Federated Learning for 6G: Applications, Challenges, and Opportunities

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Abstract

Traditional machine learning is centralized in the cloud (data centers). Recently, the security concern and the availability of abundant data and computation resources in wireless networks are pushing the deployment of learning algorithms towards the network edge. This has led to the emergence of a fast growing area, called federated learning (FL), which integrates two originally decoupled areas: wireless communication and machine learning. In this paper, we provide a comprehensive study on the applications of FL for sixth generation (6G) wireless networks. First, we discuss the key requirements in applying FL for wireless communications. Then, we focus on the motivating application of FL for wireless communications. We identify the main problems, challenges, and provide a comprehensive treatment of implementing FL techniques for wireless communications.

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I. BACKGROUND AND OVERVIEW ON FEDERATED LEARNING FOR WIRELESS COMMUNICATIONS

A. Motivation

Due to the explosive growth in data traffic, machine learning and data driven approaches have recently received much attention and are anticipated to be a key enabler for the to be developed sixth generation (6G) wireless networks [1]. Nowadays, standard machine learning approaches require centralizing the training data on a single data center or cloud. Since massive data samples need to be uploaded to the data center, transmission delay can be very high and user privacy is not guaranteed in standard centralized machine learning approaches. However, low-latency and privacy requirements are important in the emerging application scenarios, such as unmanned aerial vehicles, extended reality (XR) services, autonomous driving, which makes centralized machine learning approaches inapplicable. Moreover, due to limited communication resources, it is impractical for all the wireless devices that are engaged in learning to transmit all of their collected data to a data center that uses a centralized learning algorithm for data analytic or network self-organization.

Therefore, it becomes increasingly attractive to process data locally at edge devices. This has led to the emergency of distributed optimization methods. In distributed optimization, each node can compute on its own data and sends the results to its neighbours or a central node. Distributed optimization has many applications, such as user selection optimization, resource allocation optimization, trajectory optimization, and distributed machine learning design [2].

Combining the advantages of distributed optimization and machine learning, distributed learning ing frameworks are needed to enable wireless devices to collaboratively build a shared learning model with training taken place locally. One of the most promising distributed learning algorithms is the emerging *federated learning* (FL) [3]–[17] framework is anticipated in future Internet of Things (IoT) systems. In FL, wireless devices can cooperatively execute a learning task by only uploading local learning models to the base station (BS) instead of sharing the entirety of their training data, as illustrated in Fig. 1 [18]. Since the data center cannot access the local data sets at the users, FL can protect data privacy of the users.

For wireless communications, FL has the following advantages: (i) exchanging local machine learning model parameters instead of the massive training data saves energy and consumes



Fig. 1. A FL algorithm over wireless communication systems.

less wireless resources; (ii) training machine learning model parameters locally can effectively reduce transmission latency; (iii) FL preserves data privacy since the training data remains at each device and only the local machine learning model parameters are uploaded; (iv) using different learning processes to train several classifiers from distributed data sets increases the possibility of achieving higher accuracy especially on a large-size domain; (v) FL is inherently scalable since the growing amount of data may be offset by increasing the number of computers or processors, and providing a natural solution for large-scale learning where complexity and memory are the main obstacles.

FL can be used to solve complex convex and nonconvex optimization problems that arise in various use cases such as network control, user clustering, resource management, and interference alignment. Besides, FL enables users to collaboratively learn a shared prediction model while keeping their collected data on their devices for user behaviour predictions, user identifications, and wireless environment analysis. Based on the predicted results, the BS can efficiently allocate the wireless resources for the devices.

B. Classification

For FL, there are two main classifications: federated reinforcement learning (FRL) and federated supervised learning (FSL). In [19], the goal of FRL is to enable wireless devices to remember what they have learned and what other wireless devices have learned. FRL can be used in the case where multiple wireless devices make decisions in different environments. In FRL, each wireless device builds a learning network with the help of other wireless devices.

- 1. Initially, one edge device first obtains its private strategy model learning network through reinforcement learning (RL) in its own environment and then uploads it to the BS as the shared model.
- 2. After a while, the wireless devices download the shared model from the BS as the initial actor model in RL. Wireless devices get their own private learning networks through RL in new environments. After training is completed, wireless devices upload their private learning networks to the BS.
- 3. At the BS, the private learning networks are fused into the shared model, and then a new shared model will be generated. The new shared model can be used by other wireless devices. Other wireless devices will also upload their private learning networks to the BS to evolve and update the shared model.

The FSL technique builds a uniform learning model through iteratively updating information between the BS and wireless devices, where the local private data is fully labeled. The FSL procedure contains three steps at each iteration: local computation at each wireless device, local FSL model parameters transmission from each wireless device, and result aggregation and broadcast at the BS.

- 1. Every wireless device needs to compute the result by using its fully labeled data set locally.
- 2. All wireless devices upload the local prediction parameters to the BS via wireless links in the uplink.
- 3. The BS aggregates the prediction model parameters and broadcasts the global prediction model parameters to all the wireless devices in the downlink.

C. Relevant Surveys and Our Contributions

There are some interesting surveys about FL in wireless communications such as [20]–[25]. The unique characteristics and challenges of FL were discussed in [20]. Moreover, this work provided an overview of the current approaches, and outlined several directions of future work. The work in [21] introduced the challenges of FL implementation and reviewed the existing solutions. In [22], the authors described the challenges of machine learning systems that are

Subject	Contributions	Related Work
FL	Introductory tutorial on unique characteristics and challenges of FL	[20]
FL	Challenges of FL implementation	[21]
Edge machine learning	Challenges of machine learning systems at the edge computer networks	[22]
FL	FL and RL for optimizing mobile edge computing and caching	[23]
Edge machine learning	Edge machine learning architectures	[24]
FL	FL application and use-cases	[25]

 TABLE I

 An overview of selected surveys about FL in wireless communications.

configured at the edge computer networks. Considering RL, the authors in [23] proposed to integrate deep RL techniques and the FL framework with mobile edge systems, for optimizing mobile edge computing, caching and wireless communication resource. In addition, the work in [24] explored the key building blocks of edge machine learning and different wireless network architectural splits for wireless communications. The study about FL application was surveyed in [25] including software and hardware platforms, protocols, real-life applications and use-cases.

We aim to gather the state-of-the-art contributions that address the key challenges of applying FL techniques for wireless networks. In particular, our objectives are three-fold: to provide a comprehensive descriptions of FL algorithm, to identify the key open problems in wireless communication that can be addressed using FL methods, and to point out the emerging applications in wireless communication with FL.

II. PERFORMANCE AND REQUIREMENTS FOR FEDERATED LEARNING

A. Performance Evaluation

The procedure of FL over wireless networks is shown in Fig. 2. The FL procedure contains three steps at each iteration: local computation at each device (using several local iterations), local FL parameter transmission for each device, and result aggregation and broadcast at the BS. The local computation step is essentially the phase during which each device calculates its local FL parameters by using its local data set and the received global FL parameters. There are four main performance indicators for FL: delay, energy, reliability, and massive connectivity.



Fig. 2. FL procedures over wireless networks.



Fig. 3. Energy performance of FL over wireless networks.

1) Delay: According to Fig. 3, the delay of FL includes: local computation delay of wireless devices, uplink transmission delay, BS aggregation delay, and downlink transmission delay. Considering the tradeoff between local computation delay and wireless transmission delay, it is of importance to minimize the delay for FL via joint transmission and computation optimization.

2) *Energy:* Due to limited energy budget of wireless devices, both local computation energy and transmission energy must be considered during the FL process. The calculation of local computation energy involves the number of iterations for local computation at each device, and

the transmission energy is related to the number of iterations for the FL algorithm to converge.

3) Reliability: To train an FL algorithm in a distributed manner, the devices must transmit the training parameters over wireless links which can introduce training errors, due to limited wireless resources (e.g., bandwidth) and the inherent unreliability of wireless links. For example, symbol errors introduced by the unreliable nature of the wireless channel and by resource limitations can impact the quality and correctness of the FL updates among users. Such errors will, in turn, affect the performance of FL algorithms, as well as their convergence speed.

4) Massive connectivity: To meet the low latency requirement of FL, we need to collect data distributed among a huge number of devices rapidly through wireless communications. However, with enormous number of devices, conventional interference-avoiding channel access schemes become infeasible since they normally result in excessive latency. To overcome this challenge, over-the-air computation is a promising approach for fast wireless data aggregation via exploiting the superposition property in a multiple access channel [26].

B. Potential to Meet 6G Requirements

It is expected that 6G communication systems will hence to accommodate 125 billion wireless devices by 2030. As a result, it is important to develop an automatic data processing framework to allow edge learning to take place. As one of the key enabling technologies, FL has the potential to meet the following 6G requirement [1].

1) Massive ultra-reliable, low latency communications (mURLLC): Due to the explosive growth in the number of wireless devices in 6G, the 5G URLLC requirements will be changed to the mURLLC. With FL, multiple edge computing units can be used to cooperatively learn a shared model for the network, which can decrease service delay and provide high reliability.

2) Scalable architecture: Different from a central cloud, edge intelligence, such as FL, is built in a distributed manner, which includes many edge servers with computing and communication capabilities. To serve a massive number of devices in the future 6G, it is important to provide a scalable and decomposable architecture to allow simultaneous computing among multiple edge servers. It is expected that the FL architecture will play an important role in the future 6G services and applications.

3) Human-centric services: Different from the rate-reliability-latency metrics in 5G, 6G involves human-centric services, which requires quality of experience related to the physical movement of the users. FL can be used to predict the movements and gestures of users, and the BS can utilize the predicted results to improve the quality of experience for users.

III. FEDERATED LEARNING FOR WIRELESS COMMUNICATIONS: MOTIVATING APPLICATIONS

Machine learning tools can exploit big data analytic for wireless network state estimation and find the relationship between the optimized variables and objective functions in an online manner so as to reduce the computational complexity for solving the nonconvex problems in wireless communication. Besides, machine learning is powerful because it can optimize problems that no one knows how to describe the problems. However, given that multi-cell network needs global channel state information (CSI), centralized learning algorithms may require the BSs to continuously upload their collected data to a centralized processing server, which can lead to a high network overhead and significant delays. As a consequence, using a centralized learning algorithm for resource management or network control may need a large number of iterations to converge. Thus, centralized machine learning algorithms will not be able to handle the resource allocation, signal detection and user behaviour prediction problems in future networks. To this end, FL is needed, which enables users or BSs to manage the resource in a distributed manner and analyze their collected data locally.

A. Driving Application of FL for Wireless Problems

1) Resource management: Spectral efficiency and connectivity optimization of multi-cell network always leads to nonconvex resource allocation problems, which were often solved by conventional algorithms such as successive convex approximation and matching theory with high complexity and impractical implementation. Therefore, there is a need to introduce new FL techniques that can be used to address a variety of resource management challenges such as distributed power control for multi-cell networks, joint user association and beamforming design, and dynamic user clustering.

For multi-cell power control, as shown in Fig. 4, FRL enables each BS to build the relationship between the power control schemes and utility values so as to find the optimal power control scheme. In FRL, the BSs on a connected network process data locally by minimizing small



Fig. 4. Multi-cell power control problem.

optimization problems, and exchange the local results among the neighbors to arrive at a global solution.

Further, FRL can be used for dynamic user clustering, where users individually learn the clustering parameters by RL and the BS builds the unified clustering parameters based on the received clustering parameters from all users.

2) User behavior predictions: Due to the heterogeneous quality-of-service requirement of users, user behaviour prediction is of great importance for the implementation of wireless networks.

FL can be used to predict the users behaviors such as mobility patterns where each user performs a local FL algorithm to train the learning model using its own user behavior data and upload the trained model to the BS. Then the BS generates and broadcasts the unified FL model parameters to all users. Based on the mobility predictions, the users can dynamically choose a subchannel to upload data in the uplink, the BS dynamically allocates multiple subchannels to multiple users in the downlink, and multiple users which occupy the same subchannel can perform non-orthogonal multiple access (NOMA) or full duplex.

The quality of service of users can be predicted by FL, where each BS uses the FL algorithm based on its stored information such as users' requested data, gender, job, and device type and all BSs transmit the FL model results to a server to get a unified FL model.



Fig. 5. A RIS-assisted wireless communication system.

3) Channel estimation and signal detection: Channel estimation and signal detection is a major challenge due to the random features of wireless channels in wireless communication networks. For downlink systems, FL algorithms are used for channel estimation and multi-user detection, where each user performs a FL algorithm for channel estimation and signal detection, and sends their local FL model parameters to the BS that will generate the global FL model. For multi-cell uplink systems, multi-user signals can be detected via iteratively transmitting individually FL model parameters from all BSs to a server and broadcasting the unified FL model parameters from the server to all the BSs. Further, FL algorithms can be utilized to automatically design the codebook of BSs and decoding strategy of users to minimize the bit error rate, where users upload the learned result to the corresponding BSs and the BSs forward their unified learned result to a server.

B. Reconfigurable Intelligent Surface

Reconfigurable intelligent surface (RIS)-assisted wireless communication has been proposed as a potential solution for enhancing the energy efficiency of wireless networks [27]–[38]. An RIS is a meta-surface equipped with low-cost and passive elements that can be programmed to turn the wireless channel into a partially deterministic space. In RIS-assisted wireless communication networks, a BS sends control signals to an RIS controller so as to optimize the properties of incident waves and improve the communication quality of users. The RIS acts as a reflector and does not perform any digitalization operation. Hence, if properly deployed, an RIS promises much lower energy consumption than traditional amplify-and-forward (AF) relays [39]–[41]. However, the constraint on the diagonal phase shift matrix and unit modulus of the reflecting RIS makes the joint design of transmit beamforming and phase shifts extremely challenging. To address high-dimension, complex EM environment, and mathematically intractable nonlinear issues of communication systems, the model-free FL method as an extraordinarily remarkable technology can be used.

1) CSI Detection: In the RIS-enhanced system, to achieve the full advantages of the architecture, several efficient technologies are required including the joint active and passive beamforming, resource allocation, and energy-efficient design. It is noted that all of above designs rely on the perfect CSI between the BS and RIS, and the perfect CSI between the RIS and users. However, it is infeasible for the RIS-enhanced systems to estimate the accurate CSI when the radio frequency (RF) chains or sensors are not equipped on the RIS. To this end, it is meaningful to use FL for CSI detection in RIS-assisted wireless communications.

The FL-based model training approach can be used in RIS-assisted massive multiple-inputmultiple-output (MIMO) systems [42]. The FL approach mainly includes three steps: data collection, training and prediction. In the first step, each user collects its local training data set, where the pilot sequence is the input and the received signal is the output. Then, each user computes the updated model by using its own local data set, and the BS generates a global model after receiving the updated models from all users. In the last step, each user estimates its own channel by feeding the received pilot data into the trained model.

2) Distributed joint passive and active beamforming: In RIS, the phase shift of each RIS element can be adjusted to improve the performance of RIS-assisted wireless communication

systems. Different from conventional communications, it is of importance to jointly optimize the passive beamforming (phase shift matrices at the RIS) and active beamforming (beamforming at the multi-antenna transmitter) [43], [44]. To solve the complicated joint passive and active beamforming, deep learning (DL) has been used to design the best reflection matrix of RIS elements in indoor communication environments [45]. In practice, similar to multi-hop relaying systems, multiple RISs can be used to overcome severe signal blockage between the BS and users to achieve better service coverage. The authors in [46] presented a multi-hop RIS-assisted communication scheme to overcome the severe propagation attenuations and improve the coverage range at Terahertz (THz) band frequencies, where the hybrid design of transmit beamforming at the BS and phase shift matrices is obtained by the advances of RL. Due to the high complexity of using centralized RL, FRL can be utilized to solve the joint passive and active beamforming problem, where all users can individually optimize the phase shift matrices and transmit beamforming via RL, and the BS broadcasts the aggregated learning model to all users.

3) Phase shift prediction: Due to the randomness of wireless communication channels, it is required to adjust the phase shift matrixes as the wireless channel changes. By exploiting the time-correlated property of channel fading, the phase shift matrixes of the RIS can be predicted with FL. To predict the phase shift, each user uses long short-term memory (LSTM) network to predict the future CSI and phase shift matrices using local data set, while the BS aggregates the received results from all users.

C. Semantic Communication

Semantic communication, is similar to a brain communication, where the difference between meaning of the transmitted symbols and that of recovered ones is correlated [47]. This correlation can be useful for joint encoding and decoding when the bandwidth of the system is limited or the bit error rate is high for some typical communication systems.

1) Channel encoder and decoder design: Using semantic communication technique which enables the devices only to transmit semantic information to the server, rather than traditional bit or symbol, the network bandwidth utility can be effectively improved. However, semantic communication model requires the training data from multiple distributed devices, which induces huge communication cost for data transmission. To solve this problem, a FL based DL enabled

semantic communication can be proposed for channel encoder and decoder design. First, a DL model can be used to extract the semantic information from text or audio with robustness to noise. Then, in an FL approach, the devices and the server obtain practicable DL models with the server aggregating devices locally trained models and sending the aggregated model back to the devices.

2) Distributed semantic communication for IoT: The emerging technologies, such as smart city, IoT and machine to machine (M2M) networks, require the intelligent communication between different ends, such as human to machine. For those applications, the intelligent communication depends on the background and interface language model [48]. Besides, there are always a large number of devices in IoT. The above factors motivate the design of distributed semantic communication for IoT with FL. The distributed semantic communication with FL includes three steps. In the first step, the BS computes the semantic communication model using DL. In the second step, the BS broadcasts the trained DL model to all users. In the third step, each user obtains the semantic features to the BS and the BS accordingly updates the semantic communication model.

D. XR

XR refers to all real-and-virtual environments generated by computer graphics, which includes augmented reality (AR), mixed reality (MR), and virtual reality (VR), as in Fig. 6. Deploying XR over wireless communication networks is an essential step for realising XR applications [1]. Due to the seamless and immersible requirements, it is important to introduce wireless communication technologies to meet the stringent quality of service requirements, such as high data rate and ultra low latency. For XR allocation over wireless communications, the location and orientation information needs to be sent to the BSs and the BSs construct the 360 degrees images for users based on the received information

1) User movement prediction: In a wireless XR network, the user body movement can heavily influence the wireless resource allocation and network management [49]. To deal with the user movement challenge, FL is effective at predicting the users' movements and actions. Based on the predicted movements and actions, the BSs can improve the generation of the XR images and optimize the resource management for wireless XR users.



Fig. 6. Classification of XR.

2) *Resource allocation:* FL can be used to develop self-organizing algorithms for solving dynamic resource management problems for XR networks [50]. In particular, FL can be used to adaptively optimize the wireless resource and construct the format of the XR images based on the wireless environment.

E. Non-Orthogonal Multiple Access

NOMA is envisioned to be a promising technique for the development of next-generation wireless networks [51]. By serving multiple users at the same time and frequency resource, NOMA can scale up the number of served users, increase spectral efficiency, and improve user-fairness compared to existing orthogonal multiple access (OMA) techniques. Recently, significant research efforts have appeared focusing on various challenge of NOMA [52]–[54], that include modeling, performance analysis, signal processing, and emerging NOMA applications such as heterogenous networks (HetNets), cognitive radio networks and millimeter wave (mmWave) communications. The non-orthogonal resource allocation nature of NOMA necessitates the introduction of novel models and algorithms for addressing several challenges that include: joint user

clustering and resource allocation for devising a scalable multi-cell NOMA design, advanced channel estimation and signal detection for large-scale NOMA networks, and dynamic user behaviour prediction in NOMA based mobile networks.

Due to non-orthogonal resource allocation, intra-cell interference always exists in NOMA networks compared to OMA networks, which usually leads to nonconvex resource allocation problems. Traditional optimization methods, which are used to solve the nonconvex problems for optimizing the performance of NOMA networks, mostly operate in an offline manner with high computation complexity and depend largely on accurate CSI [55]–[58]. Machine learning tools [59]–[62] can exploit big data analytics for wireless network state estimation and find the relationship between the optimized variables and objective functions in an online manner so as to reduce the computational complexity for solving the nonconvex problems in NOMA. However, given that multi-cell NOMA needs global CSI, centralized learning algorithm may require the BSs to continuously upload their collected data to a centralized processing server, which can lead to a high network overhead and significant delays. Besides, in NOMA, each subcarrier can be occupied by multiple users. In consequence, using a centralized learning algorithm for resource management or network control may need a large number of iterations to converge. Thus, centralized machine learning algorithms such as in [63]–[66] will not be able to handle the resource allocation, signal detection and user behaviour prediction problems in NOMA. For NOMA, FL have two important use cases: 1) FRL can be used to solve complex convex and nonconvex optimization problems that arise in various NOMA use cases such as network control, user clustering, resource management and interference alignment and 2) FSL enables users to collaboratively learn a shared prediction model while remaining their collected data on their devices for user detection and CSI prediction.

1) Resource management in NOMA: With superposition coding at the transmitter and successive interference cancellation (SIC) at the receiver, NOMA can achieve higher spectral efficiency than OMA. Moreover, NOMA can serve multiple users at the same resource (e.g., time/frequency) by exploiting the user differences in the power domain [67], [68]. This power domain feature provides rich opportunities for NOMA to support massive connectivity and meet the users' diverse quality of service.

The spectral efficiency and connectivity optimization of NOMA always leads to nonconvex resource allocation problems, which were solved by conventional algorithms such as successive

convex approximation and matching theory with high complexity and impractical implementation [52]. Therefore, there is a need to introduce new distributed learning techniques that can be used to address a variety of resource management challenges such as distributed power control for multi-cell NOMA [57], joint user association and beamforming design [54], and dynamic user clustering [69]. For multi-cell power control, FRL enables each BS to build the relationship between the power control schemes and utility values so as to find the optimal power control scheme. FRL can also be used to study the user association and beamforming of a multi-antenna NOMA network [70]. Further, the use of FRL for dynamic user clustering in NOMA, where users individually learn the clustering parameters by RL and the BS builds the unified clustering parameters based on the received clustering parameters from all users.

2) Channel estimation and signal detection in NOMA: Channel estimation and signal detection in NOMA is a major challenge due to error propagation in SIC for NOMA networks. FSL algorithms can be used for channel estimation and multi-user detection in downlink NOMA networks, where each user performs a supervised learning (SL) algorithm for channel estimation and signal detection of multiple users due to SIC and send their local federated learning model parameters to the BS that will generate the global FL model. As in [71], FSL can detect multiuser signal in multi-cell uplink NOMA networks via iteratively transmitting individually learning model parameters from all BSs to a server and broadcasting the unified learning model parameters from the server to all BSs. Further, FSL can be used to automatically design the codebook of BSs and decoding strategy of users for code-domain NOMA networks so as to minimize bit error rate [72], where users upload the learned result to the corresponding BSs and the BSs forward their unified learned result to a server.

3) User behaviour prediction in NOMA: Due to the heterogeneous quality-of-service requirement of users in NOMA, where users in the same cluster forming NOMA should have diversified channel gains and quality of service, user behaviour prediction is of great importance for the implementation of NOMA networks. To predict the users behaviors such as mobility patterns, each user in FSL scheme performs a supervised learning algorithm to train the learning model using its own user behavior data and upload the trained model to the BS via NOMA. Then the BS generates and broadcasts the unified learning model parameters to all users by using NOMA. Based on the mobility patter predictions, the users can dynamically choose subchannel to upload data in the uplink, the BS dynamically allocates multiple subchannels to multiple users in the downlink, and multiple users which occupy the same subchannel can perform NOMA. For multiple BSs to predict the quality of service of users [73] in FSL, each BS uses supervised learning algorithm based on its stored information such as users' requested data, gender, job, and device type and all BSs transmit the learning model results to a server via NOMA to get a unified federated learning model.

IV. RESEARCH DIRECTIONS AND CHALLENGES

FL ensures that the resource allocation or behavior prediction problem can be solved in a distributed manner for wireless networks. The utilization of FL for wireless networks has the following five main directions and challenges.

- Convergence analysis: Due to the limited number of resource blocks (RBs) in a wireless network, only a subset of users can be selected to transmit their local FL model parameters to the BS at each learning step. Moreover, since each user has unique training data samples, the BS prefers to include all local user FL models to generate a converged global FL model. Hence, the FL performance and convergence time will be significantly affected by the user selection scheme. Most of the FL convergence proof is established on the assumption that the loss function in convex [74], [75]. However, the loss function of the popular neural network is non-convex. It is a challenge to investigate the convergence rate for FL with non-convex loss function.
- 2. Privacy and security: In FL, the raw data set at each user can be protected since only the local FL model is transmitted to the BS. However, it is also possible for Eavesdropper to reconstruct the raw data approximately, especially when the local and global model parameters are not well protected [76]. Besides, the local FL model may leak private information. In FL, the security can be classified into two categories: global security and local security. Global privacy requires that the model updates generated at each round are private to all untrusted third parties other than the central server, while local privacy further requires that the updates are also private to the server.
- 3. Asynchronous communication: Fl involves the information exchange between wireless devices and the BS. Synchronous communication methods are simple, which introduce stragglers among all devices. Asynchronous schemes are an attractive approach to mitigate stragglers in heterogeneous environments. server. While asynchronous parameter servers

have been successful in distributed data centers, classical bounded-delay assumptions can be unrealistic in federated settings.

- 4. Non-iid device: Challenges arise when training federated models from data that is not identically distributed across devices, both in terms of modeling the data, and in terms of analyzing the convergence behavior of associated training procedures. limited computation capacity at some wireless devices causes delays.
- 5. Joint communication and computation design: To deploy FL in wireless networks, devices are required to transmit their multimedia data or local training results over unreliable wireless links. This exposes the performance of learning and inference to degradation caused by limited radio resources (e.g., power, time and bandwidth). This makes it important to jointly manage communication and computation resources for efficient and robust FL.

V. OPEN PROBLEMS AND FUTURE DIRECTIONS

This section is to discuss open research problems in each one of the covered areas, in order to shed light on future opportunities. Despite a considerable number of studies on FL, there are still many key open problems that must be investigated about FL for wireless communications.

- 1. Convergence: For FL convergence rate, there are still some key problems. For example, there is a need for exact/more accurate convergence formulation with less assumptions and approximations [74], which should consistent with real FL experiment data. Although there are some studies in this area, most of them related to convex loss function. Besides, due to the heterogeneous property of quality of service, it is possible to simultaneously conduct multi-task FL. In addition, for large-scale system, the multi-cell and multi-hop FL should be considered, which require one must have more insights on FL convergence analysis. Moreover, one challenge is to study the mobility of wireless devices for FL convergence. Due to the mobility, the channel gains between devices and BS are dynamically changed and it is possible that some devices will quit the FL process due to serious channel state information, which affects the convergence of the whole FL process.
- 2. Privacy and security: In terms of open problems for privacy and security, there is a need for the following study: privacy protection at each user, privacy protection at the BS, and security for the whole FL algorithm. For privacy protection at each user and the BS, one of the key problem is to study the coding scheme and physical layer security technique.

For security of the whole FL algorithm, there is a need to study the encryption (such as quantum key distribution) and defender.

- 3. Performance evaluation: One of the challenges is to investigate communication bandwidth for FL delay performance. FL on mobile phones relies on wireless communication to collaboratively learn a machine learning model. Although compute resources of mobile phones are becoming increasingly powerful, the bandwidth of wireless communication has not increased as much. As such, the bottleneck is shifted from computation to communication. As a consequence, limited communication bandwidth could incur long communication latency, and thus could significantly slow down the convergence time of the FL process.
- 4. FL for emerging technologies: The interplay between FL and emerging technologies introduces new challenges. For instance, the very high propagation attenuations in THz can affect the convergence analysis. For instance, in satellite communication, FL can used to optimize beam and location of the satellite. For brain-computer, one of the challenge is to use FL extract deep knowledge of the brain's neural network. In quantum communication, there is a need to use FL optimize the parameters (such as base probability) for quantum key distribution.

VI. CONCLUSIONS

In this tutorial, we have provided a comprehensive study on the use of FL for wireless networks. We have investigated two main classifications of FL, namely, FRL and FSL. Besides, we have provided the motivation applications of using FL for wireless communications. Meanwhile, we have described the techniques needed to meet the challenges of using FL for wireless communications. Such an in-depth study on FL for wireless communications provides unique guidelines for optimizing, designing and operating FL-based wireless communication systems.

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