.9660
Precision	0.9521	0.9618
Recall	0.9259	0.9502
F1-score	0.9290	0.9560
Training time	5 min. 15 sec.	5 min. 50 sec.
Inference time	50 ms	65 ms

Table 9. LSTM performance - FL scenario

LSTM	Scenario A	Scenario B
Accuracy	0.9107	0.9309
Precision	0.9259	0.9346
Recall	0.8929	0.9259
F1-score	0.9091	0.9302
Training time	1 min. 35 sec.	1 min. 58 sec.
Inference time	30 ms	42 ms

However, this degradation can be characterized as small enough relevant to the gain in the total training time of the FL approach compared to the CL one. In fact, the gain in this metric (total training latency) is about ~70% to ~75%.

5. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

5.1 Challenges and Solutions

From the literature presented in paragraph III and the indicative use case presented in paragraph IV, it is visible that FL is of primary interest in 6G orientations, to enhance the potential PHY gains and, also, support the growing user requirements. The aforementioned research, though, has identified several challenges that have to be addressed and solved for the feasibility of such approaches. These can be summarized as follows (see also Table 10):

- **Distributed training and Models' scalability:** In 6G networks interconnected devices number is growing, resulting in the densification of the networks. However, the processing units and the computational power of these devices may be limited. Thus, a key challenge that the proposed FL schemes have to consider is the training time required and the efficient allocation of the total computational resources.
- **Secure communication and device-to-centralized entity transmissions:** By definition FL secures local datasets, as only model parameters transmission is performed to the centralized entity.

Table 10. Challenges in FL models construction in 6G wireless networks

Challenge	Solutions presented at
Distributed learning computational and scalability considerations	(Fantacci & Picano, 2022), (Vu *et. al.*, 2020), (Vu *et. al.*, 2021), (Liu *et. al.*, 2021), (Mao *et. al.,* 2022)
Security and Privacy concerns	(Yang *et. al.*, 2022), (Sirohi *et. al.*, 2023), (Liu *et. al*, 2020)
Non-IID data	(Li *et. al.*, 2022), (Yang *et. al.*, 2022)
Computation and communication trade-off	(Samarakoon *et. al.,* 2019), (Chen *et. al.*, 2020), (Li *et. al.*, 2022)

However, challenges exist in the transmission of models parameters, where information may be vulnerable to eavesdropping capable of reconstruction.

- **Non-IID data:** As is already pointed out, the different users devices connected to 6G networks, that perform FL training have different characteristics concerning processing and computational power, battery life etc. This heterogeneity, affects parameters such as convergence time, training latency, and others.
- **Computation and communication trade-off:** The goal of an effective and efficient FL mechanism is twofold. On the one hand, the communication links and uninterrupted interconnection between the enrolled devices should be present, while, on the other hand, computational complexity and total training times should be minimized as possible.

5.2 Future Directions

Despite the fact that there is a growing interest in FL implementation in the context of 6G networks, there is more research work to be performed in order for the aforementioned challenges to be fully addressed and resolved. However, as 3GPP standardization activities for 6G networks are about to start with a horizon until 2030, there is time for more research to be done.

More specifically, some key aspects that will be of interest in the aforementioned process are the following:

- **Scalability and user characteristics:** Some of the key usage scenarios of 6G networks is the holographic, AR/VR and UxV communications. In these scenarios, user density and mobility are of vital interest. The research works performed until now, assume either static UEs or established CSI conditions. Thus, an escalation of the current approaches towards more complex evaluation scenarios will be significant for the feasibility of the proposed FL solutions.
- **Privacy and security:** As addressed in the previous subparagraph, FL by definition provides a level of security in the inter-communication between the different edge devices and the centralized entity. However, as addressed by (Yang *et. al.*, 2022), traditional encryption and/or authentication solutions could be of interest. On the same framework, modern-era physical layer security algorithms could, also, be of interest, in order to handle massive connectivity IoT or vehicular network scenarios.
- **Coexistence with other enabling technologies:** 6G networks are expected to both use and leverage current 5G technologies, but also utilize new-coming ones to support the extended requirements presented in paragraph I. In this framework, the deployment of FL schemes in 6G networks

where satellite communications (Chen *et. al.*, 2022), quantum communication (Kaewpuang *et. al.*, 2023) or even blockchain (Zhang *et. al.*, 2023) technologies, are existing is of increasing interest for future research works.

6. CONCLUSION

This chapter presents a review/survey of the recent research works regarding the deployment of FL-based approaches in the context of different PHY sub-problems in 6G wireless networks. FL, as a distributed learning approach, has been proposed as an efficient way to deal with the ever increasing user demand in new era wireless networks. A categorization of these approaches, based on the sub-problem, is provided, in order to point out the different potential usage scenarios of FL algorithms.

Based on the above, we conclude that FL-enabled approaches can overcome limitations that existing (non-ML or non-distributed ML) approaches could not, such as non-conventionality, real-time integration, hardware availability, and energy consumption minimization. Moreover, we point out the challenges that are present in the process of deploying efficient and effective FL frameworks in 6G networks. Moreover, future trends and enabling technologies are, also, discussed. Finally, in order to demonstrate the effectiveness of FL-based schemes in PHY, we investigate via simulations the problem of RN placement in 6G networks. Two schemes are under test, where the first one considers CL, while the other considers FL. According to the presented results, the FL approach overperforms CL one, in terms of training time, while performance regarding ML KPIs (accuracy, F1-score) is similar. In other words, FL approach overperforms CL one regarding the trade-off between training times and ML KPIs. Results evaluation is consistent with other state-of-the-art approaches.

Table 11. Acronyms

5G	Fifth Generation
6G	Sixth Generation
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Access Point
AR	Augmented Reality
B5G	Beyond 5G
BS	Base Station
CAeC	Contextually Agile eMBB Communications
CD	Code Domain
CF	Cell Free
CL	Centralized Learning
COC	Computation Oriented Communications
CPU	Central Processing Unit

continued on following page

Table 11. Continued

CSI	Channel State Information
D2D	Device-to-Device
DL	Deep Learning
DRL	Deep Reinforcement Learning
EE	Energy Efficiency
eMBB	Enhanced Mobile Broadband
FL	Federated Learning
IID	Identically and Independently Distributed
IMT	International Mobile Telecommunications
IoT	Internet of Things
KPI	Key Performance Indicator
LSTM	Long-Short Memory
MARL	Multi-Agent Reinforcement Learning
MEC	Mobile Edge Computing
ML	Machine Learning
mMTC	Massive Machine Type Communications
mmWave	Millimeter Wave
NOMA	Non-Orthogonal Multiple Access
OFDMA	Orthogonal Frequency Multiple Access
OSI	Open Systems Interconnection
PD	Power Domain
PHY	Physical Layer
PRB	Physical Resource Block
QoS	Quality of Service
QoW	Quality of Experience
RIS	Reconfigurable Intelligent Surface
RMSE	Root-Mean-Square-Error
RN	Relay Node
RNN	Recurrent Neural Network
RRM	Radio Resource Management
SBA	Service-Based Architecture
SE	Spectral Efficiency
SVM	Support Vector Machine
UE	User Equipment
URLLC	Ultra-Reliable-Low-Latency Communications
UxV	Unmanned Ground, Air, Surface or Undersea Vehicle
VR	Virtual Reality
WWWW	Worldwide Wireless Web

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KEY TERMS AND DEFINITIONS

6G: The sixth generation of mobile networks.

Cell-Free Massive MIMO (CF mMIMO): An alternative to the established cellular orientation in wireless networks, which receives significant interest recently. CF mMIMO utilizes a very large number of distributed Access Points (APs) with multiple antenna elements on them, to serve a significantly smaller number of UEs over the same radio resources based on current CSI.

Centralized Learning (CL): The traditional type of distributed learning, where multiple nodes (or edge devices) transmit their local gathered data in a centralized entity (serve, cloud infrastructure, etc.), where all the model's training and process is performed.

Federated Learning (FL): A distributed learning approach that doesn't require dataset exchange between nodes (edge devices) and centralized entity. Locally gathered data are used only for local model training. Each local model's parameters or updates are transmitted to the centralized entity, which performs aggregation of the local updates, global model construction and optimization.

Machine Learning (ML): A subset of artificial intelligence which utilizes different types of data to predict classes, exact values or behaviors and support decision-making, without specifying the exact underlined algorithm.

Non-Orthogonal Multiple Access (NOMA): A newly proposed multiple access technique that is based on the non-orthogonality of the available resources, which can be overlapping each other to improve wireless systems' performance and fairness. Subcarrier assignment can be performed either based on different power levels (PD-NOMA) or coding schemes (CD-NOMA).

Physical Layer (PHY): The lower level of the Open Systems Interconnection (OSI) model. PHY refers to the bit level transmissions in the physical medium for synchronized communications over mechanical and electrical interphases.

Radio Resource Management (RRM): The set of policies that are employed in wireless (or not) networks in order to manage efficiently the available radio resources (subcarriers, PRBs), control the transmitted and received power, maintain QoS levels and mitigate various types of interference.

Reconfigurable Intelligent Surface (RIS): A novel wireless technology technique, where a two-dimensional reflecting surface with non-static (reconfigurable) properties, intercedes in the traditional transmitter-receiver link. This surface consists of numerous discrete elements, which are differentiated by amplitude.