Distributed Learning for Wireless Communications: Methods, Applications and Challenges

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***Abstract*—With its privacy-preserving and decentralized features, distributed learning plays an irreplaceable role in the era of wireless networks with a plethora of smart terminals, an explosion of information volume and increasingly sensitive data privacy issues. There is a tremendous increase in the number of scholars investigating how distributed learning can be employed to emerging wireless network paradigms in the physical layer, media access control layer and network layer. Nonetheless, researches on distributed learning for wireless communications are still in its infancy. In this paper, we review the contemporary technical applications of distributed learning for wireless communications. We first introduce the typical frameworks and algorithms for distributed learning. Examples of applications of distributed learning frameworks in the emerging wireless network paradigms are then provided. Finally, main research directions and challenges of distributed learning for wireless communications are discussed.**

***Index Terms*—Distributed learning, federated learning, wireless communications.**

I. Introduction

With the fast development of smart terminals and emerging new applications (e.g., real-time and interactive services and Internet-of-Things (IoT)), communication data traffic has drastically increased, and current communication networks cannot sufficiently match the quickly rising technical requirements [1]–[3]. As a result, the expectation and development of next generation mobile networks, e.g., the sixth generation mobile networks (6G), have attracted great attention [4]–[7]. Recently, machine learning-based methods have been viewed as a key enabler for 6G, since the key issues behind synchronization, channel estimation, equalization, multiple-input multiple-output (MIMO) signal detection, iterative decoding, and multi-user detection in communication systems can be solved by using carefully designed machine learning algorithms [8]–[10]. In addition to academia and industry, the standardization bodies are considering to include machine learning in future mobile networks [11]. For instance, in Release 16, 3GPP has started to improve the data exposure capability to support data-driven machine learning [12].

To date, most existing machine learning approaches and solutions for communication networks require centralizing the training data and inference processes at a single data center [8], [10]. In other words, the collected data have to be first sent to a center server (or cloud) and analyzed, and then, the results are sent back to the actuators. However, due to privacy constraints and limited communication resources for data transmission in networks, it is impractical for all communication devices that are engaged in learning to transmit all of their collected data to a data center or a cloud that can subsequently use a centralized learning algorithm for data analysis. To elaborate further, the centralized machine learning approaches have inherent disadvantages that limit their practicality, such as significant signaling overhead, increased implementation complexity and high latency in dealing with communication problems [13]–[15]. Moreover, emerging wireless networking paradigms, e.g., cognitive radio networks, industrial control networks, device-to-device (D2D) communications and unmanned aerial vehicle (UAV)-based swarming networks are inherently distributed [16]–[18]. Furthermore, in view of future applications, the centralized approaches may not be suitable for applications that require low latency, such as controlling a self-driving car or sending instructions to a robotic surgeon. For mission-critical tasks, wireless systems must make quick and reliable decisions at the network edge.

To solve this massive scalability challenge while addressing privacy, latency, reliability and bandwidth efficiency, distributed learning frameworks [19]–[23], e.g., federated learning (FL) [24]–[26] and MapReduce [44], are needed, and consequently intelligence must be pushed to the network edge in future communication systems with optimization algorithms, e.g., alternating direction method of multipliers (ADMM) [27], [28] and distributed gradient descend [29]. In these frameworks, communication units/devices/nodes are capable of collaboratively building a shared learning model with training their collected data locally. Considering their potential applications across industry, business, utilities and the public sector, distributed machine learning techniques have attracted significant research attention in communication system design. For example, FL has been proposed to enable users to collaboratively learn a shared prediction model while keeping

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their collected data on their devices for user behavior prediction, user identification, and wireless environment analysis [24]. Similarly, to increase robustness, ADMM is widely considered for large scale distributed learning. Likewise, distributed gradient descend methods are also studied for various potential applications [27], [28].

However, the field of decentralized/distributed machine learning is still at its infancy as there are many open theoretical and practical problems yet to be addressed, such as robustness, privacy, communication costs, convergence, complexity and combinations with physical layer transmission networks [19], [24], [30]. To provide solutions to these challenging problems, it is necessary to take advantage of local and global information including the background information (i.e., the environment knowledge) as well as their locally collected information. Then, advanced signal processing techniques are also required to achieve high robustness, ultra-low latency, massive connectivity, and ultra-high reliability through network/information cooperation.

Several papers have studied distributed learning in wireless communications, but the focus is less consistent. [31] summarizes the technical challenges of distributed learning and existing frameworks and their limitations. Machine learning and communication techniques are also applied to achieve efficient communication. In addition, [32] addresses the challenges in distributed learning in three aspects: learning algorithms, system architecture and network infrastructure, and conducts an experimental study on communication optimization techniques. [44] provides a systematic summary of the algorithms and architecture of distributed machine learning, which focuses on the topology configuration and recovery of wireless networks, power management, wireless resource allocation, quality of service (QoS), and mobile edge computing (MEC).

In addition, there are articles that focus on FL. [40] compares federation learning with other machine learning and presents applications of federation learning in edge computing and spectrum management. [33] presents a distributed learning architecture for 6G and the challenges for the high performance requirements of 6G networks. [36] provides an introduction to the research and progress of federated learning in IoT specifically. [34] classifies the contributions of federated learning in research and industry, establishes a classification of federated learning application domains, and provides a focused analysis of federated learning applications in privacy and resource management. [35] provides the future challenges of federal learning and introduces the potential techniques to address them.

Against this background and to explore whether distributed learning is suitable for wireless communication scenarios, we review the research on distributed learning for wireless communications in recent years. The framework and algorithms of distributed learning and other meritorious variants are provided. Besides, we discuss the potential applications of distributed learning in wireless communications. In particular, we focus our attention on the physical layer, the media access control layer, the network layer, and other novel fields such as blockchain and tensor-based technologies. Then, we also discuss the main future research directions and challenges that distributed learning may face in wireless communication, including communication cost, low-latency communication, security, and robustness.

This paper is organized as follows. Section II reviews the conventional distributed learning architectures, algorithms, and their relevant variants. The potential distributed learning applications in wireless networks and primary future research directions as well as challenges are presented in Sections III and IV. Finally, Section V concludes the paper.

II. Distributed Learning Architectures And Algorithms

Researches on distributed learning have been conducted for more than a decade, during which many frameworks and algorithms have emerged. The vast majority of the research content is based on the FL framework. In this section, we present some typical distributed machine learning architectures and algorithms in the following two subsections, respectively.

A. Distributed Learning Architectures

1) Parameter Server Architecture: The parameter server framework, such as the 3GPP implementation in [37], is a classical architecture in distributed machine learning. It is the most widely used centralized multi-node machine learning approach, consisting of one or several server nodes and other worker nodes. Server nodes and worker nodes can send messages to each other, and the parameter model is shared globally. Worker nodes obtain the model parameters from server nodes, compute parameters (e.g., gradients) with the locally collected data sets, and return them to server nodes. Then, server nodes update the parameter model once by using some optimization algorithms (e.g., stochastic gradient descent (SGD)). This process is repeated until the parametric model converges to a certain precision. It can be seen from the above that the computing cost occurs mainly at worker nodes. Besides, since local data does not leave worker nodes, this framework has a certain degree of privacy protection.

- *Federated Learning:* FL is an emerging distributed machine learning approach, first proposed by Google in [38], which has an extension framework of the parameter server architecture. The difference is that the worker nodes in the parameter server framework belong to the server modes and the computational performance and availability are guaranteed, while the worker nodes in FL are autonomous and their capacity, distribution of data samples and computational performance vary, and the availability is also not stable, which may cause some traditional algorithms such as parallel stochastic gradient descent to be inapplicable in FL.

The sever modes in FL need to aggregate parameters uploaded by worker nodes to update the global parameter model. The learning process of FL has two main phases: the local training phase and the global aggregation phase. Next, we will utilize federated averaging algorithm (FedAvg) to illustrate these two phases [38], [39].

Algorithm 1 Federated Averaging Algorithm (FedAvg).

Input: Number of worker nodes K, number of local training epochs I, number of global aggregation epochs J, learning rate α, global parameter model ω_G, local parameter model ω_t, and the gradient of the loss function $\nabla F(\omega_t)$.

Output: ω_G

Local learning phase:

Step1: The worker nodes get the global parameter model ω_t that the server node has initialized or updated.

Step2: For local training epochs $i = 1, \cdots, I$, the kth device, does $\omega_t^k \leftarrow \omega_t - \alpha \nabla F(\omega_t; k)$.

Global aggregation phase:

For global aggregation epochs $j = 1, \cdots, J$, do

Step1: Randomly select K new devices as worker nodes and send the initialized or updated global parameter model ω_G to the worker nodes.

Step2: $\omega_G = \frac{1}{K}\sum_{k=1}^{K}\omega_t^k$.

Return result

In the local training phase, the server node first acts as a task publisher, selecting K devices in the alternative device sets as working nodes and shielding the other remaining devices. The server node sends the initialized global parameter model ω_0 to each device for training, $\omega_t \leftarrow \omega_0$. The kth device is taken as an example ($k = 1, \ldots, K$), and this device performs several rounds of parameter updates with local data, $\omega_t^k \leftarrow \omega_t - \alpha \nabla F(\omega_t; k)$, where α denotes the learning rate and $\nabla F(\omega_t; k)$ denotes the gradient of the loss function on the kth device. Afterwards, each device returns the updated parameters ω_t^k to the server node.

In the global aggregation phase, the server node aggregates the parameters computed by the local working nodes to perform the global parameter model update, $\omega_G = \frac{1}{K}\sum_{k=1}^{K}\omega_t^k$. The server then reselects the new K devices as worker nodes, and sends the updated global parameter model to each device for a new round of iteration. The whole process is iterated over several rounds until a specific accuracy is met. The learning process of FedAvg is summarized in Algorithm 1.

FL also differs from most traditional distributed learning in several aspects. First, the user at the worker node has control over the local device and data, and the user can control whether the device has sufficient computing power and memory to participate in the training. Second, the devices at the worker nodes are unstable, and they may vary greatly in computational power, battery capacity, and memory overhead. Third, the local data participating in FL are usually non-independent and identically distributed (non-i.i.d), and the data varies in the amount and size from a worker node to another worker node [40]. Last, the communication overhead in FL is usually much larger than the computational overhead.

We then compare the communication loads of centralized learning and FL in Fig. 1. The setup of FL goes as follows: 100 agents are connected to a centralized parameter server to collaboratively learn a general model via the MNIST dataset [38] for digit recognition tasks. 60, 000 training samples are uniformly partitioned over 100 agents, each of which is only viable at one agent. For each communication round, 10 percent of clients are randomly selected to upload updated local FL model. We consider a convolutional neural networks (CNN), consisting of two 5×5 convolutional layers, a fully connected layer and a final softmax output layer. As shown in Fig. 1, FL can significantly reduce the communication loads. Specifically, at the communication rounds of 50, the communication loads of FL is 1/100 of the centralized learning, and at the communication rounds of 250, the communication loads of FL is still less than 1/10 of the centralized learning.

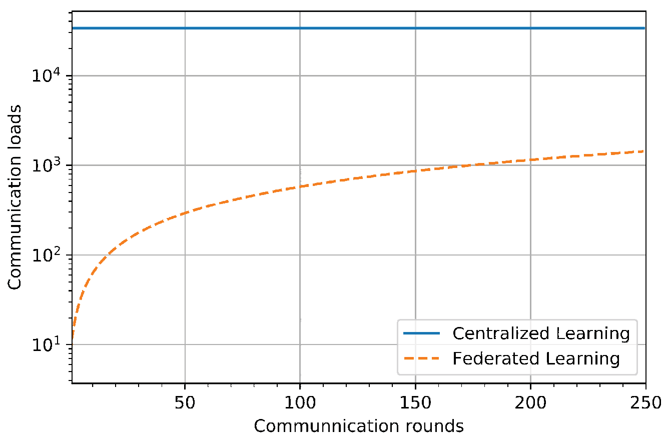

Fig. 1. Communication loads versus communication rounds in centralized learning and federated learning.

- *Federated Learning Based on Fog Learning:* Fog learning is a novel learning framework proposed in [41], which considers the network topology between devices, D2D communication and the collaboration among wired or wireless nodes. Fog learning encapsulates all IoT elements among edge devices to the main server, such as edge computing devices, local area servers, UAVs, cloud servers and core servers, which drives its multi-layer structure. The fog learning first clusters the devices at the bottom layer, which enables parameter or data sharing in the same group network. Second, the upper layer servers are also clustered, and the compute nodes in each server are able to communicate and share parameters via wired, wireless or even various relay devices (e.g., reconfigurable intelligent surfaces, UAVs). The above illustrates that horizontal communication and vertical parameter transfer among nodes is possible.

The learning process of fog learning can be roughly described as follows: the computational nodes in the bottom layer are trained through data and parameter sharing. The updated parameters are uploaded to the nodes in the upper layer, which first perform local aggregation and then upload to the nodes in the higher layer for next local aggregation. Finally, the parameters are sent to the core server node for global aggregation. The D2D communication and local aggregation features of fog learning meet the requirements of contemporary data-intensive and latency-sensitive applications to a certain extent. Besides, the upstream dimensionality reduction also significantly

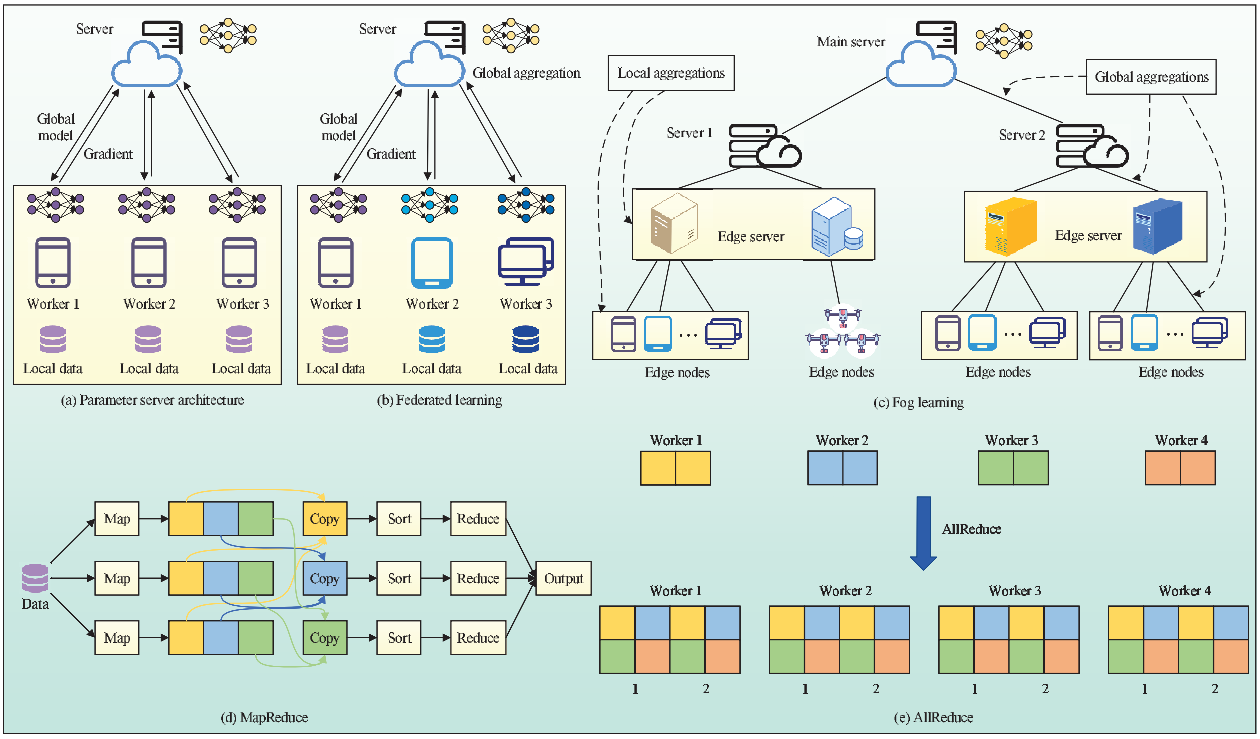

Fig. 2. Distributed learning architectures. The workers of the same color in (a) indicate computing terminals with the same computational power and capacity and the local data of the same color indicate that they are i.i.d. The workers of different colors in (b) indicate computing terminals with different computational power and capacity and the local data of different colors indicate that they are non-i.i.d. Figure (c) shows the multi-layer learning structure of fog learning, where the nodes of the same layer (horizontal) perform local aggregations first, and the lower layer transmits the updated model parameters to the upper layer (vertical) nodes for global aggregations. Figure (d) shows the process of MapReduce architecture. The input data is divided into several blocks, which are then processed to produce intermediate key-value pairs, and the same ones are merged for processing to output the results. Figure (e) shows the process of AllReduce architecture, which reduces data in all worker nodes to a single data blocks and returns all these processed blocks to them.

reduces the transmission traffic and the communication cost between different network layers.

2) Other Distributed Learning Architectures: The above learning frameworks are based on parameter server frameworks, in which all have core server nodes that act as aggregators for centralized learning frameworks. Some of the most adopted decentralized learning frameworks are introduced below, which do not contain core server nodes.

- *MapReduce:* MapReduce is a parallel programming paradigm in which users can perform computations through map or reduce operations [44], [45]. In this framework, the input data is partitioned into several data blocks for parallel computation on multiple worker nodes. The MapReduce model consists of a Map phase and a Reduce phase. In the Map phase, the key-value pairs in the original input data are processed to produce a set of intermediate key-value pairs, and then all the same intermediate key-values are collected for processing in the Reduce phase. Finally, output the processed data.

Although MapReduce is highly scalable, it has a serious weakness in machine learning and does not support iteration. Authors in [46] propose an extension to the MapReduce programming paradigm called iterative MapReduce and developed an optimizer for iterative MapReduce programs covering most machine learning techniques. A distributed real-time optimization method for MapReduce frameworks in emerging cloud platforms supporting dynamic speed scaling capabilities is presented in [47], capable of dynamically scheduling input data of sufficient size and synthesizing intermediate processing results based on the state of the application and the data center, and the proposed method is able to significantly improve throughput. It is shown in [48] how MapReduce parameters affect the distributed processing of machine learning programs that are supported by the Hadoop Mahout and Spark MLlib machine learning libraries. A virtualized cluster is built on Docker Containers and Hadoop parameters such as number of replicas and data block size are changed to measure DML performance.

- *AllReduce:* AllReduce is another paradigm for parallel programming. It mainly deploys an operation to reduce task tensors in all worker nodes to a single tensor block and return these blocks to them. One worker node needs to be selected as a master node to gather all task tensors and perform reduction operations locally and then return the processed tensors to other worker nodes. [49] proposed a synchronous AllReduce SGD algorithm for parameter updating. [50] proposed a communication-efficient asynchronous decentralized parallel SGD (D-PSGD) method to speed up the training speed. The proposed algorithm is also compared with three state-of-the-art decentralized machine learning techniques, Prague, Allreduce-SGD and asynchronous decentralized parallel SGD, which achieve 3.7 times, 3.4 times and 1.9 times speedups, respectively.

However, the bottleneck in the master node may cause costs of communication and reduction operations to surge with the number of worker nodes increases.

Ring-AllReduce is an algorithm that alleviates the above challenge. In Ring-AllReduce model, no master node is selected and each worker node can communicate with the neighbouring nodes. The computation of task tensors is performed through the exchange of those between neighbouring nodes. In each communication between worker nodes, each worker node sends and receives a part of these task tensor. The received task tensor part are added to the corresponding part that are already processed at the node. This process iterates until all tasks have been transferred or processed. [51] studied the D-PSGD algorithm and showed that the decentralized algorithm may outperform the centralized algorithm in distributed stochastic gradient descent. And compared the distributed PSGD algorithm with the CNTK framework implemented with AllReduce, D-PSGD requires less inter-node communication. [52] used the correlation of gradients between nodes to improve the compression efficiency and proposed two examples of gradient compression according to the communication protocol parameter server or Ring-AllReduce, respectively.

- *Other Decentralized Learning Frameworks:* As for other decentralized learning frameworks, they are briefly described below because they are not applied widely in wireless communication. The all-to-all (A2A) architecture in [42] and [43] has no central server, and its nodes use message passing or other similar functions to communicate data among themselves. The previously mentioned learning framework also supports only data parallelism, while the graph processing architecture supports model parallelism. The graph processing-based framework distributes the training data and model parameters among computational nodes within the same cluster, distributing the computational and communication overhead locally [44], [53].

Fig. 2 shows the basic frameworks of the parameter server architecture, FL, fog learning, MapReduce, and AllReduce.

B. Distributed Learning Algorithms

1) Deep Learning: Deep learning (DL) is often used to automatically learn implicit functional relationships or data features between inputs and outputs data, avoiding a lot of manual operations (e.g., modeling complex systems, manually characterizing features). DL is widely used in areas such as voice/image processing, auto-encoders, sparse coding, and sparse channel estimation [54], [55].

A widely used DL method is deep neural network (DNN), which is a neural network with multiple layers, including an input layer, several hidden layers and an output layer. DNNs use the nonlinear processing units between multiple layers of neural networks to perform the computation, using optimization algorithms and back propagation mechanisms to minimize the loss function and obtain the model parameters. The mapping relationship of the feed-forward DNN with L layers can be given by

$$y_L = F_{L-1}(F_{L-2}(\cdots(F_1(y_0; w_1), \cdots); w_{L-2}); w_{L-1}), \quad (1)$$

where y_L is the output vector through L iterations, and w_l and $F_l(r_l; w_l)$ represent the parameter and activation function of the lth layer ($l = 1, \cdots, L$), respectively.

Authors in [56] proposed a fully autonomous power allocation method based on distributed deep learning for cellular network-based IoT D2D communication to achieve higher cell throughput by bringing the power set close to optimization. In [57], an enhanced federation learning technique is proposed with an asynchronous learning strategy on the client side and a time-weighted aggregation of local models on the server. In the asynchronous learning strategy, the different layers of the deep neural network are divided into shallow and deep layers, and the parameters of the deep layers are updated less frequently than the shallow layers. Experimental results show that the proposed asynchronous joint deep learning algorithm outperforms the baseline algorithm in terms of communication overhead and model accuracy. To reduce the communication cost in distributed deep learning, [58] proposed a sparse binary compression framework based on distributed deep learning, combining existing communication delay and gradient sparsification techniques with a new binarization method and optimal weight update coding. In [59], an entropy-based distributed deep learning method for gradient compression is proposed, mainly consisting of an entropy-based threshold selection algorithm and an automatic learning rate correction algorithm. The experimental results show that the method can achieve a gradient compression ratio of about 1000 times while keeping the accuracy constant or even higher compared to existing work.

2) Reinforcement Learning: Reinforcement learning (RL) is a learning algorithm that can cope with dynamic environments and control systems to maximize long-term benefits. It has been widely used in vehicle to everything (V2X) and MEC networks [60]. An intelligent agent takes an action in the initial state to interact with the environment and receives a corresponding reward to move on to the next state until the state with the optimal reward is achieved.

In the case of Q-learning, for example, the intelligent agent interacts with the environment by taking an action a_t at state s_t according to a certain strategy (e.g., ϵ-greedy), and then observes the next state s_{t+1} and gets the reward $r_t(s_t, a_t)$ for state s_{t+1}. As a result, the Q function is updated as

$$\begin{aligned} Q_{t+1}(s_t, a_t) \leftarrow & Q_t(s_t, a_t) + \alpha[r_t(s_t, a_t) \\ & + \gamma max_{a_{t+1}} Q_t(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t)], \end{aligned} \quad (2)$$

where $Q_t(s_t, a_t)$ represents the Q value of state s_t by taking an action a_t, α denotes the learning rate, γ denotes the discount factor and $max_{a_{t+1}} Q_t(s_{t+1}, a_{t+1})$ represents the highest Q value among all actions under state s_{t+1}. This process is repeated until the action of the optimal Q value is obtained.

Q-learning requires computing the Q-values and storing them in a table, which has a very good performance in small-scale models. However, it does not perform well in large-scale models because these practical models often have to compute more than ten thousand states and the speed of learning will have a significant impact on the latency of the system [61]. In this case, deep reinforcement learning (DRL) or deep Q-learning (DQL) is employed to approximate the Q value by using neural networks instead of computing it, which speeds up the data processing and greatly reduces the system latency [62], [63].

In large-scale machine-type communication scenarios, [64] proposed a distributed Q-learning-assisted unauthorized random access scheme to mitigate inter-device conflicts. [65] proposed a novel collaborative distributed Q-learning mechanism for resource-constrained machine-type communication devices to enable them to find unique random access time slots for their transmissions and reduce the possible conflicts. Simulation results show that the proposed learning scheme can significantly reduce random access channel congestion in cellular IoT. [100] proposed an improved distributed Q-learning algorithm to address the optimization of energy efficiency and delay trade-offs in the cellular network underlying energy harvesting device-to-device communication. Simulation results show that the algorithm proposed in the paper can obtain performance comparable to classical centralized reinforcement learning at a faster convergence rate by sacrificing an appropriate tolerable additional signaling overhead.

3) Alternating Direction Method of Multipliers: ADMM decomposes a problem into several parallel sub-problems and orchestrates overall scheduling across them to solve the original problem [66]. In the ADMM algorithm, the "multiplier method" refers to a dual ascending method using the augmented Lagrange function (with quadratic penalty term). Further, the "alternate direction" means that two variables are updated alternately, and the alternating update of two variables is the key reason for the decomposition of the problem.

The optimization problem solved by the ADMM algorithm is as follows:

$$\begin{aligned} &\min f(x) + g(z) \\ &s.t. Ax + Bz = c, \end{aligned} \tag{3}$$

where x and z are variables, $x \in R^n$, $z \in R^m$, $A \in R^{p\times n}$, $B \in R^{p\times m}$, and $c \in R^p$. Assume that both $f(x)$ and $g(z)$ are convex functions. The augmented Lagrangian function can be obtained as follows:

$$\begin{aligned} L_\rho(x,z,y) = f(x) + g(z) + y^T(Ax + Bz - \mathrm{c}) \\ + \tfrac{\rho}{2}\left\| Ax + Bz - c \right\|_2^2, \end{aligned} \tag{4}$$

where y denotes the Lagrangian multiplier vector and $\rho > 0$ is the penalty factor. The iterative process of the ADMM algorithm is described as follows:

$$\begin{cases} x^{k+1} = \arg\min\limits_{x} L_\rho(x, z^k, y^k), \\ z^{k+1} = \arg\min\limits_{z} L_\rho(x^{k+1}, z, y^k), \\ y^{k+1} = y^k + \rho(Ax^{k+1} + Bz^{k+1} - c). \end{cases} \tag{5}$$

In ADMM, the variables x and z are updated in an alternating manner. The advantage of ADMM is that when $f(x)$ and $g(z)$ are separable structures, the update of x and z is decomposed into two steps, so that the task can be assigned to different nodes for processing, enabling a more efficient distributed optimization algorithm.

To solve the large-scale problem, [67] proposed the proximal Jacobian ADMM for parallel and distributed computing with parallel updated variables. In order to reduce the number of communications, the communication-censored linearized ADMM (COLA) was proposed in [68], where the nodes do not communicate directly after each update by the COLA algorithm and have to wait for the communication review. By reviewing the update information of the nodes, if the difference between two iterations is small, the nodes can continue to use the previous iteration values for computation, and communicate only when the difference is sufficiently large. In order to reduce the amount of data transmitted for communication, [69] proposed a quantized ADMM. To solve the problem of working points competing for communication resources in the network, [70] proposed group ADMM (GADMM) that divides the network nodes connected to one line into two groups, head and tail, such that each working point in the head group is connected to other working points through two tail working points. The working points in the head group update their model parameters, and each head working point transmits its updated model to its directly connected tail neighbors. The tail working points update their model parameters to complete an iteration. In this way, each working point (except edge working points) communicates with only two neighbors to update its parameters. With GADMM, only half of the working points, in each round of communication, compete for the limited bandwidth.

4) Other Distributed Algorithms: Apart from the mainstream algorithms described above, there are some other commonly used distributed algorithms.

• *DANE:* A communication efficient distributed approximate Newton (DANE) algorithm is proposed in [71], [72] for solving stochastic optimization and learning problems.The DANE algorithm performs two distributed averaging calculations per iteration. First, the host obtains the global gradient by averaging the local gradients over all machines and sends it to all machines. Then, each machine independently updates the parameters based on the received global gradient and the local optimization problem. Finally, the host receives the local parameters from each machine and obtains the global parameters by averaging over the local parameters.The DANE algorithm converges faster than the gradient descent algorithm and also avoids the disadvantage of high computational complexity due to the need to calculate the inverse of the Hessian matrix by the traditional Newton method.

• *CoCoA:* Authors in [73] proposed the CoCoA framework for distributed computing environments. It is a communication efficient primal-dual framework that successfully exploits convex duality to decompose the global problem into subproblems solved in parallel, then solves the subproblems by local solvers on each machine, and finally uses the primal-dual structure of the global problem to efficiently combine the local updates. Two key CoCoA advantages are communication efficiency and the ability to use off-the-shelf single-machine solvers internally. (1) Sharing information between machines through a highly flexible communication scheme allows for significant reductions in communication in a distributed environment. (2) Allowing the use of arbitrary local solvers in parallel on each machine, which allows the framework to directly merge state-of-the-art, application-specific stand-alone solvers into a distributed setup. The CoCoA method is generalized and improved in [74], making the theoretical convergence rate applicable to both smooth and nonsmooth losses, and giving a more general framework.

III. Applications Of Distributed Learning For Wireless Communications

With the gradual implementation of IoT, the coverage of smart hardware devices further increases, while the

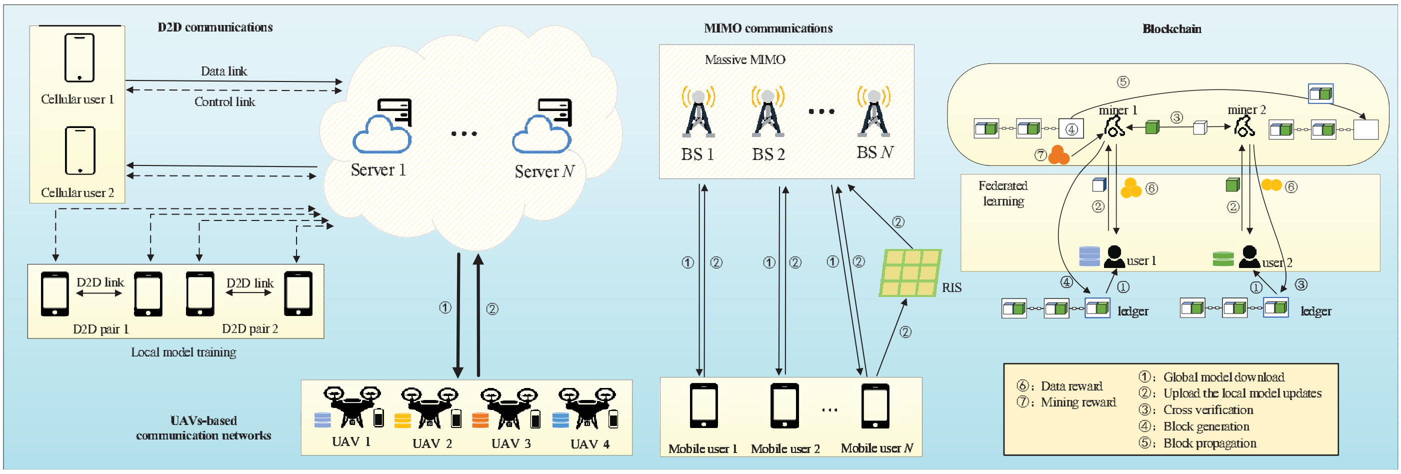

Fig. 3. Applications of distributed learning for wireless communications.

requirements of 5G/6G for low-latency and ultra-reliable communications, and a variety of smart communication scenarios prompt the development of wireless communication forward a distributed architecture. Next, we present the applications of distributed learning frameworks in some potentially novel communication scenarios and show potential application scenarios in Fig. 3 with subsection concentrations in different layers and give a taxonomy of those applications in Fig. 4.

A. Physical Layer

1) MIMO Communications: The large-scale MIMO technology has a broad prospect as an important direction of 5G development, and plays an important role in the improvement of communication capacity and coverage. For the deep learning problem in large-scale MIMO technology, a distributed approach can be used to deal with it effectively.

As in [75], a new cell-free large-scale multiple-input multiple-output (CFm-MIMO) network scheme is proposed to support the FL framework. It is also shown how the performance of FL can be improved based on minimizing the training time, and the effects of local accuracy and user processing frequency, etc. on the effective training time are analyzed. In [76], the distributed algorithm is then used to find the gradient estimation in large-scale MIMO. A central server equipped with a large number of antennas has to work collaboratively with multiple wireless devices, and the central processor has to accurately estimate the gradient vectors from the wireless devices. The new gradient estimation algorithm proposed in the paper, which exploits the sparsity of the local gradient vectors, has been validated on the MINIST dataset and its performance is very close to that of the centralized algorithm. On the other hand, it reduces the computational complexity by more than 70% compared to the linear minimum mean squared error (LMMSE) method. Also distributed algorithms can be applied to solve dynamic resource allocation problems in multi-cell MIMO, and in [77] the authors use algorithms for collaborative deep learning and game theory to train the base stations and master their reconciliation strategies. The algorithm automatically optimizes the spectrum allocation of all base station users and later translates into a power allocation problem. All base stations obtain the optimal system capacity by iterating their power allocation until convergence to the equilibrium state.

2) Communications with Reconfigurable Intelligent Surfaces: The propagation of electromagnetic waves is largely uncontrollable due to scattering and bypassing in complex environments. Reconfigurable intelligent surface (RIS/IRS) is a general term for a class of special surfaces that can change the propagation characteristics of incident signals [78]. RIS consists of a large number of passive units, and by adjusting the parameters and positions of the structural units on the surface, the incident signals can be changed in amplitude and phase to enhance the useful signal quality and improve the system. The combination of RIS and FL can protect users' privacy while improving spectrum utilization. [79] applies both RIS and FL in smart IoT. [80] and [81] use RIS to reduce the dropout problem in over-the-air FL, and [82] employs RIS to achieve over-the-air model aggregation without channel state information at the transmitters in a joint edge learning system. To achieve more access and increase the throughput, [83] uses RIS to combine over-the-air FL and non-orthogonal multiple access (NOMA) in a single framework. Although the FL does not directly transmit raw data, the local model transmitted by each edge device reflects the information about the local data to certain extent. To further protect data privacy, [84] introduces differential privacy in the RIS-assisted wireless FL system. In addition, [85] utilizes RIS and FL-assisted millimeter-wave channel estimation to maximize the reachable rate of the received signal for high-speed communication by training the optimal model through FL and establishing a mapping function between the channel state information (CSI) and the RIS configuration matrix.

B. Media Access Control Layer

Since the physical layer performs bitstream transmission and cannot perform error control, measures to ensure reliable transmission have to be implemented at the media access control layer. To ensure reliable transmission, one of the most important aspects is to optimize channel allocation to ensure transmission quality, reduce transmission conflicts, and maximize spectrum efficiency.

In distributed systems, a large number of edge users and central processors work in coordination for information transmission. To prevent mutual interference or interference to other users, dynamic spectrum access techniques are often used for effective transmission while improving spectrum utilization efficiency. A distributed adaptive learning and access strategy is proposed in [86]. Each user learns to dynamically adjust the channel selection among users to avoid collisions from its own historical access to the communication, the channel availability and the collision situation of all users in the network . Finally, the channel selection problem is transformed into a non-cooperative policy game problem. The resulting algorithm is valid for a variety of average availability distributions across primary channels. The multi-carrier dynamic spectrum access cross-layer technique with adaptive power allocation proposed in [87] decomposes the spectrum and power allocation problem into two sub-problems to be solved separately. In the first stage, the spectrum allocation problem is solved by a learning approach. In the second stage, the power allocation problem is solved by a conventional optimization solver. In [88], the dynamic spectrum access method under high dynamic interference scenarios is analyzed, and a distributed multi-intelligence strategy is proposed, where all nodes can effectively predict and avoid dynamic interference and reduce collision conflicts.

For different application scenarios, different channel allocation methods can be targeted. For example, [89] proposes a distributed Q-learning algorithm to mitigate the collision problem of channel random selection in massive machine type of communication (mMTC) scenarios. The effectiveness of the algorithm is demonstrated by the access success probability. In [90], a cellular spectrum sharing scenario is considered and a dynamic access mechanism for distributed mobile network operators (MNOs) sharing cellular frequency bands is proposed. Simulation results show that the scheme not only improves the throughput, but also ensures fairness for operators. There are also relatively novel approaches to study channel allocation, such as in [91], which combines the advantages of traditional graph models and physical models by building a hypergraph interference model for analysis. The channel allocation problem is transformed into a local altruistic game problem, and the simulation results show demonstrate the spectrum efficiency can be significantly improved.

C. Network Layer

1) Device-to-Device Communications: Agents in distributed learning systems are usually connected in a star topology, e.g., in a main working architecture, or in a D2D topology. The D2D technology aims to allow two user nodes to play the roles of both server and client and communicate directly to reduce the pressure of communication interference in the cell [92], [93]. At present, terminal devices are becoming more intelligent and have stronger computing power, based on which the development of D2D has a good prospect.

Distributed algorithms are often used to solve problems such as resource allocation in D2D. A distributed channel allocation scheme for end-to-end communications is proposed in [94], which transforms the channel allocation problem into a local altruistic game by hypergraph modeling and finds its optimal pure policy Nash equilibrium. This distributed algorithm significantly improves the spectral efficiency [95]. In [96], a binary log-linear learning algorithm (BLLA) is proposed considering D2D wireless network resource allocation under the noisy-potential games framework. As in [94], it also finally converges to the optimal Nash equilibrium problem of finding the resource allocation game.

Rational allocation of communication resources by distributed algorithms can effectively reduce transmission power and maximize throughput. For example, in [97], the resource allocation problem for distributed two-dimensional communication in heterogeneous networks is considered to reduce the total transmission power based on the original one. In [98], the channel and power allocation problem is solved using distributed federation. A fully autonomous power allocation method based on distributed learning for IoT D2D communications is proposed in [99], which is pervasive in ensuring that every D2D communication device can use the same model after the training is completed in addition to improving the capacity. In addition to pure resource allocation performance optimization, some distributed algorithms applied to D2D also consider the balance between resource allocation rationality and delay is [100], [101]. Further, in [102], the distributed learning is used to predict the quality of service of D2D and the interference it generates, the optimal communication policy selection from the network perspective, etc.

2) Unmanned Aerial Vehicle Communication Networks: UAV communication networks are widely considered for military and civilian applications, industry data transmission, anti-jamming, surveillance and reconnaissance. Due to the high mobility and flexibility of UAVs, communication service facilities can be rapidly deployed by UAVs, making UAV-assisted communication systems outstandingly advantageous in many application scenarios. [103] investigates FL-assisted multi-UAV networks for scene image classification tasks. The large amount of data generated by the drone devices requires high network bandwidth for transmission to the server, consuming the energy of the drone. Second, the generated data may contain private data such as location. To protect the privacy of the data, a distributed learning solution is used to efficiently process the datasets generated by the UAV devices.

The learning convergence of the UAV swarm is affected by the wireless channel because the updates of the learning model are transmitted through the wireless network. In [104], the influence of wireless factors on the FL convergence is investigated, which is optimized by jointly designing the power allocation and scheduling of the UAV network.

In order to provide energy-efficient UAV-based communication network services, UAVs need to be deployed in suitable locations to guarantee transmission efficiency. In [105], UAVs are investigated to be deployed as wireless powered users to achieve sustainable FL-based wireless networks. The UAV transmission power efficiency is maximized through joint optimization of transmission time and bandwidth allocation, power control, and UAV layout.

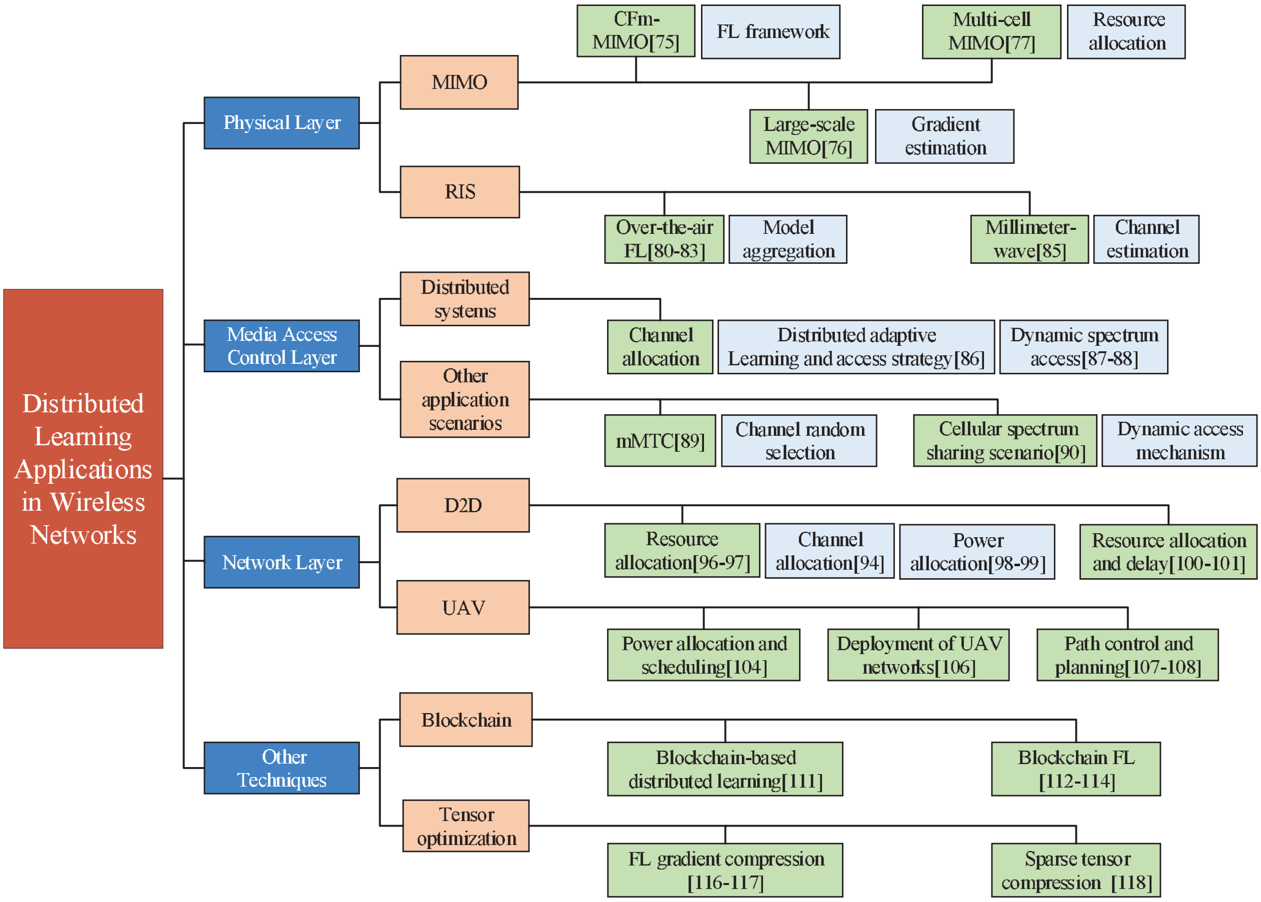

Fig. 4. Taxonomy of applications of distributed learning for wireless communications in each network layer.

However, UAVs deployed as airborne base stations for wireless communication with ground users may compete for limited RF resources and cause interference to ground equipment. In addition, the limited energy of UAVs hinders the applicability of UAVs that use RF to provide high data rate communication. In [106], the deployment of UAV networks based on visible light communication is investigated. The authors proposed a FL framework based on a convolutional autoencoder machine learning algorithm to predict the light distribution across the service area and determine the optimal UAV deployment that minimizes the total UAV transmit power.

Real-time control of UAVs helps to accomplish the mission when responding to critical tasks such as disaster scenes and rescue missions; moreover, real-time control of UAV positions is required to reduce collisions between UAVs. [107] investigates online path control of large-scale UAVs for efficient communication and proposed a mean field game strategy based on FL to reduce communication costs. [108] studies the radio mapping and path planning problem for cellular connected UAV networks and proposes a fast search random tree based path planning algorithm. [109] introduces a framework based on decentralized DRL to navigate each UAV in a distributed manner to provide long-term communication coverage for ground mobile users.

D. Other Techniques with Distributed Learning in Communication Networks

1) Blockchain Based Distributed Learning: Blockchain is a new application model of distributed data storage, peer-to-peer transmission, consensus mechanism, encryption algorithms and other computer technologies, which is essentially a decentralized database [110]. In order to secure large-scale intelligent applications, researchers use blockchain-based distributed machine learning as a solution.

Due to the slow convergence speed of distributed learning optimization solution algorithms, high requirements for computational and memory resources, and training difficulties, [111] investigates blockchain-based distributed learning and proposes a distributed computing framework for the limited-memory BFGS algorithm (a method to solve unconstrained nonlinear programming problems) based on variance reduction to speed up the convergence process by reducing the variance of gradient estimation during stochastic iterations.

FL is implemented through a central server that aggregates all local model updates to produce a global model update. Each device then downloads the global model update and computes its next local model update until the global model training is complete. FL relies on a single central server, and a server failure can result in inaccurate global model updates, thus making all local model updates incorrect. Second, it does not reward local devices that contribute more to the global training, such that devices with more data samples are less willing to train with devices with fewer data samples. [112] and [113] propose a blockchain FL (BlockFL) architecture where the blockchain network is able to exchange and verify local model updates of devices while providing corresponding rewards. BlockFL overcomes the single point of failure problem and facilitates training among more devices.

Traditional blockchain consensus mechanisms such as proof of work can cause great resource consumption and greatly reduce the efficiency of FL. In order to solve the device asynchronous and anomaly detection problems in FL, while avoiding the extra resource consumption caused by blockchain, [114] proposes a framework for enhancing FL in blockchain systems based on direct acyclic graph (DAG-FL). The DAG-FL can well satisfy the asynchronous nature of devices and allow nodes to participate in FL iterations without considering the state of other nodes. At the same time, the workload of model validation is distributed to each node in DAG-FL, enabling anomaly detection and immunity to anomalous nodes.

2) Tensor Optimization Based Distributed Learning: FL requires exchange of model parameters between nodes at each model update, which requires significant communication costs. To reduce the size of the transmitted model parameters, tensor decomposition is an effective approach that uses low-rank representations to approximate the high-dimensional model parameters and significantly reduces these parameters without losing classification accuracy [115]. For example, [116] proposes a FL gradient compression algorithm based on the tensor-train decomposition. In the framework of edge computing, [117] introduces a distributed hierarchical tensor deep computation model for FL, which compresses the model parameters from a high-dimensional tensor space to a set of low-dimensional subspaces to reduce the bandwidth consumption and energy consumption of FL. In addition, [118] proposes a sparse tensor compression communication framework applicable to distributed DNN training.

IV. Research Directions And Challenges Of Distributed Learning For Wireless Communications

Although distributed learning is not a new technology and has been researched for many years, there is still a long way to practical implementation. In this section, we discuss the primary future research directions and their challenging issues in distributed learning for wireless communications, which is summarized in Fig. 5.

A. Communication Cost

Distributed learning relies on frequent communication between working nodes to exchange parameters to complete training. The high communication cost is a serious bottleneck due to uplink bandwidth limitations and slow, unreliable network connections between the worker nodes and the central server. There are generally two ways to reduce the communication overhead during model training: reducing the traffic and the frequency of communication.

1) Reduce the Traffic of Communication: Gradient compression is an effective method to reduce the communication content without changing the model structure and communication process. Gradient compression reduces the amount of data to be transmitted by gradient quantization or gradient sparsification. Gradient quantization, where each gradient value is represented using fewer bits, reduces the bit width of the gradient. For example, [119] proposes a federally trained ternary quantization (FTTQ) algorithm, which optimizes the quantization network at the working point by a self-learning quantization factor. [120] uses Grassmannian codebooks for quantization of high-dimensional stochastic gradient vectors. On the other hand, in gradient sparsification, gradient sparsification then selectively transmits gradients according to a specific threshold, reducing the number of gradients that need to be transmitted. For example, [121] and [122] propose the general gradient sparsification (GGS) adaptive optimization framework. The sparse binary compression (SBC) framework is proposed in [123], and the sparse ternary compression (STC) framework for FL is proposed in [124], while compressing upstream and downstream communication. Gradient sparsification can achieve a higher compression rate than gradient quantization, but it can seriously affect the convergence and accuracy of the model. The standard deviation-based adaptive gradient compression (SDAGC) method is proposed in [125], which can achieve higher model performance in simultaneous training.

A FL alternative framework to reduce the communication overhead, called federal distillation (FD), has been recently proposed, which only requires devices to exchange the average model output. A wireless protocol for FD and its enhanced version are studied in [130]. Moreover, FD can be applied simultaneously with other techniques, and [131] introduces a two-step joint learning framework, robust federated augmentation and distillation (RFA-RFD), which improves communication efficiency while preserving data privacy and resisting Byzantine devices.

2) Reduce the Frequency of Communication: One way to reduce the number of communications is to increase the convergence speed of the training algorithm, for example, by decentralized gradient descent (DGD) [133], momentum gradient descent (MGD) [134], overlap local-SGD [135], decentralized ADMM [136], asynchronous decentralized consensus ADMM [137] and proximal Jacobian ADMM [67]. There are also some studies that incorporate the censorship idea in distributed learning, where workers transmit only highly informative updates and eliminate unnecessary communication. If the difference between the worker's two transmitted gradients is small, the communication is skipped and the server reuses the previously sent but still accurate gradients. [126] investigates an orthogonal approach that identifies irrelevant updates made by the worker and prevents them from being uploaded based on the feedback provided by the server about the model updates. Censorship in distributed learning reduces communication, but some useful information may be lost. [127] studies an ordered gradient method that uses sorting to eliminate some of the worker-to-server upstream communication typically required in gradient descent methods. [128] and [129] study gradient coding to reduce communication costs while being able to reduce the latency caused by slow-running machines. In particular, [132] applies the two-stream model commonly used in migration learning and domain adaptation to FL, using a two-stream model

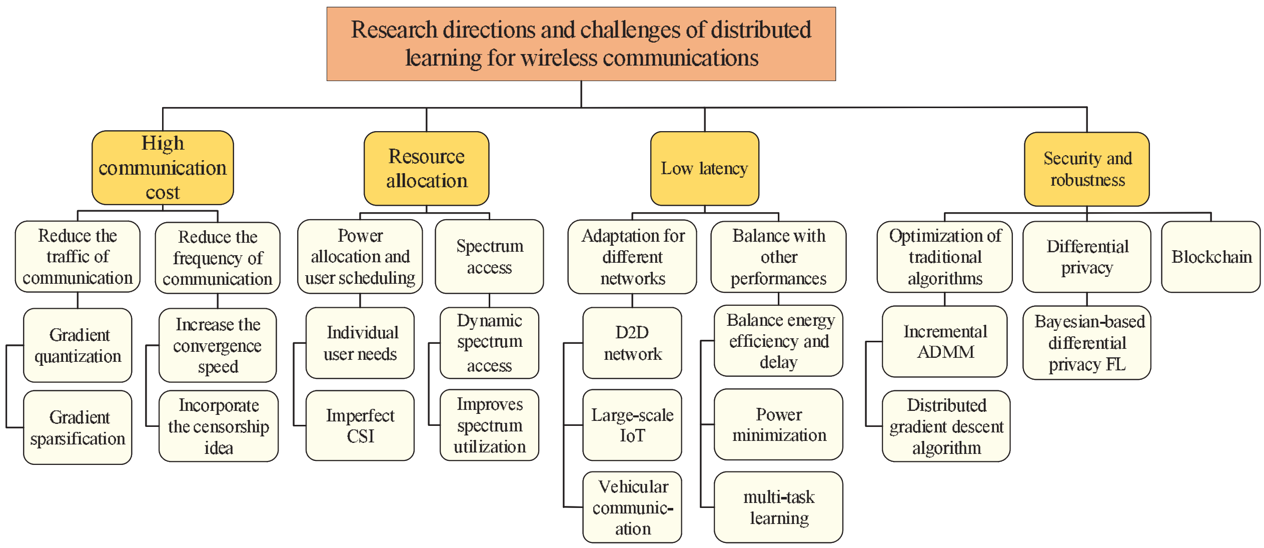

Fig. 5. Future research directions and challenges of distributed learning for wireless communications.

trained on each client instead of a single model, and introduces a maximum mean deviation constraint to the training iterations of federation learning, forcing the local two-stream model to learn more from other devices, thus reducing the number of communications.

B. Resource Allocation

The massive access to mobile devices and the growing demand for wireless services have brought about an explosion of data traffic and mobile connections, resulting in a tighter supply of wireless spectrum resources. A reasonable and effective resource allocation strategy can effectively reduce interference and improve data transmission rate [138], [139].

In [140], user scheduling and power allocation schemes in FL uplink communication in wireless fading channels are studied to maximize the data rate by using NOMA as the transmission scheme in the FL model update. In addition to data rate as the optimization objective, common optimization objectives include reducing power consumption, increasing throughput, and reducing mean squared error (MSE). [141] proposes a fully autonomous power allocation method for D2D communication in cellular networks based on distributed deep learning to maximize the total throughput of D2D links. [142] studies the optimal power control problem during wireless channel fading to minimize the model aggregation error of MSE measurements by jointly optimizing the transmit power of each device and the denoising factor of the edge server. In [143], the distributed joint channel and power allocation problem based on D2D communication networks is studied using a game-theoretic learning approach. The joint channel and power allocation problem is described as a multi-intelligent learning problem with discrete policy sets, and a fully distributed learning algorithm is proposed to determine the channel metrics and power levels used by each device pair. In [144], distributed learning-based adaptive power allocation for multi-carrier dynamic spectrum access across layers is investigated, allowing dynamic spectrum access (DSA) users to efficiently locate and exploit unused spectrum opportunities. In [145], the problem of distributed power allocation for edge users in decentralized wireless networks based on FL framework is studied, and a joint learning framework algorithm based on cooperation and augmentation (FL-CA) is proposed. Each edge device obtains the power allocation policy locally by training a local actor-critic model, and then periodically uploads the gradients and weights generated by the actor network to the base station for information aggregation.

Due to the unbalanced data distribution in distributed learning, the complex environment in real application scenarios and the individual needs of users, the data size of each user's computational task varies over time and the resource allocation scheme needs to be dynamically adjusted to meet the users' needs. In [146], a support vector machine-based joint learning approach is proposed for cellular networks with MEC capabilities to actively determine user associations. Given a user association, the base station can collect information related to the computational tasks of its associated users, and utilize this information to optimize the transmit power and task allocation for each user while minimizing the energy consumption of each user. To address the dynamic malicious interference problem in communication networks, [147] proposes a distributed multi-intelligent spectrum access strategy without interactive communication overhead; it employs a simplified Q-reinforcement learning algorithm to mitigate spectrum conflicts among nodes.

Due to the dramatic growth in the number of mobile devices and the unbalanced data distribution in distributed learning, further research on the dynamic allocation of resources in wireless communication networks is needed to propose a power allocation scheme that better meets individual user needs and further improves spectrum utilization. The computational capacity and energy consumption of each terminal device in distributed learning are different, and the required energy is also different. A reasonable design of power allocation ratio based on the different residual energy of terminal devices can further improve energy utilization and avoid wasting resources. In distributed learning, a large number of devices are non-stationary, the wireless channel state between devices and the central server is often uncertain, and accurate CSI is often difficult to obtain. Further research on the power allocation scheme under imperfect CSI is thus required.

C. Low-Latency Communications

Ultra-reliable and low-latency communication is one of the three major directions of 5G application scenarios defined by 3GPP. In the envisioned future applications of B5G/6G, some virtual reality scenarios require sufficiently low latency to ensure user experience, while in the case of autonomous driving, remote control, etc., latency is directly related to the system implementation and safety factor.

One advantage of distributed systems is that multiple computers are interconnected, which can dynamically distribute tasks and improve the speed of task execution. However, how to cope with different scenarios or communication needs, coordinate the task interaction between the central processor and the end devices, and find the algorithm to achieve the best performance remains an important research direction. For example, [148] optimizes data sharing and radio resource allocation for a D2D-enabled network model, with good convergence for non-independent and homogeneously distributed data samples and reduced iterative training delays. A distributed learning framework is proposed in [149] for low-latency model communication in large-scale IoT, and the effectiveness of the learning algorithm is analyzed in IoT networks with different latency targets.

The low-latency performance of the algorithm is also affected by other conditions such as computational accuracy, energy efficiency, user capacity, and power. The latency problem has to make a balance with these conditions to meet different requirements for different scenarios. In this regard, the power minimization problem for distributed FL for vehicular communication while ensuring low-latency and high reliability for probabilistic queue length is studied in [150]. An improved distributed algorithm is used in [100] to compute the balance problem of energy efficiency and delay in D2D, which improves the convergence speed. Also in [151], the corresponding low-latency problem for joint multi-task learning in MEC networks is presented, and the effects of the number of participants, edge node capacity, local accuracy, and energy threshold on low-latency are considered.

D. Security and Robustness

With the rapid growth of the Internet, the scale of data transfer has expanded dramatically, but the ensuing issues regarding data security and privacy have received widespread attention. Effective privacy protection against single points of failure has been achieved by using a blockchain-enabled FL approach, such as the use of a fog server to interact with and update end devices in [152]. In [153], the reliability of task execution is improved by setting up reputation screening of reliable computing endpoints and effective reputation management by setting up a blockchain. Privacy can also be protected by optimizing the algorithm. The ADMM algorithm is commonly used to solve distributed convex optimization problems, and the incremental ADMM algorithm proposed in [154], is an improvement of the traditional ADMM method. Random initialization and step perturbation are used to communicate efficiently while maintaining privacy.

Messages from distributed staffs are prone to errors due to hardware failures or software errors, computational errors, data corruption and network transmission problems. There are even malicious attacks on the system by unreliable distributed workers who actively send erroneous and malicious messages to the master server. Among these interference models considered, the most important one is the Byzantine threat model. In this model, computing nodes can act arbitrarily and maliciously. Therefore, it is important to study distributed algorithms with good capability to deal with Byzantine attacks. Several papers investigated this aspect, such as [155] which considers a total variation canonical penalty approximation formula to deal with Byzantine attacks, and a specially structured ADMM proposed with fault tolerance to cope with Byzantine attacks at the same iterative computational cost as the random subgradient method. A distributed gradient descent algorithm proposed in [156] performs a simple thresholding based on the gradient parametrization to mitigate the failure of blocking Byzantine style. A two-step learning framework is proposed in [157] that generates independent same-distribution datasets at edge devices and only requires uploading local model output information, reducing private data uploads and achieving robustness to Byzantine attacks.

Differential privacy is also a way to improve data security. The most common method of distributed algorithms based on differential privacy is to add a certain amount of noise in the transmission of data from the client to the central server, with the aim of making it difficult for an attacker to find the private information of a single endpoint. For example, typically there are Bayesian-based differential privacy FL algorithms [158]. A differential privacy-based non-coding transmission scheme that does not affect the learning performance under privacy constraints below a certain threshold is studied in [159]. Both [160] and [161] are also studies of distributed algorithms based on differential privacy. A theoretical analysis of the tradeoff between privacy and convergence performance during algorithm training is presented in [160]. In [161], on the other hand, the tradeoff between communication efficiency and privacy performance is analyzed, and the impact of multiple medium design parameters on communication efficiency is pointed out.

Although has been conducted, research on improving the security and privacy distributed algorithms with higher attack tolerance and lower computational cost is still required, which is an important future direction for research.

V. Conclusion

In this paper, we have provided an overview of distributed learning techniques in wireless communications. We have presented typical distributed learning frameworks and algorithms that lay the foundation for subsequent application discussions. We have highlighted promising applications of distributed learning in emerging wireless communication scenarios in the physical layer, media access control layer and network layer. We have also highlighted the primary future research directions of distributed learning techniques in wireless communications and their challenges in recent years.

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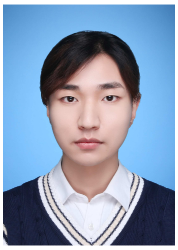

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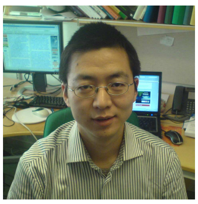

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